Application of Hybrid SST Algorithm to the Seas around Korea using COMS MI Data

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Abstract

In this study, we applied the hybrid algorithm to estimate sea surface temperature (SST) from the Korean geostationary satellite, Communication, Ocean and Meteorological Satellite (COMS) Meteorological Imager (MI) data in the seas around Korea. SSTs estimated by the hybrid algorithm and a previous empirical regression method were validated by the comparison of *in-situ* temperatures in the Northwest Pacific Ocean (10 − 60°N, 100 – 180°E) for the period of May 2014. As a result, the hybrid SSTs showed a higher accuracy of a small root-mean-square error (RMSE) (~0.45°C) than that of the empirically-derived SSTs (~0.84°C) with *in-situ* SST measurements. The hybrid SSTs significantly reduced large biases from *in-situ* measurements in the Northwest Pacific. The hybrid SSTs presented much higher accuracy, especially in nighttime than daytime. As the nighttime RMSE compared with *in-situ* SST was improved from 0.88°C to 0.38°C. In particular, considerable improvement of hybrid SSTs was detected at pixels near thin clouds or cloud edges as compared with the empirical regression method. Differences between hybrid SST and regression SST tended to be larger as closer to a cloudy pixel.

Introduction

For several decades, many researchers have retrieved the SST using the empirical regression method such as Multi-Channel SST (MCSST) and Non-Linear SST (NLSST). Recently, the fast RTM enables us to obtain near real-time atmospheric simulations of clear-sky Brightness Temperatures (BTs) using the atmospheric variable inputs, which can be used to retrieve SST. Ignatov et al. (2010) and Petrenko et al. (2011) suggested the concept of hybrid SST by using real-time RTM simulation. This method is a kind of mixture of the traditional empirical regression method and the RTM inversion method.

Objectives

(1) to produce a matchup database between COMS/MI data and *in-situ* temperature measurements in the Northwest Pacific Ocean
(2) to retrieve empirical coefficients of linear and non-linear multi-channel SST algorithms
(3) to apply a hybrid algorithm to estimate SST coefficients
(4) to compare the two SSTs from the hybrid algorithm and the empirical algorithm
(5) to estimate the statistics of the errors

Data

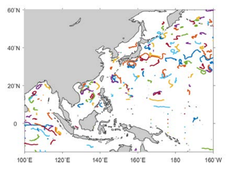
Satellite Data

- COMS MI L1B and L2 Data
- Period : May 2014 (1 month)
- Area : 10 − 60°N, 100 − 180°E

Data		Spatial Resolution	Temporal Resolution
COMS MI L1B and L2 Data	Ch4 (10.3-11.3 ㎛) Brightness Temperature	4 km	6 hr [15 min*]
	Ch5 (11.5-12.5 ㎛) Brightness Temperature		
	Cloud Mask		
	Fog Mask		
	Sea Ice Mask		
	Land/Sea Mask	4 km	-

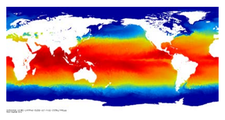
In-situ Data

- GTS Data
- 20,000-30,000 each day, real-time



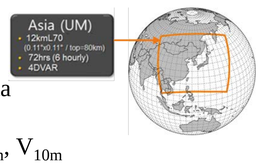
First-Guess SST Data

- OSTIA data
- Daily composite SST
- Spatial resolution : 0.05°



NWP Data

- United Model (UM) data
- T, p, q vertical profiles
- p_{sfc}, T_{skin}, T_{2m}, q_{2m}, U_{10m}, V_{10m}



Method

SST Retrieval Algorithm

Empirical Regression SST Algorithm

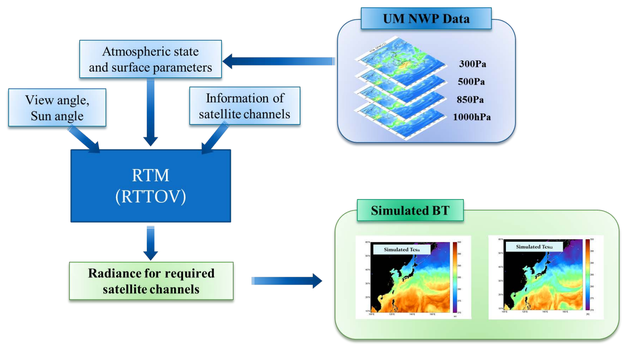
Reading Data
- T_{IS} : in-situ SST (e.g., Drifter SST)
- T_{FG} : first-guess SST (e.g., MCSST)
- $T_{11,12}$: *in-situ* 11 and 12 ㎛ brightness temperature (e.g., COMS MI BT)

Regression
- $T_S = a_0 + \vec{a}^T \vec{Y}$
- $\vec{Y} = [T_{11},\ T_{FG}\ (T_{11} - T_{12}), (T_{11} - T_{12})(sec\theta - 1)]^T$
- i.e., $T_S^{ER} = a_0 + a_1\,(T_{11}) + a_2\,T_{FG}\,(T_{11} - T_{12}) + a_3(T_{11} - T_{12})(sec\theta - 1)$

Empirical Regression SST

T_s : estimated SST
a_0 , $\vec{a}$: regression coefficients
$\vec{Y}$: vector of regressors
θ : satellite zenith angle

Simulation of Clear-sky BT



Hybrid SST Algorithm

Reading Data
- T_{IS} : in-situ SST (e.g., Drifter SST)
- T_{FG} : first-guess SST (e.g., OSTIA SST)
- $T_{11,12}$: *in-situ* 11 and 12 ㎛ brightness temperature (e.g., COMS MI BT)
- $T_{CS11,12}$: first-guess clear-sky 11 and 12 ㎛ brightness temperature (from **RTM** (e.g., RTTOV))

Regression
- $T_{IS} = T_{FG} + \boldsymbol{b}_{LS0} + \vec{\boldsymbol{b}}_{LS}^{T}\,(\vec{Y} - \vec{Y}^0)$
- $\vec{Y}^0 = [T_{CS11},\ T_{FG}\,(T_{CS11} - T_{CS12}), (T_{CS11} - T_{CS12})(sec\theta - 1)]^T$
- i.e., $T_S^{HLS} = T_{FG} + b_0 + b_1\,(T_{11} - T_{CS11}) + b_2\,T_{FG}\,((T_{11} - T_{CS11}) - (T_{12} - T_{CS12})) + b_3((T_{11} - T_{CS11}) - (T_{12} - T_{CS12}))(sec\theta - 1)$

Least Square Hybrid Coefficients

T_s : estimated SST
T_{FG}: first-guess SST
b_{LS0}, $\vec{b}_{LS}$: least square hybrid coefficients
$\vec{Y}$, $\vec{Y}^0$: vector of regressors (Sat BT, Sim BT)
θ : satellite zenith angle

Scaling Coefficient
- $\sigma_{ER} = std\ \{T_S^{ER} - T_{FG}\}$
- $\sigma_{HLS} = std\ \{T_S^{HLS} - T_{FG}\}$
- To equalize σ_{ER} and σ_{HLS}
- $\vec{\boldsymbol{b}}' = (\sigma_{ER}/\sigma_{HLS})\,\vec{\boldsymbol{b}}_{LS}$
- $b_0' = mean\,(T_{IS} - T_{FG}) - \vec{\boldsymbol{b}}'^{T}\{mean\,(\vec{Y} - \vec{Y}^0)\}$
- i.e., $T_S^H = T_{FG} + b_0' + b_1'\,(T_{11} - T_{CS11}) + b_2'\,T_{FG}\,((T_{11} - T_{CS11}) - (T_{12} - T_{CS12})) + b_3'((T_{11} - T_{CS11}) - (T_{12} - T_{CS12}))(sec\theta - 1)$

Hybrid SST

T_S^{HLS} : least square hybrid SST
σ_{ER} : standard deviation of non − local component of T_S^{ER}
σ_{HLS} : standard deviation of T_S^{HLS}
b_{LS} : least square hybrid coefficients
$\vec{b}'$: (final) hybrid coefficients

[Petrenko et al., 2011]

Matchup Procedure

- Temporal interval : within 30 minutes
- Spatial criteria : 4 km (pixel size of COMS MI image)

Collocations between COMS and *In-situ* Data

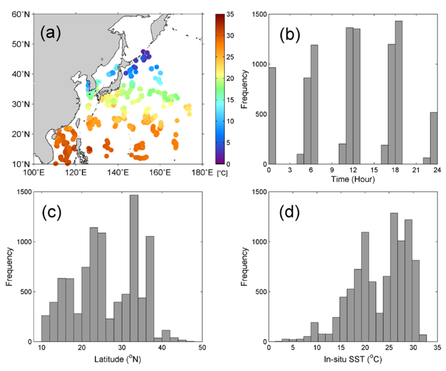


Fig. (a) Sea surface temperatures (°C) at matchup points between COMS data and *in-situ* temperatures, histograms of the matchup temperatures with respect to (b) hour, (c) latitude(°N), and (d) *in-situ* temperature in the northwest Pacific Ocean.

Simulated Clear-sky BT

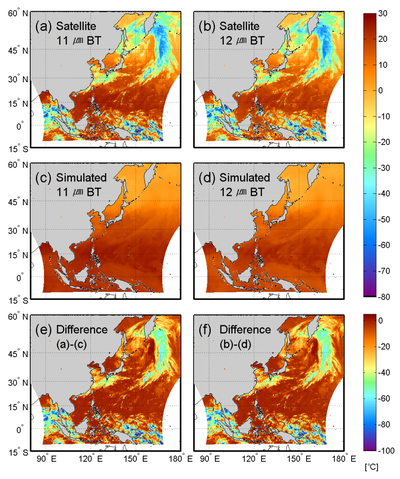


Fig. Example of satellite-observed (a) 11- and (b) 12-㎛ BTs and RTM-simulated (c) 11- and (d) 12-㎛ clear-sky BTs at 12 UTC on May 12th 2014. BT difference (observed BT – simulated BT) for (e) 11- and (f) 12-㎛.

Most of high differences between the two appear over the cloud pixels and near the edge of clouds. The BT differences of cloudy pixels were distributed over a wide range of −110°C to 10°C, while those corresponding to clear pixels were mostly near zero.

Comparison of Hybrid SST retrieval to Regression SST retrieval

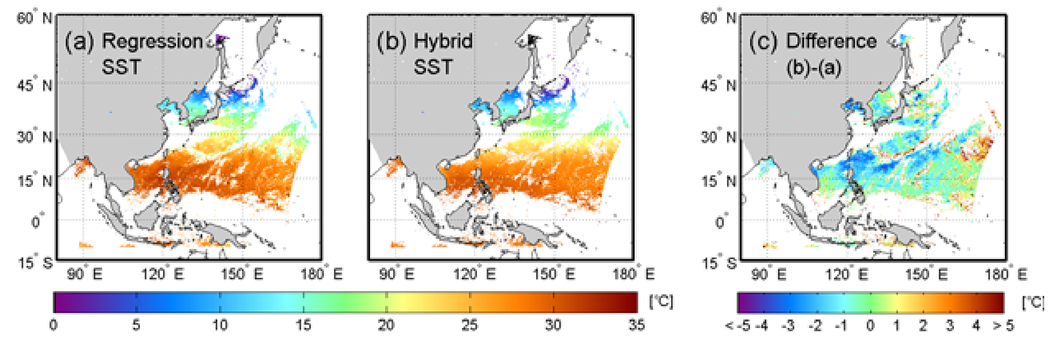


Fig. Example of (a) regression SST and (b) hybrid SST at 12 UTC on May 12th 2014, and (c) difference between hybrid SST and regression SST. The pixels which had a large biases over 5℃ were located near cloudy pixels.

Accuracy of Empirically Regressed MCSST/NLSST

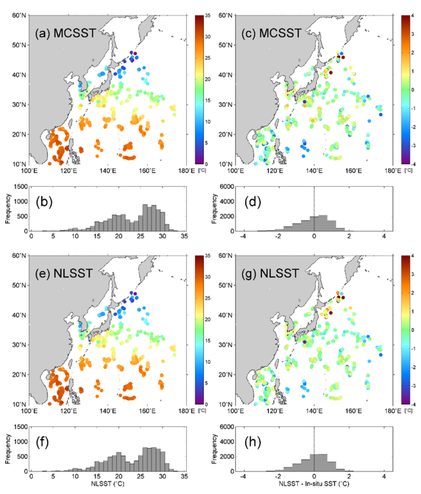


Fig. (a) Estimated MCSST at the collocated points and (b) their histogram with respect to MCSST, (c) MCSST minus *in-situ* temperatures and (d) their histograms with respect to MCSST, and (e) to (h) corresponded to the results of NLSST.

The RMSEs of the MCSST algorithm ranged from 0.67°C to 0.95°C and the bias errors were very small of about 10^{-8}°C. In case of NLSST, the RMSEs and bias errors were somewhat reduced to 0.58°C to 0.88°C as compared to those of MCSST.

Table. Regressed coefficients of MCSST and NLSST algorithms and their RMSE and bias errors (°C).

Algorithm	Time	Number of matchups	Coefficient a_0	a_1	a_2	a_3	RMSE (°C)	Bias (°C)
MCSST	Day	3,634	−6.01	1.02	1.65	0.60	0.67	1.89×10^{-8}
	Night	5,891	−7.16	1.03	1.64	0.41	0.95	4.85×10^{-8}
	Total	9,525	−3.74	1.02	1.68	0.24	0.94	6.61×10^{-8}
NLSST	Day	3,634	19.19	0.94	0.06	0.73	0.58	6.07×10^{-8}
	Night	5,891	14.44	0.96	0.06	0.77	0.88	1.02×10^{-7}
	Total	9,525	20.75	0.93	0.06	0.53	0.84	1.46×10^{-7}

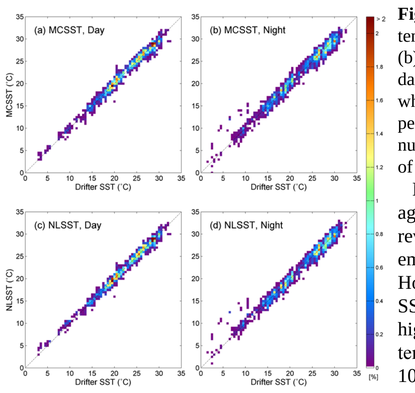


Fig. Comparison of *in-situ* temperatures with (a) daytime and (b) nighttime MCSSTs and (c) daytime and (d) nighttime NLSSTs, where the color represent the percentage of the data to the total number of matchup points in a bin of 0.5°C × 0.5°C.

Most of high density aggregated along the central line revealed high performance of the empirical regression algorithms. However, some of the estimated SSTs in nighttime were much higher up to 5°C than the *in-situ* temperatures at a range of 0 − 10°C.

Accuracy of Hybrid SST

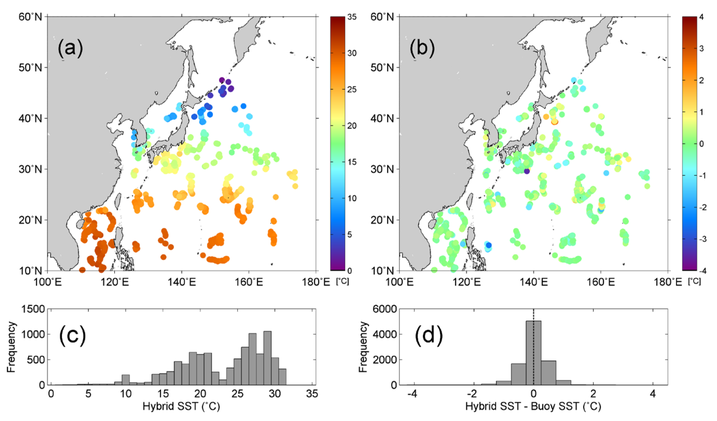


Fig. (a) Retrieved hybrid SST on the collocation point and (b) its difference from *in-situ* SST. (c) Distribution of (a), and (d) as (c) but for (b). The differences from *in-situ* temperatures ranged from −4.36°C to 5.95°C without any dependence as to a latitude. Histogram of the differences showed insignificant bias at all.

Table. Regressed coefficients of Hybrid SST algorithms and their RMSE and bias errors (°C).

Time	The number of matchups	Coefficient b_0	b_1	b_2	b_3	RMSE (°C)	Bias (°C)
Day	3,634	0.25	0.95	0.04	2.03	0.57	−0.08
Night	5,891	0.99	1.00	0.06	-0.77	0.38	0.02
Total	9,525	0.87	1.00	0.04	0.99	0.45	−0.02

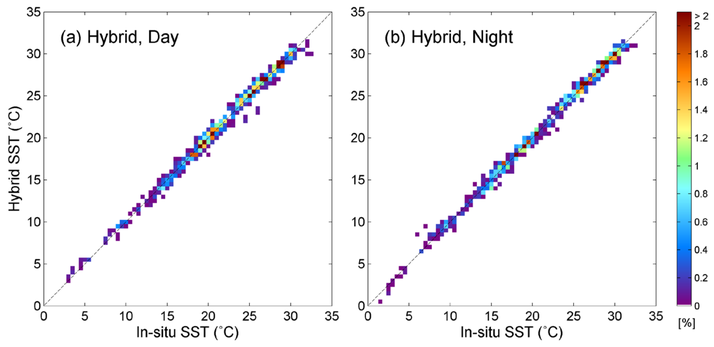


Fig. Comparison between hybrid SST and *in-situ* SST in (a) daytime and (b) nighttime. The color scale represent the percentage of the data in each 0.5°C × 0.5°C bin.. The RMSE of hybrid SSTs in nighttime was estimated to be much smaller by 0.38°C (NLSST error of about 0.88°C in nighttime). The SSTs based on the hybrid algorithm showed less deviations from the *in-situ* temperatures as well as the associated errors.

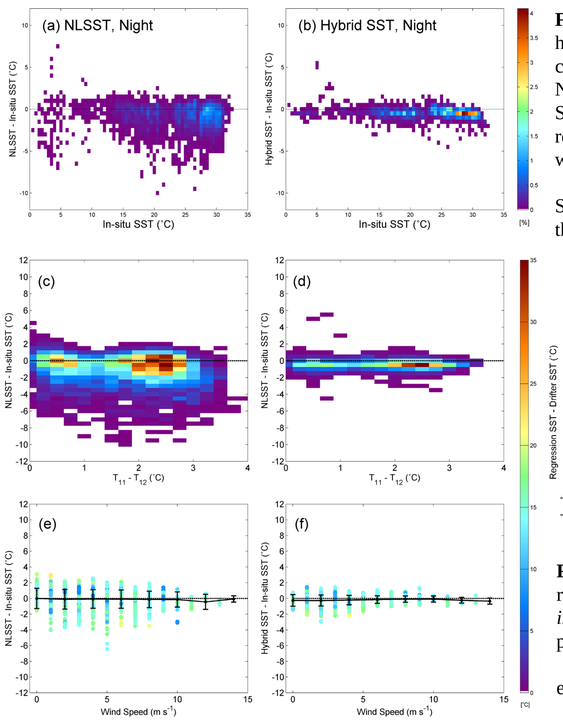


Fig. Error dependency of (a) NLSST minus *in-situ* SST and (b) hybrid SST minus *in-situ* SST on *in-situ* SST in nighttime. The color scale represents the frequency. Error dependency of (c) NLSST minus *in-situ* SST and (d) hybrid SST minus *in-situ* SST on atmospheric moisture in nighttime. The color scale represents the *in-situ* SST. (e) and (f) as (c) and (d) but for wind speed.

Considering the atmospheric and oceanic conditions, hybrid SST retrievals are evaluated to be much more accurate than the empirical SST retrievals.

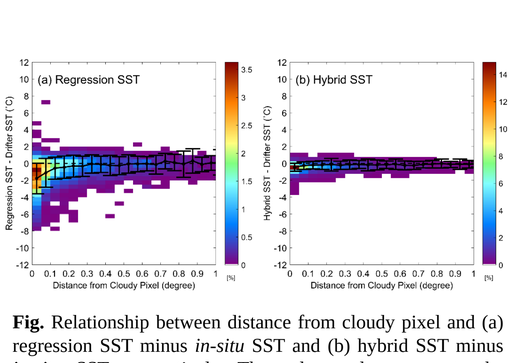
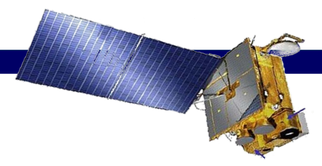


Fig. Relationship between distance from cloudy pixel and (a) regression SST minus *in-situ* SST and (b) hybrid SST minus *in-situ* SST, respectively. The color scale represents the percentage of the data in each bin.

The hybrid SST was much more accurate than the empirically regressed SST, particularly near the cloud edge.



Summary and Conclusion

- Hybrid SST algorithm is one of the most up-to-date method for the satellite-based SST retrievals.
- The hybrid algorithm ensures higher accuracy than the regression algorithm, considering atmospheric variation through RTM, especially in nighttime. As the nighttime RMSE compared with *in-situ* SST was improved from 0.88°C to 0.38°C, the RMSE for whole matchups was also improved from 0.84°C to 0.45°C.
- The difference between hybrid SST and regression SST tended to be larger as closer to a cloudy pixel. Analysis of the difference between two SST retrievals with the distance from a cloudy pixel and the cloud type are beyond the scope of this study and will be performed in the future work.

Acknowledgement

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