DEFINING OPTIMAL BRIGHTNESS TEMPERATURE SIMULATION ADJUSTMENT PARAMETERS TO IMPROVE METOP-A/AVHRR SST OVER THE MEDITERRANEAN SEA

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Abstract

Sea surface temperature (SST) multispectral algorithms applied to infrared (IR) radiometer data exhibit regional biases due to the intrinsic inability of the SST algorithm to cope with the vast range of atmospheric types, mainly influenced by water vapor and temperature profiles. Deriving a SST correction from simulated brightness temperatures (BT), obtained by applying a Radiative Transfer Model (RTM) to Numerical Weather Prediction (NWP) atmospheric profiles and first guess SST, is one of the solutions to reduce regional biases. This solution is envisaged in the particular case of Metop-A Advanced Very High resolution (AVHRR) derived SST. Simulated BTs show errors, linked to RTM, atmospheric profiles or guess field errors. We investigated the conditions of adjusting simulated to observed BTs in the particular case of the Mediterranean Sea over almost one year. Our study led to define optimal spatio/temporal averaging parameters of the simulation observation differences, both during day and night and summer and colder season. Each BT adjustment has been evaluated by comparing the corresponding corrected AVHRR SST to the AATSR SST that we adopted as validation reference. We obtained an optimized result across all defined conditions for a spatial smoothing of 15 deg and a temporal averaging between 3 and 5 days. Specifically, time series analyses showed that a standard deviation based criterion favors spatial smoothing above 10 deg for all temporal averaging, while a bias based criterion favors shorter temporal averaging during daytime (< 5 days) and higher spatial smoothing (>10 deg) for nighttime. This study has shown also the impact of diurnal warming both in deriving BT adjustment and in validation results, leading to more appropriate separate BT adjustment for day and night in areas and seasons of intensive diurnal warming conditions.

1 INTRODUCTION

Real time simulated Brightness Temperatures (BTs) are increasingly used in operational Sea Surface Temperature (SST) calculations, either in Optimal Estimation (OE) methods [*Merchant et al.*, 2008, 2009] or coefficient based methods [*Le Borgne et al.*, 2011; *Petrenko et al.*, 2011]. BTs are simulated in the adequate infrared window channels by applying a Radiative Transfer Model (RTM) to Numerical Weather Prediction (NWP) atmospheric profiles, using a guess SST field (guess SST) as surface temperature. Referring to BT simulations as simBTi and to the corresponding BTs radiometer measurements as obsBTi, we can express the final SST based on the coefficient or OE methods in following form:

$$SST = guessSST + \sum a_i(obsBT_i - simBT_i) \quad (1)$$

In the case of coefficient based method envisaged here [*Le Borgne et al.*, 2011], a correction to a SST multispectral algorithms (non-linear split window and triple window, *McClain et al.*, 1985; *Walton et al.*, 1998) used to operationally derive SST is determined by applying the coefficients of this algorithms to simulations in order to produce a simulation derived SST. This “simulated” SST is compared to the “true” guess SST (a priori estimate of the SST) and the difference is used as a correction term to the operational SST derived with this algorithm. In this case, a_i in Eq. (1) are the coefficients of the SST multispectral algorithms to which the correction is applied.
BT simulations can differ from observations due to the several reasons: differences between the surface guess field and the actual SST field (guess errors); differences between the model atmospheric profiles and the actual profiles (NWP errors); RTM uses erroneous filter functions (filter

errors); RTM may be inaccurate (model errors); profile sampling induces errors (profile sampling errors) In the case of a coefficient based method applied here, guess errors are accounted for by Eq. (1), but the other sources of errors should be corrected prior to using simulations in the SST correction scheme. In practice adjustments are made by deriving empirical adjustment values from comparisons between simulations and observations. Two approaches have been used in literature: analytical expressions of the simulation errors as a function of water vapor and satellite zenith angle [*Merchant et al.*, 2008; *Petrenko et al.*, 2011] or a dynamic determination of the error geographical distribution [*Le Borgne et al.*, 2011; *Merchant et al.*, 2009]. We decided to derive BT adjustments from the geographical distribution of the errors averaged over space and time and to perform sensitivity analysis to find optimal time and space scales used in adjustment process. Each time and space combination has been evaluated by validating corrected SST against Advanced Along-Track Scanning Radiometer (AATSR), which were the only validation data covering the whole Mediterranean Sea. The next section present the data used in the study, BT simulations and adjustments method are briefly described in Section 3, results are described in Section 4 and conclusions in the last section.

2 DATA

All data span the time range between June 2011 and March 2012 over the Mediterranean Sea. Two different sets of satellite data have been used: Metop-A 12 hourly L3C files and AATSR L3C files. Regular grid 0.05° has been chosen as a common grid for all used datasets. Used SST products contain information about the quality of each pixel (quality flags) that follow the principles defined by GHRSST project [Donlon et al., 2007]. Metop-A/AVHRR L3C products are derived operationally at OSI-SAF from L2 granules aggregated twice daily from 18:00 to 06:00 UTC (centered on 00:00 UTC) and from 06:00 to 18:00 UTC (centered on 12:00 UTC) and spatially averaged on a global grid at 0.05° resolution. SST is calculated using non linear split window during day and triple window equation during night [EUMETSAT, 2010]. Orbit times over the area vary between 07:00 and 10:00 UTC by day and 19:00 to 22:00 UTC by night. This corresponds to about 10±1 h LST by day and 21±0.3 h LST by night.

AATSR L2P files obtained from ESA in GHRSST format were remapped (to the nearest neighbor) to the common 0.05 deg grid. From all remapped orbits, L3C files were created centered at 00:00 and 12:00 UTC time, with a ±6 hour time window centered at those times. Orbit times over the area vary between 07:30 and 10:30 UTC by day and 19:30 to 22:30 UTC by night. This corresponds to about 10.5±0.1 h Local Solar Time (LST) by day and 21.5±0.5 h LST by night. To ensure highest possible validation quality we used AATSR data with the quality level 5.

3 BRIGHTNESS TEMPERATURE ADJUSTMENTS AND SST CORRECTION

BT simulations have been done using RTTOV (v10.1) radiative transfer model applied to ECMWF analysis fields with 91 vertical levels (interpolated in time of the mean Metop-A overpass over Mediterranean Sea) and using OSTIA [*Donlon et al.*, 2012] as guess SST field. Simulations are calculated on ECMWF grid (0.1125 deg) and then interpolated to the Metop-A L3C working grid (0.05 deg).

Time series of 10 day averaged BT simulation minus observation differences (Figure 1) show practically no bias for channels 3.7 and 10.8 µm and small positive bias of 0.2 K for channel 12 µm. Standard deviations are relatively small, generally below 0.5 K with the smallest values for 3.7 µm channel (0.37 K).

This comparison showed differences due to the combined effect of guess errors, NWP errors, filter errors, RTM errors or profile sampling errors, as introduced in Section 1. The bias correction method we use is able to account for differences between guess field and true SST, through Eq. (1), but not for the other sources of errors. An adjustment of simulations is therefore needed to solve this issue. Our simulated BT adjustments are based on temporal averaging and spatial smoothing of the simulation minus observation differences. We assume a zero mean difference between the guess SST (used in simulations) and the true SST (corresponding to observations), we assume also that there is no systematic profile or RTM error differences between the adjustment conditions, and the conditions when we apply these adjustments. Finding optimal combination of space/time criteria is part of the research, therefore we tested a range of averaging sizes. For temporal averaging, we used averaging up to 30 days (1, 3, 5, 10, 15, 20, 30), where 1 day means no averaging. For spatial smoothing we used different window sizes from 0.1 deg to 50 deg and smoothing over the whole domain (Inf).

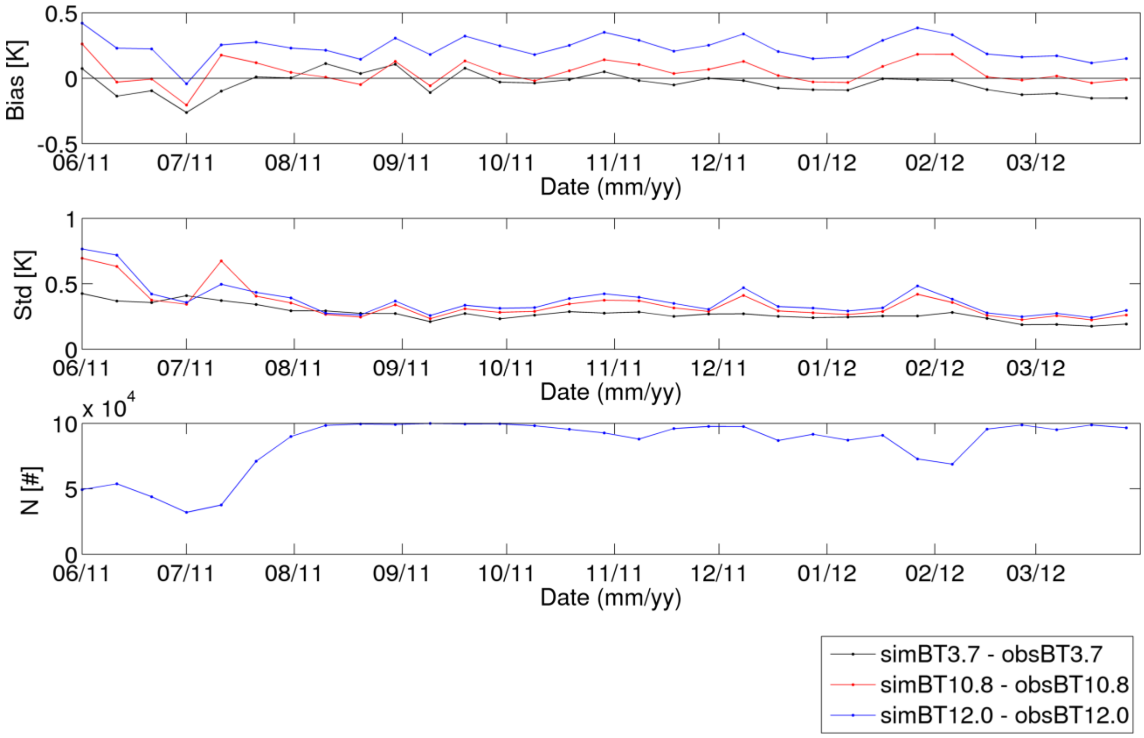


Figure 1. Metop-A/AVHRR differences between BT simulations and observations for channel 3.7 μm (black curve), channel 10.8 μm (red) and channel 12.0 μm (blue) for nighttime. First panel represents 10 day averaged biases, second panel represents standard deviation from 10 days files and third panel shows number of points in 10 days period.

BT adjustment process consists of preparing data (based on selected number of days and predefined filtering), satellite zenith normalization due to the different satellite zenith angles of polar orbiter AVHRR sensor, building mean difference fields and applying adjustment fields to BT simulations (only nighttime because we are using OSTIA guess SST in simulations that represents nighttime measurements). In the first step of preparing data, special care was taken due to the intensive diurnal warming (DW) episodes in summer time. Therefore, (among the other filtering), we used only data with wind speed above 4 m/s. For details of the whole procedure see *Tomažić et al.* [2013]. Finally, corrected SST is calculated by applying nighttime BT adjustments both to day and night simulations. After that, applying the Metop-A SST algorithm to adjusted BT gives a "simulated" SST and SST algorithm error is defined as a difference between simulated adjusted SST and the guess SST used in simulation step (OSTIA in our case). The corrected SST is then obtained by applying the Metop-A SST algorithm to BT observations and subtracting the derived SST algorithm error for each space-time combination.

Figure 2 shows that adjustment procedure (an example based on 20 days of time averaging and 15° spatial smoothing) reduces biases mainly for channel 12.0 μm.

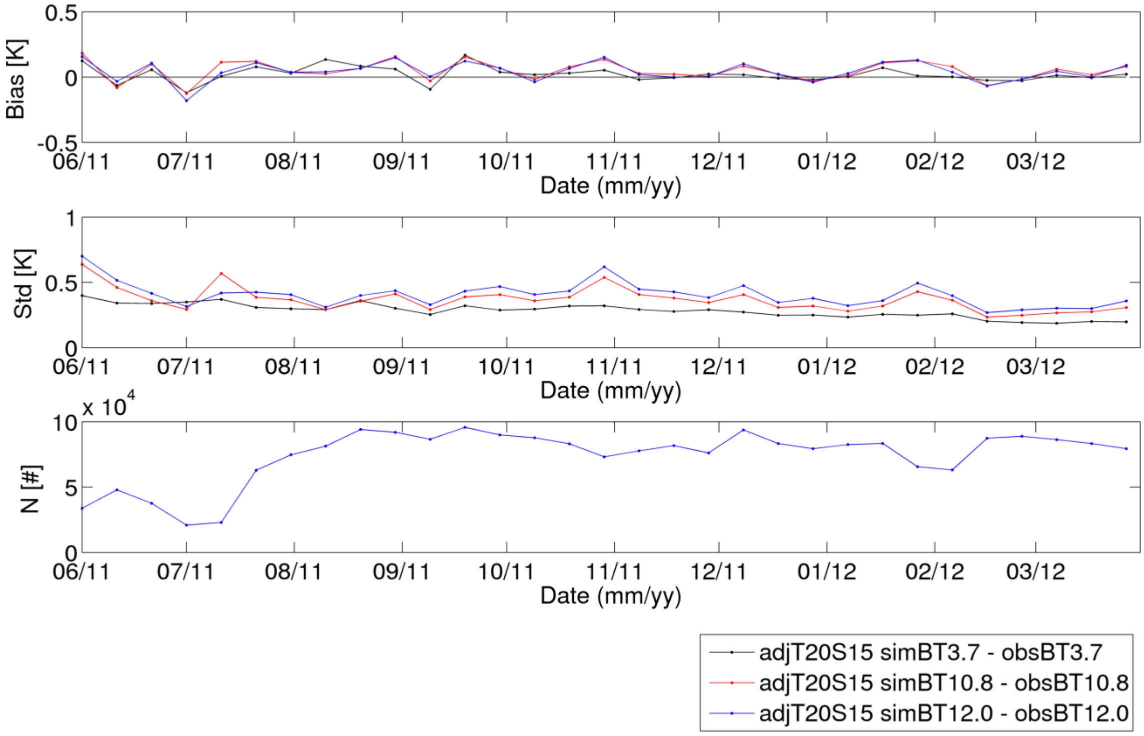


Figure 2. Nighttime 10 day averaged differences between adjusted delayed mode BT simulations and observations for all channels, where 20 days of time averaging and 15° spatial smoothing were chosen as an example of correction.

4 RESULTS

Each time and space adjustment combination produces a set of simulations that are used to derive correction terms to the operational Metop-A AVHRR algorithm. The efficiency of the adjustment is measured by the validation results of the corrected SST compared to coincident AATSR data. For validation we used highest quality flags (5) both for Metop-A/AVHRR and AATSR, maximum time absolute difference of 15 min in daytime and 60 min in nighttime, we discarded all cases with Saharan Dust Index (SDI) [*Merchant et al.*, 2006] larger then 0.1 and all cases with wind speed below 4 m/s due to the intensive DW issues. We will present results separately for day and night in two types of figures: a) time series of 10 day statistics (bias, standard deviation and number of points) of the differences between Metop-A/AVHRR SST not corrected (black line) and corrected using either operational bias correction (dotted line) or using typical combinations of simulation adjustments: temporal - T - (1, 3 and 30 days) and spatial – S - (0.05, ~15 and ~50 deg) for day and night separately; b) aggregated figures presenting the three parameters (bias, bias stability and standard deviation) as a function of all time and space smoothing combinations, where bias stability is defined as a standard deviation of 10 day averaged biases.

Analysing both day and night time series of biases (Figure 3) we see the main difference is between summer and the cold season, where in the summer the correction is overestimated in most cases (more pronounced for daytime) and leads to negative corrected SST biases. The correction is deduced (with opposite sign) from the difference between the simulated and the guess SST. If simulated SST is larger than it should, then the correction is too (negatively) large. A simple cause of overestimating simulated SST is to overestimate the simulated brightness temperatures. Residual nighttime diurnal warming affected AVHRR observations are larger than the foundation SST (OSTIA) and the resulting BT adjustment is too large and leads to overestimated simulations and corrections [*Tomažić et al.*, 2013]. Different space/time realizations produce prominently different results in the summer season, while in the colder season all realizations produce similar results. Analyzing standard deviation (2nd panels) results, we see that smaller time averaging (1 day, blue lines) produce the highest standard deviation values, and again this is more pronounced during daytime.

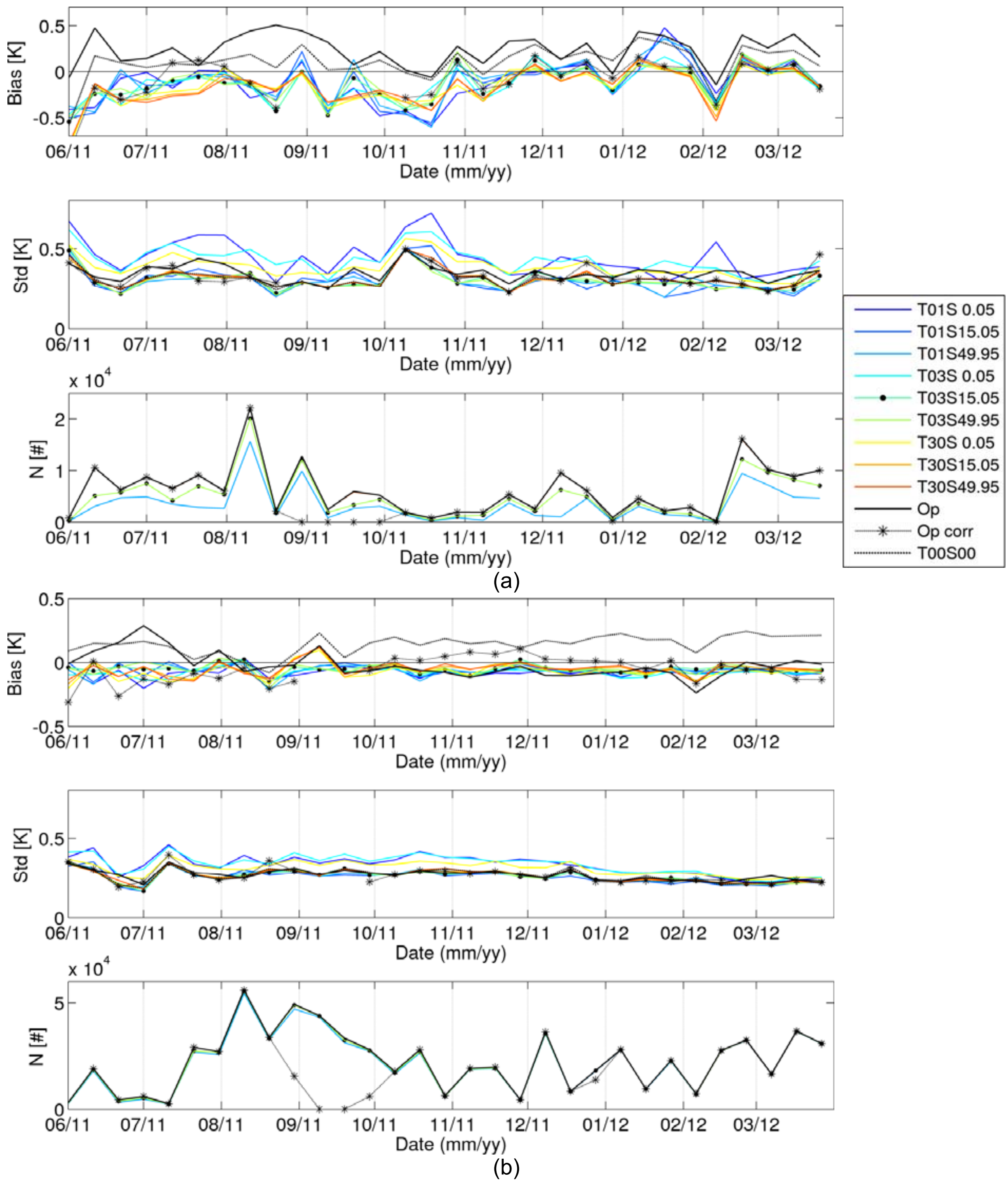
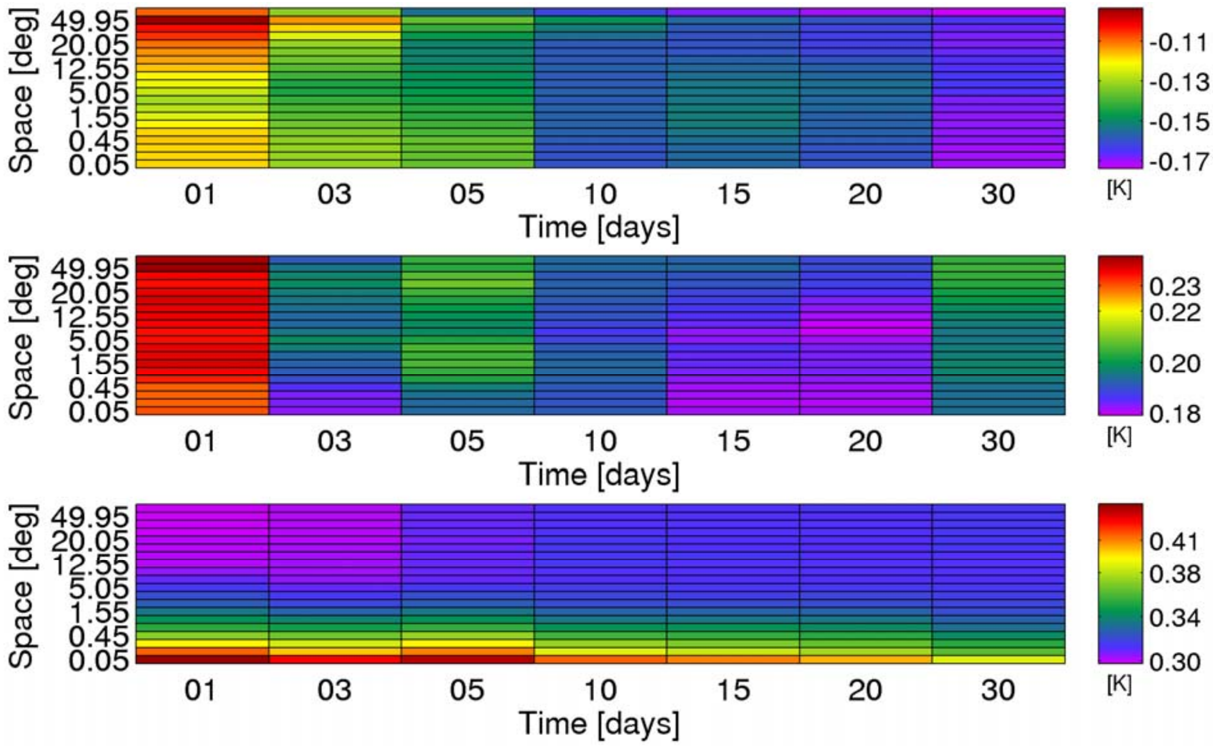
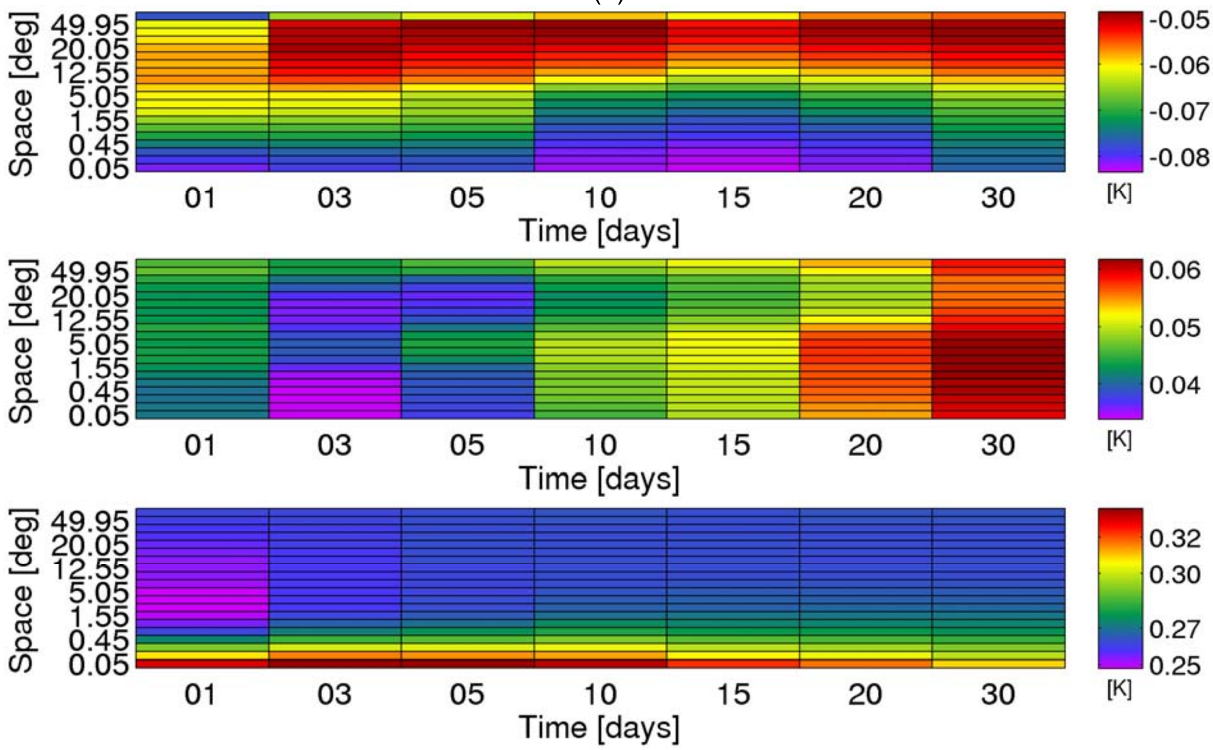


Figure 3.: Time series of a) daytime and b) nighttime 10 day averaged SST differences between corrected Metop-A SST and AATSR SST. Metop-A SST is corrected using combination of several spatial (0.05, 15 and 50 deg) and temporal (1, 3 and 30 day) criteria's with spatial criteria's labeled with "S" and temporal with "T". For comparison additional lines were plotted showing Metop-A SST difference to AATSR without any correction ("Op" - black line), without applying BT adjustment ("T00S00" - dotted) and correction applied in operational environment ("Op corr" - gray line with star). Colored line with black dots represents the results obtained with optimum parameters (3 days; 15 deg). Each subfigure has three subpanels: time series of 1) biases; 2) standard deviations and 3) number of points.



(a)



(b)

Figure 4. Aggregated delayed mode results for different spatial and temporal parameters over the whole period by a) day and b) night. First panel in each subfigure shows biases; second panel shows bias stability and third panel shows standard deviation. Each cell represents averaged value of statistical parameter throughout the analyzed period.

When we look at the daytime results from aggregated tables (Figure 4a) the best results when using bias as the selection criteria (1st panel) is obtained without time averaging (T01) and with higher spatial smoothing. Using bias stability (2nd panel) as a criterion favors temporal averaging between 10 and 20 days, and using standard deviation (3rd panel) favors higher spatial smoothing, above 10 - 15 deg. During nighttime, the operational bias is already close to zero (-0.024 K) and it would be hard to improve the result if we rely only on a bias as selection criteria. Time series (Figure 3b), show a seasonality in the operational bias signal producing positive biases in warmer season and negative in colder season, giving an overall bias to near-zero. Therefore, the bias stability value is an interesting criterion in these conditions, and we obtained improvement in all time and space realizations (range is between 0.03 and 0.06 K), with the minimum in temporal averaging of 3 days and spatial smoothing below 1 deg. Considering the standard deviation parameter (3rd panel) we got similar values as in daytime, where all smoothing above 2.5 deg give overall SD values in the very small range (within 0.02 K), with the most favorable conditions obtained without time averaging (1 day) and smoothing over the medium windows sizes (6-10 deg).
Analyzing both day and night we see that most consistent results are obtained for standard deviation results, where in all cases high spatial smoothing, above 10 deg is always favorable almost regardless of time averaging parameters. The main reason for this is that by smoothing over a larger area we decrease the noise introduced in the simulations through errors in the guess field, atmospheric profiles and RT model. Next, bias results diverge between day and night, where daytime results are dependent to the time window averaging (improving from high to low temporal window), while during nighttime, results are dependent on the spatial smoothing window size, with optimum values above 10 deg. This day/night difference suggest that daytime biases are affected by more transient features (mainly diurnal warming) while nighttime results are affected by long range weather patterns that change atmospheric structure. Last, bias stability shows highest variability between day and night and smallest change within each analysis. During daytime, applied correction shifts constantly positive results to near zero values and bias stability values are similar before and after correction, but during nighttime all corrections cancel seasonality signal and therefore give improvement in bias stability values.

5 CONCLUSION

We assessed the impact of BT simulation adjustment conditions in correcting Metop-A SST over the Mediterranean Sea. BT simulations were derived using radiative transfer model (RTTOV) applied to full vertical (91) ECMWF NWP profiles combined with concurrent OSTIA SST field. BT adjustments and SST corrections were performed separately for day and night over different temporal (1 day to 30 days) and spatial (0.05 deg to 50 deg) averaging window sizes. To validate the method we used AATSR data and statistical parameters derived from 10 day averaged differences between Metop-A and AATSR: bias, bias stability and standard deviation. Special care was taken in analyzing daytime condition in summer time during intensive DW episodes that tends to mask out atmospheric problems. The final choice results from compromising between different conclusions according to each of these parameters that are used as selection criterion.
Based on all different conditions we found optimum temporal averaging between 3 to 5 days and spatial smoothing of 15 deg. Specifically, based on the standard deviation cost function we consistently obtained that smoothing above 10 deg is the most favorable, almost regardless of temporal averaging. Bias based results diverge between day and night, where daytime analysis are mostly time averaging dependent and favors short temporal averaging (1 to 5 days) while nighttime results are spatial smoothing dependent and favors higher smoothing (above 10 deg) for any temporal averaging (except no averaging).

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