

A comparison of remote-sensing SST and *in situ* seawater temperature in near-shore habitats in the western Mediterranean Sea

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ABSTRACT: Remote sensing of sea surface temperature (SST) is widely used in climate science because it provides a quasi-synoptic coverage of the ocean. However, the use of these data for near-shore habitats is hindered by the proximity of the coast, therefore further investigation is needed. We compared remote-sensing SST from the MODIS sensor (aboard the Aqua satellite) to near-shore seawater temperature (ST) recorded *in situ* with data loggers at 5 locations in the western Mediterranean Sea. *In situ* ST data were collected at 5 m depth over a ~6 yr period and at depths below 5 m at 3 of the locations. We evaluated the suitability of MODIS to represent the temperature at shallow subtidal depths relative to different modes of variability. MODIS reproduced seasonal variability with high correlations ($r > 0.98$) and biases ($0.59 \pm 0.03^\circ\text{C}$) only slightly higher than the accuracy of the loggers (0.50°C). MODIS also captured interannual variability with no systematic biases. When evaluated for intra-seasonal temperature variability, MODIS showed limited biases (up to 0.79°C) with a tendency to overestimate the variability (between 4 and 64%) in both cold and warm seasons. Finally, MODIS over-/underestimated only the most extreme unseasonably cold/warm events (by 1.51 and -0.79°C , respectively). The observed limited differences between the 2 methods can be explained by the particular hydrodynamics of the area and by methodological constraints. Overall, MODIS SST data proved to be a reliable proxy for near-shore ST in the western Mediterranean Sea, and are thus considered suitable for studies requiring temperature reconstruction in shallow near-shore environments.

KEY WORDS: MODIS-Aqua · Seawater temperature · Shallow-water ecosystems · Near-shore ecology · Mediterranean Sea · Balearic Sea

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INTRODUCTION

Coastal marine ecosystems are threatened by several stress factors linked to global change (Parmesan & Yohe 2003, Gattuso et al. 2015). Among these factors, one of the most significant is seawater temperature (ST), which increased by $0.11^\circ\text{C decade}^{-1}$ between 1971 and 2010 (Hoegh-Guldberg et al. 2014), with the highest increases recorded in coastal areas (Lima & Wetthey 2012). ST is a fundamental oceanographic

control over physiological and ecosystem processes, affecting the biogeographical patterns of coastal marine environments (Hoegh-Guldberg & Bruno 2010, Pandolfi et al. 2011). Therefore, it is important to have accurate records of ST across a range of marine environments. Because of its mid-latitude location, the Mediterranean Sea is characterized by a defined seasonal cycle. Increasing solar radiation in spring and summer leads to stratification of the water column and high surface temperatures,

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whereas increasing wind forcing and decreasing solar radiation induce vertical mixing leading to a period of vertical homogeneity and relatively low temperatures during fall and winter (Bernardello et al. 2012).

However, despite the regularity of the seasonal cycle, the Mediterranean Sea is among the most rapidly warming areas of the global ocean (Hoegh-Guldberg et al. 2014), with concomitant severe impacts on its biota (Calvo et al. 2011, Marbà et al. 2015). Over the last 2 decades, mass mortality events directly or indirectly linked to elevated summer ST have affected benthic organisms such as gorgonians (Coma et al. 2009, Garrabou et al. 2009), sponges (Maldonado et al. 2010, Cebrian et al. 2011) and aquacultured bivalve molluscs (Gazeau et al. 2014). Moreover, during winter, minimum temperature may be a controlling factor in the poleward expansion of warm-water species (Coll et al. 2010). The frequency and severity of ST anomalies and the associated impacts on marine organisms are predicted to rise with climate warming (Coma et al. 2009). Monitoring near-shore ecosystems has revealed highly variable impacts of thermal anomalies at small spatial scales of 10s of km (Garrabou et al. 2009). Therefore, spatio-temporal coverage and resolution are crucial aspects of ST time series to ensure an improved understanding of the response of near-shore ecosystems to climate change.

Although *in situ* direct and logged measurements are the most recommended methods to acquire accurate ST time series, their collection is costly and time-consuming, making such records generally scarce (Bahamon et al. 2011). Moreover, the record of *in situ* data needs to be planned *a priori*, and is not commonly available in most *a posteriori* ecological studies based on unexpected observations. As a consequence, freely accessible, quasi-synoptic remote-sensing sea surface temperature (SST) data for the global ocean have become a widely used proxy for the ambient shallow ST in near-shore ecology (e.g. Raitsos et al. 2010, Marbà et al. 2015).

Remote-sensing SST data acquired for the open ocean undergo an array of quality-control procedures aimed at removing biases due to clouds, aerosols, dust and rain (Donlon et al. 2002, 2010). However, factors operating across distinct temporal and spatial scales may diminish the suitability of remote-sensing SST to estimate near-shore *in situ* ST. These include coastal features (such as bays and river mouths), topographic orientation of the substratum, width of the continental platform and hydrodynamic regimes (e.g. tides and wave exposure). Cap-

turing environmental variability at these small spatial scales is critical for predicting biological responses because of nonlinearity and threshold effects in physiological and performance responses of organisms to ST (Howard et al. 2013). Therefore, satellite data first need to be validated with *in situ* ST measurements in order to determine their suitability as a proxy for ambient ST in near-shore environments.

Such validation has been carried out in several areas worldwide, including Australia (Smale & Wernberg 2009, Lathlean et al. 2011, Baldock et al. 2014), South Africa (Smit et al. 2013), Argentina (Delgado et al. 2014) and the Caribbean Sea (Castillo & Lima 2010), and, in general, the differences between remote sensing and *in situ* data have been considered too large to accurately determine the effect of temperature on the physiological responses of organisms (e.g. Castillo & Helmuth 2005, Leichter et al. 2006). In the Mediterranean Sea, Alvera-Azcárate et al. (2011) compared satellite *in situ* data over a 1 yr period, pointing out the impact of the diversity of sources for *in situ* data. Sacristán-Soriano et al. (2012) found a high correlation between remote-sensing SST and *in situ* logged data and therefore used the former to complement the latter in Portbou (NW Mediterranean). This suggests that, in the western Mediterranean, loggers can be an appropriate source of data to conduct a large-scale and long-term comparative examination of satellite SST vs. *in situ* ST data.

In this study, we compared remote-sensing SST measured by the Moderate Resolution Imaging Spectroradiometer (MODIS) carried aboard the NASA satellite Aqua (since May 2002) to *in situ* ST recorded near the surface with data loggers at 5 locations distributed along 4.5° latitude of the Balearic Sea (western Mediterranean Sea) over different periods of time (from 30 to 75 mo). The objective of this study was to assess the suitability of MODIS-Aqua remote-sensing SST as a proxy for *in situ* ST in near-shore habitats. Particularly, we evaluated the ability of MODIS to detect 4 modes of ST variability, namely: overall variability, intra-seasonal variability, interannual variability and unseasonably extreme events. We further evaluated the distribution of temperature values in each series to assess the ability of MODIS to represent the cumulated ST exposure of near-shore ecosystems to a given range of temperatures. Finally, in order to assess the depth limit of representativeness of MODIS data for the overall variability of near-shore conditions, we assessed ST variability over a bathymetric gradient down to 40 m depth.

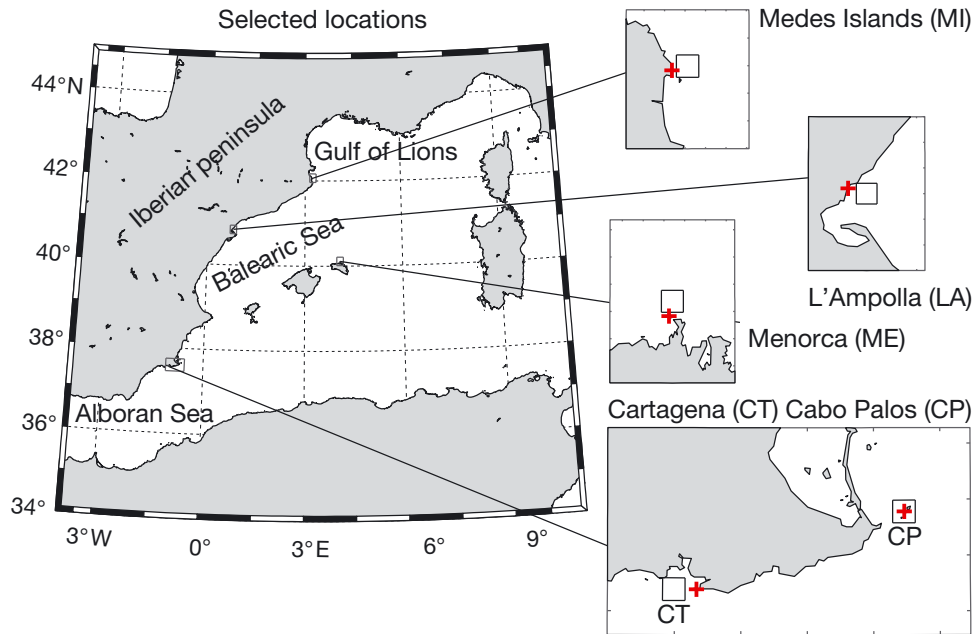


Fig. 1. Map of the Western Mediterranean Sea, showing the 5 study locations along the eastern Iberian coastline in the Balearic Sea. The exact locations of the *in situ* data loggers are marked with red crosses in the enlarged areas on the right, together with the corresponding MODIS search areas (black squares)

The present study goes beyond the work of Sacristán-Soriano et al. (2012) and Alvera-Azcárate et al. (2011) because it considers a period that spans more than 6 yr and a variety of coastal environments with different topographies and hydrodynamic regimes. Additionally, we focused our analysis on 4 different modes of variability in order to cover a wide spectrum of frequencies for events with ecological importance. Finally, as a novelty with respect to previous studies, we also considered a wide range of depths for the *in situ* ST in order to assess the depth limit of representativeness of remote-sensing data.

MATERIALS AND METHODS

Study area (Balearic Sea)

The study area covered 5 locations distributed across $\sim 4.5^\circ$ latitude ($42.1\text{--}37.6^\circ\text{N}$) of the Balearic Sea (western Mediterranean; Fig. 1, Table 1). The locations of Montgri, Medes Islands and Baix Ter

Natural Park (hereafter, Medes Islands, MI), L'Ampolla (LA), Cape Palos (CP) and Cartagena (CT) were located along ~ 700 km of coastline on the eastern Iberian Peninsula, whereas the fifth location, Menorca (ME), was located in the Balearic Islands (~ 300 km offshore from LA).

In situ logger ST data

At each location, *in situ* ST was recorded hourly using a HOBO Pendant self-recording temperature data logger (UA-002-64, Onset Computer) placed at 5 m depth between 2007 and 2013 for periods ranging from 30 to 75 mo (Table 1). In an ST range from 10 to 30°C , the accuracy reported by the manufacturer is $\pm 0.50^\circ\text{C}$ and the resolution is $\pm 0.15^\circ\text{C}$. For locations MI, CP and ME, the loggers were deployed at additional depths from 10 to 40 m at intervals of 5 m for periods ranging from 12 to 75 mo (Table S1 in the Supplement at www.int-res.com/articles/suppl/m559_p021_supp.pdf). Loggers were placed in a naturally

Table 1. Period of deployment and coordinates of the data loggers (5 m depth) and coordinates of the centre of the MODIS search area for the 5 study locations. Dates are given as dd/mm/yyyy

Location	Code	From	To	Days	—Data logger—		——MODIS——	
					Lat.	Lon.	Lat.	Lon.
Medes Islands	MI	01/04/2009	30/09/2013	1644	42.061°N	3.212°E	42.066°N	3.238°E
L'Ampolla	LA	01/06/2008	10/12/2013	2019	40.840°N	0.749°E	40.833°N	0.781°E
Menorca	ME	01/07/2007	31/07/2013	2223	40.094°N	4.075°E	40.112°N	4.080°E
Cabo Palos	CP	01/05/2007	31/07/2013	2284	37.652°N	0.654°W	37.652°N	0.654°W
Cartagena	CT	01/05/2010	31/10/2012	915	37.559°N	0.967°W	37.559°N	1.001°W

occurring shaded habitat on the rocky reef and were regularly replaced by SCUBA divers for data downloading and battery replacement. Hourly ST logger data were averaged to obtain mean daily ST series.

Remote-sensing SST data

Level 2 daytime remote-sensing SST data recorded by MODIS-Aqua (Reprocessing 2013.1) were provided by the US NASA Goddard Space Flight Center, Ocean Ecology Laboratory, Ocean Biology Processing Group, and downloaded for the period 2007 to 2013 from the OceanColor Web (<http://oceancolor.gsfc.nasa.gov/>). Level 2 data provide swaths of derived geophysical variables at full resolution on the original grid (~1 km). Time series of SST were routinely extracted for the 5 locations corresponding to our *in situ* ST measurements, using an appositely designed algorithm. A search radius of 1 pixel was allowed, resulting in a search area of ~3 × 3 km with the point of interest contained within the limits of the central pixel, when possible. Valid SST data obtained from pixels contained in the search area were then averaged to obtain a single SST datum for each swath and location.

The locations of the *in situ* loggers were close to the coast, and only for CP, the search area for valid SST data actually contained the location of the logged ST sensor (Fig. 1). In the other 4 locations, the interference from land or the limited spatial resolution prevented us from obtaining a sufficiently continuous time series to allow a robust comparison with the correspondent *in situ* time series. Therefore, the centre of the MODIS search area for these 4 locations was moved towards open waters (at ~2 km offshore), such that the entire search area was at sea (Fig. 1, Table 1). Valid MODIS data are flagged according to their quality from 0 (best) to 4 (worst). For this analysis, we considered only high-quality SST readings (flag values of 0 or 1).

Extracted SST data were further filtered in order to discard residual outliers using a second appositely designed algorithm composed of 3 iterations, as follows. In iteration 1, the algorithm searched for days with more than 1 SST value and calculated the difference between each possible pair of values from the same day. If all the differences were <1.6°C, then all values from the same day were averaged. Otherwise, each value from that day was compared to the average of the values from the day before and the day after, and the value presenting the highest absolute difference was discarded. This threshold was based

on the 90th percentile (1.6°C) of the diel variability (based on the hourly collected data) for all locations (n = 9085). In iteration 2, the algorithm detected consecutive daily values showing an SST gradient >2.6°C d⁻¹. If such a pair of values was found, they were compared to the average of the values from the entry before and after the 2 consecutive data, and the one showing the highest absolute difference was discarded. This threshold was chosen based on the 99.9th percentile (2.6°C) of the logger ST gradient over time (in absolute values) for all locations (n = 9080). In iteration 3, if a period longer than 10 d was found with no valid data, the difference between the last and first valid entries on both sides of this period was computed. If this difference was >0.50°C d⁻¹, then the entry showing the highest absolute difference with respect to the average of the 2 entries immediately before and after was discarded. The threshold applied for detecting outliers in periods longer than 10 d with no valid SST data was chosen after pragmatically balancing the negative impact of not having any valid data for more than 10 consecutive days and the negative impact of having an outlier affecting such an extended portion of the final time series. Finally, the filtered SST series were linearly interpolated to obtain continuous series with daily values.

Data analysis

Logger data were initially used to characterize the general spatio-temporal patterns of our study locations. We then compared the 5 m depth logger ST time series with remote-sensing SST data (hereafter MODIS data) throughout the deployment period for each location. We performed an additional comparison between MODIS and logger data collected at depths below 5 m. However, unless explicitly stated otherwise, hereafter 'loggers' (or 'data loggers') will refer to data collected at 5 m depth.

Differences between MODIS and loggers in reproducing overall variability, intra-seasonal variability, interannual variability and unseasonably extreme events were quantified by calculating Pearson's correlations, mean bias, mean absolute bias and the ratio of the standard deviations (SDs) for each of 5 pairs of time series (Table 2). Each statistic provides different information about the ability of MODIS to reproduce the variability recorded by loggers. Mean bias reveals the eventual tendency of MODIS to systematically under-/overestimate logger data, and mean absolute bias gives a concise measure of the distance between the 2 time series. Finally, the ratio

Table 2. Definition of statistics used and symbols adopted in the figures. *M*: MODIS, *L*: loggers, *n*: number of days in the time series

Metric	Symbol	Definition
Pearson's correlation	r	Between <i>M</i> and <i>L</i>
Mean bias	δ	$\frac{1}{n} \sum (M - L)$
Mean absolute bias	Δ	$\frac{1}{n} \sum M - L $
Ratio of standard deviations (SD)	α	SD of <i>M</i> divided by SD of <i>L</i>

of SDs gives an indication of how much more ($\alpha > 1$) or less ($\alpha < 1$) variable MODIS data are with respect to loggers. The combined information provided by these statistics allows us to evaluate particular aspects not revealed when considered individually. For example, when the mean bias and mean absolute bias are of a similar magnitude (in absolute value), the systematic over- or underestimation by MODIS can be corrected by that amount, as long as it is $> 0.50^\circ\text{C}$ (the accuracy of the data loggers).

The time series were defined according to the 4 modes of variability. For overall variability, MODIS time series were compared with the respective logger time series. For intra-seasonal variability, we considered only those pairs of daily values (MODIS–logger) for which the logger value was above/below a certain threshold. Only summer (threshold of $\geq 25^\circ\text{C}$; $\geq 22^\circ\text{C}$ for MI) and winter seasons (threshold of $\leq 15^\circ\text{C}$) were considered. For inter-annual variability, to obtain anomalies (η) for each time series, we subtracted trend and seasonality. These were fit using mixed generalized additive models. The package ‘mgcv’ (Wood 2011) in R (R Core Team 2015) was used with the restricted maximum likelihood (REML) approach (see ‘Estimation of trend and seasonality’ in the Supplement at www.int-res.com/articles/suppl/m559p021_supp.pdf). For unseasonably extreme events, we extracted from the daily time series those days for which the absolute value of logger temperature anomaly (η) was larger than 1, 2 or 3 times the SD of the logger temperature anomaly (η) itself. These were extracted for each location and then combined together for a general evaluation of MODIS skills.

We used 2 additional indicators of the MODIS fitness for purpose: cumulated ST exposure and depth limit of representativeness. To examine up to which depth MODIS was representative of the cumulated

ST exposure during cold/warm seasons, we sorted values in each time series (including loggers deeper than 5 m) and determined the lower/upper range of percentiles (1st to 50th / 51st to 100th) for each annual ST cycle between summer solstices/spring equinoxes. To compare quantiles between time series, we used the non-parametric Wilcoxon signed-rank test for paired samples because the population cannot be assumed to be normally distributed and because of the relatively small sample size (results are expressed as mean \pm SE). We also repeated the same analysis described for 5 m depth for the overall variability for MODIS vs. loggers at depths below 5 m.

RESULTS

MODIS vs. loggers

Overall variability

All locations were characterized by a marked seasonality, with an annual thermal amplitude in daily mean ST ranging from 12.1°C in 2011 at MI to 18.0°C in 2012 at LA (Table 3). The correlation coefficient (r) between MODIS and loggers was higher than 0.98 for all locations, while mean bias was negative in 3 cases and positive in 2, ranging between -0.27°C and

Table 3. Seawater temperature (ST) recorded by data loggers at 5 m depth for the 5 study locations (see Fig. 1) and each year of study. Mean annual ST based on daily mean values, and the minimum and maximum daily mean values recorded over the year are indicated

Code	Year	Mean	SD	SE	Min	Max
MI	2010	16.3	3.7	0.2	10.7	23.4
	2011	17.3	3.7	0.2	11.6	23.7
	2012	17.0	3.6	0.2	11.1	24.7
LA	2009	18.9	5.3	0.3	11.7	28.6
	2010	17.7	4.9	0.3	10.1	26.6
	2011	18.8	4.9	0.3	11.2	28.0
	2012	18.6	5.1	0.3	10.5	28.4
ME	2008	19.1	4.4	0.2	13.3	27.1
	2009	19.0	4.7	0.2	12.6	27.5
	2010	18.9	4.5	0.2	12.8	26.6
	2011	19.7	4.5	0.2	13.3	27.4
	2012	19.4	4.2	0.2	13.3	27.7
CP	2008	19.3	4.2	0.2	14.1	27.3
	2009	19.8	4.8	0.3	13.4	27.5
	2010	19.1	4.7	0.2	13.0	27.5
	2011	20.0	4.7	0.2	13.3	27.3
	2012	19.3	4.3	0.2	13.7	27.0
CT	2011	20.4	4.7	0.2	13.6	27.7

0.24°C. Mean absolute bias was similar for all locations, with values between 0.52 and 0.67°C, and the ratio between MODIS and logger SDs was always close to 1 (between 0.97 and 1.03). Therefore, the combined information provided by the statistics point to very similar seasonal variability between the series and no systematic trend towards either under- or overestimation of seasonal fluctuations of ST by MODIS (Fig. 2).

Intra-seasonal variability

Fig. 3 shows that correlations between the 2 series for daily ST above the warm season threshold were always significant ($p < 0.05$) and ranged from 0.57 (MI) to 0.71 (CT). In general, during the warm seasons, MODIS tended to underestimate ST with a mean bias between -0.71°C (CT) and 0.03°C (MI). The absolute mean bias during warm seasons was between 0.53°C (ME) and 0.79°C (CT), and the ratio

of SDs pointed to a general tendency for MODIS to overestimate intra-seasonal variability, ranging between 1.15 (LA) and 1.47 (MI and CP). Correlations between the 2 series for daily ST below the cold season threshold ($\leq 15^\circ\text{C}$) were always significant ($p < 0.05$), with values of the coefficient similar to those found for the summer (between 0.52 at CT and 0.88 at MI). During the cold seasons, MODIS tended to overestimate ST at 3 locations and to underestimate it at the other 2, with a mean absolute bias that was somewhat lower than during the summer, ranging from 0.37°C (CP) to 0.52°C (ME and LA). Similarly to the summer, MODIS tended to overestimate intra-seasonal variability, ranging between 1.04 (MI) and 1.66 (ME).

Interannual variability

Fig. 4 shows that the correlation coefficients were lower than for the overall variability but were always

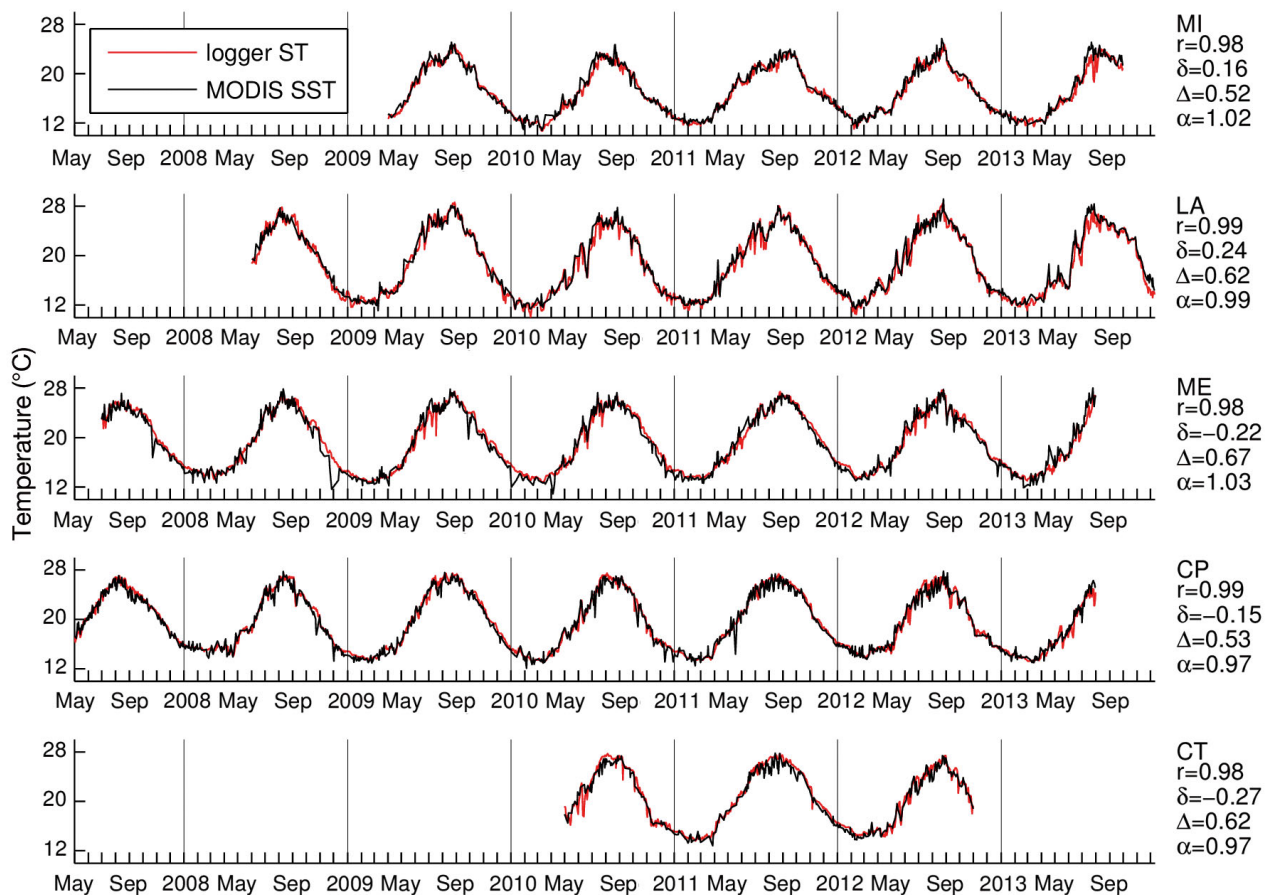


Fig. 2. Comparison of overall variability between logger seawater temperature (ST) and MODIS SST. The beginning of years is marked with thin vertical lines. Statistics for each location are noted on the right of each panel (see Table 2 for definitions). Pearson's correlations are significant at 99%

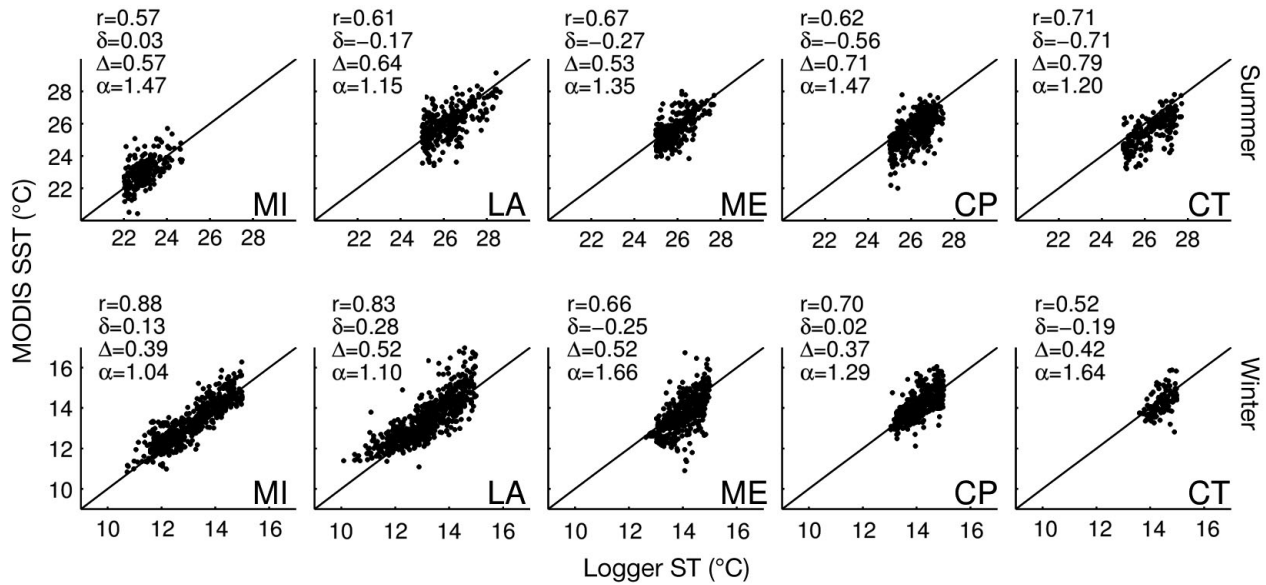


Fig. 3. Comparison of intra-seasonal variability between logger seawater temperature (ST) and MODIS SST. Data were selected above/below a summer/winter ST threshold reference to logger time series. For all locations, the winter threshold was chosen at 15°C while the summer threshold was set at 25°C for ME, LA, CP and CT and at 22 °C for MI (see Fig. 1 for study sites). Statistics for each comparison are noted on each panel (see Table 2 for definitions). Pearson's correlations are significant at 99 %

significant ($p < 0.05$) and ranged from 0.54 (CT) to 0.75 (LA). There was no indication of a tendency for MODIS to systematically under- or overestimate the amplitude of the interannual variability (mean bias between -0.04 and 0.01°C), and the mean absolute bias was around 0.50°C everywhere, similar to the accuracy of the loggers. The ratio of SDs was between 0.92 (CT) and 1.40 (ME), with the variability around the mean captured by MODIS higher than that recorded by loggers at ME and CP.

Unseasonably extreme events

Based on logger data, our 5 study locations differed in mean annual ST by $\sim 4^\circ\text{C}$, increasing from the northernmost location (MI) with 16.3°C in 2010 to the southernmost location (CT) with 20.4°C in 2011 (Table 3). However, the latitudinal ST gradient was not strictly maintained for annual minimum or maximum daily mean STs because LA showed the most extreme seasonal values among the study locations, ranging from a minimum of 10.1°C in 2010 to a maximum of 28.6°C in 2009. Fig. 5 shows that MODIS was able to capture unseasonably extreme events whether these referred to either negative or positive ST anomalies. Only positive anomalies for events with ST larger than 3 SDs had a non-significant correlation between MODIS and logger data, likely due

to the low number of events ($n = 6$). There was a systematic tendency for MODIS to overestimate (i.e. warmer) unseasonably cold events (1.03°C below 2 SDs and 1.51°C below 3 SDs) and to underestimate (i.e. colder) large unseasonably warm events (-0.79°C above 3 SDs). The mean absolute bias was higher for cold events (between 0.81 and 1.60°C) than for warm events (between 0.61 and 0.86°C), and MODIS-captured variability around the mean of these events was only slightly higher than that of loggers for cold events and similar for warm events.

Cumulated ST exposure and depth limit of representativeness

Here we consider all locations and years in a single series for simplicity (Fig. 6). During the warm seasons, MODIS and loggers were similar up to 10 m depth, with differences within $\sim 0.3^\circ\text{C}$ that rapidly increased with depth (0.7°C at 15 m and 6.4°C at 40 m). During the cold seasons, the similarity between time series extended to 20 m depth (differences within 0.4°C) and increased below (0.6°C at 25 m and 1.0°C at 40 m). Interestingly, the mean absolute differences in the 0 to 20th percentiles (the coldest temperatures) were within 0.4°C up to 40 m depth. These results indicate that during the cold seasons, MODIS SST data are representative of log-

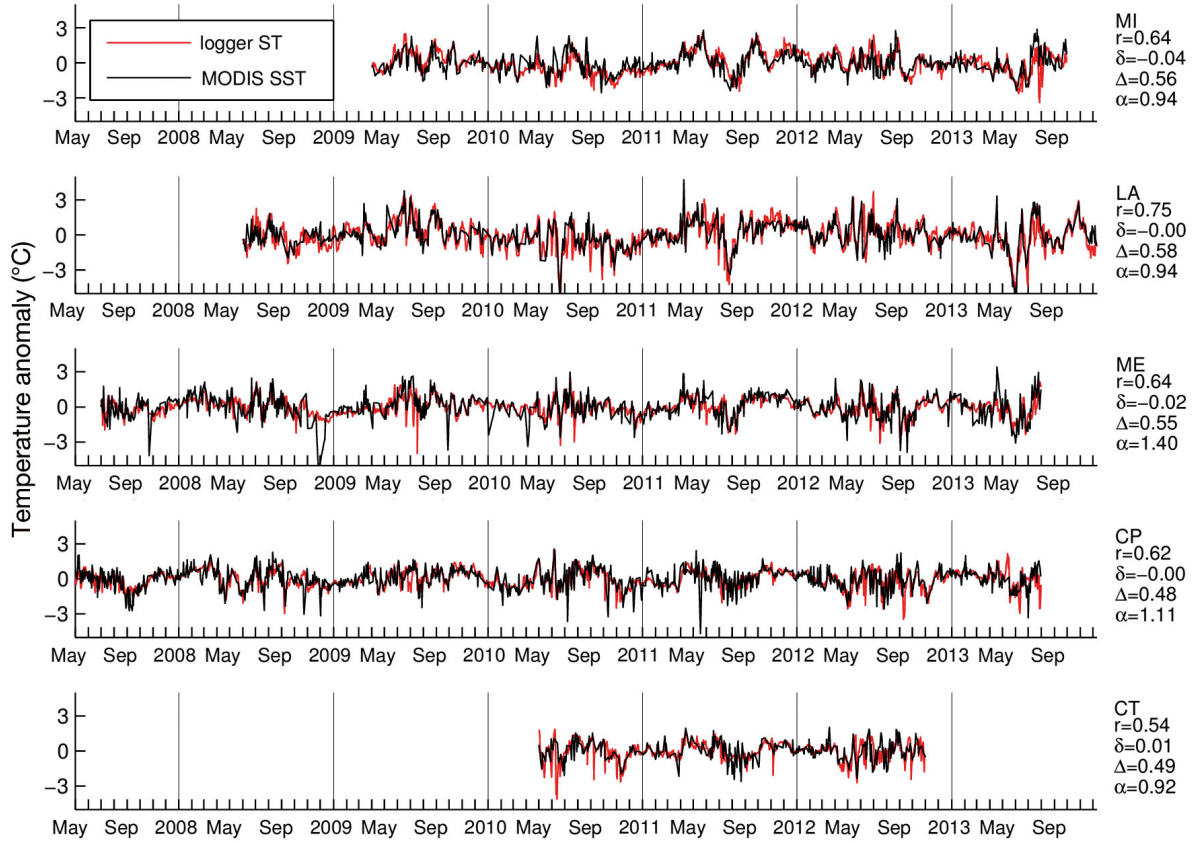


Fig. 4. Comparison of interannual variability between logger seawater temperature (ST) and MODIS SST. Time series refer to anomalies (η) obtained after subtracting trend and seasonality from each time series (see ‘Materials and methods’ and Supplement). Thin vertical black lines mark the beginning of the year. Statistics for each location are shown on the right of each panel (see Table 2 for definitions). Pearson’s correlations are significant at 99 %

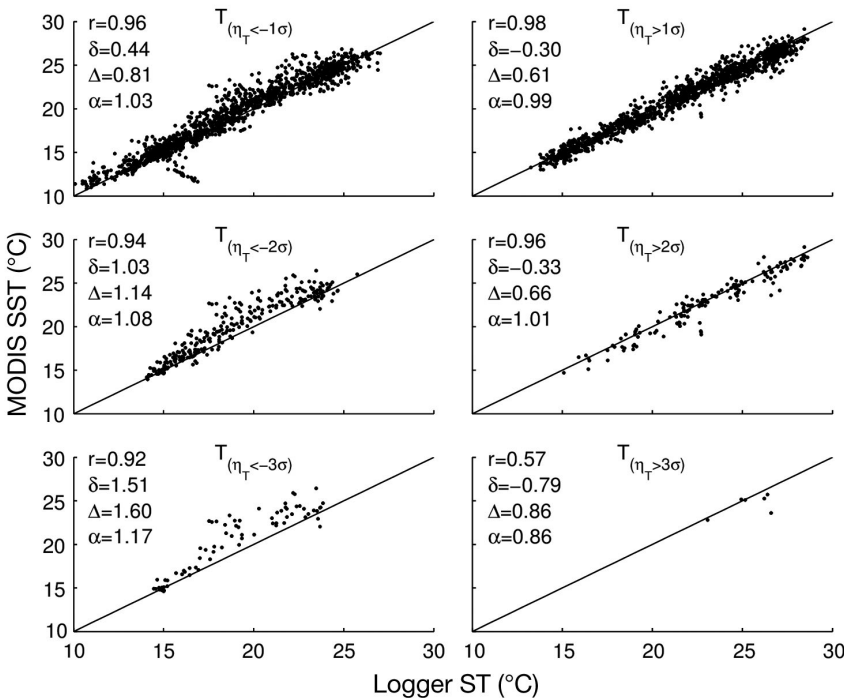


Fig. 5. Comparison of unseasonably extreme events between logger seawater temperature (ST) and MODIS SST. Extreme events are defined as those days when the loggers recorded a temperature anomaly (η) that was larger than 1 (first row), 2 (second row) or 3 (third row) times the standard deviation (σ) of the temperature anomaly itself. Negative anomalies are in the left column, separated from positive anomalies in the right column. Statistics for the selected extreme events are reported on the left of each plot (see Table 2 for definitions). Pearson’s correlations are significant at 99 % except for $T(\eta_T > 3\sigma)$, where the correlation was not significant due to the low number of cases

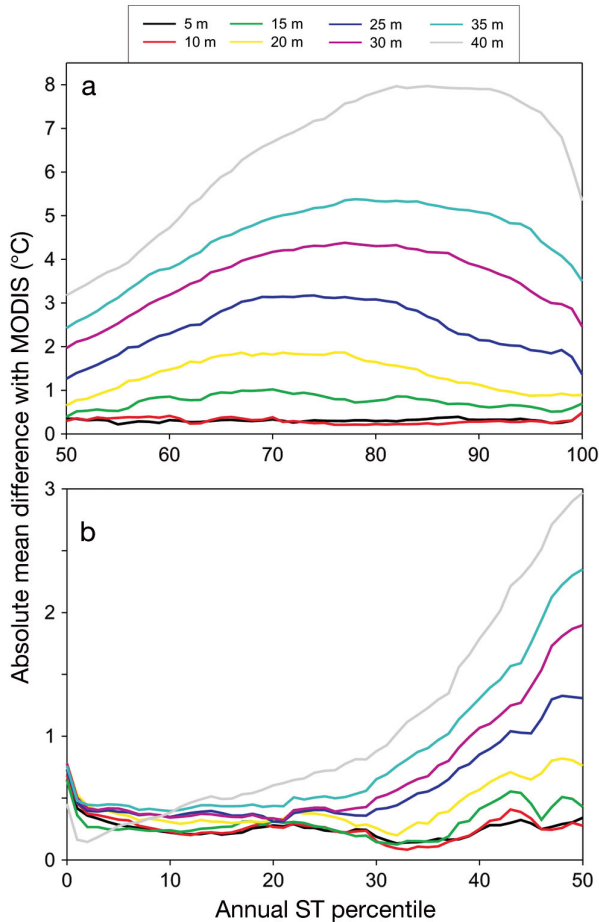


Fig. 6. Comparison of cumulated thermal exposure between logger seawater temperature (ST) and MODIS SST data at depths from 5, 10, 15, 20, 25, 30, 35 and 40 m throughout the study period for the 5 studied locations. Mean absolute differences between MODIS and loggers in the annual percentiles of ST over entire annual cycles based on (a) spring equinoxes (51st to 100th ST percentiles) and (b) summer solstices (1st to 50th ST percentiles)

ger cumulated ST exposure up to a greater depth than during the warm seasons.

Statistics calculated between MODIS and logger time series for depths below 5 m are reported in Table 4 for all locations combined in a single series (and in Table S2 in the Supplement at www.int-res.com/articles/suppl/m559p021_supp.pdf for each location separately). Here we consider only the overall variability. MODIS and logger time series were significantly correlated up to 40 m depth, although mean bias and mean absolute bias increased with depth from -0.001 and 0.662°C at 10 m, respectively, to 3.7 and 3.9°C at 40 m, respectively. Although correlation coefficients were high (0.98 at 10 m and 0.50 at 40 m), the ratio of SDs of the 2 time series indicates that MODIS already overestimated the overall variability by 8.4 % at 15 m depth.

Table 4. Statistics relative to the overall variability between MODIS SST and data logger seawater temperature with loggers placed at depths from 10 to 40 m for 3 of the 5 locations, here considered together. See Table 2 for symbol explanations. Pearson's correlations are significant at 99 %

Depth (m)	N	r	δ	Δ	α
10	5579	0.977	-0.001	0.662	1.018
15	4975	0.952	0.375	0.920	1.084
20	5455	0.919	0.692	1.222	1.145
25	4552	0.848	1.356	1.803	1.260
30	4507	0.750	1.966	2.404	1.428
35	4187	0.661	2.498	2.905	1.609
40	1964	0.501	3.735	3.906	2.617

Impact of filtering on remote-sensing temperature data

The 3-iteration filter applied to the MODIS data series flagged, on average, $4 \pm 1\%$ of the values as outliers. The resultant filtered MODIS time series had valid daily values covering on average $47 \pm 3\%$ of the period of deployment of their respective logger time series. Missing values were on average almost equally distributed across each season (for details, see Table S3 in the Supplement). The effects of each filter iteration are synthesized in Table 5. MODIS series (here merged together) obtained after each iteration were linearly interpolated in time to obtain a continuous time series of daily values. Iterations 1 and 2 had stronger impacts on the performance of MODIS. Correlation improved only marginally, but both mean bias and mean absolute bias were significantly reduced. Iteration 2 also slightly reduced the variability around the mean of the MODIS time series with respect to logger data, while iteration 3 improved the correlation only slightly.

Table 5. Effect of the 3 iterations of the appositely designed filter on the ability of MODIS time series to reproduce the overall variability of seawater temperature (ST) as recorded by *in situ* loggers. All locations are considered together in a single series and MODIS data are linearly interpolated in time after each iteration to allow the comparison with the continuous logger time series. See Table 2 for symbol explanations. Pearson's correlations are significant at 99 %

ST series	r	δ	Δ	α
Raw data	0.976	-0.110	0.669	1.002
Iteration 1	0.977	-0.086	0.647	1.000
Iteration 2	0.983	-0.040	0.595	0.994
Iteration 3	0.984	-0.037	0.592	0.993

DISCUSSION

When considering the overall variability, MODIS mean biases were always low and the mean absolute biases were only a few hundredths of a degree above the accuracy of data loggers. This was true across the marked latitudinal ST gradient recorded by loggers at the different locations. The information provided by these statistics, together with the high correlation coefficients, allows us to conclude that MODIS data are reliable at reproducing near-shore seasonal variability, the dominant component of the overall variability (Fig. 2). When considering the intra-seasonal variability, mean biases were generally higher than for the overall variability (Fig. 3). However, these trends were not systematic, as the mean biases were usually lower than the mean absolute biases, pointing to compensation of positive and negative deviations. These 2 statistics were of comparable magnitude only for locations CP and CT, pointing to a systematic tendency for MODIS to record lower than *in situ* temperatures during the warm season. However, even in the worst case (CT), the mean absolute bias was 0.79°C, only 0.29°C above the accuracy of the data loggers. The analysis of the intra-seasonal variability also revealed a general tendency for MODIS to overestimate variability, albeit with very different values depending on season and location. However, most of the differences observed can be explained taking into account the design of our subsampling of remote sensing data and the particular regional hydrodynamics regime.

With regard to the summer underestimation, MODIS SST was obtained from the average of valid data found within a search area of 3×3 km that is likely to include relatively deep waters, while loggers were usually placed in shallow waters where heat tends to accumulate more efficiently. On the other hand, the tendency of MODIS to overestimate the intra-seasonal variability was surprising, considering that the filtered MODIS time series resulted in an average of only 47% of valid data for the period considered. The resultant gaps were filled by linear interpolation which should have smoothed some of the variability rather than accentuating it. However, valid MODIS data are snapshots (i.e. instantaneous values) and as such they might be subject to daily short-term variability because the satellite pass does not always occur at the same time of the day. These 2 factors (linear interpolation and snapshot nature of MODIS) tended to compensate each other with the latter probably dominating and thus inducing a higher than *in situ* variability. Furthermore, we aver-

aged logger data over periods of 24 h, and this probably resulted in less variable logger time series even if the general distribution of temperature did not show considerable changes (see Fig. S1 in the Supplement at www.int-res.com/articles/suppl/m559p021_supp.pdf).

Moreover, despite the general tendency to overestimate intra-seasonal variability, correlation coefficients between the 2 series for the warm seasons were always significant (Fig. 3; $p < 0.05$). The location with the lowest correlation ($r = 0.57$) for the summer subset was MI. This is the closest examined location to the Gulf of Lion. Here, temperatures are usually lower than in the rest of the locations considered because of the proximity of the Catalan front which is associated with the presence of the Northern Current that flows along the coast from NE to SW (Millot 1999). The Catalan front is a permanent horizontal density gradient that has been described as maintained by a cool plume of water that originates in the Gulf of Lion and flows along the Iberian Peninsula (La Violette et al. 1990), as a salinity front due to the continental runoff (Font et al. 1988), or both (García-Ladona et al. 1996). During summer, a general warming takes place over the Balearic Sea, strengthening the horizontal thermal gradient, and the Catalan front appears to separate the warm waters of the Balearic Sea from the cold waters of the Gulf of Lion (Lopez-García et al. 1994). Location MI happens to be approximately where the summer Catalan front intersects the coast. This is why the summer warm threshold for this location had to be lowered to 22°C. This is a highly dynamic region because of the presence of frequent mesoscale structures detaching from the Northern Current. These structures transport heat, momentum and biogeochemical tracers, inducing a high degree of variability in the surface properties of the sea (Rhines 2001). In September 2001, Rubio et al. (2005) used satellite thermal images to monitor a group of mesoscale anticyclonic eddies which, after being generated in the Gulf of Lion, drifted along the Catalan coast. The horizontal scale of mesoscale eddies is related to the Rossby radius of deformation, which, in the Mediterranean, is about 10 to 14 km (Robinson et al. 2001), comparable to the size of our search areas for MODIS (9 km²). Therefore, it is likely that the passage of mesoscale structures could have introduced some variability in the MODIS MI series (located ~2 km offshore) that would be attenuated at the coastal logger location, partly explaining the relatively low correlation coefficient and the MODIS tendency to overestimate ST variability (i.e. $\alpha = 1.47$, Fig. 3).

Another location showing a comparatively low correlation between MODIS and logger time series for the intra-seasonal variability was LA ($r = 0.61$). This location is on the northern side of the Ebro River delta, and a possible explanation for the relatively low correlation found is differences in riverine discharge between the MODIS search area and the logger location.

Since the sign of the bias was always negative when significant, one could argue that MODIS summer data were systematically underestimated and should therefore be corrected by a few tenths of degree. However, such a correction would be justified only for stations CP and CT because only there the mean absolute biases were above the accuracy of the loggers and comparable to the respective absolute value of the mean biases, pointing to systematic underestimation.

During winter, correlation coefficients were ≥ 0.66 everywhere except at location CT ($r = 0.52$; Fig. 3). Here, the differences between the 2 series might partly be due to the distance between data loggers and their respective MODIS search areas, as already stated with regard to the cold mean bias during summer. Moreover, the relatively low correlation in winter between the 2 series could be related to the variability of the Almeria-Oran density front (Viúdez et al. 1996). This front separates the new fresh incoming Modified Atlantic Water (MAW) from the older salty resident MAW, with related effects on surface temperature because in winter new MAW is warmer than old MAW while the opposite is the case in summer. The position of the front is related to the presence of the Eastern Alboran Gyre, whose location and extension are very variable (Prieur & Sournia 1994). Although location CT is not directly within the observed span of the front, it is close enough for the influence of the front migration to be felt through mesoscale features detaching from the front and propagating northward. As previously mentioned, mesoscale structures might introduce variability in the MODIS search area that may become attenuated at the respective coastal logger location, contributing to the increased ratio between the 2 SDs ($\alpha = 1.64$, Fig. 3).

The comparison of the 2 methods in winter showed a mean bias within the accuracy of the logger and far below the mean absolute bias, indicating that a systematic correction for the whole Mediterranean Sea could not be evinced from our results. Therefore, the contained magnitudes of the absolute values of the biases together with the significant correlations allow us to conclude that MODIS was able to capture well the winter intra-seasonal variability.

MODIS-Aqua also appears to be a reliable tool to capture the interannual variability of *in situ* near-shore surface temperature. In spite of some of the locations being in dynamic regions where the interannual component of the overall variability is affected by the occurrence of fronts and mesoscale structures, Fig. 4 shows that correlations were significant at all 5 locations and the mean bias was within the accuracy of the loggers. Because of their importance for near-shore benthic ecology, we specifically assessed the ability of MODIS to capture unseasonably extreme events, a specific component of the interannual variability (Fig. 5). MODIS was able to detect these events with a general tendency to overestimate the more extreme cold events (by 1–1.5°C), with the bias being higher for stronger anomalies. This is also consistent with the logistic constraints related to the comparison between the 2 methods and the fact that shallow waters (such as those in which the loggers were deployed) exhibit lower temperature inertia than the open sea. Coastal locations are more affected by meteorological forcing and, therefore, usually become both colder in winter and warmer in summer than the open sea. For example, the disruption of the latitudinal ST gradient at LA may be related to the very shallow slope of the sandy bay at this location. Our comparison contributes to provide a basis for correction of these unseasonably extreme events when detected by MODIS.

The differences between MODIS and logger data below 5 m depth were lower during the cold seasons than during the warm seasons. Water column stratification (with the thermocline at ~20 m depth) occurs during warm seasons, and enhances the decrease in the accuracy of MODIS with depth, being reliable from 0 to 10 m (Fig. 6). The vertical mixing during cold seasons produces a period of vertical homogeneity (Coma et al. 2009) that improves the accuracy of MODIS up to 20 m depth (Fig. 6).

A previous satellite SST to *in situ* ST comparison conducted over 1 yr in the Mediterranean Sea indicated a large bias between *in situ* and satellite data (Alvera-Azcárate et al. 2011). The differences between the wide variety of *in situ* sources (e.g. CTD, drifters, bottles), was pointed out among the main problems of the comparison. Temperature in near-shore areas is difficult to monitor because these are variable environments largely affected by the complexity of the coast and the bathymetry. Nevertheless, our results point to a strong correspondence between remote-sensing MODIS and *in situ* data recorded with HOBO loggers. These instruments should be used taking into account some recommen-

dations about their exposure to direct sunlight. Bahr et al. (2016) found an overestimation of ST by 2.5°C when loggers were exposed to direct sunlight in shallow waters. Although the HOBO loggers used in this study were all placed in naturally shaded habitats, we noticed a similar effect at location CT where we had placed an accompanying sensor in a location directly exposed to sunlight (data not shown). Consequently, in line with Bahr et al. (2016), we also recommend that HOBO loggers be placed in naturally occurring cryptic shaded habitats, and, when this is not possible, to insert the instruments in a protective plastic tube open at both ends. Therefore, with some precaution during their deployment, HOBO loggers offer the advantage of providing an almost continuous source of *in situ* data with an accuracy of 0.50°C at a fixed location. This enables a large reduction in error for *in situ* ST in near-shore habitats with respect to the large variety of sources for *in situ* ST in open-sea environments.

Overall, our results highlight the suitability of MODIS SST as a proxy for ST in shallow near-shore ecosystems (5–10 m) in the Balearic Sea, western Mediterranean. This is consistent with previous studies that considered single locations in other regions of the Mediterranean Sea and short periods of time (Sacristán-Soriano et al. 2012, Deidun et al. 2016). Despite their limited spatio-temporal coverage, these studies suggest that the high accuracy we found in the Balearic Sea may apply to other biogeographic regions across the Mediterranean Sea. In general, several characteristics of the Mediterranean may contribute to the agreement between satellite SST and *in situ* logged ST methods, such as small tides (e.g. Tsimplis & Shaw 2010) and the excess of evaporation over precipitation and runoff that largely attenuates the influence of land on near-shore water (Millet & Taupier-Letage 2005). In addition, the relatively narrow Mediterranean continental shelf (Sánchez-Arcilla & Simpson 2002, Coll et al. 2010) further contributes to the coupling of near-shore and open-ocean processes. Nevertheless, our study was limited to 5 locations so more pronounced differences between MODIS and local near-shore temperatures cannot be excluded everywhere. Although our locations covered a wide latitudinal gradient and were characterized by different dynamic environments, we recommend to extend the comparison to other biogeographic regions. Nevertheless, our results are encouraging and suggest that MODIS remote-sensing SST can be used to provide spatial and temporal coverage for where and when *in situ* ST observations are not available.

CONCLUSIONS

We evaluated the suitability of remote-sensing SST from MODIS-Aqua as a proxy for ST near-shore habitats in the western Mediterranean Sea. MODIS proved to be able to capture seasonal and interannual variability ($r > 0.98$) without any systematic tendency towards either under- or overestimation and with mean absolute biases only slightly above the accuracy of the loggers in the worst cases (0.67°C at ME). With regards to intra-seasonal variability, MODIS showed low biases but also a tendency towards the systematic overestimation of the variability (between 4 and 64 %). This feature was likely caused by the instantaneous nature of satellite data that may have introduced short-term sub-daily variability resulting in a more variable time series relative to the daily averages of hourly logger data. Moreover, the particular hydrodynamic regime of some locations may have contributed to the overestimation of the intra-seasonal variability. MODIS also showed a tendency to over-/underestimate the most extreme unseasonably cold/warm events (by 1.51 and -0.79 °C, respectively). This tendency, together with some moderate systematic bias towards the underestimation of summer temperatures at 2 locations, is probably related to the distance between the search areas considered for MODIS and the actual locations of the data loggers. While the former inevitably include open waters, the latter are usually characterized by shallow waters with lower thermal inertia, thus leading to more extreme seasonal excursions. Finally, MODIS data were representative of ST up to 10 m depth during the warm seasons and up to 20 m depth during the cold seasons, due to vertical mixing. Although more *in situ* sensors are needed to exclude more pronounced differences between MODIS and local near-shore temperatures in particular locations of the western Mediterranean Sea, we conclude that MODIS data provide a reliable proxy for studies requiring temperature reconstruction in shallow near-shore environments.

Acknowledgements. We thank the Ocean Biology Processing Group (OBPG) at NASA for assistance and for making MODIS-Aqua data freely available. R.B. acknowledges support from the Natural Environment Research Council (UK). We thank Manel Bolivar for assistance in the field. We are grateful to the 'Parc Natural del Montgrí, les Illes Medes i el Baix Ter', 'Parc Natural de Cap de Creus', 'Reserva Marina de Cabo de Palos-Islas Hormigas (Servicio de Pesca y Acuicultura de la Comunidad Autónoma de Murcia)' and 'Reservas Marinas de España, Dirección General de Recursos Pesqueros y Acuicultura, Ministerio de Agricultura, Alimentación y Medio Ambiente' for permits and continuous sup-

port of our research. The study was funded in part by the Spanish Government through CSI-Coral Project (CGL2013-43106-R). This is a contribution from the Marine Biogeochemistry and Global Change research group funded by the Catalan Government (2014SGR1029).

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*Editorial responsibility: Steven Morgan,
Bodega Bay, California, USA*

*Submitted: June 14, 2016; Accepted: September 15, 2016
Proofs received from author(s): October 21, 2016*