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Development and evaluation of SST algorithms for GOES-R ABI using MSG SEVIRI as a proxy

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ABSTRACT

Cross-evaluation of sea surface temperature (SST) algorithms was undertaken using split-window channels of Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager (SEVIRI) as a proxy for the Geostationary Operational Environmental Satellites-R (GOES-R) Advanced Baseline Imager (ABI). The goal of the study was to select the algorithm which provides the highest and the most uniform SST accuracy within the area observed by the geostationary sensor. The previously established algorithms, such as Non-Linear Regression (NLR) and Optimal Estimation (OE) were implemented along with two new algorithms, Incremental Regression (IncR) and Corrected Non-Linear Regression (CNLR), developed within preparations for the GOES-R ABI mission. OE, IncR and CNLR adopt the first guesses for SST and brightness temperatures (BT) and retrieve deviations of SST from the first guess (increments). OE retrieves SST increments with inversion of the radiative transfer model, whereas CNLR and IncR use regression equations. The difference between CNLR and IncR is that CNLR uses NLR coefficients, whereas IncR implies optimization of coefficients specifically for incremental formulation. Accuracy and precision of SST retrievals were evaluated by comparison with drifting buoys. The major observations from this study are as follows: 1) all algorithms adopting first guesses for SST and BTs are capable of improving SST accuracy and precision over NLR; and 2) IncR delivers the highest overall SST precision and the most uniform distributions of regional SST accuracy and precision. This paper also addresses implementation and validation issues such as bias correction in simulated BTs; preserving sensitivity of incremental SST retrievals to true SST variations; and selection of criteria for optimization and validation of incremental algorithms.

1. Introduction

Sea surface temperature (T_S, SST; see Tables 1 and 2 for list of abbreviations and notations used in the paper), derived from satellite observations of top-of-the atmosphere thermal infrared radiation, is used in many environmental applications. SST retrievals from geostationary platforms such as Meteosat Second Generation (MSG — e.g., Schmetz et al., 2002) and Geostationary Operational Environmental Satellites (GOES — e.g., Maturi et al., 2008; Wu et al., 1999) benefit from continuous observations of a vast ocean area over the full diurnal cycle. Another aspect of a geostationary sensor is that each individual element on the earth's surface within the observed area is viewed at a nearly constant view zenith angle (VZA, θ). This emphasizes the need for taking special care to ensure uniformity of accuracy and precision of SST retrievals within a wide range of VZA, compared with polar-orbiting sensors.

SST will be one of the key products of the Advanced Baseline Imager (ABI, e.g., Schmit et al., 2005) scheduled for launch in 2015 onboard the new generation GOES-R series. In 2005, NOAA formed the GOES-R Algorithm Working Group (AWG) to ensure that a full suite of algorithms is developed and tested on proxy data and is available for product generation from ABI shortly after the launch. The SST Application Team, which is a part of the GOES-R AWG, has proposed implementation and cross-evaluation of prospective SST algorithms within a consistent framework, using the Advanced Very High Resolution Radiometer (AVHRR) onboard polar-orbiting NOAA and MetOp satellites and the Spinning Enhanced Visible and Infrared Imager (SEVIRI) onboard the geostationary MSG satellites as ABI proxies. This study began with implementation of existing SST algorithms, such as regression (e.g., McClain et al., 1985; Walton et al., 1998) and radiative transfer model (RTM) — based Optimal Estimation (OE — e.g., Rodgers, 1976) and eventually has led to development of the Hybrid or Incremental Regression (IncR) algorithm, which is aimed at combining the advantages of both approaches (Ignatov et al., 2010; Petrenko et al., 2010b). This paper describes the results of implementation and cross-evaluation of SST algorithms using Meteosat-9 SEVIRI data.

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Table 1
List of abbreviations.

ABI	Advanced Baseline Imager
ACSM	ACSPO Clear-Sky Mask
ACSPO	Advanced Clear-Sky Processor for Oceans
AVHRR	Advanced Very High Resolution Radiometer
AWG	Algorithm Working Group
BT	Brightness temperature
CNLR	Corrected Non-Linear Regression
CRTM	Community Radiative Transfer Model
MDB	Matchup Database
DSST	Daily High-Resolution Blended SST
ESD	Estimated SST Error Standard Deviation
ECMWF	European Center for Medium-range Weather Forecasting
GFS	Global Forecast System
GOES	Geostationary Operational Environmental Satellites
*i*Quam	In situ SST Quality Monitor
IncR	Incremental Regression
LUT	Lookup table
MSG	Meteosat Second Generation
NCEP	National Centers for Environmental Prediction
NESDIS	National Environmental Satellite, Data and Information Service
NLR	Non-Linear Regression
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
ODSF	Optical Depth Scaling Factor
OE	Optimal Estimation
OSTIA	Operational Sea Surface Temperature and Sea Ice Analysis
RTM	Radiative transfer model
RTTOVS	Radiative Transfer for TIROS Operational Vertical Sounder
SD	Standard deviation
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SNR	Signal-to-Noise Ratio
SST	Sea surface temperature
TPW	Total Precipitable Water Vapor Content
VZA	View zenith angle

Table 2
List of notations.

T_S	SST
T_S^0	First guess SST
T_S^i	SST measured in situ
T_B	Observed BT
T_{B11}	Observed BT in 11 µm channel
T_{B12}	Observed BT in 12 µm channel
T_B^0	First guess brightness temperature
T_{B11}^0	First guess BT in 11 µm channel
T_{B12}^0	First guess BT in 12 µm channel
T_B^{CRTM}	BT simulated with CRTM
a_0	NLR offset
$\mathbf{a}=[a_1, a_2, a_3]^T$	Vector of NLR coefficients
b_0	IncR offset
$\mathbf{b}=[b_1,b_2, b_3]^T$	Vector of IncR coefficients
b_{0LS}	IncR offset
$\mathbf{b_{LS}}$	Vector of IncR coefficients calculated with the least-squares method
$\mathbf{Y}$	Vector of regressors, constructed from observed BTs
$\mathbf{Y^0}$	Vector of regressors, constructed from first guess BTs
θ	Satellite view zenith angle
W	Total column water vapor content in the atmosphere
M	Bias in retrieved SST
σ	Standard deviation of retrieved SST
r	Incremental correlation coefficient
M_B	Bias in $T_B-T_B^{CRTM}$
τ	Optical depth of water vapor absorption
τ_0	A priori estimate of water vapor absorption
β	ODSF
$\mathbf{z}$	Vector of variables retrieved with OE
$\mathbf{z^0}$	A priori value of $\mathbf{z}$
$\mathbf{S}$	A priori covariance matrix of $\mathbf{z}$
$\mathbf{\Delta}$	Covariance matrix of radiometric noise
$\mathbf{K}$	Jacobian
η	Multiplication factor at S^{-1} in OE equation
σ_{SST}	A priori SD of SST
σ_β	A priori SD of ODSF
σ_{cell}	Regional average SD of retrieved SST minus DSST

At present, the majority of operational SST products are generated using regression algorithms. Although the forms of regression SST equations are devised to decouple SST variations from variations in atmospheric transmission and emission, residual atmospheric effects can cause significant regional biases in retrieved SST. For SEVIRI, these biases were explored by Merchant et al. (2009a) and Le Borgne et al. (2011). The OE and IncR algorithms represent an alternative approach to SST retrieval, which can be defined as “incremental”. This approach implies adopting the first guesses for SST, T_S^0, from SST analysis fields and first guesses T_B^0 for observed brightness temperatures (BT, T_B) from RTM simulations. Given T_S^0 and T_B^0, the task of the incremental algorithms is to retrieve SST increments, $T_S-T_S^0$, from BT increments, $T_B-T_B^0$, rather than T_S from T_B. Along with selection of the algorithm which provides the highest and most uniform SST accuracy and precision within the area observed by a geostationary sensor, the objective of this study was to gain experience in implementation and validation of incremental SST algorithms.

The SST algorithms were implemented within the Advanced Clear-Sky Processor for Oceans (ACSPO), initially developed at the National Environmental Satellite Data and Information Service (NESDIS) to generate clear-sky radiances, SST, and aerosols from the AVHRR sensors onboard NOAA and MetOp satellites (Liang & Ignatov, in press; Liang et al., 2009; Petrenko et al., 2010a) and later adopted for MSG SEVIRI (Shabanov et al., 2009, 2010). The regression-based ACSPO SST algorithms are trained against buoy measurements without correction for the thermal skin effect. ACSPO enables on-line simulations of clear-sky BTs using the Community Radiative Transfer Model (CRTM, Han et al., 2005; Liang et al., 2009) with analysis SST and Numerical Weather Prediction (NWP) atmospheric fields as input. In this study, CRTM version 1.1 is used in conjunction with the AVHRR-based 0.25° Daily High-Resolution Blended SST analysis (DSST, Reynolds et al., 2007) and the 6-hour 1° atmospheric forecast fields from the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS, available at http://nomad3.ncep.noaa.gov/pub/gfs/rotating/). The DSST field is anchored to buoy and ship SST, and thus it is expected to be consistent with ACSPO regression algorithms, which are also trained against in situ measurements. CRTM BTs, T_B^{CRTM}, are computed on the GFS grid and interpolated in space and time to the sensor's pixels. Similar interpolation is applied to selected GFS atmospheric variables, such as Total Precipitable Water Vapor Content in the atmosphere (TPW, W). The pixel-level first guess SST is produced by spatial interpolation of DSST. The ACSPO also incorporates Clear-Sky Mask (ACSM) — the module that identifies clear-sky ocean pixels suitable for SST retrieval (Petrenko et al., 2010a). The ACSPO infrastructure allows implementation and testing, in a real-time setting, of SST algorithms based both on regression and on CRTM simulations.

Split-window SEVIRI Channels 9 and 10, centered at 10.8 µm and 12 µm, were used in this study as the proxies of the ABI channels 14 and 15, centered at 11.2 µm and 12.3 µm. Note that since the spectral responses for SEVIRI and ABI channels are different, the performance of SST algorithms reported in this study for SEVIRI can be different from that for the future ABI sensor. The SEVIRI Channel 4, centered at 3.9 µm, was not used because our initial analyses (Shabanov et al., 2009), consistent with Le Borgne et al. (2011), have shown that this SEVIRI channel does not improve the accuracy of nighttime SST retrievals but introduces inconsistency between daytime and nighttime retrievals.

2. SST algorithms

In this Section, the SST algorithms implemented for this study are briefly reviewed. More implementation details are provided in Sections 5 and 6.