Fusion of Multisensor SSTs Based on the Spatiotemporal Hierarchical Bayesian Model

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(Manuscript received 27 June 2017, in final form 27 September 2017)

Abstract

This study focuses on merging MODIS-mapped SSTs with 4-km spatial resolution and AMSR-E optimally interpolated SSTs at 25-km resolution. A new data fusion method was developed—the Spatiotemporal Hierarchical Bayesian Model (STHBM). This method, which is implemented through the Markov chain Monte Carlo technique utilized to extract inferential results, is specified hierarchically by decomposing the SST spatiotemporal process into three subprocesses, that is, the spatial trend process, the seasonal cycle process, and the spatiotemporal random effect process. Spatial-scale transformation and spatiotemporal variation are introduced into the fusion model through the data model and model parameters, respectively, with suitably selected link functions. Compared with two modern spatiotemporal statistical methods—the Bayesian maximum entropy and the robust fixed rank kriging—STHBM has the following strength: it can simultaneously meet the expression of uncertainties from data and model, seamless scale transformation, and SST spatiotemporal process simulation. Utilizing multisensors’ complementation, merged data with complete spatial coverage, high resolution (4 km), and fine spatial pattern lying in MODIS SSTs can be obtained through STHBM. The merged data are assessed for local spatial structure, overall accuracy, and local accuracy. The evaluation results illustrate that STHBM can provide spatially complete SST fields with reasonably good data values and acceptable errors, and that the merged SSTs collect fine spatial patterns lying in MODIS SSTs with fine resolution. The accuracy of merged SSTs is between MODIS and AMSR-E SSTs. The contribution to the accuracy and the spatial pattern of the merged SSTs from the original MODIS SSTs is stronger than that of the original AMSR-E SSTs.

1. Introduction

The sea surface temperature (SST) is one of the important parameters in coupling of the ocean and atmosphere through exchanges of heat, momentum, moisture, and gases (Donlon et al. 2002). It is required as a key input to forecasting systems to constrain the modeled upper-ocean circulation and thermal structure, and for the exchange of energy between the ocean and the atmosphere (Donlon et al. 2007). In situ measurements from buoys, ships of opportunity, and voluntary observing ships are inadequate at providing frequently sampled SST maps with the dense spatial resolution and global coverage required for input into ocean forecasting models (Donlon et al. 2007). Only Earth-observing satellite instruments provide 1) the high temporal resolution but with only regional coverage and 2) the global coverage with repeat times from 12 h to several days. No single source by itself can meet the GODAE SST specification, but this can be achieved by exploiting the synergy when several sources of SST data are combined and validated against in situ measurements (Donlon et al. 2007), for example, microwave sensors and infrared radiometers. Infrared products have higher spatial resolution but lower spatial continuity as a result of cloud contamination, while microwave
products have higher spatial continuity as a result of their cloud penetration but lower spatial resolution. Thus, there is complementation between infrared and microwave SST products. A new generation of satellite SST products is required based on the complementary aspects of different satellite instruments by merging data to provide increased fidelity, consistency, and resolution (Donlon et al. 2002). Therefore, in our study, we focused on merging multisatellite-derived SST products, as derived by MODIS and AMSR-E, to obtain merged SSTs with complete spatial coverage, fine local spatial structure, higher accuracy, and spatial resolution.

Many methods for filling in gaps in satellite-derived SST products have been developed, including the optimum interpolation method (Chao et al. 2009; Reynolds et al. 2002; Reynolds and Smith 1994; Reynolds et al. 2007), objective analysis (Guan and Kawamura 2004), blended analysis (Reynolds 1988), data interpolating empirical orthogonal functions (DINEOF) (Ganzedo et al. 2011; Nechad et al. 2011), the wavelet transformation method (Zhang 2006), the Kalman filter method (Wang et al. 2010), 3D variation assimilation (Zheng et al. 2009), Bayesian maximum entropy (BME) (Li et al. 2013), and robust fixed rank kriging (R-FRK) (Zhu et al. 2015).

In the optimum interpolation method, statistical errors must be clearly defined. However, we usually cannot obtain the statistical errors. In addition, the inverse of a high-dimensional matrix is computed during the calculation; thus, this method is not suitable for a massive dataset. DINEOF is used to reconstruct the time series of a single sensor. Complete coverage data cannot be obtained based on only the wavelet transformation. The Kalman filter method also cannot obtain complete coverage data and needs scale transformation before merging using the interpolation method. Thus, the new uncertainties are introduced into the fusion model. The R-FRK method, which is based on the spatial random effects model, performs dimension reduction through multiresolution wavelet analysis, which models the spatial dependence through a fixed number of spatial basis functions so that it can dramatically reduce the computation cost of various kriging methods over an irregular region because the R-FRK method is linearly scalable to the number of observations, that is, $O(n)$ (Zhu et al. 2015). Though the R-FRK method can improve computing efficiency through dimension reduction, especially for massive satellite-derived data, the spatial pattern in the original data cannot be maintained.

BME is a nonlinear spatiotemporal geostatistical methodology (Christakos 2000; Christakos and Serre 2000; Christakos et al. 2001) that can theoretically integrate data from different sources of different accuracies (Li et al. 2013). As a probabilistic method, it is capable of using uncertain data that enrich the subject information and it considers their uncertainties in obtaining much more objective results (Li et al. 2013). Using the BME method to integrate different resolution data, quality control for the data is first the step; second, the data are detrended; third, the covariance functions are modeled. Although fusion data with high accuracy and more local information existing in fine-resolution data can be achieved and the problem of scale transformation can also be resolved through BME, the spatiotemporal procedure model of true SST cannot be expressed and the computing efficiency is low, especially for massive satellite data.

The methods mentioned above cannot meet the expression of uncertainties from data and model, seamless scale transformation, and SST spatiotemporal process simulation simultaneously. In this paper, we developed a novel model—the Spatiotemporal Hierarchical Bayesian Model (STHBM)—to merge infrared SST and microwave SST products into a time series empirical model that benefits from the complementary characteristics of each sensor type. Comparing this method with other methods, the advantages of STHBM are that it is easier to implement in modeling complicated, high-dimensional spatiotemporal SST settings; it can account for the various uncertainties from different sources, such as the uncertainties in SST observation, sampling, the model, and parameters; and it achieves the spatial-scale transformation seamlessly, that is, the different spatial resolution compositions between MODIS and AMSR-E.

Although the hierarchical Bayesian model has existed for a long time in statistics (Berliner et al. 2003, 2000; Gelfand et al. 2001; Wikle 2002, 2003; Wikle et al. 1998, 2003; Wikle and Hooten 2006; Wikle et al. 2001), in the remote sensing realm its application is limited (Katzfuss and Cressie 2012). For SST data, Guo (2010) used the hierarchical Bayesian model to merge MODIS and AMSR-E SSTs; however, he achieved a coarser resolution (an AMSR-E spatial resolution of 25 km) by converting a fine resolution (a MODIS spatial resolution of 4 km) into a coarser resolution, and the hierarchical characteristics are manifested through the nesting parameters and superparameters but not a process model. Our method emphasizes the fusion of data from sensors of different spatiotemporal resolutions seamlessly and focuses on how to receive a spatiotemporal continuous SST field with a fine local spatial pattern (the temperature gradient) and how to minimize cloud contamination from MODIS and land effects from AMSR-E by building the potential SST spatiotemporal process model.
The remainder of the article is organized as follows: section 2 describes the data and data preprocessing; section 3 describes the methodology used in this paper; section 4 evaluates the merged SSTs, presents an analysis of the results, and compares the results with that from R-FRK and BME; and section 5 consists of the discussion and conclusions.

2. Data and preprocessing

The geographical area of interest in our study is the rectangular area at 30°S–46°N, 30°–180°E, as illustrated in Fig. 1 (gray represents land and white represents the ocean). This study region covers the joining area of Asia, Africa, Australia, and the Indian–Pacific Ocean. We selected it as our study region because it has the largest warm pool with the highest SST in the world. It also has the strongest tropical convection activity in the world. The air–sea interaction in this region is very strong. It is a key area for the short-term climate variation and prediction in China (Guoxiong et al. 2006). So, it is important to obtain high-accuracy satellite SSTs with finescale and spatially complete coverage in this region.

a. MODIS SST data

One of the satellite-derived SSTs used in this paper includes MODIS *Aqua* nighttime level-3 mapped products at 0130 local time (LT) that are processed and distributed by the Ocean Biology Processing Group (OBPG) at the NASA Goddard Space Flight Center (http://gcmd.nasa.gov). Data at 0130 LT are selected because the effect of diurnal warming of the surface ocean can be minimized. The MODIS SSTs are available in a variety of spatial resolutions and temporal periods, such as a spatial resolution of 4 or 9 km, and at daily, 8-day, monthly, and annually temporal resolutions. Data with coarser temporal resolutions are generally obtained by averaging observations over the corresponding period of time. All these data are now available online. The empirical coefficients in the MODIS SSTs’ retrieval algorithm are derived from regression analysis between MODIS thermal infrared brightness temperatures and the collocated in situ SST observations from drifting and moored buoys. Measurements from the Marine–Atmosphere Emitted Radiance Interferometer (M-AERI) in situ radiometer are then used to convert the regressed SST to a skin SST measurement (approximately −0.2°C adjustment) at a depth of 0.01 mm classified based on Donlon et al. (2002) and Donlon and GHR SST-PP Science Team (2005).

In our study we used the 8-day composite MODIS SSTs at 4-km spatial resolution. The higher spatial resolution was selected to obtain merged SSTs with higher spatial resolution. We selected the 8-day data product because it provides better coverage than the daily product; in fact, such 8-day composite SST information is often used to compute the temperature anomaly (Li and He 2014). In the following analysis, we use the spatiotemporal SST dataset from all of 2003, which includes 46 images in total and we call them weekly data. There are two layers of MODIS SST product, a temperature layer and a quality control layer. In the quality control layer, the pixel number is the same as that in the temperature layer; the pixel value is flagged as either 255, 0, 1, or 2, which describes the quality of the corresponding pixel in the temperature layer. The number 255 represents land, gross clouds, and other errors; 0 represents good pixels; 1 represents questionable pixels; and 2 represents cloud-contaminated pixels. Based on this information, we screened out the missing pixels, the cloud-contaminated pixels, and the error pixels in the temperature layer. Using AMSR-E SSTs as a reference with the cross-checking method, we screened out the ocean pixels that had 255 pixels flagged incorrectly. For the good SST pixels in the temperature layer, which are flagged as 0 in the quality control layer, the digital number was transformed into the valid temperature based on

\[
\text{SST}_{\text{MODIS}} = 0.000717185 \times \text{DN} - 2
\]

where SST\textsubscript{MODIS} represents converted temperature (°C), DN represents the digital number of the pixel in the temperature layer, and coefficient 0.000717185 and intercept −2 are obtained from online (http://grasswiki.osgeo.org/wiki/MODIS). For the converted SSTs, we rejected the pixels whose SST was less than −2°C and greater than 32°C, because the highest retrieved value of MODIS is 32°C and the lowest is −2°C.

b. AMSR-E SST data

Other satellite-derived SSTs come from AMSR-E. AMSR-E, flown on NASA’s *Aqua* satellite on 4 May 2002,
was the first microwave radiometer capable of accurately measuring global through-cloud SSTs. We selected the AMSR-E SSTs because they have higher spatial coverage and offset the spatial incompleteness of the MODIS SSTs. AMSR-E datasets are provided as daily maps, 3-day mean maps, weekly mean maps, and monthly mean maps (http://www.remss.com). Time series data started from the 152th day of 2002. In our study we select daily products of the Optimum Interpolation Sea Surface Temperature, version 3, in a 0.25° × 0.25° grid for all of 2003, which were produced and provided by Remote Sensing Systems Inc., which is supported by NASA (http://www.remss.com). There are 365 maps for all of 2003. Using a simple empirical model of diurnal warming that depends on solar insolation, wind speed, and the local time of observation (Gentemann et al. 2003), the AMSR-E daily SSTs were “normalized” to a daily minimum SST that was defined to occur at approximately 0800 LT. AMSR-E measured the subskin temperature at approximately 1-mm depth (Dong et al. 2006). Pixels flagged as 255 represent landmass; 251, 253, and 254 represent missing data; 252 represents sea ice; and 0–250 represent valid SST data (http://www.ssmi.com/sst/microwave_oi_sst_data_description.html). The digital number is converted into a valid SST based on

\[
SST_{\text{AMSR-E}} = 0.15 \times DN - 3, \quad (2)
\]

where \(SST_{\text{AMSR-E}}\) represents converted temperature (°C), \(DN\) represents the digital number of the pixel, and coefficient 0.15 and intercept −3 were obtained from specification (ftp://ftp.discover-earth.org/sst/daily/). The valid retrieval range of AMSR-E SST is between −3° and 34.5°C (http://www.ssmi.com/amsr/amsr_data_description.html). So, pixels less than −3°C and more than 34.5°C are screened out.

Note that the spatiotemporal resolution of MODIS SSTs is different from that of AMSR-E SSTs. We need to equalize the temporal resolution of the AMSR-E data with that of the MODIS data to apply the merging model. Because the heat capacity of seawater is very large, the SST is not expected to change significantly during a period of up to 10 days (Abe 1984). We compute the average value of each pixel over 8 days; that is, by computing the average value of each pixel from 1 to 8 January 2003, from 9 to 16 January 2003, etc., the 8-day composite data are obtained. The matchup of the spatial resolution is resolved in STHBM. In the following analysis, the AMSR-E SSTs are all averaged SSTs with the same temporal resolution as MODIS SSTs.

c. Drifting buoy SST data

In our study we also use drifting buoy SSTs in 2003 obtained from the Atlantic Oceanographic and Meteorological Laboratory (AOML; http://www.aoml.noaa.gov) for the satellite SST correction and the validation study of the merged data from STHBM with the same spatiotemporal resolution as the original MODIS SSTs. These data are interpolated into 0000, 0600, 1200, and 1800 UTC at the drifting buoy location based on raw observation. Note that the MODIS nighttime SSTs are retrieved at 0130 LT and that the AMSR-E SSTs are obtained at 0800 LT. To temporally match up the satellite SSTs with the drifting buoy SSTs, we chose the drifting buoy SSTs suggested by Zhu et al. (2015) to correct satellite SSTs and to validate the merged SSTs as reference; that is, buoy SSTs at 0000 UTC over regions at 30°–105°E in longitude and at 1800 UTC over regions at 105°–180°E in longitude are selected so that the drifting buoy SST observations were mostly close to the satellite SSTs in time and to minimize the effects of the ocean diurnal warm layer (Donlon et al. 2002). For the drifting buoy data, we applied a simple gross error quality check. The gross error check removed drifting buoy data below −2°C or above 35°C (Hoyer et al. 2012). The drifting buoy data were then transformed into grid data with the same spatiotemporal resolution as the MODIS and AMSR-E data through averaging, that is, computing the 8-day mean value of the drifting buoy data located at the same pixel using the time composite method.

3. Methods

The data fusion procedure involves a combination of merging data and filling in the gaps in the data through complementation between data to improve their availability. We construct a STHBM to merge the MODIS SSTs and AMSR-E SSTs. The spatial-scale conversion is introduced into STHBM. STHBM allows the incorporation of information from diverse sources and can account for statistical uncertainty. These uncertainties are expressed in terms of conditional probabilities; that is, STHBM allows one to specify uncertainty in components of the problem conditionally, ultimately linked together via formal probability rules. However, only through the fusion method can the systematic and stochastic error of satellite data not be reduced. So, we developed a data-driven regional bias correction model to correct satellite SSTs before fusion implementation. The general process is shown in Fig. 2.

a. Data-driven regional bias correction model

Satellite-derived SSTs can be biased for various reasons, such as the instability of sensors and contamination
by cloud, water vapor, and aerosols (Dong et al. 2006; Jones et al. 1996), and these biases can be spatially heterogeneous (Zhu et al. 2015). For MODIS SST, its biases are mainly due to diurnal variability, water vapor attenuation, the presence of atmospheric aerosols, and the incomplete removal of cloud contamination (Brown et al. 1985; Chen et al. 2017; Emery et al. 1994; McClain 1989), while the AMSR-E SST is more sensitive to the effects of sea surface wind, waves, and inland interference signals (Guan and Kawamura 2003).

We first investigate the relationship between satellite SSTs and drifting buoy SSTs by scattergraph (Figs. 3b and 3d) (Zhu et al. 2015). The matchup points between MODIS and AMSR-E SSTs and drifting buoy SSTs are divided into two regions spatially (cool region: lower than 12.5°C for MODIS SSTs and 15°C for AMSR-E SSTs; warm region: more than 12.5°C for MODIS SSTs and 15°C for AMSR-E SSTs) at critical values 12.5°C and 15°C, respectively. The selection of the critical value 12.5°C and 15°C is using an iterative procedure (Zhu et al. 2015): first, we empirically determine a temperature as an initial critical value based on Figs. 2b and 2d—for example, 14°C for MODIS and AMSR-E SSTs—and build the bias-correction equation based on this empirical value. Then, the mean bias of bias-corrected MODIS and AMSR-E SSTs was calculated. Second, the initial critical value of ±0.1°C was the new critical value and was used to build the new bias correction equation. The bias of the MODIS and AMSR-E SSTs corrected by the model built based on the new critical value was calculated. This procedure was iteratively repeated until we got the critical value that came up with the minimum bias of the corrected MODIS and AMSR-E SSTs (Zhu et al. 2015). The critical value for cool and warm regions is 12.5°C for MODIS SSTs and 15°C for AMSR-E. The relationship of the two regions between satellite SSTs and drifting buoy SSTs shows different statistical characteristics (Table 1).

Based on the spatiotemporal characteristics mentioned above, we develop a data-driven regional bias correction model. The model procedure is described as follows.

First, all the matching points are divided into two groups spatially with 12.5°C and 15°C as the critical values for MODIS and AMSR-E, that is, the warm temperature region and the cool temperature region. Second, a linear relationship for each week between satellite SSTs and drifting buoys by the regression model with drifting buoy SSTs as the independent variable and satellite SSTs as dependent variable is simulated at the warm temperature region and the cool temperature region. Matching points of the current week do not participate in the simulation of the regression model; that is, the regression equation of the first week is simulated using the matching points from the 2nd week to the 46th week. The matching points of the current week are used to validate the corrected satellite SSTs. Last, the satellite SSTs are fitted into the correction model with weeks as

![Fig. 2. Workflow for the fusion of MODIS and AMSR-E SSTs based on STHBM.](image)
the unit. And then the corrected satellite SSTs are obtained. The parameters of the regression model for partial weeks are described in Table 2.

Taking drifting buoy SSTs of the current week as reference, we validate the corrected and original satellite SSTs in terms of mean bias $\bar{B}$, error standard deviation (std dev), root-mean-square error (RMSE), and correlation coefficient $R$. The validation results are presented in Figs. 3a and 3c. The $\bar{B}$, std dev, and RMSE of the original MODIS SSTs are corrected to $-0.0072^\circ$C, $0.6805^\circ$C, and $0.6806^\circ$C respectively. The $\bar{B}$, std dev, and RMSE of the original AMSR-E SSTs are corrected to $4.5673 \times 10^{-5}^\circ$C, $0.4782^\circ$C, and $0.4782^\circ$C respectively. The effect of the correction model is obvious for the cool temperature region, especially for MODIS.

### b. Spatiotemporal analysis of SST

We analyze the spatiotemporal characteristics of SST based on the AMSR-E SSTs as a result of its spatiotemporal completeness (He 2003; Shumway and Stoffer 2000; Wikle et al. 1998). Figure 4 indicates the temporal mean of each pixel in 2003. The SST is approximately linear with latitude and longitude. So, the temporal mean of the SST can be simulated as a linear structure model with intercept, latitude, and longitude as covariate.

Figure 5 shows the characteristics of the seasonal mean of the SST based on $2^\circ$ latitude, which is the removed time mean. The time series of the SST, which is the removed time mean, show the sine and cosine curve features, and the difference of the seasonal trend between the Southern Hemisphere and Northern Hemisphere is obvious. So, the seasonal mean of the SST can be modeled as the spectral curve in the frequency domain.

![Validation of corrected and original satellite SSTs](image)

**FIG. 3.** Validation of corrected and original satellite SSTs: (a) corrected MODIS SSTs, (b) original MODIS SSTs, (c) corrected AMSR-E SSTs, and (d) original AMSR-E SSTs.

<table>
<thead>
<tr>
<th>MODIS</th>
<th>AMSR-E</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\geq 12.5^\circ$C</td>
<td>$&lt; 12.5^\circ$C</td>
</tr>
<tr>
<td>Median</td>
<td>$-0.2050$</td>
</tr>
<tr>
<td>25th percentile</td>
<td>$-0.5701$</td>
</tr>
<tr>
<td>75th percentile</td>
<td>$0.1158$</td>
</tr>
</tbody>
</table>

**TABLE 1.** Median, 25th percentile, and 75th percentile of bias between satellite SSTs (MODIS) and drifting buoy SSTs.
Figure 6 shows the spatial tendency of the residual, which is defined as the SST removed temporal mean and the seasonal mean from the original SST. There are spatial structures obviously.

Figure 7 presents the results of the time autocorrelation function between the current state and the other state of the residual. There is strong autocorrelation when the time lag (weeks is the basic unit) is less than 3. Specially, the strongest autocorrelation is when the time lag is 1. So, the residual cannot be modeled simply as white noise. In this paper we develop a spatiotemporal random effects model to simulate the residual, that is, the first-order vector autoregression model based on a space-weighted eight-neighborhood.

c. Spatiotemporal hierarchical Bayesian model

The spatiotemporal hierarchical Bayesian model, including a data model, a process model, and a parameter model, is constructed. During the data model stage, the conditional distribution of corrected MODIS and AMSR-E SSTs is created, and the spatial-scale transformation is implemented through two intermediate variables, that is, the mean of every corrected MODIS and AMSR-E SST. During the process model stage, spatiotemporal data decomposition methodology is utilized to create the potential SST spatiotemporal process model based on the spatiotemporal analysis of SST in section 3b. In the parameter model stage, the prior value is assigned to every parameter of the data and the process model based on the analysis of corrected AMSR-E SSTs as a result of its complete coverage spatially. The postdistribution of the average value of the potential true SST process, which varied during a 1-yr period, is estimated through STHBM. Considering the SST variation with latitude to be stronger than that with longitude, we divide the geographical region into 38 subregions per 2° latitude. To increase the computing performance, the parallel computation is implemented based on 2° longitude.

1) Hierarchical structure of the SST

We think of SST as a spatiotemporal random field. We will estimate the postdistribution of the average value
from the potential true SST process updated by the observation via the Bayesian theorem [Eq. (3)]:

\[
\begin{align*}
&[\text{process}|\text{data}] \times [\text{data}|\text{process, parameters}] \\
&\times [\text{process}|\text{parameters}] [\text{parameters}], \tag{3}
\end{align*}
\]

where \([\text{process}|\text{data}]\) denotes the postdistribution of the average value from the potential true SST process; \([\text{data}|\text{process, parameters}]\) denotes the measurement model, where the measurement is thought of as an observation with errors; \([\text{process}|\text{parameters}]\) denotes the potential true process that cannot be observed but can be modeled in the process model stage; and \([\text{parameters}]\) denotes the parameter model, including all parameters of the model which are distinguished between the hierarchical Bayesian and the other Bayesian method.

We know that the true value of a potential SST process cannot be obtained. Our observation is affected by measurement error and cannot be achieved at every location. Let \(Y(s, t)\), where \(s\) is a spatial location in two-dimension Euclidean space and \(t\) denotes time, be a potential true SST process that we cannot observe but will be modeled in the process model stage, and an inference of potential true SST can be made based on the observation data with measurement errors. Now, we have only a series of observations \(Z(s, t)\), where \(s\) and \(t\) have the same meaning as \(Y(s, t)\), with errors \(\epsilon\) at each time point. The relationship between observations and potential true SSTs can be expressed by Eqs. (4) and (5):

\[
Z(s, t) = Y(s, t) + \epsilon(s, t), \tag{4}
\]

where \(\epsilon(s, t)\) denotes white Gaussian noises over space and time, with mean zero and \(\text{var}[\epsilon(s, t)] = \sigma^2_{\epsilon(s, t)}\); and

\[
Y(s, t) = T + S_i + R_i + \gamma_i, \quad t = 1, 2, \ldots, 46. \tag{5}
\]
where $T$ denotes the time mean trend, $S_i$ denotes the seasonal mean trend, $R_i$ denotes the spatiotemporally random effect model, and $\gamma_i$ denotes error from the SST spatiotemporal decomposition process.

2) DATA MODEL AND SPATIAL-SCALE TRANSFORMATION

Applying STHBM, the conditional distribution of the observations must be defined. The MODIS observations are treated as a normal distribution with mean $Y_{\text{MODIS}}(s_1, t)$. The AMSR-E observations are treated as a normal distribution with mean $Y_{\text{AMSR-E}}(s_2, t)$. In our study for each computation unit, the pixel number of MODIS is $48 \times 48 \times 46 = 105,984$ and that of AMSR-E is $8 \times 8 \times 46 = 2944$. If there are land pixels among them, they are removed. Recall that the spatial resolution is different between MODIS and AMSR-E SSTs; thus, there is the problem of spatial-scale transformation. There is a nesting relationship between MODIS and AMSR-E pixels; that is, 36 pixels of MODIS are nested in one pixel of AMSR-E at the same spatial location. In this paper, we develop the nesting-scale transformation model spatially. We linked the two scales through a normal distribution; that is, $Y_{\text{MODIS}}(s_1, t)$ per $6 \times 6$ subwindows, corresponding to one pixel of AMSR-E, is treated as the normal distribution with mean $Y_{\text{AMSR-E}}(s_2, t)$ (Guo 2010; Hooten and Wikle 2008; Wikle 2002). In this manner, the spatial resolution match problem of the two products is resolved seamlessly. Therefore, the data model can be expressed as Eqs. (6)–(8):

\[
Z_{\text{MODIS}}(s_1, t) \sim N[Y_{\text{MODIS}}(s_1, t), \sigma_{s_1}^2], \quad (6)
\]
\[
Z_{\text{AMSR-E}}(s_2, t) \sim N[Y_{\text{AMSR-E}}(s_2, t), \eta_{s_2}^2], \quad \text{and} \quad (7)
\]
\[
Y_{\text{MODIS}}(s_1, t) \sim N[Y_{\text{AMSR-E}}(s_2, t), \tau_{s_2}^2]. \quad (8)
\]

where $\sigma_{s_1}^2$, $\eta_{s_2}^2$, and $\tau_{s_2}^2$ represent error variances; and $N$ denotes the normal distribution.

Equations (6) and (7) express the error model of the MODIS and AMSR-E SSTs, respectively. Equation (8) expresses the spatial-scale transformation.

3) PROCESS MODEL

This stage includes modeling all of the subprocesses, that is, the spatial trend surface of the time series process, the seasonal term, and the spatiotemporal random effect term. The true value $Y_{\text{AMSR-E}}(s_2, t)$ is controlled by a potential true spatiotemporal process of SST, which should display both strong seasonal variation and regional structure. The model $Y_{\text{AMSR-E}}(s_2, t)$ is conditional on a spatiotemporal additive structure with three subprocesses based on the analysis of SST spatiotemporal structure in section 3b, denoted by $T$ and $S$, and $R$ respectively.

The spatiotemporal additive structure of the potential true SST process, $Y_{\text{AMSR-E}}(s_2, t)$, for each pixel and time point is expressed as

\[
Y_{\text{AMSR-E}}(s_2, t) = T(s_2) + S(s_2, t) + R(s_2, t) + \gamma(s_2, t), \quad (9)
\]

where $T(s_2)$ denotes the spatial trend surface of the time series process varying with spatial location. Each pixel value is a time average of SSTs in 2003. The second term, $S(s_2, t)$, represents the seasonal term expressed by the cosine spectral curve in the frequency domain. The third term, $R(s_2, t)$, denotes the spatiotemporal random effect term, which describes the local spatial variation and time-dependent relationship, which depends on the spatial eight-neighborhood pixel value and last state. The last term, $\gamma(s_2, t)$, is the zero-mean random variable, which models the noise that accounts for the error introduced by the construction of the process model.

Each term on the right-hand side of Eq. (8) is a sub-process with parameters. The spatial trend surface is described by multinomial regression with the deterministic independent variables “latitude” and “longitude”: [Eq. (10)] (Agarwal et al. 2005; Wikle et al. 1998):

\[
T(s_2) = \mu(s_2) + \alpha_1 \times \text{latitude} + \alpha_2 \times \text{longitude} + \gamma_T(s_2), \quad (10)
\]

where latitude is positive in the Northern Hemisphere and negative otherwise, $\alpha_1$ and $\alpha_2$ are regression coefficients that are treated as stochastic variables with normal distributions, $\gamma_T(s_2)$ are the regression residuals,
and \( \mu(s2) \) is a stochastic variable with a normal distribution.

The seasonal term is formulated as follows (Shumway and Stoffer 2000; Wikle et al. 1998):

\[
S(s2, t) = \beta_1(s2) \times \cos(2\pi ft) + \beta_2(s2) \times \sin(2\pi ft),
\]

\[
\beta_1(s2) = a_0 + a_1 \times \text{latitude} + a_2 \times \text{longitude},
\]

\[
\beta_2(s2) = b_0 + b_1 \times \text{latitude} + b_2 \times \text{longitude},
\]

where latitude and longitude have the same meaning as in Eq. (10), and \( f \) and \( t \) denote frequency and period, respectively. In our study, \( t \) is from 1 to 46 because the temporal resolution of data is 8 days and there are 46 weeks data every year. Terms \( a_0, a_1, a_2, b_0, b_1, b_2 \) are all stochastic variables with normal distributions.

Term \( R(s2, t) \) accounts for local spatial variation. In our study, we do not treat this parameter simply as a random variable with zero mean but as a random variable with spatial structure (Agarwal et al. 2005; Besag 1974; Cressie 1992). The distribution of \( R(s2, t) \) is specified conditionally given all of its eight-neighbor pixels, and the last time state is defined as in Eqs. (14) and (15).

We call it spatiotemporal random effect model

\[
R(s2, t + 1) = H_iR(s2, t) + \xi_{t+1},
\]

\[
R(s2, t) | R(s2, t) \sim N\left[ \sum_{j=1}^{8} W_j \times R(s2, t), \nu^2_R \right],
\]

where \( H \) denotes the propagation matrix; and if pixel \( i \) is contiguous with pixel \( j \), then \( W_j = 1 \), otherwise \( W_j = 0 \). Term \( \nu^2_R \) is the spatial variance component; that is, \( R(s, i) \) varies with its weighted eight-neighborhood pixel value and last state (Agarwal et al. 2005; Besag 1974; Cressie 1992).

4) PARAMETER MODEL

The primary parameter set here is \( \{\theta_1, \theta_2\} \), where \( \theta_1 = \{\sigma_a^2, \sigma_{a2}^2, \gamma_{T(s2)}, \nu^2_R\} \) and \( \theta_2 = \{\mu(s2), a_1, a_2, a_0, a_1, a_2, b_1, b_2\} \). The error variance terms in set \( \theta_1 \) are all normal distributions with zero mean and specific variance \( \xi_i \).

In set \( \theta_2 \), the prior distribution of parameters is described as follows:

\[
\mu(s2) \sim N(\mu(s2), \sigma^2_p),
\]

\[
\alpha_0 \sim N(0, \sigma^2_{a0}), \alpha_2 \sim N(0, \sigma^2_{a2}),
\]

\[
a_1, a_2, a_0 \sim N(0, \sigma^2_e), a_1, a_2 \sim N(0, \sigma^2_{a1}, \sigma^2_{a2}),
\]

\[
b_1, b_2 \sim N(0, \sigma^2_b), b_1, b_2 \sim N(0, \sigma^2_{b1}, \sigma^2_{b2}),
\]

where \( \{\xi_i, \sigma^2_e, \sigma_{a1}, \sigma_{a2}, \gamma_{T(s2)}, \nu^2_R\} \) and \( \{\mu(s2), \alpha_0, b_0\} \) are superparameters.

5) PRIOR INFORMATION AND EXPLORATORY ANALYSIS

The prior distribution of each parameter is taken as a conjugate prior. We performed some simple exploratory analyses to specify our prior distribution of all parameters.

Considering the incompleteness of the drifting buoys and MODIS SSTs and the better spatial continuity of the AMSR-E SSTs, simple exploratory analysis is implemented based on the AMSR-E SSTs over every 2°-latitude region because the SST clearly varies with latitude. The time average of each pixel over every 2°-latitude region is selected as the prior value of \( \mu(s2) \). Then, we simulate the seasonal trend and obtained the coefficients of the cosine spectral curve. We treat the coefficients of sine and cosine as the prior values of \( a_0 \) and \( b_0 \), respectively. The partial prior value is provided in Table 3. The prior distribution of set \( \{\xi_i, \sigma^2_e, \sigma^2_{a0}, \sigma^2_{a2}, \sigma^2_{a1}, \sigma^2_{a2}, \sigma^2_{b1}, \sigma^2_{b2}\} \) is an inverse gamma distribution whose shape parameter and scale parameter are both 0.1 (Xu et al. 2005).

4. Results and comparison

This section introduces the sample results after applying STHBM to bias-corrected MODIS and AMSR-E SSTs. The accuracy of the merged SSTs is assessed in terms of \( B, \text{ std dev or error, RMSE, and } R \) using the drifting buoy SSTs as reference. And in this section the performance of STHBM was also compared with that of R-FRK and BME, which are both new modern spatio-temporal methods our team has worked with before.

The STHBM introduced above is implemented using a sketch of the Markov chain Monte Carlo (MCMC) algorithm. For the results presented here, the MCMC runs for 1500 iterations, with the first 1000 considered burn-in from a single chain until the chain reaches convergence. After the Markov chain has converged and the parameters are reliably estimated, the goodness of fit of the model is confirmed. We attempt other iteration numbers and determine that with an increase in the iteration number, the estimation of the posterior distribution of the average value of the potential true SST process varied very negligibly. Therefore, considering the computational efficiency and the prediction accuracy, we selected 1500 iterations.

| Table 3. Partial prior value of parameters at every 2° latitude. |
|-----------------|-----------------|-----------------|
| Latitude        | \( \mu(s2) \)    | \( \alpha_0 \)  | \( \beta_0 \)  |
| 46°–44°N        | 7.3262          | –6              | –3             |
| 22°–20°N        | 27.3547         | –2              | –1             |
| 28°–30°S        | 21.4918         | –2              | –0.1           |


**Table 4. Sample results of the MCMC algorithm at 4°–6°S, 122°–124°E.**

<table>
<thead>
<tr>
<th>Node</th>
<th>Mean</th>
<th>Std dev</th>
<th>MC error</th>
<th>2.5%</th>
<th>Median</th>
<th>97.5%</th>
<th>Start</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>mu1[14,46,21]</td>
<td>27.3</td>
<td>0.1889</td>
<td>0.01099</td>
<td>26.95</td>
<td>27.3</td>
<td>27.66</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,22]</td>
<td>27.97</td>
<td>0.1848</td>
<td>0.00739</td>
<td>27.61</td>
<td>27.97</td>
<td>28.33</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,23]</td>
<td>27.58</td>
<td>0.1871</td>
<td>0.008235</td>
<td>27.2</td>
<td>27.58</td>
<td>27.95</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,24]</td>
<td>27.46</td>
<td>0.1826</td>
<td>0.007854</td>
<td>27.1</td>
<td>27.46</td>
<td>27.82</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,25]</td>
<td>27.56</td>
<td>0.1937</td>
<td>0.007887</td>
<td>27.15</td>
<td>27.56</td>
<td>27.93</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,26]</td>
<td>26.89</td>
<td>0.1992</td>
<td>0.008925</td>
<td>26.48</td>
<td>26.9</td>
<td>27.3</td>
<td>1001</td>
<td>500</td>
</tr>
<tr>
<td>mu1[14,46,27]</td>
<td>27.33</td>
<td>0.1746</td>
<td>0.007811</td>
<td>26.99</td>
<td>27.34</td>
<td>27.69</td>
<td>1001</td>
<td>500</td>
</tr>
</tbody>
</table>

**a. Sample results and merged SST**

Table 4 provides the results of the MCMC algorithm for one sample from 4° to 6°S and from 122° to 124°E. The MC error is very small, and the chain reached convergence; thus, the estimation of the postdistribution of the potential true SST process is credible.

The spatial pattern of the merged original MODIS SSTs and the original AMSR-E SSTs is shown in Fig. 8. From Fig. 8 the merged SSTs keep a fine spatial pattern lying in the original MODIS SSTs at 4 km with spatial complete coverage, especially over the equatorial region.

**b. Assessment of spatial completeness**

From Fig. 8, we note that the spatial coverage and continuity have been greatly enhanced. The contamination of cloud coverage and land is eliminated completely.

We assess the spatial completeness of the original MODIS, AMSR-E and the merged SSTs using the availability of ocean pixels, which is defined as the ratio of the number of effective ocean pixels to the number of all ocean pixels. The annual-mean availability of ocean pixels of the original MODIS, AMSR-E, and merged SSTs is 80.38%, 87.53%, and 100%, respectively. Figure 9 indicates that the weekly mean availability varies with time.

The data with spatial complete coverage are derived from STHBM. The weekly mean availability of the original AMSR-E is better than that of the original MODIS because of the microwave’s advantage of cloud penetration. It is nearly constant through the year. The changes in the availability of the original MODIS SSTs are much larger than that of the AMSR-E and merged SST because of cloudy contamination.

**c. Assessment of accuracy**

The drifting buoy SSTs are used as reference to evaluate the accuracy of the merged SSTs, the original MODIS SSTs, and AMSR-E SSTs in terms of $\bar{E}$, std dev, RMSE, and $R$. The grid size of the merged and MODIS SSTs is set to 0.04° and that of the AMSR-E SSTs is set to 0.25°. First, we match the drifting buoy SSTs with the satellite-derived SSTs; that is, the temporal window is 8 days and the spatial window is 0.04° and 0.25° for MODIS and AMSR-E, respectively. All available drifting buoy SSTs situated in the same pixel for 8 days are averaged.

To verify the overall accuracy and local accuracy of the merged data, we divide our evaluation into two stages. In stage I, we evaluate the overall accuracy of the merged data; in stage II, we evaluate the local accuracy of the merged data. In each validation stage, we also compared the accuracy of the merged SSTs with that of the original MODIS and AMSR-E SSTs.

Figure 10 shows the scattergraph between merged SST, original MODIS SSTs, original AMSR-E SSTs, and the drifting buoy SSTs. Table 5 shows the evaluation results.

The mean bias, the standard deviation of errors, the root-mean-square error, and the correlation coefficient of the merged SSTs are $-0.1605$, 0.6860, 0.7045, and 0.9826, respectively; while that of the original MODIS are $-0.3697$, 0.7002, 0.7918, and 0.9815, respectively; and that of the original AMSR-E are $-0.054$, 0.4800, 0.4830, and 0.9898, respectively. The overall accuracy of the merged SSTs is better than that of the original MODIS SSTs, and the spatial coverage is enhanced greatly. Though the overall accuracy of the merged SSTs is a little worse than that of the original AMSR-E SSTs, the spatial resolution is higher than that of AMSR-E, and the spatial pattern of the merged is better than that of the AMSR-E. These results indicate that the merged data have kept not only the better accuracy of coarse-scale data (AMSR-E SSTs) but also the spatial pattern of finescale data (MODIS) using STHBM and the bias correction model. Of course, for improving accuracy the contribution of the bias correction model is more important, while for keeping the spatial pattern the contribution of the STHBM is most important.

On the basis of overall accuracy only, we cannot obtain the details of local accuracy from a partial location. Therefore, in stage II we evaluate the local accuracy with the same assessment index. All the matching point
pairs are divided into four groups, that is, 1) point pairs from locations where available oceanic pixels of both the original MODIS and AMSR-E SSTs exist; 2) point pairs from locations where available oceanic pixels of the original MODIS SSTs exist, while those of original AMSR-E SSTs are missing; 3) point pairs from locations where available oceanic pixels of the original MODIS SSTs are missing, while those of the original AMSR-E exist; 4) point pairs from locations where available oceanic pixels of both the original MODIS and AMSR-E SSTs are missing. Figure 11 indicates the scattergraph between the merged, the original MODIS and the AMSR-E SSTs, and the drifting buoy SSTs at local regions. Tables 6 and 7 sum the assessment results.

From Figs. 11a, 11c, and 11e, we can see that the merged SSTs are in good agreement with the drifting buoy SSTs whether valid oceanic pixels of the MODIS or AMSR-E SSTs exist or not. Especially at low SST regions

FIG. 8. Spatial patterns of the merged, MODIS, and AMSR-E SSTs: (a) merged SSTs of the 5th week, (b) merged SSTs of the 17th week, (c) merged SSTs of the 29th week, (d) merged SSTs of the 40th week, (e) original MODIS SSTs of the 5th week, (f) original MODIS SSTs of the 17th week, (g) original MODIS SSTs of the 29th week, (h) original MODIS SSTs of the 40th week, (i) original AMSR-E SSTs of the 5th week, (j) original AMSR-E SSTs of the 17th week, (k) original AMSR-E SSTs of the 29th week, and (l) original AMSR-E SSTs of the 40th week.

FIG. 9. Spatial completeness assessment of the original MODIS SST, AMSR-E SST, and merged SST.
(approximately less than 12.5°C), the merged SSTs and the drifting buoy SSTs distributed on either side of the 1:1 line more symmetrically than the MODIS SSTs.

From Table 6, the mean bias, the standard deviation of errors, and the root-mean-square error of the merged SSTs are $-0.1084^\circ$, $0.6241^\circ$, and $0.6335^\circ$C, respectively, at locations where valid oceanic pixels of both the MODIS and AMSR-E exist, while that of the MODIS SSTs are $-0.3739^\circ$, $0.6883^\circ$, and $0.7833^\circ$C, respectively; the mean bias, the standard deviation of errors, and the root-mean-square error of the merged SSTs are $0.0150^\circ$, $0.7537^\circ$, and $0.7537^\circ$C, respectively, at locations where only valid oceanic pixels of MODIS exist, while that of the MODIS SSTs are $0.3168^\circ$, $0.8314^\circ$, and $0.8895^\circ$C, respectively. These results show that the accuracy of merged SSTs is superior to that of the MODIS SSTs at locations where valid oceanic pixels of the MODIS exist whether valid oceanic pixels of the AMSR-E exist or not.

From Table 7, at locations with valid oceanic pixels of MODIS missing, the accuracy of merged SSTs is relatively lower than that at locations where valid oceanic pixels of MODIS exist whether valid oceanic pixels of AMSR-E exist or not. Although the accuracy is relatively lower, the mean bias meets the requirements of the GODAE (less than $0.5^\circ$C). These results from Tables 6 and 7 indicate that the contribution of the MODIS SSTs is more obvious than that of the AMSR-E SSTs in STHBM.

From an analysis of the overall and local accuracy, we can see that the merged SSTs have features of both the MODIS and AMSR-E SST, that is, the accuracy of the merged SSTs is between MODIS SSTs and AMSR-E SSTs, and the contribution of the MODIS SSTs may be more obvious than that of the AMSR-E SSTs in STHBM. Certainly, the contribution of the data-driven regional bias correction model is obvious for improving the accuracy of the merged SSTs.

d. Assessment of ability to keep spatial pattern

Using local variance, we evaluate the ability of the merged SSTs to keep the spatial pattern lying in the MODIS SSTs at 4-km scale, and compare it with MODIS and AMSR-E SSTs. Local variance is a scene texture statistic that has been shown to characterize the relationship between spatial resolution and objects in the scene (Coops and Culvenor 2000; Woodcock and Strahler 1987). So, local variance can express the pattern information in the scene, and it can be used to describe the information richness of the merged SSTs. Local variance is defined as (Li et al. 2013)

$$lVar = \frac{1}{N} \sum_{j=1}^{N} \left( \frac{1}{n-1} \sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2 \right),$$

where $lVar$ denotes the local variance, $x_{ij}$ denotes the $i$th pixel in the $j$th window, $\bar{x}_j$ denotes the mean value of the $j$th window, $n$ denotes the valid observed pixel value in a moving window, and $N$ denotes the number of the window.

Table 5. Overall accuracy comparison of merged, MODIS, and AMSR-E SSTs.

<table>
<thead>
<tr>
<th>Points</th>
<th>$\overline{B}$</th>
<th>Std dev</th>
<th>RMSE</th>
<th>$R$</th>
<th>Regression formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Merged SST</td>
<td>41 808</td>
<td>-0.1605</td>
<td>0.6860</td>
<td>0.7045</td>
<td>0.9826</td>
</tr>
<tr>
<td>MODIS SST</td>
<td>33 889</td>
<td>-0.3697</td>
<td>0.7002</td>
<td>0.7918</td>
<td>0.9815</td>
</tr>
<tr>
<td>AMSR-E SST</td>
<td>30 190</td>
<td>-0.0540</td>
<td>0.4800</td>
<td>0.4830</td>
<td>0.9898</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$y_{\text{MODIS}} = 0.9604 \times x_{\text{buoy}} + 0.6800$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$y_{\text{AMSR-E}} = 0.9715 \times x_{\text{buoy}} + 0.7066$</td>
</tr>
</tbody>
</table>
The local variance of the merged and MODIS SSTs is computed within a $24 \times 24$ moving window at 4-km scale; the local variance of AMSR-E SSTs is computed within a $4 \times 4$ moving window at 25-km scale, which covers the same area as the MODIS $24 \times 24$ moving window at 4-km scale. To keep computation stability, we reject the moving window in which the number of valid oceanic pixels is less than 30 for the merged and MODIS SSTs, and less than 2 for AMSR-E SSTs. A high local variance indicates the data have large variability: the larger the local variance is, the finer the spatial pattern that lies in SST images (Li et al. 2013). Figure 12 presents the weekly local variance of merged, MODIS, and AMSR-E SSTs.

The annual-mean local variance of the merged, MODIS, and AMSR-E SSTs is $0.2134^\circ C$, $0.2409^\circ C$, and $0.0562^\circ C^2$, respectively. At 4-km scale, the local variance of the merged SSTs is similar to that of the MODIS SSTs. The local variance of the AMSR-E SSTs is lowest among the three datasets. This shows that the merged
SSTs keep the fine pattern of MODIS SSTs and contain more information. For example, the fine pattern of the Kuroshio south of Japan is clearly revealed from the merged data, while the MODIS and AMSR-E data do not clearly demonstrate this structure (see Fig. 8). This also indicates that STHBM can keep local information details lying in data with fine resolution.

e. Assessment of fusion uncertainty

STHBM provides the posterior standard deviation of fusion to evaluate the uncertainty of the merged data. Figure 13 shows the spatial pattern of the posterior standard deviation from the merged SSTs. North of 30°N and at regions where MODIS SSTs miss—for example, equator regions—the fusion posterior standard deviation is relatively large. It is between 0.5°C and 1°C. At regions where valid oceanic pixels of both MODIS and AMSR-E are missing, the fusion posterior standard deviation is the largest, for example, near land, where they are larger than 1°C. At other regions, the fusion posterior standard deviation is small, where they are less than 0.25°C.

f. Comparison analysis

In this section, we compared the performance of STHBM with that of R-FRK and BME, which are new modern spatial or spatiotemporal methods our team has worked with before.

First, for the availability of ocean pixels the STHBM is 100% and the R-FRK is also 100% (Zhu et al. 2015), while the BME it is close to 100% (Li et al. 2013).

Second, for overall accuracy, the absolute mean bias of merged SSTs based on STHBM is 0.063 and 0.0145 higher than that of R-FRK and BME, respectively. The root-mean-square error of STHBM is 0.0007 and 0.0515 higher than that of R-FRK and BME, respectively. Although the absolute mean bias and RMSE of STHBM are slightly higher than those of the other two models, the difference is very small.

Third, for local accuracy, at locations where valid oceanic pixels of both the MODIS and AMSR-E exist, the absolute mean bias and the root-mean-square error of STHBM are 0.0074 and 0.0435 higher than that of BME, respectively; at locations where only valid oceanic pixels of MODIS exist, the absolute mean bias and the root-mean-square error of STHBM are 0.123 lower and 0.0077 higher than that of BME, respectively; at locations where only valid oceanic pixels of AMSR-E exist, the absolute mean bias and the root-mean-square error of STHBM are 0.1686 higher 0.139 higher than that of BME, respectively; at locations with valid oceanic pixels of AMSR-E and MODIS missing, the absolute mean bias and the root-mean-square error of STHBM are 0.0947 and 0.2114 higher than those of BME, respectively.

Fourth, for the spatial pattern (i.e., the ability to keep local details of SST) the local variance of STHBM is 0.03 lower than that of BME, but the prediction data from R-FRK are much smoother than those from STHBM and BME.

The analysis mentioned above has demonstrated that all three methods can improve the accuracy and the spatial completeness of the estimated data. However,
the estimated data from R-FRK maintain a small amount of spatial information in the original fine-resolution data. Although the merged data from BME maintain a large amount of spatial information in the original fine-resolution data, the same as STHBM, in the BME model the spatiotemporal process model of the potential real SST field is lacking and the accuracy of the merged data greatly depends on the original input data; while STHBM can construct a constraint spatiotemporal process of SST to partly control the accuracy of the merged data, it can greatly improve computing efficiency compared with BME.

5. Discussion and conclusions

This study explores a new data-driven regional bias correction model—STHBM—to correct satellite SSTs and to merge MODIS and AMSR-E SSTs. The merged SSTs with complete coverage and fine resolution are derived, and the accuracy of the merged SSTs conforms to the specifications of GODAE. The merged SSTs improve the spatial pattern of AMSR-E SSTs and keep the fine spatial pattern lying in MODIS SSTs. The data-derived regional bias correction model makes up for the deficiency of the fusion model based on STHBM, which cannot reduce systematic errors. The fusion results indicate that the overall accuracy of the merged data is similar to but better than that of the original MODIS SSTs at 4-km scale. Although the overall accuracy of the merged SSTs is lower than that of the original AMSR-E SSTs, the spatial resolution, the spatial pattern, and the spatial coverage of the merged SSTs are improved greatly. The local accuracy of the merged SSTs is better than that of MODIS SSTs at locations where the valid oceanic pixels of MODIS exist. At locations where the valid oceanic pixels of MODIS are missing, although the accuracy of the merged SSTs is relatively lower, it still meets the GODAE requirements. Analyzing the source of errors, the difference in measured depth from the drifting buoy, MODIS, and AMSR-E is one of factors

![Figure 12](image-url)  
**FIG. 12.** Weekly local variances of AMSR-E, MODIS, and merged SSTs for 2003.

![Figure 13](image-url)  
**FIG. 13.** Posterior standard deviation of merged SSTs through the MCMC algorithm: (a) 5th, (b) 17th, (c) 29th, and (d) 40th weeks.
that should be considered with respect to differences between the bulk SST and the skin SST, though we can reduce these differences through satellite data and the drifting buoy data’s time matching and bias correction. The decomposition of the potential real SST process model is also a factor in introducing error, though this type of error has been expressed through the parameters’ conditional distribution in STHBM.

The merged SSTs keep the fine spatial pattern lying in MODIS SSTs. The local variance of the merged SSTs is similar to that of the MODIS SSTs and much higher than that of the AMSR-E SSTs. The uncertainty of the merged SSTs is larger at locations where valid oceanic pixels of MODIS are missing than that at locations where valid oceanic pixels of MODIS exist. It is the largest at locations where valid oceanic pixels of both MODIS and AMSR-E SSTs are missing. These features demonstrate that the merged data have characteristics of the two types of satellite-derived data: the contribution of the MODIS data is stronger than that of the AMSR-E data and the latent true SST process model has a constraint effect in STHBM.

Although STHBM can achieve merged SST with high accuracy and fine spatial pattern, its limitation is mainly reflected in its scale transformation model. In the STHBM framework, the scale transformation model is suitable for two kinds of data with nested structure characteristics. Of course, STHBM is flexible; it allows any establishment of the practical experience model based on features of input data. Another limitation is that STHBM itself cannot reduce the system bias of input data. So, input data need to be corrected before STHBM is executed. In this paper, we regard the bias correction model and fusion model as two separate components. It is our intent to further research on how to nest the bias-corrected model into STHBM.

In our study all inferences are achieved according to a hierarchical Bayesian framework; that is, all the parameters are considered stochastic variables. The priori value of some parameters is important for a merging result. For example, in Eqs. (6) and (7), the priori distribution of $Y_{\text{MODIS}}(x_1, t)$ is more sensitive than that of $Y_{\text{AMSR-E}}(x_2, t)$ because the parameter $Y_{\text{AMSR-E}}(x_2, t)$ can be constrained by the SST spatiotemporal process. For all the variance parameters, their priori value needs be set to very small. The most sensitive parameter is the spatial structure of the fine-resolution data in the input. If there are many missing data over the local region, then the uncertainty of merging data will be increased greatly.

For the drifting buoy SSTs used in this paper, we take them as reference without bias because they are interpolation based on raw observations. We also ignore the temperature bias from the difference in observation depth among MODIS, AMSR-E, and drifting buoys. It would be best to take into account the difference between the skin and subskin temperatures, although we chose the nighttime MODIS SSTs and the early morning AMSR-E and drifting buoy SSTs for analysis in this paper to minimize the skin and subskin difference.

The preliminary results derived from the objective analysis mentioned above demonstrate the practicality and advantages of the hierarchical Bayesian model in combining satellite data. At the same time, this method also demonstrates the flexibility in addressing uncertainty, including the uncertainty of the observation data, process model, and parameters, and the flexibility in scale transformation seamlessly. This method can be applied to other satellite data through modifying the potential spatiotemporal process.

Acknowledgments. This work was supported by the Natural Science Foundation of China under Grant 41401405, the China Postdoctoral Science Foundation under Grant 2014M561039, the Statistics Bureau of China under Grant 2016LYY2, the Natural Science Foundation of Shandong Province under Grants ZR2013DL002 and ZR2017MD017, and the Natural Science Foundation of China under Grant 41471425. We would like to express our sincere gratitude to the people who provided excellent comments and valuable suggestions in the preparation of this manuscript.

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