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Sampling errors in satellite-derived infrared sea-surface temperatures. Part II: Sensitivity and parameterization

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ABSTRACT

In the recent work of Liu and Minnett (2016), we estimated the sampling errors in Moderate Resolution Imaging Spectroradiometer (MODIS) Sea-Surface Temperatures (SSTs) due to clouds and other causes, and characterized the global error dependence on the variability of clouds and SST. Here we report sampling error sensitivity to the choice of reference field and the error variation when data from a different year are used. We also developed an empirical model to parameterize sampling errors. Our sensitivity tests show that the sampling error quantification method developed is robust and can reveal the consequences of missing infrared SST observations primarily due to clouds. Since the previously found pronounced negative sampling errors along the Tropical Instability Waves are largely dependent on the SST gradients, here these regional sampling errors are quantified using data from an El Niño year, confirming that the weakened meridional SST gradient due to El Niño can reduce the negative sampling errors. Furthermore, the climatology-derived sampling errors are found to be a primary component that can be utilized to estimate and parameterize the sampling errors, especially for the spatial sampling errors. For the temporal sampling errors, good estimates are obtained especially in the high latitudes and stratocumulus regions, by incorporating an empirical model proposed in this study and the previously found sampling error dependence.

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1. Introduction

Clouds and inter-swath gaps are the primary reasons for incomplete coverage of satellite infrared (IR) measurements of the Earth's surface, and result in sampling errors in averaged IR Sea-Surface Temperature (SST) fields. In a recent paper (Liu and Minnett, 2016; hereafter LM16) we found that the MODIS (Moderate Resolution Imaging Spectroradiometer (Esaias et al., 1998)) monthly SST sampling error referenced to MUR SSTs (Multi-scale Ultrahigh Resolution (Chin et al., 2010), see details in Section 2) is up to O (1 K), which far exceeds the error threshold needed for climate research. The largest sampling error (>5 K in monthly SSTs) is found in the Arctic. The 30°N–30°S zonal band has the smallest errors, with a notable exception being the persistent negative errors found in the Tropical Instability Wave (TIW) region, where mesoscale ocean-atmosphere interaction leads to a more frequent satellite sampling above areas with lower SSTs; SST-cloud relationships at different time and space scales were proposed to be the causes for certain error characteristics, which could introduce misleading SST values and patterns to the final Level 4 (see Table 1 for SST processing Level definitions) SST fields and potentially adversely affect many applications. The statistics based on the studied periods show that the global mean sampling error is generally positive and increases approximately exponentially with missing data fraction (gap fraction) in a fixed averaging interval, while the error variability is mainly controlled by SST variability.

Two further questions are addressed here. First, since the MODIS sampling error was initially calculated based on the use of MUR SST fields as the reference, whether another SST reference field with presumably different embedded variability would result in different sampling error patterns. The international Group for High Resolution SST (GHRSST: https://www.ghrsst.org/) was set up to help coordinate efforts to improve the accuracy of satellite-derived SST fields at all processing levels and to standardize data formats to facilitate the analysis of different SST fields by the research and operational communities (Donlon et al., 2007). With the growing number of Level 4 SST fields that blend observations, often including model simulations, differences in the SST structure exist among the different data products, especially in many dynamic and rarely sampled regions. SST differences among sixteen daily Level 4 fields are monitored and discrepancies are revealed by the online tool, L4-SQUAM (SST Quality Monitor (Dash et al., 2012): http://www.star.nesdis.noaa.gov/sod/sst/squam/L4/). For example, compared with the GHRSST multi-product ensemble (GMPE; Martin

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Table 1
SST processing levels modified from http://science.nasa.gov/earth-science/earth-science-data/data-processing-levels-for-eosdis-data-products/ and GHRSST Science Team (2010).

Data levels	Definitions
Level 0	Reconstructed, unprocessed instrument and payload data at full resolution, with any and all communications artifacts removed.
Level 1A	Reconstructed, unprocessed instrument data at full resolution, time-referenced, and annotated with ancillary information, including radiometric and geometric calibration coefficients and georeferencing parameters (e.g., platform ephemeris) computed and appended but not applied to Level 0 data.
Level 1B	Level 1A data that have been processed to sensor units (not all instruments have Level 1B source data).
Level 2	Derived SSTs at the same resolution and location as Level 1 source data.
Level 3 Uncollated (L3U)	SSTs mapped on uniform space-time grid scales, usually with some completeness and consistency. The Level 3 can be processed from single sensor or multiple sensors and do not use analysis or interpolation procedures to fill gaps. The uncollated Level 3 are built without combining any observations from overlapping orbits.
Level 3 Collated (L3C)	SSTs mapped on uniform space-time grid scales. Multiple passes/scenes of data can be combined. Adjustments may be made to input SSTs.
Level 4	Model output or results from analyses of lower-level data (e.g., SSTs derived from multiple measurements of satellite microwave, infrared, and in situ). SST fields at this Level are usually bias corrected, gap-free, and in latitude/longitude coordinates.

et al., 2012), MUR frequently shows lower SST estimates in the Southeast Asian Maritime Continent region, Falkland Islands (Islas Malvinas), and the Pacific and Atlantic eastern equatorial upwelling areas, while higher estimates are found in the Northern Hemisphere high latitudes. Such non-negligible differences constitute a potential source of uncertainty in the previously quantified sampling errors and are examined in this paper.

The second important question is whether the error magnitudes and patterns change significantly in different years. Sampling errors may have interannual variability due to ocean-atmosphere interactions associated with long-duration climate events such as ENSO (El Niño–Southern Oscillation). It is recognized that the eastern equatorial Pacific TIW activity can be influenced by ENSO (Yu and Liu, 2003; An, 2008; Kug et al., 2010): stronger (weaker) activity due to the increased (decreased) eastern equatorial Pacific meridional SST gradient during La Niña (El Niño). Sampling errors found in LM16 were quantified using the data of year 2011, which was during the 2010–2011 moderate La Niña event. How the negative TIW sampling errors may evolve with ENSO requires a comparative error quantification using data from an El Niño event; this can yield an assessment of the interannual changes in the sampling error.

Another focus of this study is whether sampling errors caused by clouds and interswath gaps can be predicted. As the properties of the error characteristics become better known, can the sampling errors be estimated using, for example the local SST anomaly, cloud persistence (the number of consecutive days during which a location is detected to be cloudy), or season and region? It is widely known that the primary component in any time series of L4 SST fields is the annual cycle. Therefore, the seasonally induced error component can be explicitly quantified by using a seasonal climatology, assuming the additional sampling errors in the climatology are neglected.

The ultimate goal is to predict the sampling errors without relying on a specific reference field after the error characteristics are well understood. Thus, we first test the error sensitivity by comparing the sampling errors using two different reference SST fields, and explain the prevalently small error differences and the few exceptions when the magnitude of sampling errors could be affected by the reference field selection. As an exploratory test of sampling error interannual variability, we quantified the errors in the El Niño year of 2009, as opposed to the previously studied La Niña year of 2010–2011. We also examined the error component of the seasonal cycle, and by combining the previously derived error statistics and the error sensitivity to the annual cycle, a preliminary empirical model is suggested to estimate and predict the MODIS SST sampling errors.

2. Methods and data

The sampling error quantification framework is described in detail in LM16. Here we briefly review the definitions that are relevant to this paper. In LM16, to minimize the effect of existing errors in MUR, sampling errors are calculated as the difference between the means of the sampled (number of n_R) and the gap-free (number of N_R) MUR SSTs at base resolution R_0 in a fixed spatial or temporal interval defined by a coarser resolution R. R is a set of resolutions: 0.25°, 0.5°, 1°, 2.5°, and 5° and 1 day (1 d), 3 days (3 d), 1 week (1 w), 2 weeks (2 w) and 1 month (mon). What is different here is we use resampled reference fields at 0.25° and daily base resolution instead of the 4 km and daily in LM16, in order to reconcile MUR with the HYCOM (HYbrid Coordinate Ocean Model) data set used for further comparisons. The utilization of the parameters - cloud persistence and gap fraction-created in LM16 - is continued here.

We continue using masks from the thermal IR daytime and mid-IR nighttime Level 3 fields of Terra MODIS SSTs (http://oceancolor.gsfc.nasa.gov/), with quality flags >1 considered as missing data. Four monthly data sets from 2010 to 2011 are used representing four boreal seasons: winter: 20101228–20110125 (yyyymmdd); spring: 20110407–20110506; summer: 20110721–20110819; fall: 20111001–20111030. For the sensitivity test for TIW negative errors during ENSO events, we use the data of 20091001–20091030 to represent the El Niño TIW variations, and compare with the month of 20111001–20111030 during La Niña conditions.

Two very different reference fields are selected to test the sampling error sensitivity: HYCOM Global 1/12° reanalysis SSTs at 00Z and MUR SSTs. The former reference data are generated from the Navy Coupled Ocean Data Assimilation system (NCODA), which uses HYCOM model forecast as a first guess and assimilates both satellite and in situ SSTs: IR and microwave (MW) SSTs from AVHRR, AATSR, and AMSR-E, and in situ SSTs from ships, drifters and buoys. The latest distributed operational version GOFS3.0 (Global Ocean Forecast System 3.0) assimilates SST observations from the 5-day hindcast up to the nowcast time (Metzger et al., 2008; Metzger and Smedstad, 2009; Metzger et al., 2010a and 2010b; Cummings and Smedstad, 2013). The analysis SST root-mean-square-error (RMSE) assessed by comparing with temperatures measured from drifting buoys between 45°S–45°N is reported as ~0.3 K (Metzger et al., 2008). The HYCOM-NCODA SST data used here is the average temperature of the ocean top 1-meter depth layer. We refer to these temperature data as HYCOM SSTs hereafter.

On the other hand, MUR is a 1 km resolution daily analysis of foundation temperatures (without diurnal warming) derived using observations from nighttime satellite skin (AVHRR and MODIS) and subskin SSTs (AMSR-E before October 2011 and WindSat after October 2011) and in-situ SSTs (Chin et al., 1998; Chin et al., 2010), using quality-controlled in situ SSTs from iQuam (in situ SST quality monitoring system (Xu and Ignatov, 2014)) for bias corrections. For the transition from AMSR-E to WindSat MW SSTs, Banzon and Reynolds (2013) tested the impact on the consistency in their OI SSTs and found that WindSat can be used to continue the long time series of interpolated SST analyses without significant detriment. Unlike other L4 fields such as OISSTs (Reynolds et al., 2007; Banzon et al., 2014), MUR does not use any external climatology field to remove “outliers”. The GHRSST L2P SST data (L2 preprocessed; Donlon et al., 2007) from multiple satellite radiometers within the −5-day and +12-hour window of the analysis time are

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