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Sea surface temperature from a geostationary satellite by optimal estimation

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ABSTRACT

Optimal estimation (OE) is applied as a technique for retrieving sea surface temperature (SST) from thermal imagery obtained by the Spinning Enhanced Visible and Infra-Red Imager (SEVIRI) on Meteosat 9. OE requires simulation of observations as part of the retrieval process, and this is done here using numerical weather prediction fields and a fast radiative transfer model. Bias correction of the simulated brightness temperatures (BTs) is found to be a necessary step before retrieval, and is achieved by filtered averaging of simulations minus observations over a time period of 20 days and spatial scale of 2.5° in latitude and longitude. Throughout this study, BT observations are clear-sky averages over cells of size 0.5° in latitude and longitude. Results for the OE SST are compared to results using a traditional non-linear retrieval algorithm ("NLSST"), both validated against a set of 30108 night-time matches with drifting buoy observations. For the OE SST the mean difference with respect to drifter SSTs is −0.01 K and the standard deviation is 0.47 K, compared to −0.38 K and 0.70 K respectively for the NLSST algorithm. Perhaps more importantly, systematic biases in NLSST with respect to geographical location, atmospheric water vapour and satellite zenith angle are greatly reduced for the OE SST. However, the OE SST is calculated to have a lower sensitivity of retrieved SST to true SST variations than the NLSST. This feature would be a disadvantage for observing SST fronts and diurnal variability, and raises questions as to how best to exploit OE techniques at SEVIRI's full spatial resolution.

1. Introduction

The temperature of the ocean surface is routinely retrieved from broad-band infra-red brightness temperatures (BTs) observed by sensors on both geostationary and polar-orbiting satellites. Sea surface temperature (SST, also represented in this paper by variable x) is one of the most precisely derived geophysical quantities from satellite observations. Nonetheless, users' requirements for the accuracy, resolution and timeliness of SST become more demanding, and increasing attention is paid to understanding and correcting the differing bias characteristics of various SST products (e.g., Donlon et al., 2007). In this study, we explore the nature of biases in SSTs obtained from the Spinning Enhanced Visible and Infra-Red Imager (SEVIRI) on board the meteorological satellite Meteosat-9. Meteosat-9 is a geostationary platform located in the equatorial plane at 0° longitude. SEVIRI observes a given location with a constant viewing geometry every 15 min, with ground resolution of ~5 km near nadir and increasing with increasing zenith angle towards the limb view. The present operational SST product is a "split-window" retrieval (defined below) based on radiative transfer modelling and empirical offset adjustment (Merchant and Le Borgne, 2004). It is generated and distributed on a 3-hourly cycle by Météo-France in the context of the Ocean and Sea Ice Satellite Application Facility.

The advantages of the repeated observations of SST available from geostationary orbit are two-fold: greater daily fractional coverage (within the observed disk) than with a polar-orbiting sensor because of repeated opportunities to view the surface between the moving field of clouds; and the unique clarity with which large-scale diurnal variations in SST can be observed using hourly or higher temporal resolution (e.g., Merchant et al., 2008a).

The split-window retrieval technique is the "traditional" SST estimator, following the proposal of Anding and Kauth (1970). The name refers to the fact that it employs two channels (nominally centred on 11 and 12 μm) within the same band of relatively high atmospheric transmittance (the window between about 10 μm and 13 μm). For night-time retrievals, these are often augmented with a third channel around 3.8 μm. This latter channel can greatly improve the accuracy and precision of SSTs because of the extremely non-linear variation of emitted radiance with temperature at this wavelength for a surface with a temperature in the terrestrial range; however, there is significant solar radiation at this wavelength which renders the channel very difficult to use for SST retrieval for day time scenes.

The usual form of the SST estimator (whether two-channel or three-channel) is a linear (or nearly linear) combination of brightness temperatures (BTs) (Anding and Kauth, 1970):

$$\hat{x} = a_0 + \mathbf{a}^{\mathrm{T}}\mathbf{y}_o \tag{1}$$

where $\hat{x}$ is the estimated SST, a_0 is an offset coefficient, $\mathbf{a}$ is a column vector of weighting coefficients and $\mathbf{y}_o$ contains the observed BTs. The

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coefficients in the retrieval equation may be derived by regression of observed BTs to in situ measurements or by regression using BTs simulated using radiative transfer modelling. For two-channel retrievals, one widely adopted form (Walton et al., 1998) is the non-linear SST (NLSST) algorithm, in which coefficients weighting the 11 and 12 μm are a (weak) function of a prior SST, and this is the form used at Météo-France for SEVIRI SSTs.

Biases in SST may arise from: error in specifying retrieval coefficients from either forward modelling or instrumental biases (e.g., Merchant and Le Borgne, 2004); undetected cloud; stratospheric aerosol; near-surface stratification (if the target is estimation of the bulk SST); and tropospheric aerosols. Apart from these biases related to calibration and quality control, linear and near-linear retrievals of SST are fundamentally subject to two other systematic contributions to error (Merchant et al., 2006a): prior error (familiar from the theory of atmospheric sounding) and error arising from non-linearity of the physics of radiative transfer at infrared wavelengths.

The prior and non-linearity errors have complex spatial and temporal characteristics and are comparable in magnitude. Prior error arises as an intrinsic consequence of the form of the retrieval. Clear-sky BTs over the ocean are influenced by various geophysical quantities: principally by the skin SST and the total column water vapour in the atmosphere through which the SST is viewed by the radiometer; and more subtly by the leading modes of the vertical distribution of water vapour, the tropospheric lapse rate, the air–sea temperature difference, and (via their effects on emissivity and reflectivity) wind speed and salinity. Not all of the spatio-temporal variations in these geophysical quantities can be fitted simultaneously by variations in BT at only two or three surface-sensitive wavelengths; the result is that these variations manifest as geographically complex biases in retrieved SST. These biases are typically small – less than 1 K – but are not negligible relative to the demands of contemporary users (Donlon et al., 2007).

Merchant et al. (2008b) showed, for the case of the Advanced Very High Resolution Radiometer (AVHRR) on Metop-A, that optimal estimation (OE) with radiance bias correction could significantly address these biases present in traditional SST retrievals, as well as reducing single-pixel noise in SST. Here, we undertake a comparable study in the context of SEVIRI on Meteosat-9. In comparison with the previous study, this paper will have a greater focus on the relative properties of coefficient-based and OE-based SSTs, to better put the properties of the latter approach in context. The issue of bias correction of simulated BTs used in the OE process was important in the case of Metop-A and is important in this study too; however, bias correction for a geostationary imager is different because each location is viewed always at the same zenith angle; thus the bias correction technique developed here is quite different to that of the previous paper. We also discuss the question of the most appropriate prior SST to use for OE, which was not fully addressed in the previous paper.

Thus, this paper proceeds as follows. In the next section, we describe the data on which this study is based, including the available prior SSTs. Next, the operational NLSST algorithm is described and analyzed in terms of its biases compared to in situ observations, its degree of noise amplification, and the sensitivity of its retrieved SST to real changes in SST and atmospheric water vapour content. Then, a straightforward implementation of OE for SST is described and is likewise analyzed. Next, we demonstrate an approach to bias correction, of both BTs and prior SST, that is shown to be effective in reducing OE SST biases further. The paper concludes with some final discussion of the results and their implications.

2. Satellite, NWP and in situ data

The study exploits three months of data, at three-hourly intervals from 0000 UTC 1 February to 30 April, 2008, extracted from the operational chain at the Centre de Météorologie Spatiale (CMS), Lannion, France. As part of these operations, full resolution SEVIRI imagery is screened for cloud. To render the data set for this study tractable, we use observations averaged over clear-sky pixels to 0.5° resolution in latitude and longitude, on a 241 by 241 grid from 60° south to 60° north, and 60° west to 60° east. (These co-ordinates are those of the centres of the outermost cells.) The number of clear-sky pixels contributing to each 0.5° cell is also retained, varying in the data set from 1 to 186; this affects the propagation of radiometric noise into cell averages and is informative about the prevalence of cloud cover at the observation time. Four thermal channels were extracted, namely those centred near 3.8, 8.7, 11 and 12 μm, all the BTs being consistent with the EUMETSAT definition of calibration that has been operational since 17th March 2008.

Having all four surface-sensitive thermal channels allows calculation for night-time cells of an infra-red index for Saharan Dust (Merchant et al., 2006a). The Meteosat-9 version of a simplified Saharan Dust Index (SDI) is:

$$\mathrm{SDI} = 1.39 + 0.53973(y_{3.8} - y_{8.7}) - 0.820135(y_{11} - y_{12}) \tag{2}$$

where y_λ is the BT for the channel centred near wavelength λ. Saharan dust is a significant feature of the disk viewed by Meteosat-9, and is associated with SST biases if not corrected for (Merchant et al., 2006b). In this study, however, we retain only BTs where the SDI is less than 0.25; dust-related bias is not our focus here, and we thereby eliminate the most-affected data. (The SDI is an index that is by design comparable in magnitude for dust outbreaks to the 0.55 μm aerosol optical depth (AOD), although it is only loosely correlated with AOD. SDI in excess of 2 is seen for a strong dust event, and clear-sky pixels are dust contaminated with high probability for $\mathrm{SDI} > 0.25$.) Other than for this important screening step, the 3.8 and 8.7 μm channels are not otherwise used in this study: the operational retrieval of SST and the OE SST proposed here both rely on the split-window channels only. Not switching from two-channel to three-channel retrieval for night-time cells has the advantage of consistency of retrieval throughout the diurnal cycle. Lastly, in order to minimize the complications introduced by the ocean surface's diurnal cycle of temperature, we use only observations for which the solar zenith angle exceeds 90° (i.e., with the Sun below the horizon).

Optimal estimation involves forward modelling – simulation of the expected BTs in this case – before solving the inverse problem of estimating the SST. The fast radiative transfer simulation is performed here by RTTOV9 (Saunders et al., 2002). The required inputs to the forward model are atmospheric profiles of temperature and humidity, and the underlying surface temperature. Numerical weather prediction (NWP) fields supply these profiles, and we obtain forecasts at three-hourly intervals and 0.5° resolution from Météo-France's ARPEGE forecasting system. The conclusions of this study are not expected to depend on the source of NWP fields, although the geographical distribution of bias corrections would undoubtedly be changed were other sources of NWP fields to be used. For each cell for each 3-hourly slot, RTTOV9 is run on the ARPEGE profiles to provide a simulated BT for each channel and (following Merchant et al., 2008b) the partial derivatives of the BTs with respect to SST and total column water vapour (TCWV, also represented by variable w). We assume throughout that the NWP fields used are sufficiently close to reality to give an effective point for local linearization of the relationship between $\mathbf{y}$, x and w. OE will be undertaken using a reduced state vector, $\mathbf{z}(\mathbf{x}) = \begin{bmatrix} x \\ w \end{bmatrix}$. Let $\mathbf{F}$ represent RTTOV9. We can then define, for use later in the paper, the tangent linear matrix, $\mathbf{K} = \left[\frac{\partial \mathbf{F}(\mathbf{x}_0)}{\partial \mathbf{z}}\right] = \begin{bmatrix} \partial y_{11}/\partial x & \partial y_{11}/\partial w \\ \partial y_{12}/\partial x & \partial y_{12}/\partial w \end{bmatrix}$, where $\mathbf{x}_0$ is the state (a vector containing the NWP profile and SST) for a given cell and slot, around which K provides a linearized forward model.

The NWP SST, x_0, is a model field into which in situ observations of SST from drifting buoys have been assimilated. Thus, x_0 is not