

1 Evaluating operational AVHRR sea surface
2 temperature data at the coastline using surfers

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14 **Abstract**

Sea surface temperature (SST) is an essential climate variable that can be measured routinely from Earth Observation (EO) with high temporal and spatial coverage. To evaluate its suitability for an application, it is critical to know the accuracy and precision (performance) of the EO SST data. This requires comparisons with co-located and concomitant *in situ* data. Owing to a relatively large network of *in situ* platforms there is a good understanding of the performance of EO SST data in the open ocean. However, at the coastline this performance is not well known, impeded by a lack of *in situ* data. Here, we used *in situ* SST measurements collected by a group of surfers over a three year period in the coastal waters of the UK and Ireland, to improve our understanding of the performance of EO SST data at the coastline. At two beaches near the city of Plymouth, UK, the *in situ* SST measurements collected by the surfers were

compared with *in situ* SST collected from two autonomous buoys located ~7 km and ~33 km from the coastline, and showed good agreement, with discrepancies consistent with the spatial separation of the sites. The *in situ* SST measurements collected by the surfers around the coastline, and those collected offshore by the two autonomous buoys, were used to evaluate the performance of operational Advanced Very High Resolution Radiometer (AVHRR) EO SST data. Results indicate: (i) a significant reduction in the performance of AVHRR at retrieving SST at the coastline, with root mean square errors in the range of 1.0 to 2.0 °C depending on the temporal difference between match-ups, significantly higher than those at the two offshore stations (0.4 to 0.6 °C); (ii) a systematic negative bias in the AVHRR retrievals of approximately 1 °C at the coastline, not observed at the two offshore stations; and (iii) an increase in root mean square error at the coastline when the temporal difference between match-ups exceeded three hours. Harnessing new solutions to improve *in situ* sampling coverage at the coastline, such as tagging surfers with sensors, can improve our understanding of the performance of EO SST data in coastal regions, helping inform users interested in EO SST products for coastal applications. Yet, validating EO SST products using *in situ* SST data at the coastline is challenged by difficulties reconciling the two measurements, which are provided at different spatial scales in a dynamic and complex environment.

15 *Key words:* Sea surface temperature, Thermal Radiometry, Remote sensing,
16 Validation, Coastline, Surfers

17 **1. Introduction**

18 Sea surface temperature (SST) is considered by the Global Climate Observ-
19 ing System as an essential climate variable (GCOS, 2011; Bojinski et al., 2014).
20 It is a vital property of the aquatic system, controlling its physical (Moore et al.,
21 1999; Nonaka and Xie, 2003), biological (Eppley, 1972; Pepin, 1991; Keller
22 et al., 1999; Lazareth et al., 2003; Doney, 2006; Tittensor et al., 2010; Couce
23 et al., 2012) and chemical (Lee et al., 2006; Kitidis et al., In press) environment.
24 SST impacts the transfer of compounds between the ocean and atmosphere (Land
25 et al., 2013; Takahashi et al., 2002), the distributions and foraging of many ma-
26 rine vertebrates (Frederiksen et al., 2007; Scales et al., 2014; Miller et al., 2015)
27 and the regional and global climate (Sutton and Allen, 1997; Saji et al., 1999;
28 Lea et al., 2000; Bader and Latif, 2003; Yu and Weller, 2007; Raitzos et al.,
29 2011). It is also a variable that can be retrieved routinely, and operationally,
30 with high spatial coverage and good temporal resolution using Earth Observa-
31 tion (EO), through measurements of radiation in the infrared (Llewellyn-Jones
32 et al., 1984) and microwave (Wentz et al., 2000) portion of the electromagnetic
33 spectrum from radiometers mounted on satellite platforms.

34 To evaluate the use of EO SST products for various operational applications,
35 it is imperative to know the accuracy and precision of the data. This typically
36 requires direct comparison of EO data with co-located and concomitant *in situ*
37 data. In the open-ocean, our understanding of this accuracy and precision is
38 generally high, due to a large network of *in situ* instruments on a variety of plat-

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39 forms, resulting in a considerable number of co-incident *in situ* and EO SST
40 measurements distributed over a wide geographical area (e.g. see Table 3 of
41 Merchant et al., 2014). However, despite demonstrative evidence on the value of
42 SST observations for monitoring of coastal seas (e.g. Goreau and Hayes, 1994;
43 Mustard et al., 1999; Paerl and Huisman, 2008; Tang et al., 2003), the economic
44 and ecological importance of coastal waters (Costanza et al., 1997, 2014; Titten-
45 sor et al., 2010) and their high sensitivity to human pressures and climate change
46 (Jickells, 1998), the accuracy and precision of EO SST data at the coastline are
47 not well known, impeded by a lack of *in situ* data resulting in few validation
48 studies (Smit et al., 2013). The issue is complicated further by the increased
49 complexities inherent in the retrieval of EO SST data at the coastline, for in-
50 stance, from land contamination, from the complex coastal aerosol composition
51 impacting the signal received by the satellite sensor (Thomas et al., 2002), from
52 the heterogeneity of SST at the coastline in space and time, and from potential
53 differences in the relationship between the skin temperature (the top 10-20 mi-
54 crometre) measured by the satellite and the temperature at the depth typically
55 measured *in situ* (hereafter we define SST as the temperature at 1 m depth (z), or
56 SST(z) where $z = 1$ m, as defined by the Group for High Resolution Sea Surface
57 Temperature, see GHRSSST, 2017).

58 Acquiring *in situ* SST measurements in coastal regions, using conventional
59 platforms such as research vessels, buoys and autonomous vehicles, is notori-
60 ously difficult and expensive, hampered by challenges such as: biofouling; van-
61 dalisation; wave damage; complex and shallow bathymetry; and strong tidal and

62 coastal currents. This lack of *in situ* SST data at the coastline prohibits EO val-
63 idation. New solutions are required to improve *in situ* sampling coverage of
64 SST measurements at the coastline, and consequently our understanding of the
65 accuracy and precision of EO SST products.

66 Building on the work of Brewin et al. (2015b), we present results from a
67 three-year study in which a small group of recreational surfers, based primarily in
68 the south west United Kingdom (UK), were tagged with temperature sensors that
69 they used when surfing to measure SST *in situ* at the coastline. The SST data col-
70 lected by the surfers, together with SST data collected from two oceanographic
71 stations (L4 and E1, ~7 km and ~33 km from the coastline of Plymouth, UK,
72 respectively) were compared with co-incident and co-located operational 1 km
73 EO SST data from the Advanced Very High Resolution Radiometers (AVHRR),
74 to improve our understanding of the accuracy and precision of EO SST products
75 at the coastline and consequently their use for coastal applications.

76 **2. Methods**

77 *2.1. Statistical tests*

78 To compare the estimates of SST from two sources the following univariate
79 statistical tests that are commonly used in comparisons between satellite and *in*
80 *situ* data were used (e.g. Doney et al., 2009; Brewin et al., 2015c): the coefficient
81 of determination (r^2); the absolute Root Mean Square Error (Ψ); absolute bias
82 between the estimated and measured variable (δ); absolute centre-pattern (or un-
83 biased) Root Mean Square Error (Δ); and the Slope (S) and Intercept (I) of a

84 linear regression between the estimated and measured variables. The equations
85 used to compute each statistic are provided in Appendix A.

86 *2.2. Study Site: United Kingdom and Ireland*

87 The chosen study sites were beaches around the coastline of the United King-
88 dom (UK) and Ireland (Fig. 1a). Like many coastal regions, the seas surround-
89 ing the UK and Ireland are sensitive to increasing human pressure and climate
90 change (Nicholls et al., 2007; Wang et al., 2008), with implications for changes
91 in marine biodiversity and productivity (Frost et al., 2016; Holt et al., 2016), and
92 the monitoring of key environmental indicators such as SST (L'Hévéder et al.,
93 2016). Whereas a few measurements were collected on the west coast of Ireland
94 and south-east coast of the UK (Fig. 1a), the majority of SST data collected
95 by the surfers were from the south-west coastline of the UK (Fig. 1a and b),
96 in particular the coastline surrounding the city of Plymouth (Fig. 1c), which
97 also hosts two oceanographic stations (Station L4 and E1) that form part of the
98 Western Channel Observatory (<http://www.westernchannelobservatory.org.uk/>)
99 run by Plymouth Marine Laboratory and the UK Marine Biological Association.

100 *2.3. In situ datasets*

101 *2.3.1. SST collected by surfers at the coastline*

102 Between the 5th January 2014 and the 8th February 2017, five recreational
103 surfers were equipped with a UTBI-001 Tidbit v2 Temperature Data Logger and
104 a Garmin etrex 10 GPS, following methods described in Brewin et al. (2015b,
105 see their Fig. 1). The Garmin GPS device was used to extract information on

106 the location (latitude and longitude) of the surf session. It contains an EGNOS-
107 enabled GPS receiver, has HotFix[®] satellite prediction and can track both GPS
108 and GLONASS satellites simultaneously. The GPS device was stored in a water-
109 resistant Aquapac inside a waist-bag worn by the surfer (typically under the wet-
110 suit) and set to record GPS data at 1 Hz. The first and last five minutes of the
111 GPS track were removed (approximately the time between switching on (off) the
112 GPS and entering (exiting) the water), and the median latitude and longitude of
113 the remaining data were extracted to derive information on the central location of
114 data collection during the surfing session. In cases where the GPS device failed
115 (e.g. battery depletion) or was not used, the central location (latitude and longi-
116 tude) of the surf session was extracted immediately preceding the surf session,
117 using GIS software (<https://itouchmap.com/latlong.html>).

118 The Tidbit v2 temperature loggers were attached, using cable-ties, to the
119 mid-point of each surfers leash (tether connecting the surfer to their surfboard)
120 to ensure continuous contact with seawater when surfing, and measured temper-
121 ature in the top metre of the water column (see Fig. 1 of Brewin et al., 2015b).
122 Manufacturers state that the Tidbit v2 sensors have an accuracy of 0.2°C over
123 a range of 0-50°C, a resolution of ~0.02°C at 25°C, a stability of ~0.1°C per
124 year, a response time of 5 minutes in water, and a battery life of ~5 years at a >1
125 minute logging interval. To ensure good quality data collection, we monitored
126 the performance of each sensor approximately every 6 months over the study
127 period, by comparing the Tidbit v2 temperature loggers with a VWR1620-200
128 traceable digital thermometer (NIST/ISO calibrated, with an accuracy of 0.05°C

129 at the range of 0 to 100°C and a resolution of 0.001°C) at 1°C intervals in the
130 laboratory, from 6 to 25°C using a PolyScience temperature bath.

131 Figure 2a-d illustrates four laboratory comparisons between a Tidbit v2 sen-
132 sor (10308732) and the VWR1620-200 traceable digital thermometer, and Fig.
133 2e-j show variations in statistical tests (Eq. A.1 to A.5) for each laboratory com-
134 parison, for the five Tidbit v2 sensors used in the study. Over the study period, all
135 sensors performed within the manufacturers technical specifications, with high
136 r^2 , slopes (S) staying close to one, and intercepts close to zero for all laboratory
137 comparisons (Fig. 2e, i and j). Root Mean Square Errors (Ψ) were $<0.15^\circ\text{C}$
138 for all sensors (Fig. 2f). When decomposing Ψ into its precision (Δ) and ac-
139 curacy (δ) components, Ψ was dominated by a small systematic bias (δ) for all
140 sensors (Fig. 2h). We used piecewise regression to model δ as a function of
141 time (Fig. 2h) for each sensor, which was then used to correct any tempera-
142 ture data collected by each sensor. In cases where data were collected before
143 the first laboratory comparison, or after the last, the correction (δ) was set at the
144 closest laboratory comparison (rather than extrapolating the piecewise regres-
145 sion model outside of the time period it was developed for, see Fig. 2h). Having
146 removed the systematic bias, the errors in each sensor were within the accuracy
147 of VWR1620-200 traceable digital thermometer ($<0.05^\circ\text{C}$ see Fig. 2g). The
148 piecewise regression model also improved the consistency between sensors, by
149 correcting each sensor to the same common reference (see Appendix B and Fig.
150 A1 for an example of deployment at the same location for two different sensors).
151 Table 1 provides the number of times each sensor was used in a surfing session

152 during the study period, and the duration of use for each sensor.

153 HOBOWare software and HOBO USB Optic Base Station (BASE-U-4) were
154 used by the surfer to launch the Tidbit v2 temperature logger prior to each ses-
155 sion, and then to upload data post session. Temperature data were collected at
156 10 Hz during each surf. Temperature data were processed following a method
157 building on that developed in Brewin et al. (2015a,b). Briefly, the assumption
158 is made that the midpoint of the temperature data for each surf session occurred
159 while the sensor was in the water. This assumption was checked manually for
160 each surf session and found to hold when visually checked with available GPS
161 data. The data were then divided into two equal halves around the mid-point.
162 For the first half of the data, every data point was removed sequentially in time
163 and the standard deviation was calculated incrementally, with the last data point
164 representing the standard deviation of the midpoint (zero). For the second half
165 of the data, this procedure was repeated but in reverse. The standard deviations
166 for the two halves of the data were then recombined. The point at which the
167 surfer began measuring SST (entered the water) was taken as the point when the
168 standard deviation first fell below the bottom third percentile, and the point at
169 which the surfer stopped measuring SST (exited the water) was taken as the last
170 point of the session when the standard deviation was below the bottom third per-
171 centile. The bottom third percentile was chosen based on a visual comparison
172 with the timing of the first and last waves caught by the surfer, as estimated from
173 GPS data (see Brewin et al., 2015b). Appendix B illustrates an example of the
174 processing method applied to a surf session at Tolcarne Beach in Newquay, UK

175 (see Fig. A2).

176 The only difference with this method, to that described in Brewin et al.
177 (2015b), is that a percentile was used rather than determining the start and end
178 points according to when the standard deviation was less than 10 % of the largest
179 standard deviation. We found that using a percentile was slightly more robust
180 in cases where the temperature in the water was very stable, and the previous
181 technique selected data before and after the surfer entered the water. All tem-
182 perature measurements collected before and after the determined start and end
183 points were excluded, and the median of the remaining data was considered as
184 the SST for each session (see Appendix B, Fig. A2). Note that the median is
185 resistant to outliers and thus fairly resilient to variations in the derived start and
186 finish points. For example, the difference between the processing methods used
187 here and that used by Brewin et al. (2015b) to determine SST was very small
188 ($r^2 = 1.00$, $\Psi = 0.07$, $\Delta = 0.07$, $\delta = -0.02$, $S = 1.00$ and $I = -0.01$).

189 Appendix B, Fig. A3, shows a superposition of all temperature data acquired
190 by the surfer during the study period, normalised such that the start and end of
191 the surf is at the same point on the x-axis for each session. The plot demonstrates
192 the temperature of the sensor in the sea is relatively stable compared with that
193 before and after each surf. As discussed in Brewin et al. (2015b), the method
194 assumes that the mid-point of the collected data occurred in the sea and that
195 duration of data collection in the sea is longer than duration out of the water.
196 We caution against the use of the method in cases where these assumptions are
197 breached. The method is also designed specifically to determine the median SST

198 of the session. The time of data collection (GMT) was taken as the mid-point
199 (median) of all 10 Hz samples selected to compute SST.

200 In total, 297 surfing sessions took place during the study period, around the
201 coastline of the United Kingdom (UK) and Ireland (Fig. 1a), most of which
202 were in the south-west UK (Fig. 1b and c). The majority of surf sessions (233)
203 took place at Wembury Beach (latitude = 50.316 °N, longitude = -4.085 °E) and
204 Bovisand Beach (latitude = 50.332 °N, longitude = -4.122 °E) located close to
205 each other and near to the city of Plymouth, UK. The majority of measurements
206 were collected during conditions preferable for surfing. This typically involved
207 breaking waves at the coastline in the range of 0.3-3.0 m, though some measure-
208 ments were collected in calm sea during surfer paddle training. The SST data
209 collected by the surfers are publicly available through the British Oceanographic
210 Data Centre (Brewin et al., 2017).

211 2.3.2. SST from station L4 and E1

212 SST data were also acquired from two oceanographic stations in the Western
213 Channel Observatory (WCO): station L4 (latitude = 50.250 °N, longitude = -
214 4.217 °E) located ~7 km from the coastline and station E1 (latitude = 50.033 °N,
215 longitude = -4.367 °E) located ~33 km from the coastline (Fig. 1c). At both
216 stations an autonomous buoy is operated, equipped with a WET Labs Water
217 Quality Monitor (WQM), which incorporates WET Labs' fluorometer-turbidity
218 and Sea-Bird's CTD sensors, providing temperature, salinity, depth, dissolved
219 oxygen, chlorophyll fluorescence, turbidity and backscattering data. The WQM
220 are mounted on a marine-grade stainless steel cage and situated in a moon pool

221 (an opening in the floatation) at a fixed depth of 1 m. The WQM records
222 SST at hourly intervals, with an accuracy of 0.002°C at a range of -5 to
223 35 °C, and a resolution of 0.001°C. Further details on the operation of the au-
224 tonomous buoy systems can be found in Smyth et al. (2010). Quality controlled
225 datasets on SST were downloaded from the Western Channel Observatory web-
226 site (<http://www.westernchannelobservatory.org.uk/data/buoy/>) between January
227 2014 and December 2016, with some gaps in the datasets from buoy maintenance
228 and downtime.

229 *2.4. AVHRR satellite observations*

230 Operational AVHRR SST data were acquired through the UK Natural En-
231 vironmental Research Council (NERC) Earth Observation Data Acquisition and
232 Analysis Service (NEODAAS, <http://www.neodaas.ac.uk/>). This service is reg-
233 ularly used by the UK and European scientific communities, and has supported a
234 wide variety of international research (see <http://www.neodaas.ac.uk/publications.php>).
235 The AVHRR is a scanning sensor on-board the National Oceanic and Atmo-
236 spheric Administration (NOAA) family of Polar Orbiting Environmental Satel-
237 lites (POES). These platforms are sun synchronous, viewing the same loca-
238 tion roughly twice a day (depending on latitude) due to a relatively wide swath
239 (~2400 km). The AVHRR measures the radiance of the Earth at a suite of bands,
240 including bands centred around 11 and 12 micrometers, measuring emitted ther-
241 mal radiation. It is these bands that are principally used to derive SST.

242 The NEODAAS operational processing system is illustrated in Fig. 3. Dur-
243 ing the 15 minute period when each satellite is in range, a receiving station lo-

244 cated in Dundee acquires High Resolution Picture Transmission (HRPT) passes
245 over NW Europe and the Arctic, ~14 per day and ~4.6 of which cover the UK
246 (see <http://www.sat.dundee.ac.uk/coverage.html>). The passes are immediately
247 transmitted, via a fast internet link, from the receiving station to Plymouth Ma-
248 rine Laboratory for processing. The HRPT images are then processed to Level 3,
249 which involves: georeferencing, using an orbital model together with ephemeris
250 data from NOAA (Sandford and Stephenson, 1992) and an automated naviga-
251 tion adjustment that matches image features with a database of ground control
252 points (Bordes et al., 1992); generation of a land mask using the University
253 of Hawaii's Generic Mapping Tools (<http://gmt.soest.hawaii.edu/>) which is then
254 overlaid on the georectified AVHRR image; application of a hybrid cloud mask,
255 adapted from Saunders and Kriebel (1988), Thiermann and Ruprecht (1992), and
256 Roozkrans and Prangmsma (1988); application of a cloud proximity test to min-
257 imise cloud-edge effects and sub-pixel cloud contamination (Miller et al., 1997);
258 implementation of the NEODAAS operational SST algorithm adapted from the
259 standard NOAA method (Non-linear SST (NLSST) split-window equation us-
260 ing infrared channels 4 and 5, with modifications to correct for atmospheric
261 water-vapour absorption; Miller et al., 1997); application of a quality control
262 step by comparison with climatological weekly average Optimum Interpolation
263 SST (OISST) provided by the US National Meteorological Centre (Reynolds
264 and Smith, 1994; Reynolds et al., 2007), flagging any pixels that differ +2°C and
265 -4°C from the climatology; and finally image transformation to Mercator pro-
266 jection (~ 1 km resolution), using the MODIS Swath-to-Grid Toolbox (MS2GT).

267 Additional details of the NEODAAS operational processing system can be found
268 in Miller et al. (1997). SST images are available within 90 minutes of the start
269 of acquisition.

270 NEODAAS provides data extractions for various regions. Here we used
271 products provided between -15°E and 13°E and 47°N and 63°N, covering the
272 study area (Fig. 3). Level 3 mapped scenes were acquired from NEODAAS be-
273 tween 5th January 2014 and the 8th February 2017, providing SST, latitude and
274 longitude data for each pixel in the scene, and the time (GMT) of the overpass.
275 In addition to using the individual satellite passes directly for comparison with
276 *in situ* data, we also used daily median composite products, produced using all
277 the Level 3 passes available during a single day, for a given pixel.

278 2.5. Comparison of datasets

279 2.5.1. Comparison of *in situ* datasets

280 We first analysed differences in the *in situ* SST over the duration of the study
281 period at three locations near the city of Plymouth in the UK; at Station E1;
282 at Station L4; and at the coastline, using temperature measurements collected
283 from two nearby beaches in Plymouth (Wembury Beach and Bovisand Beach).
284 This was conducted qualitatively, by overlaying the SST time-series of the three
285 datasets onto the same graph which was then inspected visually, and quantita-
286 tively, by matching (with a time difference of ≤ 1 hr) co-incident SST measure-
287 ments and through the application of statistical tests.

288 2.5.2. Comparison of daily median AVHRR products

289 Next we compared daily median AVHRR SST products, at the same three
290 locations (Station E1, Station L4, and at the coastline (Wembury Beach and Bo-
291 visand Beach)), with the *in situ* data (daily median) over the duration of the study
292 period. At L4 and E1 we extracted AVHRR SST data from a group of nine pix-
293 els centred on the location of the oceanographic buoys (see Fig. 6a) for each
294 day in the time-series. At the coastline, we extracted data from six pixels that
295 run along the coastline between the two beaches (see Fig. 6a) for each day in
296 the time-series. For each group of pixels per day, we computed the median SST,
297 the standard deviation and percentage of the group of pixels with SST data. To
298 ensure reasonable homogeneity in the match-up site, required when comparing
299 observations (*in situ* and satellite) representative of vastly different volumes of
300 water, AVHRR data were discarded when the standard deviation of the group of
301 pixels was greater than 1°C and where percentage of pixels with SST data was
302 less than 50%.

303 As with the comparison of the three *in situ* datasets, we compared the daily
304 median AVHRR SST with the *in situ* data at each location qualitatively, by over-
305 laying the satellite and *in situ* SST time-series at each location onto the same
306 graph which was then inspected visually, and quantitatively, by comparing daily
307 match-ups using statistical tests outlined in section 2.1.

308 2.5.3. Validation of AVHRR satellite passes

309 We matched all *in situ* data (at Station L4, Station E1 and SST measurements
310 collected around the coastline of UK and Ireland by the surfers) to all available

311 Level 3 AVHRR SST satellite passes, within a time difference of ± 12 h. As
312 with the daily median data for E1 and L4, we extracted a group of nine pixels
313 centred at each location. However, we only used the centre (closest) pixel in
314 the comparison of satellite passes (rather than the median of the nine pixels),
315 to ensure the closest spatial agreement between data. For the *in situ* data at
316 the coastline (collected by the surfers), we used the closest pixel to the *in situ*
317 measurement within a 1 km radius, to account for cases where the closest pixel
318 was dominated principally by land (i.e. the *in situ* measurement was at the edge
319 of a land pixel, see Fig. 4c for an example). As with the daily median data, the
320 group of nine pixels were used to ensure reasonable homogeneity of the match-
321 up region. Match-ups were discarded when the standard deviation of the group
322 of pixels was greater than 1°C , and where percentage of the group of pixels with
323 SST data was less than 33% (3 pixels needed to compute the standard deviation),
324 which was lower than the daily median data (<50%), as typically, roughly half of
325 the pixels were located on land when extracting the 9 pixels at the coastline (see
326 Fig. 4c for an example). The absolute time difference (T) between the overpass
327 of the satellite data and the *in situ* was recorded, to investigate the influence of T
328 on statistical tests between datasets. Figure 4 illustrates an example of the match-
329 up process for AVHRR satellite passes, for a relatively cloud free AVHRR SST
330 image taken on the 20th April 2015 at 03:39 GMT (Fig. 4a), compared with SST
331 data collected at Station E1 at 04:04 GMT (Fig. 4b) and by a surfer at Bovisand
332 beach at 05:58 GMT (Fig. 4c).

333 **3. Results**

334 *3.1. In situ comparison*

335 Seasonal variations in the three *in situ* time-series are in good agreement
336 visually (Fig. 5b, d and f). The warmest temperatures are observed during late
337 summer and coolest in early March. Inter-annual differences are also generally
338 consistent. For instance, an unusual decrease in SST in August 2014 was seen
339 at both Station L4 and at the beaches, and sharp but brief increases in SST in
340 June and July 2016 are consistent in all three datasets (Fig. 5). Although the L4
341 and E1 buoys collect data far more regularly (per hour) than the surfers, there are
342 significant periods of time during the study period when one of the buoys were
343 not operating, which was not the case for the surfer data.

344 Quantitative comparisons among the three time-series (with a time difference
345 of ≤ 1 hr) show that the data collected by the surfer explains $\geq 91\%$ of the vari-
346 ance in the Station L4 and E1 data, with a root mean square difference (Ψ) of
347 0.74 to 0.84°C (Fig. 5c and e). These statistical results are similar to those found
348 when comparing the two oceanographic buoys (Fig. 5g). Yet, despite these simi-
349 larities, there are systematic differences seen in the three datasets consistent with
350 their spatial separation (Fig. 5a). Whereas the average bias (δ) between surfer
351 and E1 data is quite low (-0.15°C , Fig. 5e), the autumn and early winter peri-
352 ods show systematically lower SST in the surfer data when compared with E1
353 (e.g. winter 2014/2015 and autumn 2016, see Fig. 5d). This is likely linked to
354 the influence of the terrestrial environment on nearshore SST during this period.
355 The land cools more rapidly in the autumn and early winter, owing to a lower

356 heat capacity when compared with the ocean, potentially impacting nearshore
357 SST. It may also be influenced by enhanced fresh water input during this period,
358 and by the atmospheric cooling, with increased exchanges of heat between the
359 atmosphere and ocean at the coastline caused by wave breaking. Furthermore,
360 it is possible that enhanced vertical mixing at the coastline due to wave break-
361 ing could promote upwelling of colder water during autumn and winter storm
362 conditions.

363 Both the surfer and the E1 SST data show systematically higher temperatures
364 than that observed at L4 (with an average bias of between 0.33 and 0.40°C, Fig.
365 5c and g), particularly during the summer of 2015 (Fig. 5b and f). It is likely
366 that Station L4 is less strongly stratified during the summer period when com-
367 pared with E1, perhaps due to stronger tidal mixing (shallow bathymetry) and
368 estuarine outflow from Plymouth Sound. Higher SST in the summer of 2015
369 at the beaches, when compared with L4, may be related to more rapid warming
370 of shallower water at the beaches during the day. Considering good agreement
371 among the three SST datasets, with discrepancies generally consistent with ex-
372 pectations given their spatial separation and contrasting proximity to land, one
373 can be confident using the surfer SST data for coastal applications.

374 3.2. AVHRR comparison of daily median products

375 Figure 6 shows a comparison of the daily median AVHRR SST data with
376 the daily median *in situ* data at L4, E1 and the two beaches (Wembury and
377 Bovisand). With the exception of a few outliers, likely caused from miss-
378 classification of cloud-contaminated pixels (owing to a much lower SST char-

379 acteristic of cloud-contamination), there is very good agreement between the
380 AVHRR SST data and the *in situ* measurements at L4 and E1, with the satellite
381 observations tracking tightly variations in the *in situ* data (Fig. 6d and f). At
382 both L4 and E1, the AVHRR data explains 97 % of the variance in the *in situ*
383 data, with a very low bias ($\delta = -0.04^{\circ}\text{C}$), low errors (Ψ and Δ , $\leq 0.44^{\circ}\text{C}$), slopes
384 (S) close to one and intercepts (I) close to zero (Fig. 6e and g).

385 At the coastline, however, the agreement between the AVHRR SST data and
386 *in situ* data is not as good (Fig. 6b and c). The satellite observations do not track
387 the *in situ* data as tightly over the course of the seasons (Fig. 6b) as they do at L4
388 and E1, and statistical tests between daily match-ups (Fig. 6c) are not so good
389 when compared with the two offshore stations, with the AVHRR data explaining
390 only 87 % of the variance in the *in situ* data, with a systematic negative bias
391 ($\delta = -1.20^{\circ}\text{C}$), lower precision ($\Delta = 1.08^{\circ}\text{C}$), slopes less than one ($S = 0.89$)
392 and an intercept (I) of 0.31. The results indicate a degradation in the performance
393 of the AVHRR data at the coastline, when compared with Station L4 and E1.

394 3.3. AVHRR comparison of satellite passes

395 Scatter plots of AVHRR satellite passes and *in situ* SST data at Station L4,
396 E1 and measurements collected around the coastline of UK and Ireland by the
397 surfers, are shown in Fig. 7, for an absolute time difference (T) of <1 h, <3 h and
398 <5 h. In general, the statistical performance of the AVHRR data at L4 (Fig. 7d,
399 e, and f) and E1 (Fig. 7g, h, and i) are consistent with that in the comparison of
400 daily median values (Fig. 6), with high coefficient of determination (>0.95), no
401 biases ($\delta \sim 0$), slopes (S) close to one and intercepts (I) close to zero. The root

402 mean square errors (Ψ), composed principally by the precision component (Δ)
403 considering the biases were zero (Fig. 7), are slightly higher ($\Psi = 0.52$ to 0.54)
404 than the daily median comparison at L4 ($\Psi = 0.44$, Fig. 6e), and higher at L4
405 ($\Psi = 0.52$ to 0.54) than at E1 ($\Psi = 0.45$ to 0.47).

406 Consistent with the daily median comparison, statistical tests of AVHRR and
407 *in situ* data indicate a significantly better performance in AVHRR SST at the two
408 offshore stations (L4 and E1) when compared with performance at the coastline
409 (Fig. 7), with Ψ two to three times higher at the coastline than offshore (L4
410 and E1), a systematic negative bias in AVHRR at the coastline ($\delta = -0.39$ to
411 -1.07°C), slopes less than one and generally high intercepts (Fig. 7a-c). At L4
412 and E1, there is an increase in Ψ from <1 h to <5 h. The same is shown at the
413 coastline between <3 h and <5 h (Fig. 7b and c). Figure 8 shows Ψ plotted as a
414 function of T at the coastline (beaches) and at L4 and E1. In all cases, there is
415 a significant increase in Ψ with T. At E1 and L4, this increase is linear. At the
416 beaches, there is a sharp increase after 3 hr, with Ψ significantly higher at 6 hr
417 (confidence intervals do not overlap).

418 **4. Discussion**

419 The coastal zone is arguably one of the most precious marine environments
420 on the planet, containing the highest level of marine biodiversity (Tittensor et al.,
421 2010), a large proportion of the world's fish catch (Stewart et al., 2010), and sup-
422 porting a wide range of human activities, from energy extraction (Gill, 2005) to
423 waste disposal. It is also vulnerable to increasing human pressure and climate
424 change (Jickells, 1998; Lotze et al., 2006; McGranahan et al., 2007). Adequate

425 management of the coastal environment requires the monitoring of key environ-
426 mental indicators like SST (Bojinski et al., 2014). Yet, the coastal environment
427 is drastically under-sampled and the observational networks are not adequate to
428 meet management needs. Due to the paucity of data in coastal systems, there is
429 increasing reliance placed on using models. Yet, these models are often based on
430 false assumptions and are usually not verified with field data (Livingston, 2014).
431 New solutions are needed to increase the spatial and temporal sampling of *in situ*
432 data in the coastal zone.

433 *4.1. Monitoring SST at the coastline in situ using recreational citizens*

434 Here, we utilised a small group of surfers who regularly immerse themselves
435 in the coastal zone, to measure SST over a three year period. The SST collected
436 by the surfers were found to be in good agreement with measurements collected
437 at two nearby oceanographic stations giving confidence in the method (Fig. 5),
438 with discrepancies consistent with the spatial separation of sampling locations.
439 It has been estimated that in the region of 40 million measurements of SST per
440 year could be acquired in the UK coastal zone by tagging surfers with tempera-
441 ture sensors (Brewin et al., 2015b). In the US there are an estimated ~3.3 million
442 surfers who surf ~108 times per year (Thomas, 2012), suggesting a potential of
443 an additional ~350 million measurements of SST per year in the US. Surfers
444 often visit remote and uninhabited regions, countries with limited coastal moni-
445 toring infrastructure and capabilities, where few coastal observations have been
446 collected, regions that are highly vulnerable to climate change (e.g. Latin Amer-
447 ica and the East Asia Pacific).

448 There are also many other recreational watersports beyond surfing, which
449 involve direct interaction with the aquatic environment in regions that are dif-
450 ficult to measure using conventional platforms. It has been demonstrated that
451 recreational divers (Boss and Zaneveld, 2003; Wright et al., 2016), kayakers
452 (Bresnahan et al., 2016), stand-up paddle-boarders (Bresnahan et al., 2016) and
453 recreational sailors (Lauro et al., 2014), could contribute significantly to data
454 collection in the coastal zone. Considering many of these other recreational wa-
455 tersports occur in maritime conditions different to that of surfing (e.g. calm seas),
456 integrating such observations with data from surfers could increase the range of
457 environmental conditions sampled by citizens. With rapid improvements in tech-
458 nology, including: miniaturisation of sensors, wireless data transfer, cloud data
459 storage and wireless communication, the feasibility of harnessing citizens for
460 coastal monitoring is becoming a real option (Busch et al., 2016; Farnham et al.,
461 2017). Integrating these observations with other developing *in situ* techniques,
462 such as coastal gliders (Rudnick et al., 2004), autonomous beach buoy systems
463 (Shively et al., 2016) and the tagging of marine vertebrates with sensors (Fedak,
464 2004), as well as traditional *in situ* methods from ships and buoys, would signif-
465 icantly enhance the spatial and temporal sampling of *in situ* data in the coastal
466 zone.

467 4.2. *Satellite remote sensing of SST*

468 The combined spatial and temporal coverage of satellite remote sensing ob-
469 servations, and its synoptic capabilities, means it provides more observations of
470 SST than any other technique over wide spatial scales, and has significantly im-

471 pacted operational ocean forecasting (Donlon et al., 2007). Yet, satellite remote
472 sensing of SST has certain limitations. Thermal radiation emitted from the ocean
473 is impacted by clouds and is only representative of the first few millimeters (the
474 skin) of the ocean, relying on algorithmic conversions and assumptions to derive
475 SST (at 1 m depth in the ocean), which can then be compared with the *in situ*
476 datasets collected at ~ 1 m depth. To maximise the use of satellite SST data,
477 the accuracy and precision of the data must be determined, which requires direct
478 comparison with co-located and concomitant *in situ* data. The lack of *in situ*
479 SST observations at the coastline means to date, our knowledge of the accuracy
480 and precision of satellite SST at the coastline is severely limited. In light of the
481 next generation of satellite thermal sensors (e.g. ESA's Sentinel 3 programme
482 with dual-view measurement capabilities and proposed high resolution thermal
483 sensors) it is vital these *in situ* networks are improved, to maximise the use of
484 satellite SST observations for long-term monitoring and operational coastal ap-
485 plications.

486 When compared with other AVHRR SST processing systems, the operational
487 NEODAAS system works well in offshore waters (Station L4 and E1) with no
488 systematic difference ($\delta \sim 0.0$, see Fig. 7). The centre-pattern root mean square
489 error (Δ) in AVHRR data for E1 and L4 data varies between 0.45 and 0.51°C
490 respectively, within an hour absolute time difference (Fig. 7). When using the
491 robust standard deviation between match-ups rather than Δ , calculated by scaling
492 the median absolute deviation from the median (making it less sensitive to out-
493 liers), these values drop to 0.18 and 0.21°C, which fall below the range (0.26 and

494 0.58°C) presented in a global validation by Merchant et al. (2014, see their Ta-
495 ble 3) for various AVHRR sensors, giving confidence in the operational AVHRR
496 SST data provided by NEODAAS.

497 At the coastline we observe a significant degradation in the performance of
498 AVHRR at retrieving SST (Figs. 6, 7 and 8), with significantly higher root mean
499 square errors (Ψ) that at L4 and E1, in the range of 1.0 to 2.0°C (Fig. 8). This
500 clearly limits the use of AVHRR SST data at the coastline for applications that
501 require errors to be less than that in this range. This finding is consistent with
502 that of Smit et al. (2013), who caution against the use of 4 km SST MODIS Terra
503 and Pathfinder v5.2 products around the coastline of South Africa, and observed
504 significant biases between the satellite and *in situ* datasets. Yet, for applications
505 that don't require high accuracy and precision, AVHRR SST data at the coastline
506 may still have some use. For instance, in August 2014 there was a significant
507 reduction in SST in Plymouth coastal and offshore waters, of the order of 3 to
508 4°C seen in the *in situ* and satellite observations (Figs. 6). The AVHRR SST data
509 at the coastline captured this decrease (Fig. 6), which was larger than the errors
510 reported in the validation.

511 Yet, for the majority of applications where error requirements in SST are
512 lower than 1.0°C, there needs to be a significant improvement in the satellite
513 AVHRR SST processing systems at the coastline. Retrievals of SST at the coast-
514 line are inherently complex when compared with offshore waters, owing to fac-
515 tors such as land contamination (e.g. from tidal changes), land adjacency issues,
516 complexities in atmospheric-correction (e.g. from coastal aerosols), potential

517 changes in the conversions from skin temperature to SST (e.g. from more bub-
518 bles at the land-sea interface; Jessup et al., 1997; Eifler and Donlon, 2001), and
519 errors in satellite georeferencing. With better coastal *in situ* networks, we can
520 drastically increase the number of co-incident and concurrent satellite and *in situ*
521 match-ups, which in addition to validation, may help improve algorithm devel-
522 opment.

523 Even with more *in situ* data, validation of satellite retrievals of SST at the
524 coastline are more challenging than in offshore waters. SST at the coastline can
525 be notoriously heterogeneous, due to a variety of factors such as: freshwater
526 runoff at the coastline (e.g. impact of land run-off as well as nearby rivers and
527 estuaries); tidal stirring; exchanges of heat between the land and ocean; and wave
528 breaking (Farmer and Gemmrich, 1996), resulting in gradients in SST within a
529 1 km pixel that may not be captured by the surfer. Figure 1d illustrates the cov-
530 erage of a typical GPS track by a surfer within a mapped NEODAAS AVHRR
531 SST pixel, highlighting large differences in the spatial sampling in SST by the
532 surfer and by the satellite. In some cases, it may be that portion of the pixel the
533 surfer is sampling (the shallow landward boundary) has a systematically differ-
534 ent temperature than the average of the pixel. This difference could be higher
535 (consistent with the negative bias we see in Fig. 6c and 7a-c) where the shallow
536 landward boundary might heat up quicker than the average, or even lower, in
537 cases where a colder landmass (or fresh water run-off) is significantly influenc-
538 ing the shallower landward boundary of the pixel (e.g. in Autumn). This spatial
539 heterogeneity could be quantified by integrating high spatial resolution thermal

540 observations (e.g. Landsat or from aircraft platforms) with the coarser resolution
541 AVHRR data, but would be limited by infrequent concurrent overpasses. This
542 coastal heterogeneity also has a temporal component that is likely to be greater
543 than in offshore waters. Figure 8 highlights a sharp jump in the root mean square
544 error (Ψ) when increasing the absolute time difference (T) between the *in situ*
545 and satellite data beyond three hours, emphasising a requirement to minimise
546 T when validating SST retrievals at the coastline. This sharp increase may be
547 related to the semi-diurnal tidal cycle in the region.

548 **5. Conclusions**

549 To evaluate the suitability of EO SST data for coastal applications, it is es-
550 sential to know the accuracy and precision of the data. This involves matching
551 co-located and concomitant *in situ* and EO SST data. Due to a limited number
552 of *in situ* measurements, little is known about the accuracy and precision of the
553 EO SST data at the coastline. Using *in situ* SST measurements collected by a
554 group of surfers over a three year period in the coastal waters of the UK and
555 Ireland, we evaluated the accuracy and precision of operational AVHRR SST
556 data at the coastline. When compared with match-ups at two autonomous buoys
557 ~ 7 km and ~ 33 km offshore, we observed a significant reduction in the perfor-
558 mance of AVHRR at retrieving SST at the coastline. Root mean square errors
559 at the coastline were in the range of 1.0 to 2.0 °C, depending on the temporal
560 difference between match-ups, significantly higher than those at the two offshore
561 stations (0.4 to 0.6 °C). For match-ups at the coastline we also observed a sys-
562 tematic negative bias in the AVHRR retrievals of roughly 1 °C, and an increase

563 in root mean square error when the temporal difference between match-ups ex-
564 ceeded three hours.

565 Tagging recreational water-users, like surfers, with sensors has the poten-
566 tial to improve the spatial and temporal coverage of *in situ* measurements at the
567 coastline. This can aid our understanding of the accuracy and precision of the EO
568 data, improve algorithm development, and inform users interested in using EO
569 SST products for coastal applications. However, when compared with offshore
570 waters, comparing EO SST products with *in situ* SST at the coastline is chal-
571 lenging. The dynamic and inherently complex coastal environment is difficult to
572 sample remotely and *in situ*, and it is more complicated to reconcile geophysical
573 and spatial differences between the two types of SST observations. Yet, in the
574 face of increasing human pressures and climate change, our coastal seas require
575 careful monitoring. This can only be achieved through integrating observations
576 from different sources, including new *in situ* sampling and EO.

577 **A. Appendix A**

578 To compare the estimates of SST from two sources the following univariate
579 statistical tests were used.

580 *A.1. Coefficient of determination (r^2)*

581 The coefficient of determination (r^2) was taken to be the square of the Pearson
582 correlation coefficient (or squared Pearson's product moment correlation) and

583 was calculated according to

$$r^2 = \left\{ \frac{1}{N-1} \sum_{i=1}^N \left[\frac{X_i^M - \left(\frac{1}{N} \sum_{j=1}^N X_j^M \right)}{\left\{ \frac{1}{N-1} \sum_{k=1}^N \left[X_k^M - \left(\frac{1}{N} \sum_{l=1}^N X_l^M \right) \right]^2 \right\}^{1/2}} \right] \left[\frac{X_i^E - \left(\frac{1}{N} \sum_{m=1}^N X_m^E \right)}{\left\{ \frac{1}{N-1} \sum_{n=1}^N \left[X_n^E - \left(\frac{1}{N} \sum_{o=1}^N X_o^E \right) \right]^2 \right\}^{1/2}} \right] \right\}^2, \quad (\text{A.1})$$

584 where, X is the variable (e.g. SST) and N is the number of samples. The super-
 585 script E denotes the estimated variable (e.g. from the satellite sensor) and the
 586 superscript M denotes the measured variable (e.g. measured *in situ*). Note that
 587 the Pearson correlation coefficient assumes a linear relationship between vari-
 588 ables. The squared correlation coefficient may take any value between 0 and 1.0,
 589 with 1.0 indicating the estimated variable explains 100% of the variability in the
 590 measured variable.

591 A.2. Root Mean Square Error (Ψ)

592 The absolute Root Mean Square Error (Ψ) was calculated according to

$$\Psi = \left[\frac{1}{N} \sum_{i=1}^N (X_i^E - X_i^M)^2 \right]^{1/2}. \quad (\text{A.2})$$

593 The Root Mean Square Error (Ψ) can be partitioned into the bias (δ), which
 594 represent the systematic difference between variables (accuracy), and the centre-
 595 pattern (or unbiased) Root Mean Square Error (Δ), which represents the random
 596 difference between two variables (precision), such that $\Psi = \sqrt{\Delta^2 + \delta^2}$. Com-
 597 putation of δ and Δ are described next.

598 A.3. The bias (δ)

599 The absolute bias between the estimated and measured variable was ex-
600 pressed according to

$$\delta = \frac{1}{N} \sum_{i=1}^N (X_i^E - X_i^M). \quad (\text{A.3})$$

601 A.4. The centre-pattern Root Mean Square Error (Δ)

602 The absolute centre-pattern (or unbiased) Root Mean Square Error (Δ) was
603 calculated according to

$$\Delta = \left(\frac{1}{N} \sum_{i=1}^N \left\{ X_i^E - \left(\frac{1}{N} \sum_{j=1}^N X_j^E \right) \right\} - \left[X_i^M - \left(\frac{1}{N} \sum_{k=1}^N X_k^M \right) \right] \right\}^2 \right)^{1/2}. \quad (\text{A.4})$$

604 It describes the error of the estimated values with respect to the measured ones,
605 regardless of the average bias between the two distributions.

606 A.5. Slope (S) and Intercept (I) of a linear regression

607 The performance of a model with respect to *in situ* data can be tested us-
608 ing linear regression between the estimated variable (from the model) and the
609 measured variable (*in situ* data), such that

$$X^E = X^M S + I. \quad (\text{A.5})$$

610 A slope (S) close to one and an intercept (I) close to zero is an indication that
611 the model compares well with the *in situ* data.

612 **B. Appendix B**

613 In Appendix B we provide supporting information on the processing of the
614 SST data collected by surfers in the study. We demonstrate an improved con-
615 sistency between the Tidbit v2 sensors when correcting each sensor to the same
616 common reference. Figure A1 shows data collection by two surfers at the same
617 location using two different sensors at an overlapping time period in the water
618 (purple shading). The systematic difference (δ) between sensor readings were
619 reduced when correcting each sensor to the same common reference using the
620 piecewise, bias-correction model (Fig. 2h).

621 We also provide supporting information illustrating the method used to pro-
622 cess the data collected by surfers and derive SST (see Fig. A2). A superposition
623 of all temperature data acquired by the surfer during the study period, normalised
624 such that the start and end of the surf is at the same point on the x-axis for each
625 session, is provided in Fig. A3. The plot highlights the stability of the tempera-
626 ture of the sensor in the sea compared with that before and after each surf.

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Table 1: Details for each Tidbit v2 sensor of the number (N) of surfing sessions the sensor was used for during the study period and its duration of use.

Tidbit v2 sensor	N	Duration of use
10308732	141	5th Jan 2014 - 28th Nov 2015*
10551172	27	13th Sep 2014 - 6th Nov 2016#
10551173	35	12th Aug 2014 - 4th Jan 2017#
10551174	4	8th Jul 2015 - 7th Aug 2016#
10782552	90	28th Nov 2015 - 8th Feb 2017#

* Sensor ran out of battery after this date

Sensor still operational at end of study

Figure 1: Study site and locations of sampling. (a) Shows the locations of the 297 surfing sessions where SST data were collected during the study in the UK and Ireland, overlain onto a NEODAAS AVHRR SST average composite image of September, averaged between the duration of the study (2014-2017). (b) Locations where the majority of samples were collected by the surfers around the south-west UK coastline, overlain onto the same September SST composite. (c) Sample locations near the city of Plymouth, UK, showing the position of two nearby oceanographic stations (Station L4 and E1) that form part of the Western Channel Observatory, all overlain onto the same September SST composite. (d) GPS track from a surf on the 20th September 2014, overlain onto the same September SST composite, to illustrate the coverage of a typical GPS track within a mapped NEODAAS AVHRR pixel.

Figure 2: Laboratory comparisons between the Tidbit v2 sensors and a VWR1620-200 traceable digital thermometer, using a PolyScience temperature bath over the range from 6 to 25°C. (a-d) Illustrate four laboratory comparisons between Tidbit v2 sensor 10308732 and the VWR1620-200 traceable digital thermometer, and (e-j) show variations in statistical tests for each laboratory comparison, for the five Tidbit v2 sensors used in the study. Lines in (h) show the piecewise regression model used to correct the bias (δ) of each sensor over the time period of use. r^2 is the coefficient of determination, Ψ the root mean square error, δ the bias, Δ the centre-pattern (or unbiased) root mean square error, S the slope and I the intercept of a linear regression, and N the number of samples.

Figure 3: Schematic diagram of the NEODAAS system for producing the operational AVHRR SST products used in the study.

Figure 4: Example of the match-up process used in the study for Level 3 satellite passes. (a) Shows a relatively cloud free Level 3 AVHRR SST pass taken on the 20th April 2015 at 03:39 GMT, and processed by NEODAAS. (b) Shows the group of nine pixels in the AVHRR image centred on Station E1 (black and pink border) used to check homogeneity of the match-up region, with the centre pixel located closest to the E1 buoy (pink border) used for comparison with the E1 *in situ* data (circle and colour-coded to the same scale as the image) collected at 04:04 GMT on the 20th April 2015. (c) Shows the group of nine pixels (black and pink border) in the AVHRR image centred on Bovisand Beach, the location of a surfing session that took place on the 20th April 2015 at 05:58 GMT, that were used to check homogeneity of the match-up region, with the pixel with data located closest (<1 km) to the surf session (pink border) used for comparison with the *in situ* data (circle and colour-coded to the same scale as the image). Note that in this case, the closest pixel was actually dominated by land (i.e. the *in situ* measurement was at the edge of a land pixel) such that the next closest pixel with SST data within a 1 km radius was selected.

Figure 5: Comparison of *in situ* sea surface temperature (SST) datasets near Plymouth, UK. (a) Locations of SST data collected at the two beaches (Wembury and Bovisand), Station L4 and E1. (b) Time-series of SST acquired by the surfer at the two beaches overlain onto the SST data from Station L4. (c) Scatter plots of hourly match-ups between SST acquired by the surfer at the beaches and SST data from Station L4. (d) Time-series of SST acquired by the surfer at the beaches overlain onto the SST data from Station E1. (e) Scatter plots of hourly match-ups between SST acquired by the surfer at the beaches and SST data from Station E1. (f) Time-series of SST acquired at Station L4 overlain onto the SST data from Station E1. (g) Scatter plots of hourly match-ups between SST at L4 and E1. r^2 is the coefficient of determination, Ψ the root mean square error, δ the bias, Δ the centre-pattern (or unbiased) root mean square error, S the slope and I the intercept of a linear regression, and N the number of samples.

Figure 6: Comparison of daily median Level 3 AVHRR and *in situ* sea surface temperature (SST) datasets near Plymouth, UK. (a) Locations of SST data collected at the two beaches (Wembury and Bovisand), at Station L4 and E1, and the group of pixels selected from the AVHRR data to be representative of the three locations (dark grey pixels). (b) Time-series of AVHRR Level 3 daily SST at the six pixels covering the two beaches overlain onto that acquired by the surfers *in situ* at the two beaches. (c) Scatter plots of daily match-ups between SST acquired *in situ* by the surfers and by AVHRR at the beaches. (d) Time-series of AVHRR SST overlain onto *in situ* SST at L4. (e) Scatter plots of daily match-ups between SST acquired *in situ* and by AVHRR at L4. (f) Time-series of AVHRR SST overlain onto *in situ* SST at E1. (g) Scatter plots of daily match-ups between SST acquired *in situ* and by AVHRR at E1. r^2 is the coefficient of determination, Ψ the root mean square error, δ the bias, Δ the centre-pattern (or unbiased) root mean square error, S the slope and I the intercept of a linear regression, and N the number of samples.

Figure 7: Scatter plots of Level 3 AVHRR satellite passes and *in situ* sea surface temperature (SST) data for an absolute time difference (T) of <1 h, <3 h and <5 h, at the coastline (a-c), at L4 (d-f) and at E1 (g-i). r^2 is the coefficient of determination, Ψ the root mean square error, δ the bias, Δ the centre-pattern (or unbiased) root mean square error, S the slope and I the intercept of a linear regression, and N the number of samples.

Figure 8: The root mean square error (Ψ) between Level 3 AVHRR satellite passes and *in situ* sea surface temperature (SST) data plotted as a function of the absolute time difference (T) at the coastline (beaches) and at L4 and E1. Confidence intervals (red lines) were computed based on the standard error of the mean and the t -distribution of the sample size.

Figure A1: Comparison of temperature data collected by two surfers using two different Tidbit v2 sensors (10551173 and 10782552) at the same location (Bovisand Beach, Plymouth, UK) at an overlapping time period on the 14th April 2016. (a) shows the raw comparison and (b) shows the comparison after application of the bias-correction model (piecewise regression model) such that each sensor was corrected to the same common reference. The systematic differences (δ) between the two sensors readings were reduced when correcting each sensor to the same common reference.

Figure A2: Illustration of the method used to process the data collected by a surfer and derive SST at Tolcarne Beach, Newquay, UK on the 18th February 2014. (a) Shows the raw temperature data collected by the surfer as a function of time, showing when the sensor was switched on (high temp), when the surfer was in the ocean (temperature stabilised around 9°C) and the rise in temperature as the surfer exited the water and uploaded the data. The midpoint of the surf is also shown. (b) Shows how the data were divided into two equal halves around the mid-point. For the first half of the data, every data point was removed sequentially in time and the standard deviation was calculated incrementally (light blue line), with the last data point representing the standard deviation of the midpoint (zero). For the second half of the data, this procedure was repeated but in reverse (light green line). The standard deviations for the two halves of the data were then recombined, and the bottom third percentile of the standard deviations were derived (purple dashed line). (c) The point at which the surfer began measuring SST (entered the water) was taken as the point when the standard deviation first fell below the bottom third percentile, and the point at which the surfer stopped measuring SST (exited the water) was taken as the last point of the session when the standard deviation was below the bottom third percentile. This data is shown in blue and is used to compute SST by taking the median of this data. Note that the median is resistant to outliers and thus fairly resilient to variations in the derived start and finish points.

Figure A3: A superposition of all temperature data acquired by the surfer during the study period, normalised such that the start (0) and end (1) of the surfs are at the same point on the x-axis for each session. Data in dark grey were excluded and light grey included. The data in light grey were used to compute SST by taking the median of this data.