Plug and play monitoring: developing novel solutions for marine observations using divers as citizen scientists

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Abstract

There is a lack of depth-resolved sea temperature data, especially in coastal areas, which are often frequently dived by SCUBA divers. Marine citizen science is a growing phenomenon, but projects involving collection of physical parameters are underrepresented. The aim of this thesis is to explore the potential for SCUBA diver citizen scientists as a novel source of marine measurements, with a focus on temperature data collected from dive computers. Current knowledge does not quantify bias, response to temperature change, or within and between model differences across models and styles of dive computer, a shortcoming this thesis addresses. The response time (time constant), accuracy and precision of water temperature measurement in 28 dive computers from 11 models, plus three underwater cameras of the same model are assessed. In addition, using a case study of a dataset of dive computer temperature from recreational divers in the Red Sea, we ascertain bias from satellite derived sea surface temperature and depth-resolved in situ data. We do so to quantify responses, and better understand the limitations and potential uses for data collected in this way. Time constant by device ranged from (17 ± 6) s to (341 ± 69) s, with significant between model differences found. When compared with baseline mean temperature from CTDs, mean bias by model ranged from (0.0 ± 0.5) °C to (-1.4 ± 2.1) °C, with 9 of the 12 models found to have accuracy ≤ 0.5 °C overall. We show that seasonal patterns comparable with regional climatologies are observable at annual, monthly and weekly resolutions in data from anonymous online dive computer logs. Interannual variation, south-north cooling trends and data biases consistent with seasonal mixed layer depths proposed in the literature are also seen. We also develop an interactive citizen science website Diveintoscience (diveintoscience.org) using the Shiny package in R, detailing the development process, design decisions and key factors involved. We conclude that, with sufficient data points, temperature data from dive computers could form part of an integrated monitoring system, and there is potential for SCUBA divers to act as citizen scientists in the collection of other oceanographic parameters.

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Chapter 1. Introduction

1.1 Chapter summary

Current projections of the potential effects of global change on the marine environment show that the effect of our anthropogenic activities is not sustainable. The oceans drive our climate, and we need to build our knowledge and understanding to enable us to make increasingly well informed, healthy choices about how we live. However, the marine environment is under sampled, especially in coastal areas. An increased volume of data will help us understand temperature changes in local ecosystems, and how climate change is affecting ocean temperature over time. Citizen science involves the participation of volunteers in science projects and can provide volumes of data that would not otherwise be possible. There are an estimated 6 – 10 million recreational SCUBA divers globally (Cisneros-Montemayor and Sumaila, 2010, cited Wright et al. 2016), the majority wearing one, if not multiple, dive computers on each dive. Divers have been found to be an engaged group of citizen scientists, and with most recreational SCUBA diving taking place in relatively shallow, coastal regions, this offers a potential significant data resource to combat the data shortage in these areas. This chapter provides an overview of the current knowledge, highlighting the knowledge gaps this thesis aims to fill and concludes with an introduction to the overall thesis structure, aims and objectives.

1.2 Marine science

It is predicted that by 2035 3.2 billion people will live within 100 km of a coast (Maul and Duedall 2021). The marine environment here supports high levels of aquatic biodiversity (Tittensor et al. 2010) and the available resources are important for the economy, biodiversity, fisheries, tourism and coastal protection. Coastal regions are vulnerable to human pressures, are often shallow, inaccessible, or difficult to monitor using conventional techniques, such as ship-based oceanographic monitoring, which are not designed to cater to the spatial/temporal variability and are expensive to maintain. Therefore, these areas remain under sampled with a reliance on models (Brewin et al. 2017a).

In 2011, marine ecosystem services were valued at $49.7 trillion dollars per annum (Costanza et al. 2014). It is thought that over two thirds of the overall economic value of the ocean is produced by assets that rely directly on healthy ocean conditions (Hoegh-guldberg 2015). There is a growing weight of marine research focusing on climate change, and a more rapid increase in publications related to climate change rather than general marine science (Pedersen et al. 2016). Lack of sustained observations of the atmosphere, oceans and land have hindered the development and validation of models (Euro-Argo ERIC n.d.) but understanding basic oceanographic processes, both separately and in an integrated way, allows us to predict changes in the ocean. Predictions are necessary to guide global decisions, industrial policies and governmental actions (Copernicus Marine Service 2018).

Natural variability introduces uncertainty that makes prediction difficult (Dye et al. 2013), especially with small volumes of data. For example, an analysis towards the end of the last century stated that the currents transporting heat northwards in the Atlantic and influencing western European climate had weakened by 30% in the previous decade, but this was based on only 5 measurements over a 40-year period. With such small volumes of data, it is impossible to identify whether this was part of an ongoing trend, or natural variability (Argo Program n.d.). It has only been within the last 50 years that technology has advanced to the point that we can examine the ocean in a systematic, scientific, and non-invasive way (NOAA n.d.).

Both surface (SST) and subsurface sea temperature have been defined as essential ocean variables by the Global Ocean Observing System project (GOOS n.d.). Sea temperature is a vital component of climate and weather predictions, being directly linked to key processes and impacts such as sea level rise, deoxygenation (Bindoff et al. 2019) and acidification (Copernicus Marine Service 2018). Changing temperature also impacts marine life, coral bleaching (Gomez et al. 2020), increased prevalence of algal blooms and disease (Genner, Freer, and Rutterford 2017), with physiology, abundance, distribution, range and timing of key events such as spawning all affected (Genner, Freer, and Rutterford 2017; Poloczanska et al. 2013). By monitoring these key environmental variables, we collect information to help us understand and predict ocean and ecosystem changes due to natural patterns of variation or climate change. Larger temperature datasets are required to support the assessments of impacts on whole ecosystems over long periods of time, but there is currently a lack of information on seawater temperature below the surface especially for inshore and coastal areas.

Satellite data are commonly used to monitor sea temperature but there are limitations; they only measure the temperature of the upper few micrometres or millimetres (Kennedy 2014) and are interpolated to produce global scale products, impacting variation seen at local level (Merchant et al. 2019). Depending on the sensor (infrared or microwave) they are affected by cloud cover (O'Carroll, Eyre, and Saunders 2008) and the presence of land in coastal areas (Kennedy 2014). They have also been found to have poorer accuracy in coastal areas (Smit et al. 2013; Wright et al. 2016). Therefore, in situ observations are essential for calibration and verification of satellite data (Brewin et al. 2017b) and for additional depth-resolved measurements.

In situ observations are taken from a variety of platforms, including permanent moorings, ships, buoys, drifters, floats and marine life (McPhaden et al. 2009; Abraham et al. 2013; Smith et al. 2019; Doi et al. 2019), with different resolutions and uncertainties (Abraham et al. 2013; Centurioni et al. 2019). However, research vessels typically only operate offshore, and the existing coastal network of monitoring stations in the UK records only surface temperature (Morris et al. 2016). In 1999, to combat this lack of data, scientists began a publicly available, continual monitoring of temperature and salinity of the upper ocean via free-drifting Argo floats (Argo Program n.d.), significantly improving coverage. However, Argo floats are unable to resolve small scale information (Willis n.d.) and, as they are current driven, are less effective for measuring coastal areas. Unmanned, remotely operated and autonomous vehicles such as underwater gliders are also becoming more accessible, with increased performance (Garcia-Soto et al. 2017), providing specific and more generalised information about the ocean environment in conjunction with satellite remote sensing. Shipping hazards and shallow depths mean coastal environments are also challenging for gliders, although work is currently being carried out to mediate the difficulties in navigating these areas (Plymouth Marine Laboratory 2021).

There has been a global warming trend in the upper ocean over recent decades (Copernicus Marine Service 2018) and warming is projected to increase (Marine Climate Change Impacts Partnership 2020). Any bias in recorded SST will affect global temperature estimates because of the proportion of ocean covering the earth's surface (Jones 2016). But regional variation is seen in rates of SST change (Belkin 2009; Dye et al. 2013; Sutton 2018). Around the UK, the North Sea and English Channel are expected to experience increased warming comparative to outer shelf regions (Marine Climate Change Impacts Partnership 2020). So, maximising accurate, regional, data in addition to global, is key for understanding local dynamics.

There are still areas, such as the islands of the Pacific, where there is little monitoring of any kind, and limited scientific information available (Holthus 2013). However, these areas with limited monitoring infrastructure are often the location for high levels of marine recreational activity, such as surfing, SCUBA diving and fishing (Brewin et al. 2017b).

1.3 Citizen science

Citizen science, or community science, is an area of increasing growth. It has been defined in a variety of ways, and commonly involves the collection or classification of data by non-professional scientists, although this paradigm is transitioning to a broader definition where projects may be contributory, collaborative or co-created (Bonney et al. 2009a; Earp and Liconti 2020), depending on the level of involvement of non-scientists. This thesis assumes a definition of citizen science encompassed by the contributory approach: 'volunteers collecting, categorising, transcribing or analysing scientific data'.

The number of projects has been steadily increasing in the last 30 years, and this is expected to continue (Thiel et al. 2014). Projects are independent of scientific discipline, with diversity in desired outcomes (Bonney et al. 2015). There is an array of projects including topics from astronomy to microbiology ("Dark Energy Explorers" n.d.), historical research ("Heritage Quest" n.d.; Craig and Hawkins 2020), social sciences (Tauginienė et al. 2020), health sciences and community activism (van Noordwijk et al. 2021). Adults self-select to take part, choosing to give their spare time to things they are interested in (Cigliano et al. 2015).

One of the benefits of citizen science is the potential to generate a large volume of data, with increased spatial and temporal scope compared with what would be possible via traditional 'scientific' data collection alone (Bonney et al. 2009b; Dickinson et al., 2012; Vye et al. 2020). Data can be collected which augment traditional research programmes, form the basis of scientific research, and/or provide supporting evidence for public policy and management decision making (Bonney 2015; Hollow et al. 2015; Geoghegan et al. 2016). Long term time series can be generated at scales that are out of scope of funded research projects (Gonsamo and D'Odorico 2014; Earp and Liconti 2019).

1.3.1 Environmental citizen science

Within the breadth of topics, there is a prevalence of projects using citizen science to address environmental and conservation issues (Pocock et al. 2017), with 80 % of projects in Europe found to be within the natural and life sciences, and only 11 % in social sciences or humanities (Hecker et al 2018). Although the term citizen science didn't arise until the 1990s, community involvement in environmental monitoring is much older, with many of the earliest examples of citizen science being related to observations in nature, such as the Audubon Society's Christmas Bird Count, commencing in the 1900s (Foody et al. 2017) and recording of the timing of Japanese cherry blossom (Kobori et al. 2016). There are limited analyses of the monetary benefits of environmental citizen science, but Defra placed the value of volunteer environmental monitoring in the UK in 2011 at £50 million (Defra 2011, cited in Hyder et al. 2015).

Many environmental citizen science projects are designed by scientists, with volunteers being involved in some way with data collection or identification (Science Communication Unit University of the West of England 2013). Projects are wide ranging, with citizen scientists surveying an array of species, logging independently spotted species on sites such as eBird (Cornell Lab of Ornithology n.d.), contributing to biodiversity studies such as a BioBlitz (Tweddle et al. 2012; Natural History Museum n.d.), participating in weather studies (e.g. Community Collaborative Rain, Hail and Snow Network n.d.) or sampling the physical environment such as monitoring water or quality (Bristol Avon Rivers Trust n.d.; European Environment Agency, 2019). Not all projects require an ability to get outside, with many online-only projects being available such as digitization of historical weather records (Craig and Hawkins 2020), identification of species from photographs (Willi et al. 2019), or one of around 50 projects categorised by 'nature' on the citizen science website Zooniverse (Zooniverse n.d.).

The decisions people make, such as behaviours, social preferences, decisions around diet, travel and energy use, have a large impact on climate change (Corner 2018). Increased highlighting of marine issues in the populist media has coincided with a sea change in mass environmental activism on a day-to-day scale. For example, the so called 'Blue Planet' effect connected with the broadcast of the well-known television series coincided with increased awareness of environmental issues such as marine plastic (Dunn, Mills, and Veríssimo 2020), although the proportion of increased media as a response to increased activism and public interest, or vice versa, is unquantified. There is wide social media attention around projects which, as part of activism or campaigning, could lend themselves to citizen science projects.

1.3.2 Marine citizen science

The oceans are not our natural habitat and projects face logistical challenges around the environment; most of the oceans are inaccessible to most people (Garcia-Soto et al. 2017). The need for more expensive equipment such as boats, training and resources such as protective equipment can also be a limiting factor, along with safety or liability concerns (Cigliano et al. 2015). Accordingly, there are fewer marine citizen science projects than in the terrestrial or freshwater environments (Roy et al. 2012; Sandahl and Tøttrup 2020) and projects in the more accessible coastal and intertidal habitats are most commonly seen (Thiel et al., 2014).

Yet the number and diversity of marine citizen science projects has been increasing in recent years (Thiel et al. 2014, Kelly et al. 2020; Sandahl and Tøttrup 2020), with the number of published papers trebling between 2014 and 2018 (Sandahl and Tøttrup 2020). Initiatives include above the shoreline projects such as the Big Seaweed Search (Natural History Museum n.d.), taking part in coastline surveys with Coastwatch (Kathy and Gareth 2000) or Capturing Our Coast ("Capturing Our Coast" n.d.) and the Great British Beach Clean (Marine Conservation Society n.d.). Subsurface projects for SCUBA divers include Dive against Debris ("Dive Against Debris" n.d.), submitting photos of animal sightings (Manta Trust n.d.; sharkguardian n.d.) and nudibranch surveys (Gulen Dive Resort n.d.), all helping contribute to conservation efforts. In May 2017, the European Marine Board launched a position paper on advancing citizen science for coastal and marine research.

Engaging citizen scientists who are already involved in marine recreational activities to gather sub-surface information can help fill the data gap (Simoniello et al. 2019; Lamy et al. 2020). Measurement of water temperature is a common task for citizen scientists, but collection of temperature at depth is limited to divers. SCUBA divers are some of the most active citizen scientists (Martin, Christidis, and Pecl 2016; Hermoso et al. 2019). Divers 4 Oceans (Akkaynak n.d.), and Cousteau Divers' Project Hermes (Cousteau n.d.) are two examples where organisations have made efforts to start a global collection of temperature measurements from SCUBA divers. It is unclear if Divers 4 Oceans is still active, and data are not available online. Project Hermes has moved away from the idea of using dive computers directly and has developed a new sensor (which is not yet publicly available).

1.3.3 Benefits of Citizen Science to participants

A successful citizen science project has been described as one in which not only useful scientific data have been collected, but also has left contributors satisfied (Garcia-Soto et al. 2017), with benefits categorised by Broeder et al. (2018) into 3 groups: increased research capacity, improved knowledge and benefits to participants. The benefits of participation for individuals are manifold, including improved physical and mental wellbeing, personal growth and acquisition of knowledge and scientific literacy (Bonney et al. 2014; Forrester et al. 2017.

There are many benefits specific to environmentally focused citizen science projects. Engaging with citizen science and nature can promote positive environmental practices and choices (McKinley et al. 2017), increase civic engagement (Cornwell and Campbell 2012) and increase public understanding of and a sense of environmental stewardship (Moore, Townsend, and Oldroyd 2006; Dickinson et al. 2012; Lucrezi et al. 2018). Being near oceans inspires emotional connections to water and improve well-being (Cigliano et al. 2015), with marine and coastal margins found to be the areas with greatest self-reported happiness levels (using Experience Sampling Method (ESM) and Ecological Momentary Assessment (EMA) techniques) (MacKerron and Mourato 2013; de Vries et al. 2021). In addition participating in citizen science can promote support for policies related to conservation of species, habitats and Marine Protected Areas (Kelly et al. 2019).

1.3.4 Robustness of data

It has been demonstrated that data gathered by means of citizen science can be of comparable quality to that gathered using standard scientific approaches (Gardiner et al., 2012; Kosmala et al. 2016; Schläppy et al. 2017; McKinley et al. 2017). Nonetheless, there remains a perception of concern regarding data quality (Engel and Voshell 2002; Schläppy et al. 2017). These concerns are often associated with a perceived bias due to knowledge or training issues, for example, under-reporting of species (Garcia-Soto et al. 2017). However the types of errors that have been seen, such as under-reporting or misidentification, are similar to those in traditional science (Lee et el., 2020). If studies do not describe measures of data quality, this may contribute to reticence in its use (Vann-Sander, Clifton, and Harvey, 2016; Sandahl and Tøttrup, 2020). However, a study of 36 diverse citizen science projects found that 94 % of projects used at least 1 mechanism to ensure data quality, with 56 % utilising 5 or more mechanisms (de Sherbinin et al. 2021), highlighting that improved documentation is the opportunity rather than improved data practises. Riesch and Potter (2014) posit that scientists may be less concerned about the quality of the data, than of a potential negative perception by other scientists, should they use volunteer-collected data.

Fundamentally, inclusion of data, whatever the source, must be based on quality rather than simply the methodology (Cigliano et al. 2015), but the requisite accuracy will depend on the scientific question. A well-considered approach to sampling design can improve the quality of a dataset, but pre-processing, validation and data transformation may necessary before further modelling or analysis, to address bias and errors (Dickinson, Zuckerberg, and Bonter 2010; Lewandowski and Specht 2015). In conclusion, as with any scientific research programme, robustness in approach must be demonstrated, formal statements of data quality and accessibility provided, along with transparency and accessibility of methods, clearly defined data quality standards, data infrastructure and governance approach (Silvertown 2009, Hyder et al. 2015, Socientize 2015, Sherbinin et al. 2020, Bowser 2020).

1.3.5 Citizen science and policy

In 2017, the U.S. recognised the potential for cost effective acceleration of scientific research and addressing societal needs by connecting members of the public to federal science agencies in the form of the Crowdsourcing and Citizen Science Act ("Crowdsourcing and Citizen Science Act" n.d.). The European Commission's Horizon 2020 programme also emphasised the need to bring public engagement alongside responsible research and innovation to 'deliberate on matters of science and technology' (Horizon 2020 n.d.).

Where members of the public get involved with issues that they are affected by, whether local, national or global, it offers opportunity for them to influence decisions made around those issues (Garcia-Soto et al. 2017). Citizen science has been shown to inspire effective advocacy, increase public awareness of issues, increase empowerment in policymaking and the likelihood of policy change (Cigliano et al. 2015; European Commission 2020). Whilst not all citizen science projects have an aim to influence policy outcomes (Bonney et al. 2016), engaging the public in a meaningful way is essential to supporting sustainable solutions to using ecosystems and natural resources (Kelly et al. 2019).

Environmental citizen science projects fit well into the public-policy interface, as members of the public can be engaged from the start. But the citizen science - policy interface is not straightforward (Schade 2021). Evidence-based decision making is central to the policy process (Chapman and Hodges 2017), and citizen science data may not yet be widely used by decision makers (Hyder et al. 2015; Sherbinin 2021). It is hard to assess direct impact of citizen science activities on policy, as formation of policies and policy change is not a quick process (Minkler 2010). Newman et al. (2017) found that from 134 environmental conservation projects with an intention to inform decision making, 73 demonstrated some evidence of use of data outputs (where decision making was related to land use or natural resource management by landowners or institutions, either related to policy change or within existing policy).

Value can be added by delivering larger volumes of data over a wide geographic area to support evidence-based policy decisions and there are many examples of citizen science data being used by industry and governments. For example, Open Street Map, which utilises user generated mapping data (there were 2.5 million registered users in 2016) (Open Street Map n.d.; Foody et al. 2017). Citizen science projects have influenced policy or conservation efforts in areas such as air quality standards (Minker 2010; Gonzalez et al. 2011): efforts and outcomes from the West Oakland Environmental Indicators Project ("Owning Our Air", n.d., Gonzalez et al. 2011) led to regulatory changes to trucker idling activities which were contributing to poor local air quality (Bonney et al. 2016). Monitoring of invasive species (Poursanidis et al. 2013; Giovos et al. 2019): iSea citizen science project provided information about alien species in the Mediterranean Sea around Greece and Cyprus, contributing to the applied GES indicator relating to 'trends in the number of new alien species in national waters' (Giovos et al. 2019). Citizen science derived data also forms a part of the Cefas Coastal Temperature Network, a long-term time series of sea temperature observations from multiple sources around the UK, including opportunistic sampling from ferry routes (Morris et al. 2016; Morris et al. 2018), used for monitoring hydrographic changes around the United Kingdom. Other examples include monitoring the abundance and distribution of marine litter (Hidalgo-Ruz and Thiel 2015) or logging empty egg cases of sharks and rays (Roy et al., 2012).

Marine Protected Areas (MPAs) are areas of the ocean set aside with long-term conservation aims such as enhancement and protection of fish stocks, protection of biodiversity and economic benefit to fishermen (Gaines et al. 2010; Botsford et al. 2014). MPAs offer some level of protection for species or extraction of resources, and citizen science has been used to deliver useful information for supporting adaptive management and monitoring (Mateara et al. 2019; Nelms et al. 2020; Cigliano et al. 2015; Giovos et al. 2019). California, for example, has established over 100 MPAs since 1999, with citizen science programmes involved from the beginning, including SCUBA divers, recreational fishermen and high school students. (Cigliano et al. 2015).

However, the potential of citizen science has not yet been fully realised, especially relating to ocean sustainability goals. Citizen science initiatives currently only contribute to 5 of the Sustainable Development Goals, only one of these relating to goal 14, life below water: 14.1.1 "(a) index of coastal eutrophication; and (b) plastic debris density" (United Nations Statistical Commission 2017). Fraisl et al. (2020) listed additional, existing citizen science projects which are currently producing data which could support an additional 3 indicators in goal 14: 14.3, which aims to minimize and address the impacts of ocean acidification, 14.4 which aims to regulate harvesting and end overfishing, and 14.5 which aims to conserve at least 10 per cent of coastal and marine areas.

1.3.6 Citizen science and technology/ sensors

The increasing role of volunteers as a source of data has been supported by technological advancement. Smart phones, GPS devices and the interactive web have made it easy for volunteers to collect and share geographical information (Foody et al. 2017), for example, VGI (volunteered geographic information) collected for Open Street Map. These advances have made citizen science location independent. Volunteers are more easily able to collect and engage with data, but also to more simply share collected data with scientists and projects (Lewandowski and Specht 2015). Collection of sea temperature measurements is an example of non-framework VGI data, similar to weather data collected by volunteers (Foody et al. 2017). Individuals participating in marine recreational activities (such as surfers and kayakers) have been used to collect in situ temperature measurements, but these have focused on surface temperature (e.g., Brewin et al. 2020; Action 2021).

Low-cost sensors, such as wearable biosensors (Li et al. 2017) are increasingly being used for citizen science projects. Atmospheric data from smartphones have been utilised to correct bias in surface meteorological-station measurements (Li et al. 2021) and a range of sensors have been used across multiple citizen science air quality monitoring projects (Reis et al. 2013). However, data quality out of the box is variable (Giordano et al. 2021) so to ensure appropriate data quality for the intended use, it is important to consider calibration and validation requirements (Meijling et al. 2017; Giordano et al. 2021) and include a definition of measurement uncertainty (Lewis and Edwards 2016).

1.4 Dive computers

The purpose of a dive computer is to monitor length and depth of dive, with the common goal of minimising the risk of decompression sickness. Whilst different models run different decompression algorithms, the algorithm is used by the computer to calculate the length of time a diver can stay at different depths, potentially over a sequence of multiple dives, yet have a reasonable likelihood of not getting decompression sickness.

Where divers are acting as “animals of opportunity” (Brewin et al. 2017b) they are a transport mechanism for the measuring instrument (dive computer) and heterogeneity in measurement caused by the sampling itself is unlikely (Garcia-Soto et al. 2017) outside systematic device differences. To give a reliable monthly large scale area average temperature, 100 bias-free records are needed, even if the sites for those records are not the same (Jones 2016). Therefore, data collected from SCUBA sites in the same regions, even if not in the exact site, should, with sufficient samples, give useful data.

The depth reading provided to a SCUBA diver on a dive computer is an interpretation of the measured pressure (Sieber et al. n.d.), but factors such as salinity, altitude and ambient temperature can influence the conversion. Accuracy can only be achieved when taking temperature and density into account (Azzopardi and Sayer 2012). Readings are taken from the pressure sensor at specified sampling intervals, which are converted to a depth display (Azzopardi and Sayer 2010). The pressure reading may be taken at greater frequency for the purpose of decompression calculations than is converted to a reading on the display. The calculation used is unspecified (threshold, average etc.) and may vary among models or manufacturers.

Most dive computers allow a downloadable dive profile of depth against time, although the sampling rate (both recorded and downloadable) vary between makes and models. Azzopardi and Sayer (2012) compared 47 models of dive computer at a range of nominal depths in fresh and seawater environments, comparing the downloaded depths against the EU standard EN13319:2000 for depth-time measurement. Most computers give estimated depths close to nominal depths both seawater and freshwater, but with less variance in seawater (Azzopardi and Sayer 2010).

The recorded temperature is derived from a temperature-compensated pressure sensor (Azzopardi and Sayer 2010) rather than from a dedicated temperature sensor, as accurate temperature readings are not essential to the decompression algorithm. Variance against nominal temperature values has been found to be up to 5.1°c

(Azzopardi and Sayer 2012). The head engineer of diving computer manufacturer Mares (Angelini, personal comm. 2018) indicates that even within models they expect variance of ± 1°c. Satellite data are commonly used for monitoring sea surface temperature, which have been found to have biases of between 1 °C (Brewin et al. 2017a) and 6 °C (Smit et al. 2013) in coastal regions. So, depending on intended use, data of this quality may still be of value.

Trends of spatial data can be used to contextualise citizen science data and verify quality (Garcia-Soto et al. 2017), and by comparing against scientific data can assess the robustness of data collected via citizen science. In this instance, dive computer data can be compared against both satellite temperature data (for surface measurements) and in situ data. However, that does assume that the satellite data or models compared with are more accurate than the dive computers.

Dive computers are not scientifically calibrated measuring devices and there are mixed opinions in the literature with regards to the suitability for temperature data from dive computers to be part of the solution to the data gap. Egi et al. (2018) and Azzopardi and Sayer (2012) concluded that dive computers were not suitable for measuring temperature, but Wright et al. (2016) countered that, although accuracy of dive computers would need to be improved to deliver data relevant to climatology research, with processing, data from dive computers could be a useful additional data source to augment other systems, particularly in highly changeable coastal environments or under sampled areas. However, no study to date as carried out within and between model research, with replicates, into accuracy and precision of dive computers, or has quantified the response to changing temperature.

Thermoclines are strong vertical gradients in temperature, and characterisation is important in our understanding of primary production, trophic dynamics (Gray and Kingsford 2003), and ecosystems, as the thermocline is an ecological boundary (Roden and Raine 1994). One feature of dive computers is their recording of temperature profiles as a function of time and depth, giving information which is unavailable from satellite SST. Theoretically therefore, these temperature profiles offer potential for identifying local and seasonal variations in thermocline depth.

Different definitions of the thermocline depth and strength have been suggested, along with proposed mechanisms for identification (Zhang et al. 2010), such as difference, gradient, maximum curvature (Chu and Fan 2019). Data collection for identification has been carried out in various means including XBTs, AUVs (Zhang et al. 2010) and penguins (Pelletier et al. 2012). As many dive computers have single degree resolution, thermoclines of 2 °C or greater would be required to be identifiable with these devices. Devices with higher resolution theoretically have the capacity to identify smaller thermoclines.

In 2016, to collect data to enable research into whether dive computers could assist with filling the gap in depth-resolved temperature measurements in coastal regions, a website 'Dive into Science' (DiS1) was developed (Wright et al. 2016).

1.5 Summary and objectives of thesis

The primary project aim is to further investigate the potential of divers to add low-cost monitoring solutions for oceanographic data. It builds upon the work reported by Wright et al. (2016) investigating the potential of using SCUBA divers as citizen scientists and developing a proof-of-concept website 'diveintoscience.org'.

Key objectives are to:

1. Investigate accuracy, within and between-model precision of multiple dive computer models via laboratory and field trials.
2. Run comparisons of dive computer generated data against known sea surface temperatures from satellites and depth resolved in situ datasets.
3. Develop an appropriate web interface to collect temperature data from dive computers, utilising data from the existing Diveintoscience platform, focusing on improvement of the upload and visualisation features.
4. Work with sentinel dive schools, marine reserves and dive clubs on citizen science projects, data collection and community building activities: aiming to add value to the evidence-base by not only increasing the volume of

available data for analysis but increasing engagement of the SCUBA diving community.

5. Explore the possibility of detecting hydrographic features such as fronts and thermoclines from datasets.

To offer a useful and valuable potential contribution to science, the uncertainties associated with a dataset need to be understood. Accordingly, Chapter 2 addresses objective 1, detailing the accuracy, precision and temperature response of SCUBA diving computers and cameras, concluding that some models have potential for use in oceanographic monitoring. This chapter has been published as "Marlowe, C., Hyder, K., Sayer, M. D. J., and Kaiser, J. (2021). Divers as Citizen Scientists: Response Time, Accuracy and Precision of Water Temperature Measurement Using Dive Computers. Front. Mar. Sci. 8, 1–15. doi:10.3389/fmars.2021.617691".

Chapter 3 addresses objective 2, relaying a comparison between dive computer temperature data with OSTIA satellite foundation SST and a monthly in situ depth-banded dataset in the Red Sea. We find that seasonal patterns are seen at yearly, monthly, and weekly resolutions, with spatial (depth and latitude) differences in agreement with oceanographic expectations described in the literature.

Chapter 4 addresses objective 3, describing the development of an interactive citizen science website for collection of data from dive computers, and the benefits and disadvantages of the Shiny package in R (RStudio n.d.) as a tool to do so.

Chapter 5 outlines progress and challenges with the final two objectives, briefly detailing community engagement and early-stage investigations into the identification of thermoclines from dive computer profiles, in the context of a global pandemic. It then concludes the thesis, with an overall summary of the study's findings, including limitations and potential future avenues for research.

Chapter 2. Divers as citizen scientists: Response time, accuracy and precision of water temperature measurement using dive computers

This chapter has been peer reviewed as "Marlowe, C., Hyder, K., Sayer, M. D. J., and Kaiser, J. (2021). Divers as Citizen Scientists: Response Time, Accuracy and Precision of Water Temperature Measurement Using Dive Computers. Front. Mar. Sci. 8, 1–15. doi:10.3389/fmars.2021.617691".

2.1 Abstract

There is a lack of depth-resolved temperature data, especially in coastal areas, which are often commonly dived by SCUBA divers. Many case studies have demonstrated that citizen science can provide high quality data, although users require more confidence in the accuracy of these data. This study examined the response time, accuracy and precision of water temperature measurement in 28 dive computers plus three underwater cameras, from 12 models. A total of 239 temperature response times (τ) were collected from 29 devices over 11 chamber dives. Mean τ by device ranged from (17 ± 6) to (341 ± 69) s, with significant between-model differences found for τ across all models. Clear differences were found in τ by pressure sensor location and material, but not by size. Two models had comparable τ to designed-for-purpose aquatic temperature loggers. 337 mean data points were collected from equilibrated temperatures in hyperbaric chamber (n = 185) and sea (n = 152) dives, compared with baseline mean temperature from Castaway CTDs over the same period. Mean bias, defined as mean device temperature minus baseline temperature, by model ranged from (0.0 ± 0.5) to (−1.4 ± 2.1) ◦C and by device from (0.0 ± 0.6) to (−3.4 ± 1.0) ◦C. Nine of the twelve models were found to have "good" accuracy (≤0.5 ◦C) overall. Irrespective of model, the overall mean bias of (−0.2 ± 1.1) ◦C is comparable with existing commonly used coastal temperature data sets, and within global ocean observing system accuracy requirements for in situ temperature. Our research shows that the quality of temperature data in dive computers could be improved, but, with collection of appropriate metadata to allow assessment of data

quality, some models of dive computers have a role in future oceanographic monitoring.

2.2 Introduction

The oceans have a critical role in climate change, acting as a heat sink and being responsible for the uptake of 93 % of the excess heat in our climate system between 1971 and 2010 (Pörtner et al. 2019; Johnson and Lyman 2020). Warming ocean temperatures are intrinsically linked to sea level rise and projections show the rise accelerating because of nonlinear thermal expansion (Widlansky, Long, and Schloesser 2020). In addition, the number and severity of occurrences of extreme events linked to increased sea temperatures, such as heat waves, are expected to increase with global warming (Bindoff et al. 2019). Global sea surface temperature (SST) is projected to rise by up to 6.4 °C depending on the emission scenario (Aral and Guan 2016); accordingly, both sea surface and subsurface temperatures are defined as essential climate variables (Bojinski and Richter 2010; Lindstrom et al. 2012). However, there is regional variability (Kennedy, 2014); for example, SST around the British Isles has been increasing at a rate of up to six times the global average rate (Dye et al. 2013) and at twice the global rate in offshore China since 2011 (Tang et al. 2020). In contrast, parts of the North Atlantic have experienced cooling (Wright et al. 2016). Shifts in biodiversity have been seen in response to variations in temperature between 0.1 to 0.4 °C (Danovaro et al. 2020), with shallow seasonal thermoclines being important to ecosystem dynamics, horizontal and vertical distribution of fish (Aspillaga et al. 2017) and biological production (Palacios et al. 2004). Variation and oscillations in thermocline depth and temperature have been recorded during the stratification period (Bensoussan et al. 2010; Aspillaga et al. 2017).

In situ data are essential to monitor these local variations, supplement satellite sea surface temperature data and validate ocean models (Brewin et al. 2017a), but there is a lack of depth-resolved temperature data (Wright et al. 2016) and few time series on localised variations in thermoclines (Bensoussan et al. 2010). This lack in data is especially true in areas near to the coast which research vessels and Argo floats cannot commonly reach (Wright et al. 2016). Citizen science has been shown to provide opportunities for collecting data at broad spatial and temporal scales, which would not be possible by traditional means (Pocock et al. 2014b; Wright et al. 2016; D. W. Walker, Smigaj, and Tani 2021). Many case studies have shown that citizen science can provide high quality data (Kosmala et al. 2016) with comparable accuracy to dedicated research studies (Vianna et al. 2014; Albus, Thompson, and Mitchell 2019; Krabbenhoft and Kashian 2020), but with uncertainty regarding the reliability and quality of data (Burgess et al. 2016; Gibson et al. 2019). To address these concerns, and to increase the value of existing datasets, users require more confidence in the accuracy of these data (Burgess et al. 2016; Kosmala et al. 2016). In situ measurements should have associated uncertainty estimates (Barker et al. 2015). Post-hoc data quality assessment and error detection have been found to dispel doubts about data quality (Burgess et al. 2016).

SCUBA divers (from here on referred to as divers) have been involved in many marine citizen science projects (Thiel et al. 2014; Hermoso et al. 2019) including marine protected area monitoring (Pocock et al. 2014b), reef habitat/biodiversity surveys (Branchini et al. 2015; Hermoso et al. 2019) and marine debris collection (Pasternak et al. 2019). Some areas most frequently accessed by citizen scientist divers are the shallow coastal subtidal areas (e.g., to depths < 40 m; Thiel et al., 2014) where reliable physical and chemical data series are sparse. Within the estimated 6–10 million recreational divers globally (Wright et al. 2016) the use of dive computers may be approaching 100 % (Azzopardi and Sayer 2010). Dive computers are worn with the primary purpose of managing decompression limits via algorithms which calculate the level of nitrogen load in tissues. Most modern dive computers record profiles of temperature and depth, with the latter derived from a dedicated pressure sensor. Temperature data are required to correct for non-linear pressure sensor output as ambient temperature changes (Li et al. 2016), but as temperature does not have the same impact on decompression algorithms as pressure, the same level of accuracy is not required. Consequently, temperature data are obtained from thermal corrections applied to the pressure sensor (Wright et al. 2016; Azzopardi and Sayer 2010), rather than from a dedicated temperature sensor. Temperature readings are not calibrated, and only have an advertised accuracy (where published by manufacturers) of ± 2 °C (Azzopardi and Sayer 2012; Mares, n.d.), or ± 2 °C within 20 minutes of temperature change (Suunto 2018). Previous research has explored the possibility of collecting temperature data from dive computers. Wright et al. (2016) concluded that, with processing, temperature data from dive computers could be a useful resource. Other authors recommend that these data be avoided for scientific study (Azzopardi and Sayer 2012), or state that dive computers do not have sufficient accuracy to measure ocean temperature changes (Egi et al. 2018).

This study builds on the work carried out by Wright et al. (2016) and investigates a range of dive computers in replicated experiments which aim to mimic real-world scenarios, to quantify the temperature responses of different models; aiming to address some of the concerns regarding the potential use of these data. We focus on three objective measures: the time constant (τ), accuracy and precision. Time constants are used to measure a sensor's response to change, representing the time taken for 63 % of the total step change in temperature to have taken place. τ is useful in the context of oceanographic temperature change (such as thermocline identification), and, in conjunction with the sample rate, the potential to gather useful data from relatively short dive profiles. Temperature accuracy is defined as the systematic error in the devices' temperature measurement when compared with a reference temperature, such as from a calibrated microCTD. By focusing on these measures, this paper investigates the potential of different devices as alternative sources of in situ temperature for oceanographic monitoring. The response to temperature change within and between models and as a function of the dive computer's body material, size, pressure sensor location and attachment to the diver (i.e., worn on the wrist or hanging freely) are analysed to ascertain whether some models or features may offer potential for higher quality data than others.

2.3 Materials and methods

2.3.1 Equipment

28 dive computers (eleven models from seven brands), along with three Paralenz Dive Camera+ cameras (for the purposes of this study referred to collectively as 'dive computers') were analysed. All devices shared the ability to record full profiles of temperature and depth as a function of time, except Suunto Vypers, which only store a single minimum temperature per dive. All devices were able to sample at intervals of 30 s or less and were set to the highest frequency possible for each model for all dives.

Recorded temperature resolution ranged from 0.1 °C to 1 °C. The devices were categorised into four 'sizes': 'Small (diameter < 5 cm), 'Medium'(5 cm < diameter < 7.5 cm), 'Large (diameter >7.5 cm), and 'Camera' and further classified by pressure sensor location based on the identifying small holes in the housing material into 'Back' or 'Edge' with Paralenzes being defined as 'Covered' (Table 2.1; pictures of devices with pressure sensor location can be seen in Appendix Table A.1). Material was a composite category based on front, edge and back material being metal (m) or plastic (p).

All hyperbaric tests were carried out in a cylindrical two-compartment, 2000 mm diameter Divex therapeutic recompression chamber, manually controlled to compress to the simulated nominal depths, as described by Sayer et al. (2014). For all baseline temperature measurements with the exception of water bath trials, three SonTek CastAway CTDs (CTD = Conductivity, Temperature, Depth) with 0.01 °C resolution, ± 0.05 °C accuracy, sampling rate of 5 Hz (Xylem Analytics n.d.) were used. As the CastAway CTDs were brand new, they were considered to adhere to the 'out of the box' factory calibration standards, and no further calibration was carried out. For unpressurised temperature comparison a Grant R4 refrigerated bath with TXF200 heating circulator was used.

Table 2.1. Models used and their categorisations within this study. In the material column, m denotes metal and p, plastic. e.g., ppp denotes plastic for the front, edge and back of the housing respectively.

Model	**n**	**Resolution / °C**	**Pressure sensor**	**Size**	**Material (front-edge-back)**	**Sampling interval / s**
Aqualung i750TC	3	5/9 ≈ 0.56	Back	Medium	ppp	30
Garmin Descent Mk1	3	1.0	Edge	Small	mpp	1
Mares Matrix	2	0.1	Edge	Small	mmp	5
Mares Puck Pro	2	0.1	Back	Medium	ppp	5
Paralenz Dive Camera+	3	0.1	Covered	Camera	mmm	1
Ratio iX3M GPS Deep	3	0.1	Back	Large	ppp	10
Scubapro G2	3	0.4	Back	Medium	ppp	4
Shearwater Perdix	3	1.0	Back	Large	ppp	10
Suunto D4i	1	1.0	Edge	Small	mmp	20
Suunto D6i	3	1.0	Edge	Small	mmm	10 (20 first 3 dives)
Suunto EON Steel	3	0.1	Edge	Large	mpp	10
Suunto Vyper	2	1.0	Back	Medium	ppp	NA

2.3.2 Time constants (τ)

Inside the hyperbaric chamber, all devices and Castaways were immersed to (8.5 ± 2.5) cm in a tub containing 13 litres of cold (10 ± 1 °C) fresh water and allowed to acclimatise for 10 minutes, as high ambient air temperature has been demonstrated to affect temperature profiles for several minutes into a dive. Three further tubs were filled with well-mixed warm water between 18 and 25 °C. Although fitted with an environmental control unit it was not possible to regulate chamber air temperature precisely; varying between 18 and 27 °C over the course of a single dive of 1 hour's duration, caused by the heating effect of compression and subsequent cooling across the non-insulated chamber walls. To minimise the impact of the changing chamber temperature on tub temperature, warm tubs starting temperatures approximated the mid-point of potential chamber ascent temperatures (as measured with a stick digital thermometer).

Some models allow manual switching between salt and freshwater mode (densities unspecified by manufacturers), but to allow comparison between dive computers which did not have this capability, all dive computers were left in default salt-water mode for all dives with the exception of the Shearwater Perdix which was set to 'EN13319' mode (1020 kg m^{-3} water density) (Shearwater n.d.). All devices were allowed to automatically start recording temperature profiles according to their default pressure parameters, except for Paralenz Dive Camera+, which were started manually.

After acclimatisation, all tubs were compressed to a maximum simulated depth of between 9 and 10.4 m. Once the simulated depth was reached, one Castaway was moved from the cold bucket to each of the warm tubs and stirred well, followed by a further two minutes of acclimatisation. One Paralenz Dive Camera+ was then moved into each warm tub and stirred well. Early trials established that all devices reached temperature equilibrium before seven minutes. Therefore, after seven minutes all Paralenz Dive Camera+ were removed and switched off to conserve battery life. Subsequently, a dive computer was moved into each of the warm tubs, stirred well, then left for seven minutes, repeated until all the devices had been transferred. This interval approach was designed to minimise any effect of cold-water ingress by the transfer of devices between tubs, without impacting the temperature response of previously added devices. Two dives were carried out with the same depth/tub protocol using only the three Paralenz Dive Camera+ devices, and nine replicates with all devices (schematic in Figure 2.1).

Dive profiles were downloaded and imported into R Studio for processing. For each dive by device, data were aligned to the start point of the response curve (Figure 2.2, a) and sliced at the first instance of the maximum temperature (Figure 2.2, b), isolating the full temperature response. In contrast to the findings of Egi et al. (2018), not all models' temperature response had a single exponential form, and linear regression did not consistently produce a good fit. Time constants were ascertained by exponential fitting via numerical integration as defined by Jacquelin (2009), using the area under the curve to calculate τ, allowing linear regression to be applied to non-linear data without estimation of parameters (Jacquelin 2009).

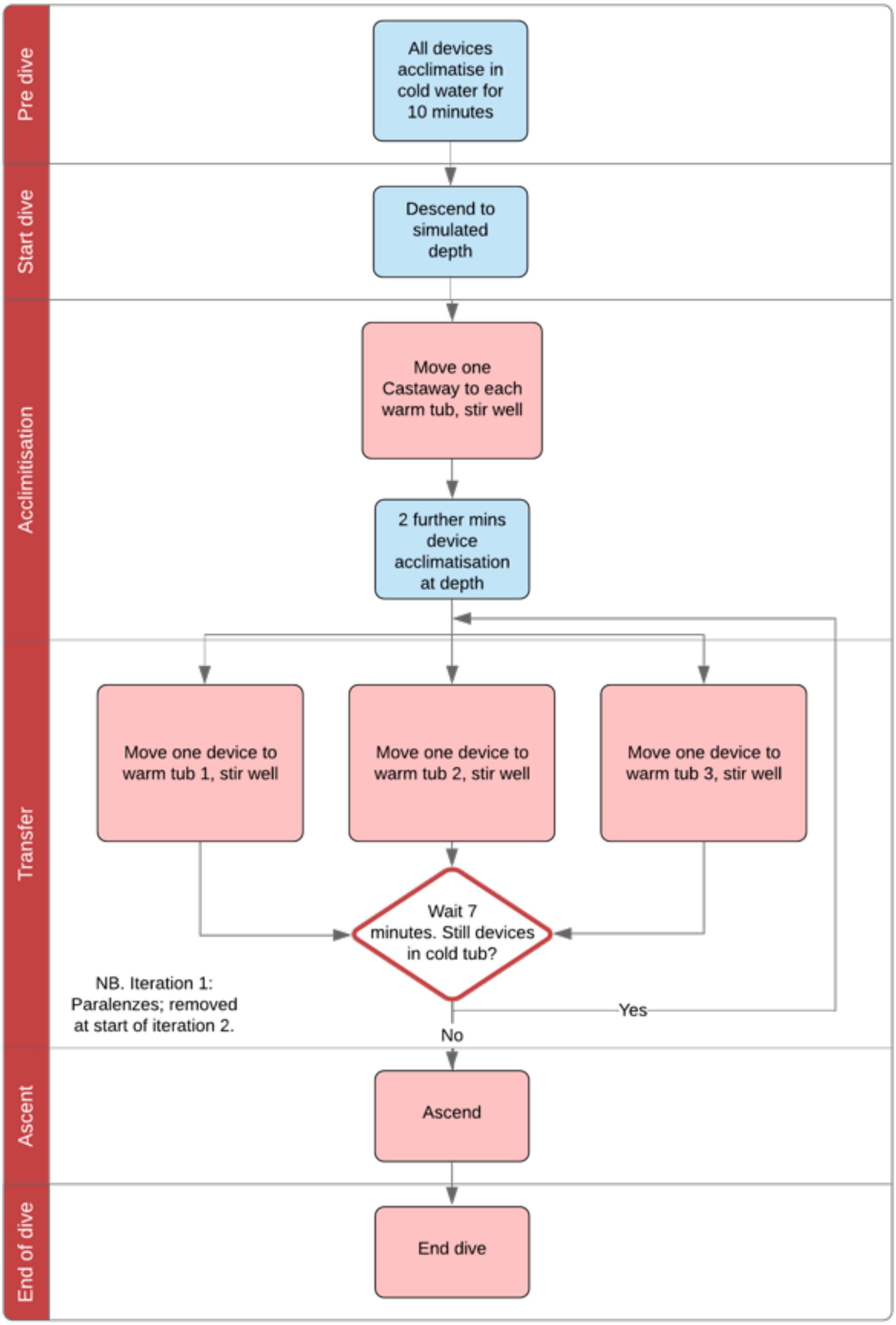


Figure 2.1. Schematic showing device movement in chamber dives for time constant

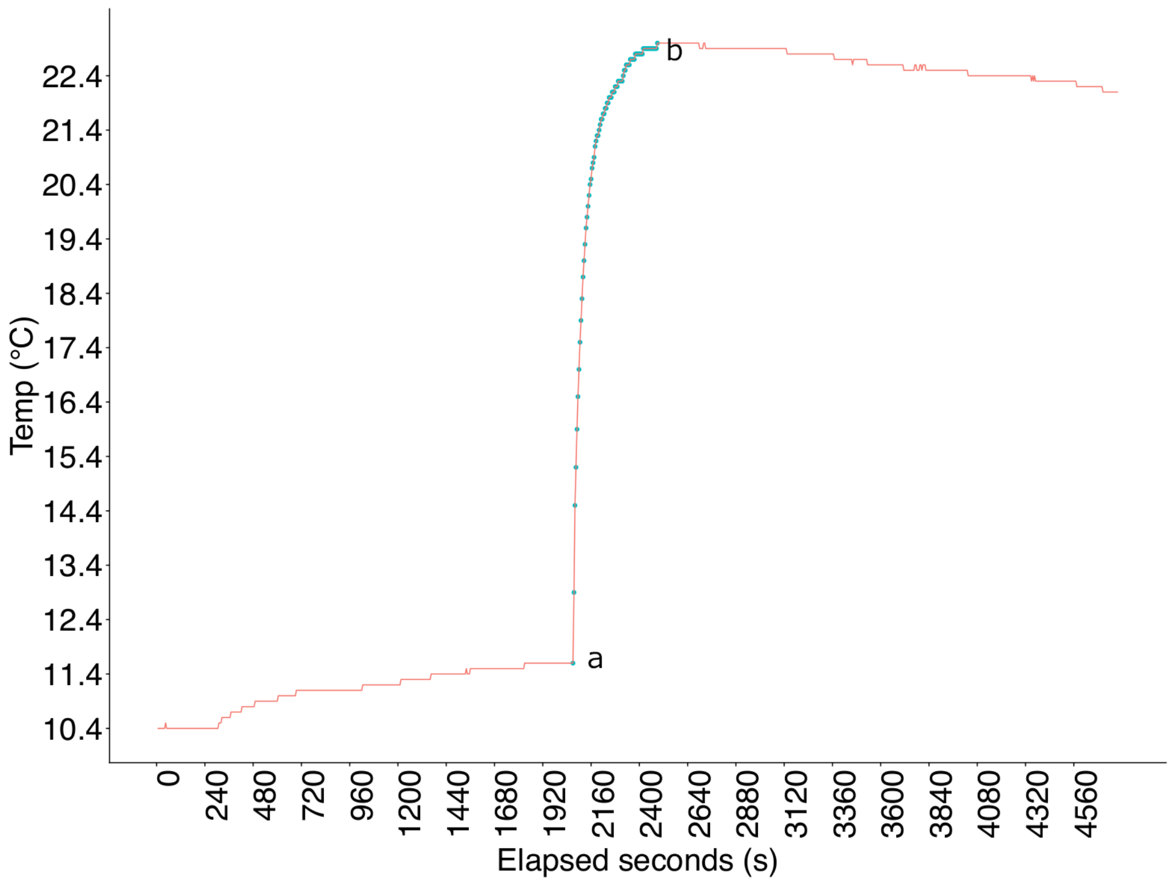


Figure 2.2. Example response curve for one dive/device. 'Elapsed seconds' is the entire profile, during which all devices were moved between cold and warm tub at 7 min intervals.

2.3.3 Accuracy

Three protocols were followed to assess the temperature accuracy and consistency of the dive computers.

2.3.3.1 Water bath

Dive computers only start to record profiles once they reach a prescribed pressure, but for safety reasons, it is not possible to put a temperature-controlled water bath in a pressurised chamber environment. Therefore, trials were conducted in an unpressurised environment and the temperatures were visually recorded from the computer displays. Water temperature was controlled using a Grant R4 refrigerated bath filled with deionised water, with the circulation set to maximum and temperature equilibrated to (20.0 ± 0.1 °C). Between nine and eleven devices could be submerged in the water bath at once, so the experiments were run in a series of batches. An initial batch was submerged in the bath for 15 minutes (three times the maximum time constant, by which time all devices have equilibrated to final temperature). Temperature was then read from the digital display of each device whilst still submerged, and the device removed from the bath. Once all device temperatures had been read the subsequent batch was submerged for 15 minutes and the process repeated. The process was then repeated at bath temperatures of 10 and 30 °C. For analysis, the deviation of on-screen temperature display from the water bath temperature was noted. On-screen temperature resolution for all devices is limited to 1 °C, except for the Ratio iX3M GPS Deep which display temperature on-screen at a resolution of 0.1 °C.

2.3.4 Chamber

Six replicate dives were carried out in the outer lock of the Divex chamber, with a maximum simulated depth of 10 ± 1 m. Three dives included a temperature change from a cold to warm environment and three a warm to cold transition, using one tub for the starting temperature and three for the contrast temperature. All devices acclimatised in a single tub for ten minutes, unpressurised, to the same starting temperature (cold or warm, depending on dive). Devices were then shared across the three tubs with contrasting temperature; one Castaway CTD in each tub to provide a baseline. All tubs were compressed to the simulated depth for 10 minutes, then decompressed and removed (schematic in Figure 2.3). Over the six dives, cold tub final temperature ranged from 10.4 °C to 12.6 °C and warm tub final temperature ranged from 16.8 °C to 19.5 °C.

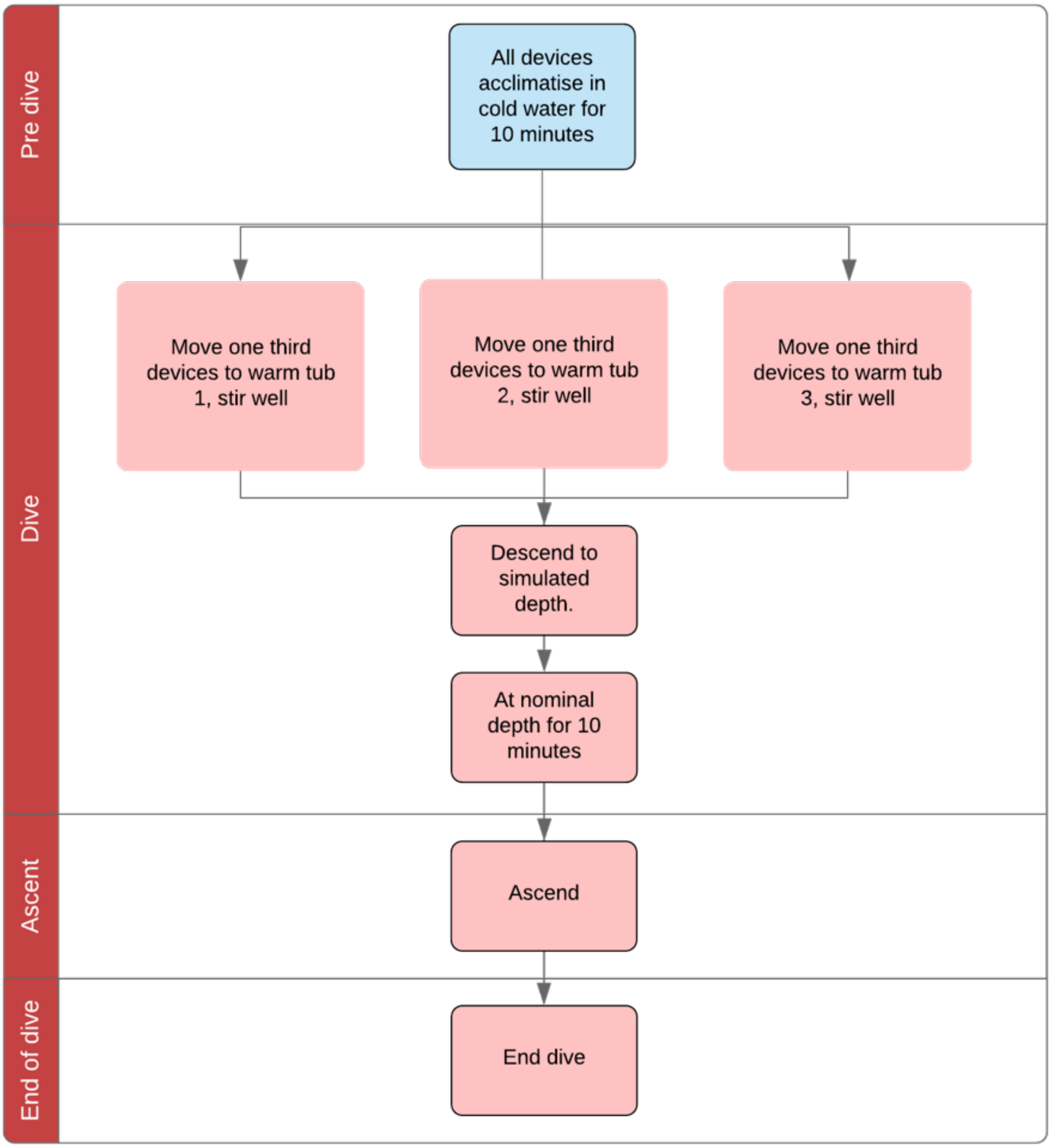


Figure 2.3. Schematic showing device movement in chamber dives for accuracy

Raw data output from the Castaways was used, retaining the full temperature profile as a function of pressure and time. Castaway depth was calculated from pressure using the swDepth function in the oce package in R (Kelley, Richards, and Layton 2021), which uses Fofonoff and Millard's refitted equation (Fofonoff and Millard 1983). Device profiles were aligned by depth and time with the relevant Castaway from the same tub. Mean device temperature from the final 180 s at > 2.5 m depth was calculated (to compensate for differences in depth at which devices start recording) by which time all devices had equilibrated to the change in temperature (Figure 2.4). The mean from the equivalent 180 s Castaway data were used as baseline temperature for comparison. Mean bias was defined as mean device temperature minus mean Castaway temperature.

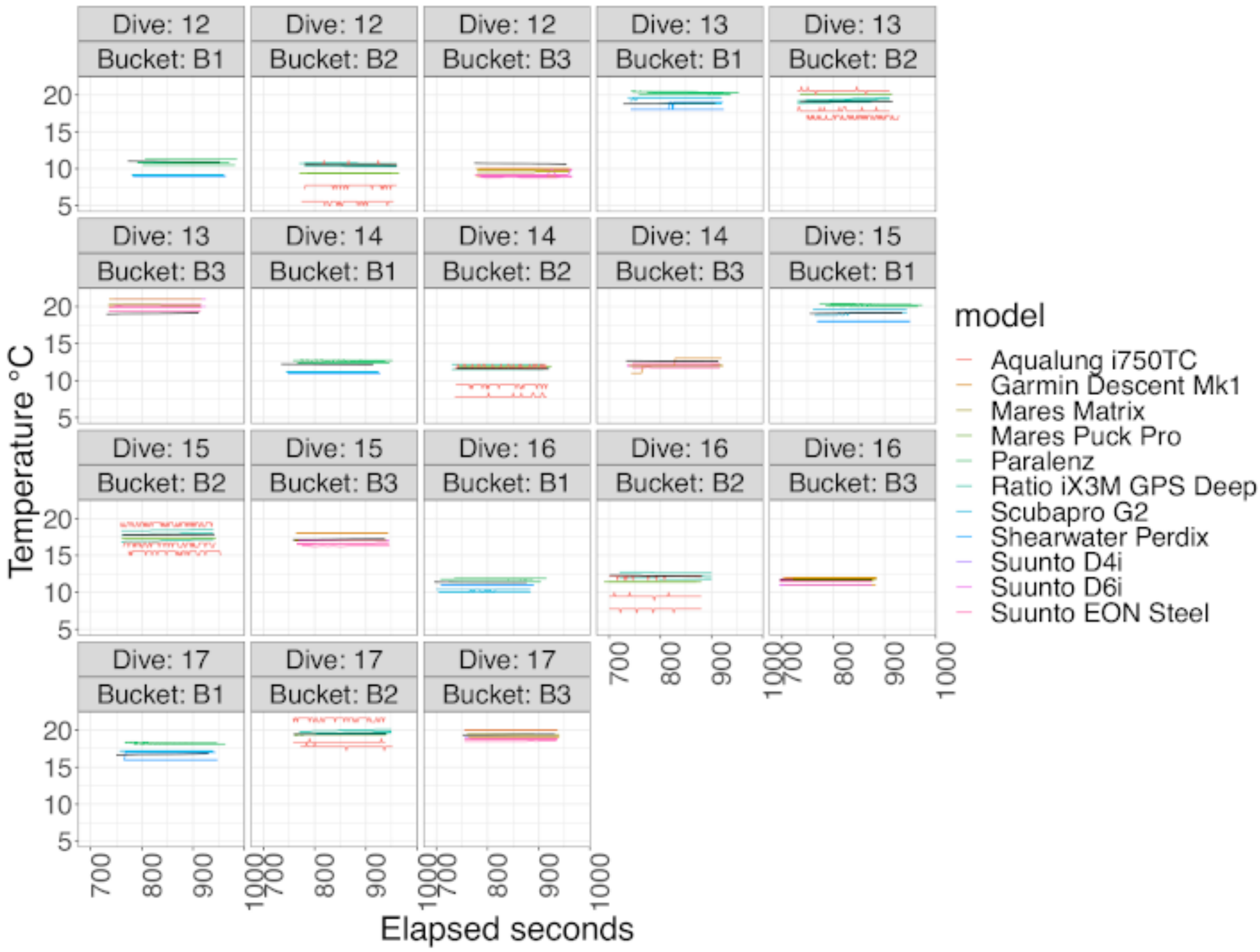


Figure 2.4. Mean device temperature in final 180 s at > 2.5 m by dive and bucket. NB. Devices in different buckets, but same dive, are not comparable in this plot due to different baseline bucket temperatures.

2.3.5 Sea dives

Six sea dives were carried out by RHIB at dive sites local to Oban (56.41535° N, 5.47184° W), with maximum depths ranging from 13.5 m to 30.7 m (mean: 18.6 m). For each pair of dives, half the dive computers were carried hanging loosely on a frame made from plastic piping, and half were worn on the arms of two divers (Figure 2.5). For subsequent dives in each dive pair, each device was switched to the other mounting position. All Paralenz Dive Camera+ were transported on the frame for all dives (as they were not wrist mountable), along with all Castaways for baseline temperature.

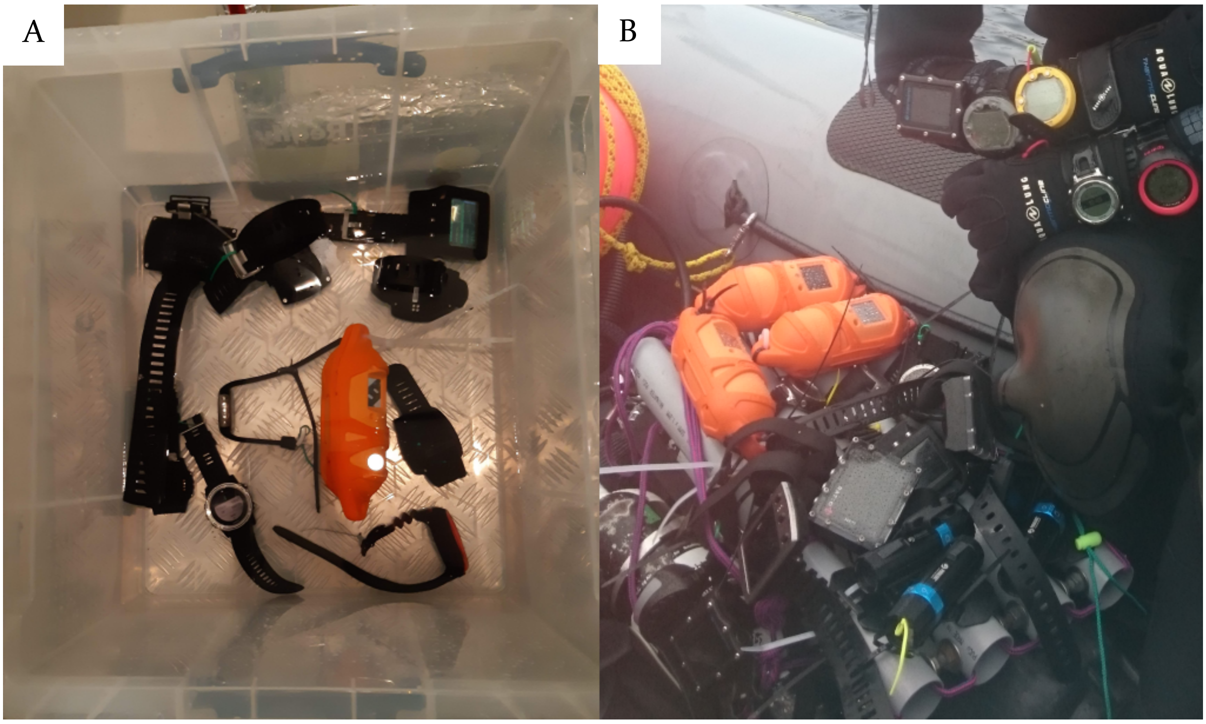


Figure 2.5. (A) Devices in tub with Castaway in chamber dive. (B) Diver wearing computers on arms, with frame shown in RHIB

Raw Castaway data was imported, depth calculated as per section 2.3.2. The sea dives had a shallow cold surface thermocline from snow melt run-off. The mean temperature below the depth at which the Castaway temperatures equilibrated (top of the bottom mixed layer) was used as a baseline temperature for comparison for each dive (Figure 2.6). In dive number order this depth was 5, 10, 10, 10, 10 and 12 m. As the frame was carried by divers, and therefore may not have been consistently horizontal, small variations were seen in Castaway depths. Device dive profiles were imported into R Studio and mean temperatures calculated for each device, Castaway and model for the final 180 seconds below the specified depth (Figure 2.7). Mean bias was defined as mean device/model temperature minus mean Castaway temperature.

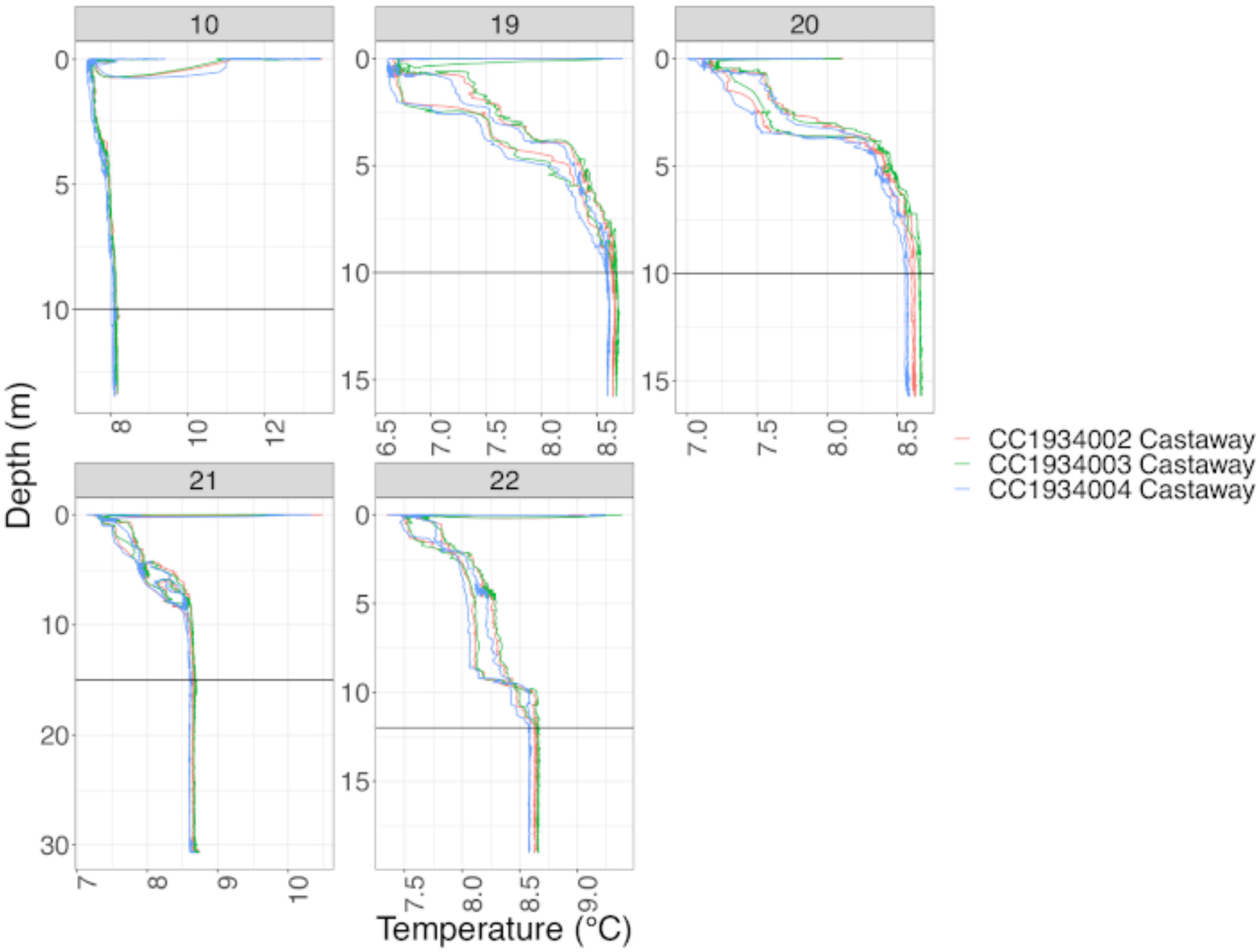


Figure 2.6. Castaway data for Oban sea dives. Horizontal lines show the cut off depth (top of the bottom mixed layer) for each dive. Baseline temperature for comparison was calculated from the mean temperature from the final 180 seconds of temperature data below this depth.

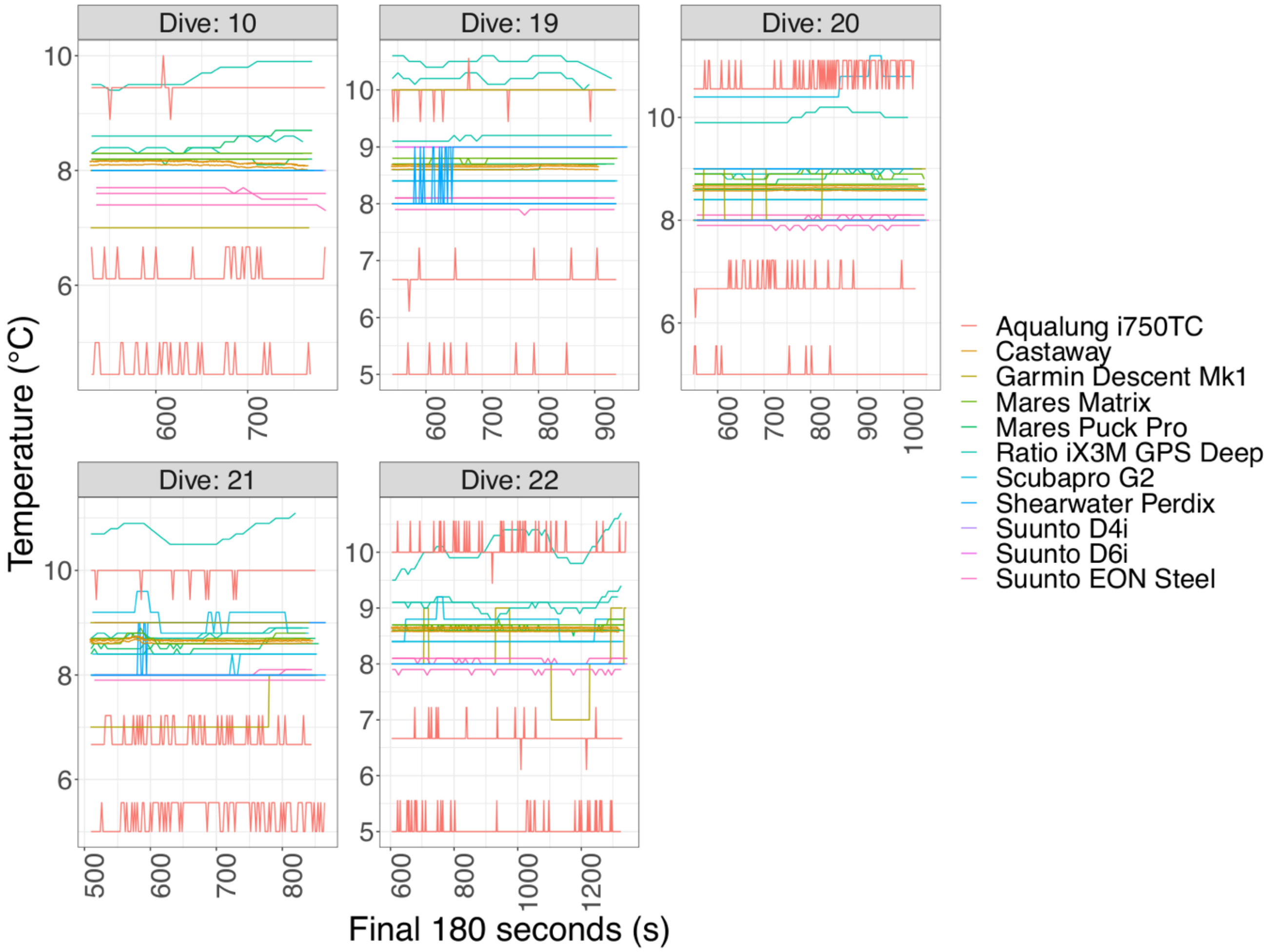


Figure 2.7. Final 180 s data below cut off depth by device.

2.4 Results

As per Wright *et al.* 2016, devices and models were categorised as accurate if the mean bias from baseline temperature was <= 0.5 °C and as precise if the standard deviation of the mean bias was <= 0.5 °C. Devices were defined as having quick, intermediate or slow response to temperature change (respectively $\tau < 60$ s, 60 s $\leq \tau$ < 120 s, $\tau \geq$ 120s).

2.4.1 Time constants

A total of 239 τ values were collected from 26 devices over 9 dives plus three Paralenz Dive Camera+ cameras which comprised of 6 dives. 13 τ values were lost because of battery failures or camera recording not initiating correctly. All Ratio iX3M GPS

Deep dives and two Shearwater Perdix dives were removed from the analyses because of a poor regression fit (Figure 2.8).

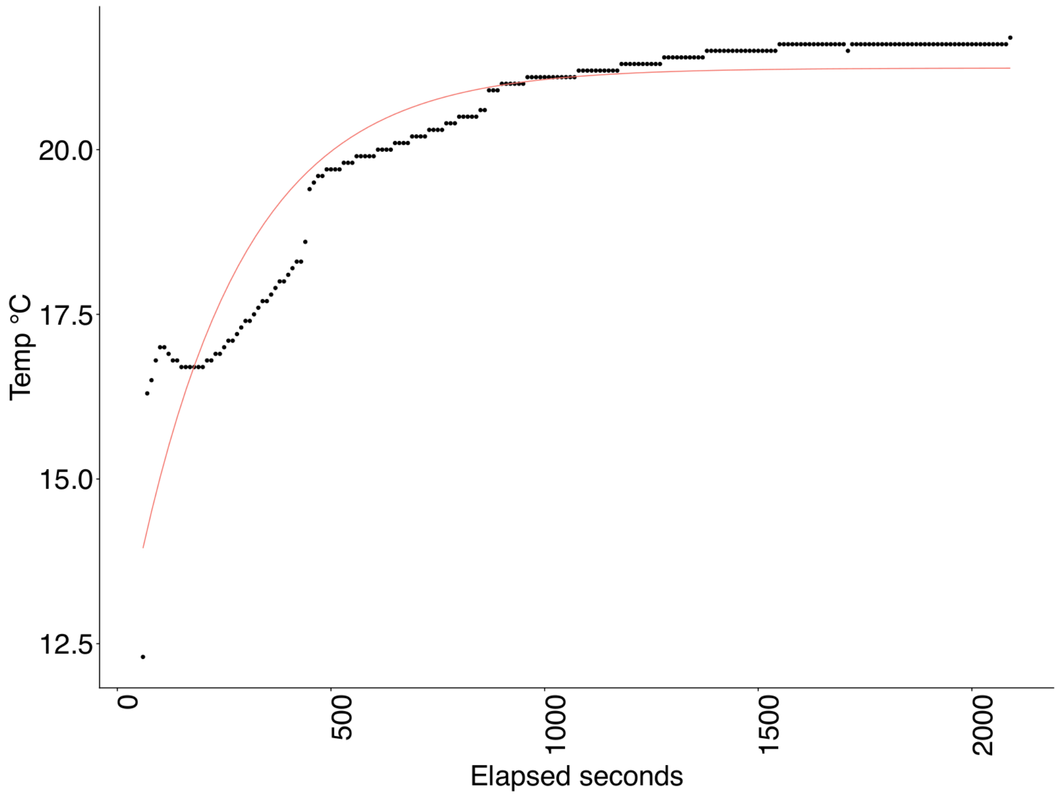


Figure 2.8. Example of a poor regression fit in Ratio iX3M GPS Deep

Mean τ by model ranged from (18 ± 5) s to (304 ± 45) s (Figure 2.9, Table 2.2). Uncertainties represent 1 s unless otherwise described. Time constants and residuals were not normally distributed; time constants were best fitted to an inverse Gaussian distribution curve. A generalised linear model (GLM) approach was used in R Studio to look for significant differences. Significant between model differences were found for τ across all models ($p < 0.001$) (Mares Puck Pro ($p < 0.01$)). Mean τ by device ranged from (17 ± 6) s to (341 ± 69) s (Figure 2.10). S(τ fit) represents 95 % confidence intervals in the regression fit, based on the standard error of the regression (full data in

Table 2.3). S(τ fit) < 10 s was defined as a good fit and applied to all profiles except for those mentioned in the first paragraph of this section.

Table 2.2. Mean response time (τ), by model.

Model	**n (dives)**	$\boldsymbol{\tau_{mean}}$ **/ s**	**sd(m)**	**Classification ($\boldsymbol{\tau}$)**
Aqualung i750TC	20	151	11	Slow
Garmin Descent Mk1	25	48	9	Quick
Mares Matrix	18	46	5	Quick
Mares Puck Pro	18	111	5	Intermediate
Paralenz Dive Camera+	16	22	3	Quick
Scubapro G2	27	73	8	Intermediate
Shearwater Perdix	25	304	45	Slow
Suunto D4i	7	46	5	Quick
Suunto D6i	27	18	5	Quick
Suunto EON Steel	27	42	5	Quick

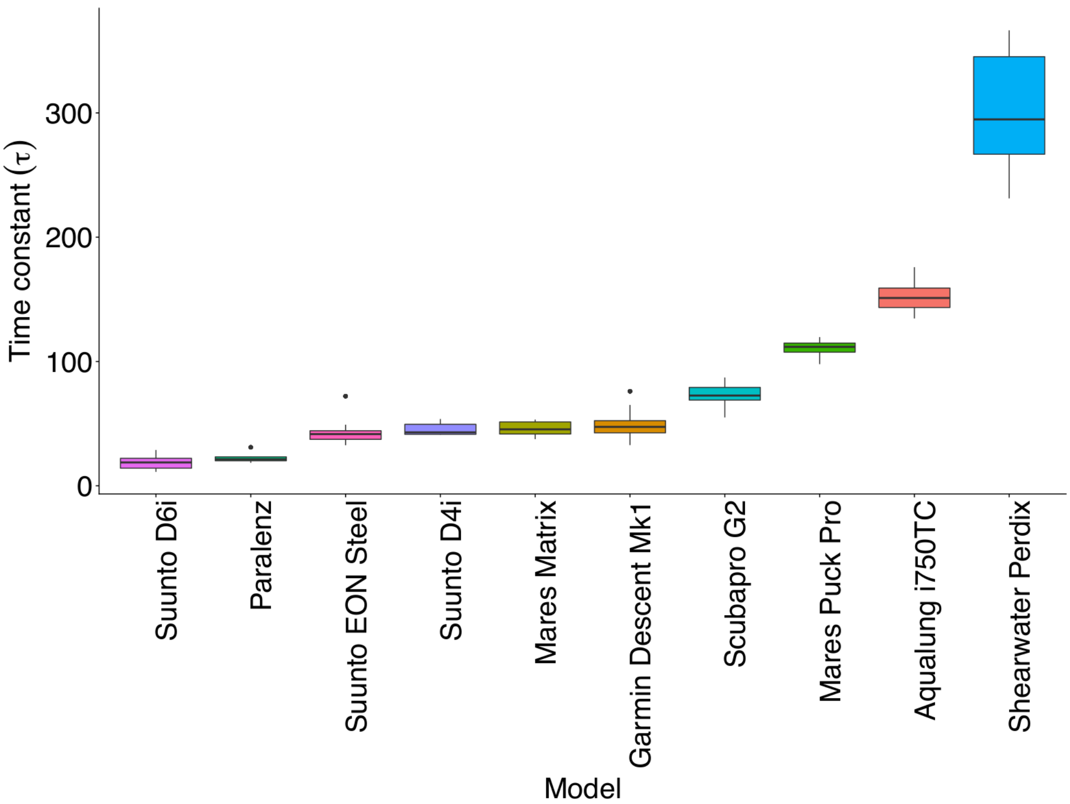


Figure 2.9. Mean response time (τ) by model. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * interquartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers

Table 2.3. Mean response time (τ), by device. S(τ fit) represents 95 % confidence intervals in the regression fit, based on the standard error of the regression.

Model	**Device ID**	**n**	**τ_{mean} / s**	**sd(τ)**	**S(τ fit)**	**Classification**
Aqualung i750TC	Aqualung 1	6	148	15	2.0 ± 1.0	Slow
Aqualung i750TC	Aqualung 2	7	149	7	2.0 ± 1.0	Slow
Aqualung i750TC	Aqualung 3	7	157	12	3.0 ± 2.0	Slow
Garmin Descent Mk1	Garmin 3	7	44	4	1.0	Quick
Garmin Descent Mk2	Garmin 2	9	52	11	0.5 ± 0.5	Quick
Garmin Descent Mk3	Garmin 1	9	46	8	0.5 ± 0.5	Quick
Mares Matrix	Mares Matrix 1	9	46	5	1.5 ± 0.5	Quick
Mares Matrix	Mares Matrix 2	9	46	6	1.5 ± 0.5	Quick
Mares Puck Pro	Mares Puck Pro 1	9	111	3	1.5 ± 0.5	Intermediate
Mares Puck Pro	Mares Puck Pro 2	9	112	7	2.0 ± 1.0	Intermediate
Paralenz Dive Camera+	Paralenz 1	6	24	4	0.5 ± 0.5	Quick
Paralenz Dive Camera+	Paralenz 2	6	20	2	0.0	Quick
Paralenz Dive Camera+	Paralenz 3	4	22	1	0.0	Quick
Scubapro G2	Scubapro 3	9	70	8	2.5 ± 1.5	Intermediate
Scubapro G3	Scubapro 2	9	74	5	1.5 ± 0.5	Intermediate
Scubapro G4	Scubapro 1	9	76	10	2.5 ± 1.5	Intermediate

Shearwater Perdix	Shearwater 1	9	291	45	2.5 ± 2.5	Slow
Shearwater Perdix	Shearwater 2	9	303	47	6.0 ± 3.0	Slow
Shearwater Perdix	Shearwater 3	7	322	45	5.5 ± 2.5	Slow
Suunto D4i	Suunto D4i 1	7	46	5	1.5 ± 0.5	Quick
Suunto D6i	Suunto D6i 1	9	18	4	4.0 ± 4.0	Quick
Suunto D6i	Suunto D6i 2	9	17	6	3.5 ± 3.5	Quick
Suunto D6i	Suunto D6i 3	9	20	6	2.5 ± 2.5	Quick
Suunto EON Steel	Suunto EON Steel 1	9	42	5	2.0 ± 1.0	Quick
Suunto EON Steel	Suunto EON Steel 2	9	41	3	2.0 ± 1.0	Quick
Suunto EON Steel	Suunto EON Steel 3	9	42	7	2.5 ± 1.5	Quick

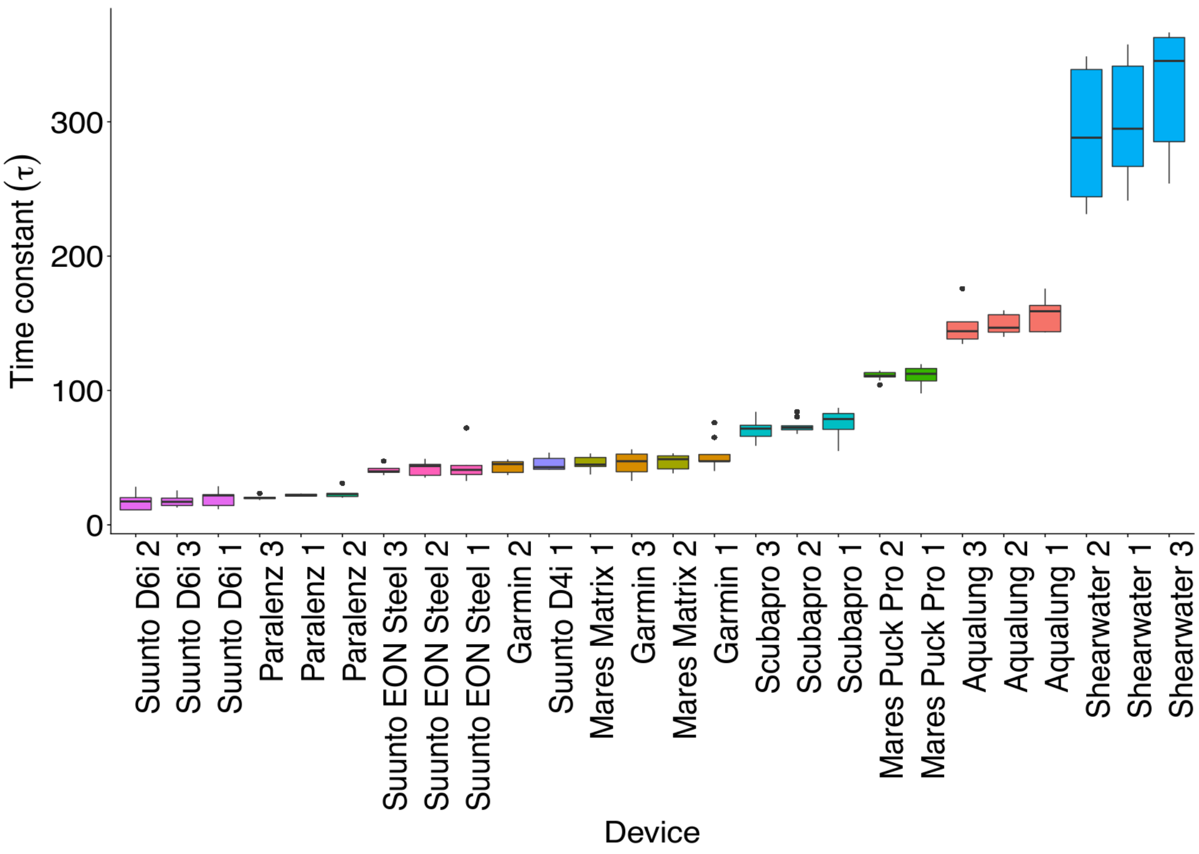


Figure 2.10. Mean response time (τ) by device. The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * interquartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

Clear differences were found in τ by pressure sensor location and material, but not by size (Figure 2.11). All devices with the pressure sensor at the edge along with the Paralenz Dive Camera+ were defined as having a quick response (17 s ≤ τ < 52 s) and all with a pressure sensor at the back were classified as intermediate or slow responders. Devices with entirely metal housing had quick mean response (17 s ≤ τ < 24 s), part metal/part plastic were intermediate (41 s ≤ τ < 52 s), and all plastic were slowest (70 s ≤ τ < 322 s).

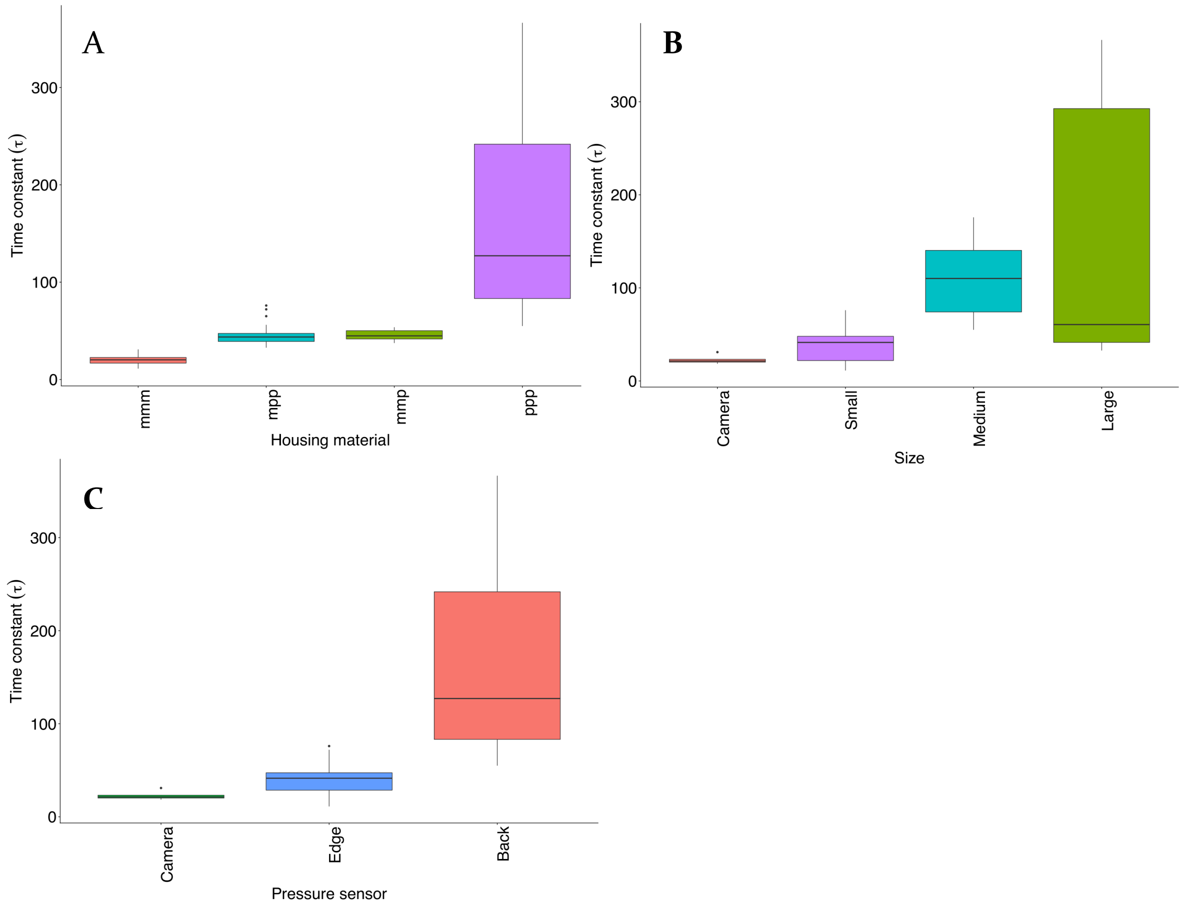


Figure 2.11. A) τ by material (B) τ by size (C) τ by pressure sensor location. (m = metal, p = plastic. e.g., mmm devices comprise metal front rim, edge and back)

2.4.2 Temperature accuracy (water bath)

A total of 78 data points were collected from 29 devices over three conditions (bath temperatures). One Suunto D6i data point was missed because of a dead battery. Paralenz Dive Camera+ were not included in the water bath deployments due to not having an on-screen temperature display. Mean bias is defined as displayed device temperature minus water bath temperature, averaged on a model or device basis. By model, this ranged from 0.0 to (-1 ± 1.7) °C (Table 2.4). The mean bias by device ranged from 0 to (-2.3 ± 1.5) °C (Table 2.5).

Table 2.4. Mean bias and uncertainties by model in water bath trials

Model	**Water bath**		
	n (dives)	**mean bias (° C)**	**sd (mean bias)**
Aqualung i750TC	9	-1.0	1.7
Garmin Descent Mk1	9	-0.7	0.5
Mares Matrix	6	-0.8	0.4
Mares Puck Pro	6	-1.0	0.0
Paralenz Dive Camera+	NA	NA	NA
Ratio iX3M GPS Deep	9	-0.2	0.4
Scubapro G2	9	0.0	0.0
Shearwater Perdix	9	-0.8	0.4
Suunto D4i	3	-0.3	0.6
Suunto D6i	8	0.0	0.0
Suunto EON Steel	9	-0.8	0.4
Suunto Vyper	6	-0.7	0.5

2.4.3 Temperature accuracy (chamber)

The chamber dives investigating accuracy comprised *n*(devices) = 31 and *n*(dives) = 185. Mean bias by model ranged from (0.1 ± 0.3) °C to (-1.4 ± 2.0) °C and by device ranged from (0.1 ± 0.1) °C to (-3.3 ± 1.4) °C. Full data on accuracy dives across conditions are shown by model (Table 2.6) and device (Table 2.7).

Table 2.5. Mean bias and uncertainties by device in water bath trials

Model	**Device ID**	**n(dives)**	**Mean bias (° C)**	**sd (mean bias)**
Aqualung i750TC	Aqualung 1	3	-2.3	1.5
Aqualung i750TC	Aqualung 2	3	-1.7	0.6
Aqualung i750TC	Aqualung 3	3	1.0	0.0
Garmin Descent Mk1	Garmin 1	3	-1.0	0.0
Garmin Descent Mk1	Garmin 2	3	-1.0	0.0
Garmin Descent Mk1	Garmin 3	3	0.0	0.0
Mares Matrix	Mares Matrix 1	3	-1.0	0.0
Mares Matrix	Mares Matrix 2	3	-0.7	0.6
Mares Puck Pro	Mares Puck Pro 1	3	-1.0	0.0
Mares Puck Pro	Mares Puck Pro 2	3	-1.0	0.0
Paralenz Dive Camera+	Paralenz 1	NA	NA	NA
Paralenz Dive Camera+	Paralenz 2	NA	NA	NA
Paralenz Dive Camera+	Paralenz 3	NA	NA	NA
Ratio iX3M GPS Deep	Ratio 1	3	-0.2	0.5
Ratio iX3M GPS Deep	Ratio 2	3	0.0	0.3
Ratio iX3M GPS Deep	Ratio 3	3	-0.3	0.4
Scubapro G2	Scubapro 1	3	0.0	0.0
Scubapro G2	Scubapro 2	3	0.0	0.0
Scubapro G2	Scubapro 3	3	0.0	0.0
Shearwater Perdix	Shearwater 1	3	-0.7	0.6
Shearwater Perdix	Shearwater 2	3	-0.7	0.6
Shearwater Perdix	Shearwater 3	3	-1.0	0.0
Suunto D4i	Suunto D4i 1	3	-0.3	0.6
Suunto D6i	Suunto D6i 1	3	0.0	0.0

Suunto D6i	Suunto D6i 2	2	0.0	0.0
Suunto D6i	Suunto D6i 3	3	0.0	0.0
Suunto EON Steel	Suunto EON Steel 1	3	-1.0	0.0
Suunto EON Steel	Suunto EON Steel 2	3	-0.7	0.6
Suunto EON Steel	Suunto EON Steel 3	3	-0.7	0.6
Suunto Vyper	Suunto Vyper 1	3	-0.7	0.6
Suunto Vyper	Suunto Vyper 2	3	-0.7	0.6

2.4.4 Temperature accuracy (sea dives)

A total of 152 mean bias values were collected from 31 devices over five sea dives. Three data points missing due to failure to recover data from Paralenz Dive Camera+. Mean bias by model, without considering experimental condition, ranged from (0.0 ± 0.1) °C to (-1.3 ± 2.2) °C (Table 2.6) and by device ranged from (0 ± 0.1) °C to (-3.5 ± 0.1) °C (Table 2.7).

Table 2.6. Bias by model across the two accuracy conditions

Model	**Sea dives**		**Chamber**	
	***n*(dives)**	**bias Δ*T* / °C**	***n*(dives)**	**bias Δ*T* / °C**
Aqualung i750TC	15	−1.3 ± 2.2	18	−1.4 ± 2.0
Garmin Descent Mk1	15	−0.3 ± 0.7	18	0.1 ± 0.9
Mares Matrix	10	0.1 ± 0.1	12	−0.1 ± 0.7
Mares Puck Pro	10	0 ± 0.1	12	−0.2 ± 0.7
Paralenz Dive Camera+	12	0.7 ± 0.1	17	0.7 ± 0.6
Ratio iX3M GPS Deep	15	0.9 ± 0.7	18	0.1 ± 0.3
Scubapro G2	15	0 ± 0.6	18	−0.4 ± 0.9
Shearwater Perdix	15	−0.3 ± 0.4	18	−0.9 ± 0.6
Suunto D4i	5	−0.5 ± 0.2	6	−0.4 ± 0.8
Suunto D6i	15	−0.3 ± 0.4	18	−0.2 ± 1.0
Suunto EON Steel	15	−0.6 ± 0.1	18	−0.4 ± 0.7
Suunto Vyper	10	−0.3 ± 0.4	12	−0.2 ± 2.9

2.4.5 Temperature accuracy (‘on frame’ vs ‘on arm’)

Wearing a computer ‘on arm’ led to a non-negative mean bias across all devices (0.0 to 2 °C) (Table 2.8) and models (0.0 to 1.6 °C) (Table 2.9) when compared to being carried on the frame (Figure 2.12). Brand, housing material, shape or response group were not found to be significant for bias in ‘on arm’/ ‘on frame’ data.

Table 2.7. Bias by device across the two accuracy conditions (sea and chamber dives)

Model	**Device ID**	**Sea dives**		**Chamber**	
		***n*(dives)**	**bias ΔT / °C**	***n*(dives)**	**bias ΔT / °C**
Aqualung i750TC	Aqualung 1	5	−3.5 ± 0.1	6	−3.3 ± 1.4
Aqualung i750TC	Aqualung 2	5	−1.9 ± 0.0	6	−1.9 ± 0.8
Aqualung i750TC	Aqualung 3	5	1.5 ± 0.4	6	0.9 ± 0.9
Garmin Descent Mk1	Garmin 1	5	−0.3 ± 0.4	6	0.2 ± 0.7
Garmin Descent Mk1	Garmin 2	5	−0.9 ± 0.3	6	−0.5 ± 0.9
Garmin Descent Mk1	Garmin 3	5	0.2 ± 0.7	6	0.5 ± 0.9
Mares Matrix	Mares Matrix 1	5	0.1 ± 0.1	6	−0.1 ± 0.6
Mares Matrix	Mares Matrix 2	5	0.1 ± 0.1	6	−0.1 ± 0.8
Mares Puck Pro	Mares Puck Pro 1	5	0.1 ± 0.1	6	−0.2 ± 0.8
Mares Puck Pro	Mares Puck Pro 2	5	0 ± 0.1	6	−0.2 ± 0.8
Paralenz DiveCamera+	Paralenz 1	4	0.5 ± 0.0	6	0.6 ± 0.7
Paralenz DiveCamera+	Paralenz 2	4	0.8 ± 0.1	6	0.9 ± 0.7
Paralenz DiveCamera+	Paralenz 3	4	0.8 ± 0.1	5	0.8 ± 0.5
Ratio iX3M GPS Dee p	Ratio 1	5	1.2 ± 0.7	6	0.4 ± 0.2
Ratio iX3M GPS Dee p	Ratio 2	5	0.5 ± 0.6	6	−0.3 ± 0.3
Ratio iX3M GPS Dee p	Ratio 3	5	0.8 ± 0.8	6	0.1 ± 0.1
Scubapro G2	Scubapro 1	5	0.2 ± 1.0	6	−0.5 ± 0.9
Scubapro G2	Scubapro 2	5	−0.1 ± 0.1	6	−0.4 ± 1.1
Scubapro G2	Scubapro 3	5	−0.1 ± 0.3	6	−0.4 ± 1
Shearwater Perdix	Shearwater 1	5	−0.2 ± 0.5	6	−1 ± 0.5
Shearwater Perdix	Shearwater 2	5	−0.4 ± 0.4	6	−0.8 ± 0.8

Shearwater Perdix	Shearwater 3	5	−0.3 ± 0.5	6	−1 ± 0.5
Suunto D4i	Suunto D4i 1	5	−0.5 ± 0.2	6	−0.4 ± 0.9
Suunto D6i	Suunto D6i 1	5	−0.3 ± 0.4	6	−0.1 ± 1.2
Suunto D6i	Suunto D6i 2	5	−0.3 ± 0.4	6	−0.3 ± 1
Suunto D6i	Suunto D6i 3	5	−0.3 ± 0.4	6	−0.3 ± 0.9
Suunto EON Steel	Suunto EON Steel 1	5	−0.7 ± 0.0	6	−0.6 ± 1
Suunto EON Steel	Suunto EON Steel 2	5	−0.5 ± 0.1	6	−0.3 ± 0.6
Suunto EON Steel	Suunto EON Steel 3	5	−0.6 ± 0.0	6	−0.4 ± 0.6
Suunto Vyper	Suunto Vyper 1	5	−0.3 ± 0.4	6	−0.3 ± 2.2
Suunto Vyper	Suunto Vyper 2	5	−0.3 ± 0.4	6	−0.1 ± 3.6

Table 2.8. Comparison of mean bias by device worn 'on arm' vs loose on a frame.

Model	**Device ID**	**'On frame' mean ΔT/°C**	**'On arm' mean ΔT/°C**	**Abs. diff ΔT/°C**
Aqualung i750TC	Aqualung 1	-3.6 ± 0.0	-3.5 ± 0.2	0.1
Aqualung i750TC	Aqualung 2	-1.9 ± 0.1	-1.9 ± 0.0	0.0
Aqualung i750TC	Aqualung 3	1.3 ± 0.1	1.7 ± 0.6	0.4
Garmin Descent Mk1	Garmin 1	-0.5 ± 0.3	-0.1 ± 0.5	0.4
Garmin Descent Mk1	Garmin 2	-0.9 ± 0.2	-0.9 ± 0.2	0.0
Garmin Descent Mk1	Garmin 3	0 ± 0.4	0.6 ± 0.6	0.6
Mares Matrix	Mares Matrix 1	0.1 ± 0.1	0.1 ± 0.1	0.0
Mares Matrix	Mares Matrix 2	0.1 ± 0.0	0.2 ± 0.1	0.1
Mares Puck Pro	Mares Puck Pro 1	0.1 ± 0.1	0.3 ± 0.4	0.2
Mares Puck Pro	Mares Puck Pro 2	0 ± 0.1	0 ± 0.1	0.0
Ratio iX3M GPS Deep	Ratio 1	0.8 ± 0.5	1.9 ± 0.4	1.1
Ratio iX3M GPS Deep	Ratio 2	0.3 ± 0.1	2.3 ± 2.3	2.0
Ratio iX3M GPS Deep	Ratio 3	0.4 ± 0.1	1.9 ± 0.5	1.5
Scubapro G2	Scubapro 1	-0.3 ± 0.0	0.7 ± 1.4	1.0
Scubapro G2	Scubapro 2	-0.2 ± 0.1	-0.2 ± 0.1	0.0
Scubapro G2	Scubapro 3	-0.2 ± 0.1	0.1 ± 0.4	0.3
Shearwater Perdix	Shearwater 1	-0.4 ± 0.4	0.2 ± 0.2	0.6
Shearwater Perdix	Shearwater 2	-0.4 ± 0.3	0 ± 0.5	0.4
Shearwater Perdix	Shearwater 3	-0.7 ± 0.1	-0.1 ± 0.5	0.6
Suunto D4i	Suunto D4i 1	-0.7 ± 0.1	-0.4 ± 0.3	0.3
Suunto D6i	Suunto D6i 1	-0.4 ± 0.3	0 ± 0.5	0.4
Suunto D6i	Suunto D6i 2	-0.4 ± 0.4	-0.1 ± 0.5	0.3
Suunto D6i	Suunto D6i 3	-0.4 ± 0.3	0 ± 0.5	0.4
Suunto EON Steel	Suunto EON Steel 1	-0.8 ± 0.0	-0.7 ± 0	0.1
Suunto EON Steel	Suunto EON Steel 2	-0.6 ± 0.0	-0.5 ± 0.1	0.1
Suunto EON Steel	Suunto EON Steel 3	-0.6 ± 0.0	-0.6 ± 0.0	0.0
Suunto Vyper	Suunto Vyper 1	-0.4 ± 0.4	-0.1 ± 0.5	0.3
Suunto Vyper	Suunto Vyper 2	-0.4 ± 0.3	-0.1 ± 0.5	0.3

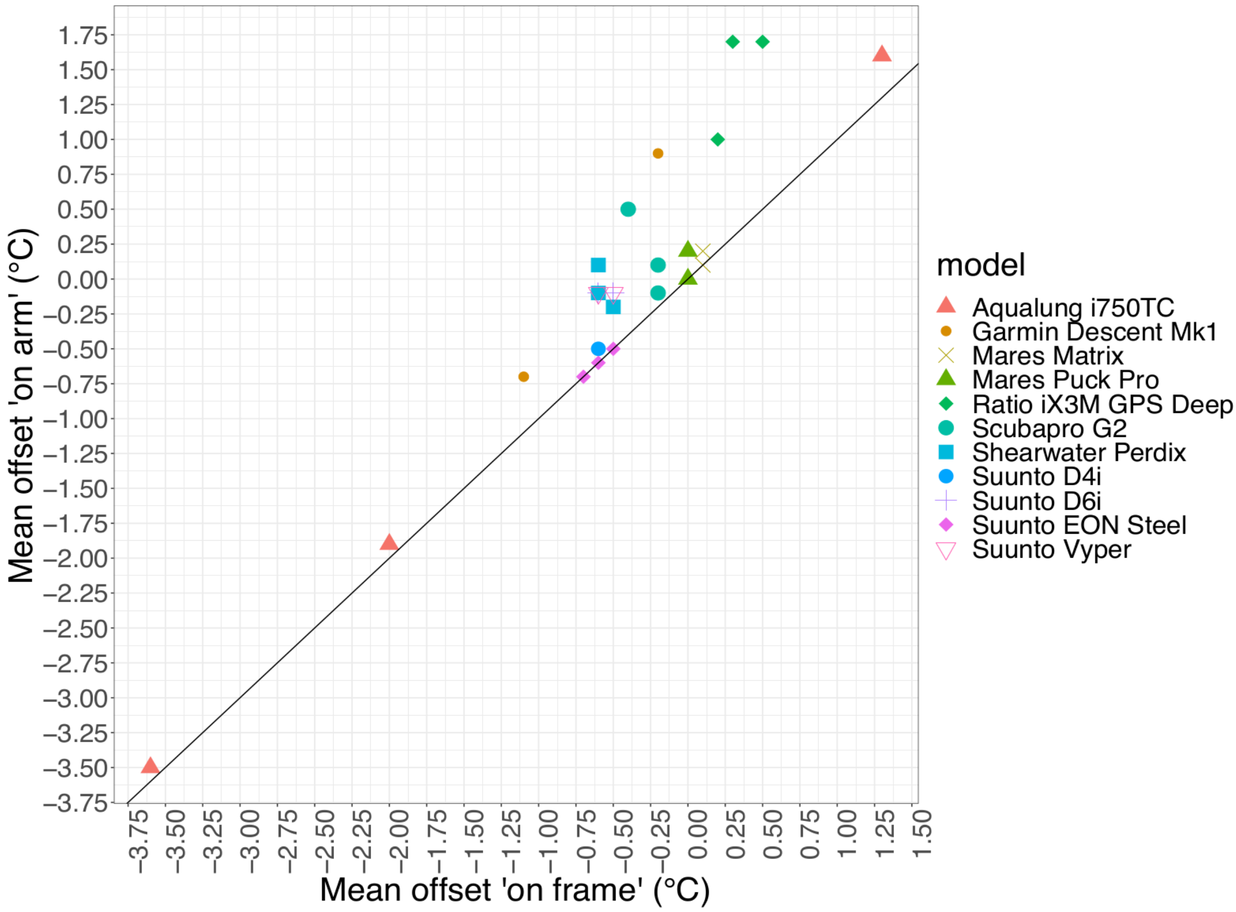


Figure 2.12. Effect of wearing devices "on arm" vs "on frame". Bias from Castaway baseline data by device, black line represents an equal bias in both conditions

Table 2.9. Comparison of bias by model worn 'on arm' with loose on a frame. Bias is defined as the mean temperature derived from the final 180 s of sea dives below the top of the bottom mixed layer, compared to baseline Castaway temperature data acquired over the same time.

Model	**On frame**	**On arm**	**On arm - On frame**
	bias ΔT/°C	**bias ΔT/°C**	**difference $\Delta\Delta T$/°C**
Aqualung i750TC	−1.4 ± 2.1	−1.2 ± 2.3	0.2
Garmin Descent Mk1	−0.5 ± 0.5	−0.1 ± 0.8	0.3
Mares Matrix	0.1 ± 0.1	0.2 ± 0.1	0.1
Mares Puck Pro	0.0 ± 0.1	0.2 ± 0.3	0.1
Paralenz Dive Camera+	0.7 ± 0.1	n. a.	−0.7
Ratio iX3M GPS Deep	0.5 ± 0.3	2.0 ± 1.2	1.6
Scubapro G2	−0.2 ± 0.1	0.2 ± 0.8	0.4
Shearwater Perdix	−0.5 ± 0.3	0.0 ± 0.4	0.5
Suunto D4i	−0.7 ± 0.1	−0.4 ± 0.3	0.3
Suunto D6i	−0.4 ± 0.3	−0.1 ± 0.4	0.4
Suunto EON Steel	−0.6 ± 0.1	−0.6 ± 0.1	0.0
Suunto Vyper	−0.4 ± 0.4	−0.1 ± 0.5	0.3

2.4.6 Temperature accuracy (overall)

As depth resolved-temperature data are required for scientific interest and collecting temperature data from dive computers in an unpressurised environment would not be recommended, only data from sea and chamber accuracy dives were combined for overall accuracy results. Across the total n = 337 data points from the two accuracy protocols, overall mean bias was (-0.2 ± 1.1) °C. Mean bias by model ranged from (0.0 ± 0.5) °C to (-1.4 ± 2.1) °C (Table 2.10; Figure 2.13) and by device ranged from (0.0 ± 0.6) °C to (-3.4 ± 1.0) °C (Table 2.11)

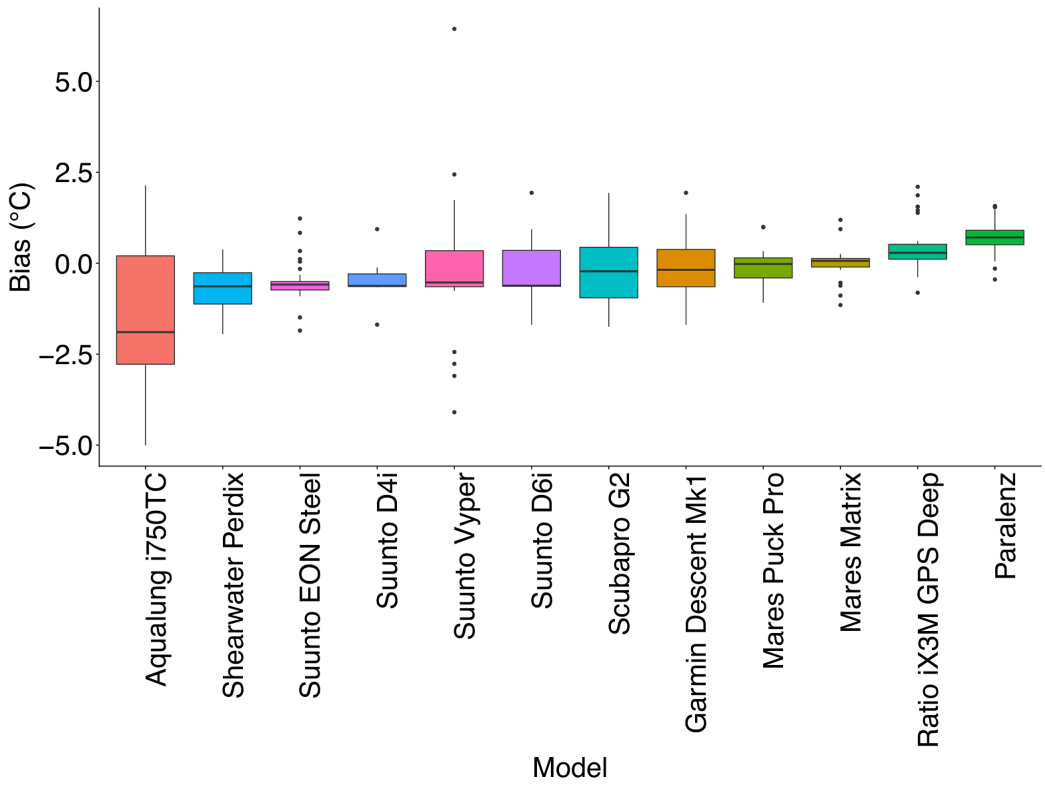


Figure 2.13. Normalised bias across sea and chamber dives.

The black line represents the median. The lower and upper hinges correspond to the first and third quartiles (25th and 75th percentiles). Upper and lower whiskers extend from the hinge to the largest/smallest value, respectively, no further than 1.5 * interquartile range from the hinge. Data beyond the end of the whiskers are plotted individually as outliers.

Table 2.10. Bias by model, averaged across sea and chamber dives

Model	***n*(dives)**	**Bias Δ*T*/°C**	**Resolution / °C**
Aqualung i750TC	33	−1.4 ± 2.1	5/9 ≈ 0.56
Garmin Descent Mk1	33	−0.1 ± 0.8	1.0
Mares Matrix	22	0 ± 0.5	0.1
Mares Puck Pro	22	−0.1 ± 0.6	0.1
Paralenz Dive Camera +	29	0.7 ± 0.5	0.1
Ratio iX3M GPS Deep	33	0.4 ± 0.7	0.1
Scubapro G2	33	−0.2 ± 0.8	0.4
Shearwater Perdix	33	−0.6 ± 0.6	1.0
Suunto D4i	11	−0.5 ± 0.6	1.0
Suunto D6i	33	−0.3 ± 0.8	1.0
Suunto EON Steel	33	−0.5 ± 0.6	0.1
Suunto Vyper	22	−0.3 ± 2.1	1.0

Table 2.11. Total mean bias by device across sea and chamber dives

Model	**Device ID**	**n (dives)**	**Mean bias ΔT/°C**	**Abs. mean bias ΔT/°C**	**sd (mean bias) ΔT/°C**
Aqualung i750TC	Aqualung 1	11	-3.4	3.4	1.0
Aqualung i750TC	Aqualung 2	11	-1.9	1.9	0.5
Aqualung i750TC	Aqualung 3	11	1.2	1.2	0.7
Garmin Descent Mk1	Garmin 1	11	0.0	0.0	0.6
Garmin Descent Mk1	Garmin 2	11	-0.7	0.7	0.7
Garmin Descent Mk1	Garmin 3	11	0.3	0.3	0.8
Mares Matrix	Mares Matrix 1	11	-0.1	0.1	0.4
Mares Matrix	Mares Matrix 2	11	0.0	0.0	0.6
Mares Puck Pro	Mares Puck Pro 1	11	-0.1	0.1	0.6
Mares Puck Pro	Mares Puck Pro 2	11	-0.1	0.1	0.6
Paralenz DiveCamera+	Paralenz 1	10	0.6	0.6	0.5
Paralenz DiveCamera+	Paralenz 2	10	0.8	0.8	0.5
Paralenz DiveCamera+	Paralenz 3	9	0.8	0.8	0.3
Ratio iX3M GPS Deep	Ratio 1	11	0.8	0.8	0.6
Ratio iX3M GPS Deep	Ratio 2	11	0.1	0.1	0.6
Ratio iX3M GPS Deep	Ratio 3	11	0.4	0.4	0.6
Scubapro G2	Scubapro 1	11	-0.2	0.2	1.0
Scubapro G2	Scubapro 2	11	-0.3	0.3	0.8
Scubapro G2	Scubapro 3	11	-0.3	0.3	0.7
Shearwater Perdix	Shearwater 1	11	-0.6	0.6	0.7
Shearwater Perdix	Shearwater 2	11	-0.6	0.6	0.6
Shearwater Perdix	Shearwater 3	11	-0.7	0.7	0.6

Suunto D4i	Suunto D4i 1	11	-0.5	0.5	0.6
Suunto D6i	Suunto D6i 1	11	-0.2	0.2	0.9
Suunto D6i	Suunto D6i 2	11	-0.3	0.3	0.7
Suunto D6i	Suunto D6i 3	11	-0.3	0.3	0.7
Suunto EON Steel	Suunto EON Steel 1	11	-0.7	0.7	0.7
Suunto EON Steel	Suunto EON Steel 2	11	-0.4	0.4	0.4
Suunto EON Steel	Suunto EON Steel 3	11	-0.5	0.5	0.5
Suunto Vyper	Suunto Vyper 1	11	-0.3	0.3	1.6
Suunto Vyper	Suunto Vyper 2	11	-0.2	0.2	2.6

2.5 Discussion

Despite the inherent limitations of the existing technology, our research shows that, while there is wide between-model variation in both temperature bias and τ, there is value in data derived from devices commonly carried by SCUBA divers as a source of subsurface temperature data in coastal areas. We demonstrate that there is sufficient consistency in bias within some models to offer the potential for bias correction by model. In addition, an overall bias of (-0.2 ± 1.1) °C demonstrates that, with sufficient datapoints, valuable data may be produced irrespective of the models from which data were derived. Due to variation in τ, while not all models would be recommended for use in scenarios of temperature change, some models also demonstrate a τ which, in conjunction with a sufficiently high resolution, offer the potential for identification of thermoclines.

2.5.1 Response time

τ varied widely between models, with less within-model variance than between. We saw less within-device variation in τ than Egi et al., (2018), although a similar mean τ (46 s compared with 52 s) was seen for the only model used in both papers (Mares Matrix). Within-model consistency is promising for the purposes of citizen science, as it offers projects the potential to select specific models based on the project objectives or run post-hoc corrections.

Six models were defined as quick responders ($\tau < 60$ s)(Table 2.12). Of these, the two models with the shortest τ (Suunto D6i (18 ± 5 s) and Paralenz Dive Camera+ (22 ± 3 s)) have τ comparable designed-for-purpose aquatic temperature loggers; the plastic Star-Oddi Starmon mini has an 18 s standard τ. Although more commonly used in moored scenarios, Starmon minis have been used to measure lake temperature profiles, with corrections applied (Jóhannesson et al. 2007).

Table 2.12. Model classification. Accuracy and precision across sea & chamber conditions, overall, plus response to temperature change. Accuracy/Precision = good (G), moderate (M), poor (P). τ = quick (Q), intermediate (I), slow (S), excluded (X), not applicable (NA)

	Accuracy			**Precision**			
Model	**Sea**	**Chamber**	**Overall**	**Sea**	**Chamber**	**Overall**	τ
Aqualung i750TC	P	P	P	P	P	P	S
Garmin Descent Mk1	G	G	G	M	M	M	Q
Mares Matrix	G	G	G	G	M	G	Q
Mares Puck Pro	G	G	G	G	M	M	I
Paralenz DiveCamera+	M	M	M	G	M	G	Q
Ratio iX3M GPS Deep	M	G	G	M	G	M	X
Scubapro G2	G	G	G	M	M	M	I
Shearwater Perdix	G	M	M	G	M	M	S
Suunto D4i	G	G	G	G	M	M	Q
Suunto D6i	G	G	G	G	M	M	Q
Suunto EON Steel	M	G	G	G	M	M	Q
Suunto Vyper	G	G	G	G	P	P	NA

Exponential fits proved consistent across models, exceptions causing poor fit were errant temperature data points recorded in the temperature profile (Suunto EON Steel) or a sharp rise in temperature followed by a levelling or drop before a further rise (Ratio iX3M GPS Deep). In the case of the Ratios, the response seen could be because of intermittent heating caused by internal electronic functions of the model, or, as a slow responding but higher resolution model, the devices may have been affected by cold water ingress introduced by adding additional devices.

When dive computer model was excluded as a parameter from the generalised linear model, pressure sensor location and housing material were also found to significantly influence τ. As the two features are correlated (e.g., all devices with a pressure sensor at the back are entirely housed in plastic (Table 2.1), it is not possible to fully separate the effect of the two variables. Also, while pressure sensor location is identifiable (Table A.1), it is not known whether the temperature sensor is co-located with the pressure sensor in any given model. However, it is logical to postulate that in a small device, or where a sensor is close to the edge of the device housing, a more rapid response to temperature change will be seen than that of a sensor buried deep within a larger housing, where the thermal mass of the dive computer itself may slow the response.

2.5.2 Temperature accuracy

All models performed well within the ± 2 °C advertised accuracy (Mares n.d; Azzopardi and Sayer, 2012; Suunto, 2018) overall, with only one model having a mean absolute bias >=1 °C (Aqualung i750TC), and only two (Aqualung i750TC, Suunto Vyper) having poor precision. The overall mean bias seen ((-0.2 ± 1.1) °C) is comparable with existing commonly used coastal temperature data sets, such as those using handheld digital thermometers for subsurface temperature measurement; Cefas coastal temperature datasets include data from thermometers and data loggers with accuracies of (± 0.2 to ± 0.3 °C) (Morris et al. 2018). A systematic negative bias of −1 °C has been seen in satellite sea surface temperature (satSST) (Brewin et al. 2017a) and up to 6 °C bias between coastal satSST and in situ devices (Smit et al. 2013).

Sampling requirements for the global ocean observing system in situ temperature (other than for identification of climate trend) are 0.2 to 0.5 °C (Needler, Smith, and Villwock 1999), and bias-corrected numerical oceanic models have been shown to still have up to −0.86 °C offset from baseline satellite temperature after corrections have been applied (Macias et al. 2018). As nine of the twelve dive computer models were found to have 'good' accuracy (<= 0.5 °C) overall (Table 2.12), these requirements and biases indicate that, with sufficient data points, some models of dive computers can offer an additional source of temperature data to contribute to ocean temperature monitoring, numerical models and composite satellite products.

Differences were found in both bias and variance (accuracy and precision) across the two conditions (sea and chamber). Nine models had the same accuracy categorisation in both sea and chamber dives (Table 2.12). Of these, only three models (Aqualung i750TC, Garmin Descent MK1, Scubapro G2) had the same precision across the two conditions. Precision was found to be improved in sea conditions, with eight models categorised as having 'good' precision. Only one model (Ratio iX3M GPS Deep) was found to have good precision in the chamber. The reduced precision found in nine of the models in the chamber is likely caused by differences between tub temperatures in dive repetitions, combined with the effect of a static water environment on the Castaway temperature sensor. Castaway CTDs are designed to work with a steady flow of water of around 1 m s^{-1} through the sensor channel. Collection of data in real world scenarios will always lead to differences caused by environmental variation for which it is not possible to control. In the present study, as all Castaways were positioned on a frame carried by one diver, while all the dive computers were worn on the wrists of two divers. It is therefore possible that, although precision was better than in the chamber, proximity differences combined with local variations in temperature led to additional variation being seen in the sea dives.

Except for three devices (Ratio iX3M (n = 1), Garmin Descent Mk1 (n = 1), Suunto EON Steel (n = 1)), all individual devices aligned with their model's overall accuracy categorisation, demonstrating positive within model consistency. Similarly, only one device had lower precision than its model's categorisation, with four devices (Suunto EON Steel (n = 2), Aqualung i750TC (n = 2)) having better precision than their model would indicate. This within model consistency is encouraging for post-hoc bias correction by model. Across both conditions, all models except three showed overall negative bias to the baseline temperature. In contrast, Mares Matrix had an overall bias of 0, whilst Ratio iX3M GPS Deep and Paralenz Dive Camera+ biased warm. This could be caused by an internal heating effect of the electronics due to additional active functions as both Ratio iX3M GPS Deep and Paralenz DiveCamera+ are both devices with additional functionality in comparison with some smaller devices.

Diver attachment placement also had significant effect on bias in sea dives, with all models 'on arm' having a non-negative mean bias compared with than 'on frame' (irrelevant of whether the device was biased colder or warmer than the baseline). These differences could be caused by the heating effect of the diver's body, an effect of an additional barrier between the ambient water temperature and the temperature sensor (dependent on sensor location within the housing). All divers were wearing dry suits, but the material and thickness varied (neoprene/ membrane).

Except for two models (Mares Matrix, Suunto EON Steel) there was greater variation in within-model bias in 'on arm' conditions. This could be due to differences in positioning of dive computers on arms, the amount of contact between the device and the diver's arm, or the dive suit material. When collecting or correcting data across different environments, console mounted devices which are mounted on a hose not attached to the diver may be preferable for temperature data accuracy. Alternatively, it is common for divers to have redundancy in kit, carrying two dive computers. The secondary device could be attached safely to the diver but not worn on the arm. It is recommended that attachment mechanism and thermal protection type be noted in data collection from citizen scientist divers so it can be taken into consideration.

2.5.3 Technology limitations

Accuracy in recorded or displayed temperature, or response to temperature change does not form part of primary dive computer function and dive computer manufacturers are not providing temperature data for oceanographic purposes. The results found are in no way reflective of the performance of any model in the designed purpose as diver safety devices. Whilst dive computers in the UK must adhere to standards set in British Standard BS EN13319:2020, which covers functional and safety requirements including depth and time, the Standard does not include temperature (British Standard 2000).

The greatest potential for temperature data from citizen scientist divers is to address the lack of depth-resolved data in coastal regions. To improve the overall use of dive computers as oceanographic monitoring devices in less-well performing models, manufacturers could look at improving the quality of the out of the box measurements. The addition of an accurate dedicated temperature sensor, with considered placement of the sensor would support unbiased detection of water temperature change. Whilst the majority of dive computer models tested by Azzopardi and Sayer (2010) were found to be consistently within 1% of nominal depth, the addition of conductivity sensors to measure salinity would increase the accuracy of depth values, although this would not affect temperature data quality. Inclusion of geolocation ability would allow easy identification of dive locations. A combination of all the above would maximise the citizen science potential of divers, because of their access to otherwise hard to reach locations.

Within the limitations of the current commercially available devices, a citizen science project dataset could be improved by calibrating individual dive computers in advance, simply, using an iced bucket of water. As evidenced by the water bath trials - this would be greatly improved by an additional significant figure to the unpressurised temperature display, as currently most models display only positive integers, limiting the potential accuracy by introducing truncation effects.

2.5.4 Citizen science and use of data

We need to better understand how model type effects temperature profiles so that citizen science diving projects can help fill gaps in coastal temperature datasets. To standardise data, there should be a focus on the models offering the greatest accuracy and shortest temperature response. Only one model (Aqualung i750TC) was found to have poor accuracy and precision across all conditions, along with a slow response to temperature change. Five of the six models with a quick temperature response (τ <60 s) were also found to also have good accuracy, with good/moderate precision overall (Figure 9). These comprise Mares Matrix (2/2), Garmin Descent (2/3), Suunto D6i (3/3), Suunto EON Steel (2/3) and Suunto D4i (1/1), all sharing promising characteristics as individual devices.

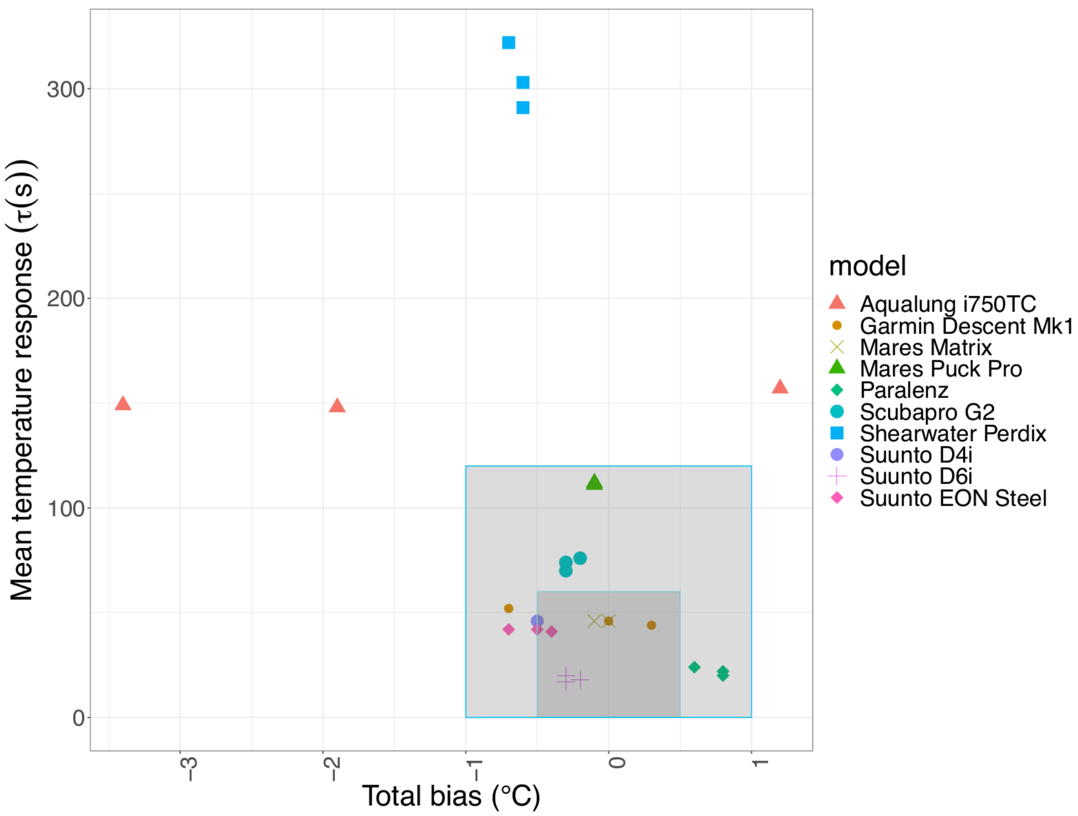


Figure 2.14. Accuracy against bias for all devices; the inner box highlights 0.5 °C bias with 60 s τ. Devices falling in the inner box are defined as having both a quick response and a good accuracy overall. The outer box highlights devices which have up to 1 °C bias and 120 s τ: an intermediate response to temperature change, and moderate accuracy. When considering models for citizen science data collection, those with the greatest potential have a high sample rate and resolution, are likely to have a pressure sensor located on an edge and have a metal or part-metal housing. In addition, a standardised model could be used by all volunteers in a project and simple corrections applied for systemic model bias. The most promising model tested here for overall use across citizen science projects is the Mares Matrix. This model had consistently good accuracy and precision and a quick response to temperature change, exhibiting an overall mean bias of (0.0 ± 0.4) °C and τ = (46 ± 5) s with a recorded resolution of 0.1

°C and a 5 s sampling rate. A close second is the Suunto EON Steel, which has good accuracy overall, moderate precision and a quick response to temperature change, with a recorded resolution of 0.1 °C and a 10 s sampling rate. Other models have shorter τ (Suunto D6i, Suunto D4i, Garmin Descent), but single degree resolution, making them less useful for monitoring temperature change.

We found that with sufficient data points, 'good' accuracy was found irrespective of originating device. Therefore, data collected by local groups or dive centres in commonly dived, discrete areas, may generate sufficient data points to provide a useful accuracy, irrelevant of model. In addition, not all sampling locations have equal value (Callaghan et al. 2019) and lower quality data may still be of use to support decision making (Buytaert et al. 2016) if uncertainties are quantified. As such, in remote, less widely sampled areas where there are limited pre-existing records, dive computer information may still be of use as indicative data, even with fewer sampling points or from devices with less accuracy/precision.

Temperature from dive computers could be used to compliment biological datasets. Thermal drivers (stratification and seasonal patterns) affect habitat choice (Freitas et al. 2021), vertical distribution (Sogard and Olla, 1993) and behaviour (Bartolini, Butail, and Porfiri 2014) in fish. Computer-derived temperature data could contribute to a better understanding of local variability in fish ecology. Temperature data can also support regional assessment of hydrological conditions (Morris et al. 2018). In highly dived areas, the data would provide a time series allowing identification of seasonal variation, albeit without complete temporal coverage. They may also be useful for marine recreation (Brewin et al. 2015) or feeding into numerical models and satellite products (Smit et al. 2013) in areas where the accuracy is known to be < 1 °C. They could be especially useful in commonly dived, poorly sampled areas, such as the South Pacific, where the volume of dive profiles could provide data of a useful resolution irrespective of model.

In conclusion, the limitation of divers as citizen scientists for temperature data collection is inherent in the devices themselves. The challenge is to understand the uncertainty in accuracy and precision recorded by the devices rather than the abilities or knowledge of the citizen science diver. Our research shows that the quality of temperature data in dive computers could be improved, but implementation would need to be driven by manufacturers, or by diver demand. As some models of dive computers can demonstrably provide data comparable to that collected by more traditional methods, within required accuracy levels for some monitoring scenarios, they have a role to play in future oceanographic monitoring.

2.5.5 Errata

The incorrect dimension and units published in Table 2.1 Sampling Interval column have been corrected to time (s) from ΔT / °C.

Section 2.3.5/2.4.4. Although 6 sea dives were completed, one was excluded from accuracy analyses as the Castaway data showed sea temperature did not come to equilibrium within the depth of the dive

Chapter 3. Comparison of temperature data recorded by dive computers with satellite SST and depth-resolved in situ observations in the Red Sea

3.1 Chapter summary

The Red Sea is one of the most dived areas in the world. This chapter discusses the comparison of 17 years of minimum water temperatures collected from SCUBA dive computers in the northern Red Sea (23–30° N, 32–39.4° E), with satellite-derived sea surface temperatures from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) optimal interpolation product (E.U. Copernicus Marine Service Information 2020), depth-banded monthly mean in-situ temperature from the TEMPERSEA dataset, which incorporates data originating from several in-situ recording platforms (including Argo floats, ships and gliders)(Agulles et al. 2019). Dive computer temperatures were found to have an overall negative bias of (−0.5 ± 1.1) °C when compared with interpolated OSTIA temperatures and (−0.2 ± 1.4) °C compared with TEMPERSEA. Our research shows clear seasonal patterns in agreement with OSTIA and regional climatology are observable in dive computer temperature data at different temporal resolutions. Depth related biases consistent with comparison mixed layer depths, and south-north mean temperature cooling trend by latitudinal band consistent with values in the literature are also identifiable. Bias remains consistent when reducing sample numbers down to n(93). We conclude that, with sufficient datapoints, dive computers offer potential as an alternative source of depth-resolved temperature data to complement existing in-situ and satellite SST data sources.

3.2 Introduction

Long term observations of ocean temperature are essential for our understanding of natural variations and trends caused by climate change (Needler et al. 1999; Rintoul et al. 2013), but there is a shortage of depth-resolved temperature data, especially in coastal areas (Wright et al. 2016). Satellite products are commonly used to measure sea surface temperature (SST) but are affected in coastal areas by proximity of land

(Ricciardulli and Wentz, 2004) or aerosol interference (Bernstein, 1982). In addition, satellite SST records only the skin or sub-skin temperature at the sea surface and measurements have been found to differ from in situ measurements by up to 6 °C (Smit et al. 2013) with root-mean-squared errors (RMSE) amplified nearer the coast (Lee and Park, 2020). Determining temporal and spatial variation via remote sensing in coastal areas is challenging (Baldock et al. 2014) and although interpolated analysis products are available, it is important to understand how temperature varies with depth for validation of these products (Kennedy et al. 2007).

Public participation in scientific research (Bonney et al. 2009a), often called citizen science, is a rapidly developing field (Bonney et al. 2016). Environmental citizen science projects have been around for well over a century; the first recorded project being the Christmas Bird Count, which has taken place annually in the US since 1900 (Silvertown, 2009). In conjunction with the developing autonomous monitoring technologies, engaging citizen scientists involved in marine recreational activities to gather sub-surface information can help fill the data gap (Hyder et al. 2015; Brewin et al. 2017b; Simoniello et al. 2019). One approach is for citizen scientists to act as sensor platforms (Haklay, 2018), providing crowdsourced 'Volunteered Geographic Information' (VGI) (Schade et al. 2010) data for research purposes, such as data from a mobile phone or biosensing watch. Dive computers are as ubiquitous as smartphones in the diving world. With as many as 10 million SCUBA divers world-wide (Wright et al. 2016), most wearing one or more dive computers, there is clear potential for divers to gather depth-resolved information that is difficult to collect by traditional means by following this crowdsourced approach. With sufficient data, dive computers have been found to have an overall mean temperature bias of (−0.2±1.1) °C (Marlowe et al. 2021), offering huge opportunity to contribute to observational datasets, given the potential numbers of available data points worldwide.

Most modern dive computers record profiles of temperature as a function of depth and time, with some older models recording a single minimum temperature for a dive. The Red Sea is one of the top diving destinations in the world (Shaalan, 2005), with in excess of 30000 dives per year in some areas (Hasler and Ott, 2008). This study collates minimum water temperatures collected from SCUBA dive computers in the northern Red Sea (longitude: 32–39.4° E, latitude: 23–30° N) between 2000 to 2017. These are compared with satellite-derived foundation sea surface temperatures from OSTIA (E.U. Copernicus Marine Service Information 2020) and in-situ depth-resolved monthly mean observations from TEMPERSEA', which brings together data from CORA (Cabanes et al. 2013) which incorporates profiles from several sources (e.g. Argo, GOSUD, OceanSITES and World Ocean Database) with data sourced from all KAUST ("King Abdullah University of Science and Technology" n.d.) platforms in the Red Sea (e.g. ships, gliders and Argo floats)(Agulles et al. 2020). We establish the quantitative validity of dive computer temperature for resolving seasonal and interannual temperature variations, exploring agreement with satellite and in situ data under different grouping conditions.

3.3 Materials and methods

3.3.1 Study area: Red Sea

The Red Sea is a marginal sea formed by continental rifting (Zolina et al. 2017) and has one of the longest reef systems in the world (Fine et al., 2019), at 4000 km (Kleinhaus et al. 2020). 40 % of the Red Sea basin is shallower than 100 m, with a maximum depth of 2800 m (Shaked and Genin, 2011). It is economically important for tourism, shipping, oil and gas (Shaltout, 2019), and is a focus for climate science and coral reef research, because of the unprecedented heat tolerance of its scleractinian, reef building corals (Kleinhaus et al. 2020). One of the hottest ocean basins (Abdulla et al. 2018; Krokos et al. 2019), the Red Sea has a pronounced annual temperature cycle (Al-Subhi and Al-Aqsum, 2008). It has an annual mean surface temperature of (27.9±2.1) °C (1982 - 2016) (Shaltout, 2019), with a summer-winter difference of 6 ºC (Berman et al., 2003). Interannual variability is greatest in the winter in the north (Karnauskas and Jones, 2018). A SST gradient of 4 ºC exists from north to south (Alraddadi et al. 2021), along with a weaker zonal gradient; eastern monthly mean surface temperatures are 0.3 °C higher in the north than on the western side (Al-Subhi and Taqi, 2014). A shallow thermohaline-driven circulation is seen above 150 m (Tragou and Garrett, 1997), with weak semi-diurnal currents in the northern parts (Sofianos and Johns, 2007).

3.3.2 Dive computer data

Dive computers (DC) have temperature bias related to model, pressure sensor location and housing material, but, with aggregation of sufficiently large numbers, a mean bias of -0.2 °C from CTD measured temperature was found (Marlowe et al. 2021). For the present study, 323 088 anonymous data points from unknown dive computers containing date, minimum temperature, maximum depth, latitude and longitude were provided by divelogs.de (Mohr, n.d). These data have been submitted as 'public' logbooks and are freely available. While most modern dive computers store full temperature-depth profiles, these were not stored in divelogs.de and were therefore not available for use. However, all dives had a minimum temperature recorded, and we were interested to see the usefulness of this basic dataset. Using anonymous data from an online dive log provided a real test of the potential of raw dive computer data as a useful source for temperature monitoring, where no additional metadata were available about the device, such as model, material, or pressure sensor location.

All data were processed using the tidyverse suite of packages in R (tidyverse Overview), with the number of dives retained decreasing at each step of the filtering process (Fig. 1). Basic validity tests were carried out (Fig. 3.1). The majority of retained dives were in the northern Red Sea. To avoid skewing the comparison (whole region) climatology with temperatures from the warmer southern Red Sea (Fishelson, 1971; Karnauskas and Jones, 2018), the study range was spatially restricted to the northern Red Sea: 23–30° N, 32–39.4° E. Only dives within standard recreational depths (maximum dive depth ≤ 40 m), years with more than 75 dives per year and with a spread of dives across most months were retained (2000 to 2017). Only dives with minimum temperatures between 20 and 31 °C were selected. These temperature constraints were applied as, in the Red Sea, temperatures as low as 20 °C have only been found in water at depths >1500 m (Shaked and Genin, 2011) and >31 °C SST only in the extreme southern Red Sea (Karnauskas and Jones, 2018). Only dives with a collocated OSTIA, and TSEA datapoint at the relevant depth band were retained (further details in section 3.3.3). A 15 arc second-resolution bathymetry (approximately 0.5 km) for the area was downloaded from GEBCO (General Bathymetric Chart of the Oceans) (GEBCO Compilation Group, 2020). Bathymetry depths associated with each dive location were found using the get.depth function in the marmap package in R (Pante et al. 2020). To exclude any incorrectly geolocated dives where the recorded latitude and longitude correlated with land rather than sea, all records for which the corresponding bathymetry depth was shallower than the maximum recorded dive depth were removed. As there were only 48 dives remaining at 7 m or shallower, only dives with maximum depths over 7 m were retained.

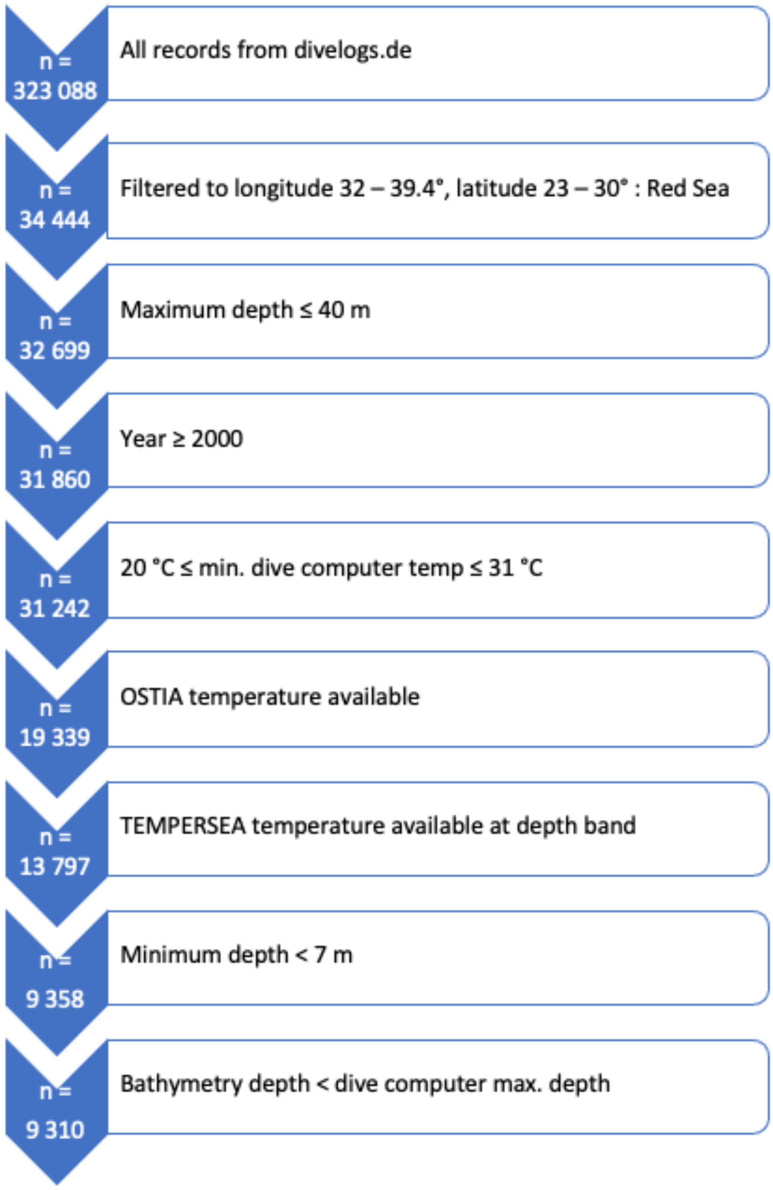


Fig. 3.1. Flow chart showing the filtering process and number of dives (n) retained at each step.

The Red Sea is an area subject to high solar radiation (Al-Aidaroos et al. 2014) and extremely low precipitation (Abdulla et al. 2018). A cooler surface stratification layer is therefore not expected. Under these conditions, we assumed that the minimum temperature is coincident with the maximum depth. However, during a short dive, a dive computer may have not been at depth sufficiently long to equilibrate to the ambient water temperature (Marlowe et al. 2021). Although an uncommon profile, in a short 'bounce' descent to maximum depth followed by an ascent straight back to the surface, the bottom time might be short and artificially high minimum temperatures may be recorded (Wright et al. 2016). No metadata were available about the length of dive, so we have no way to eliminate this potential warm bias in the dive-computer data.

3.3.3 Comparison data

Daily satellite-derived SST data were obtained from the global ocean OSTIA sea surface temperature and sea ice product (E.U. Copernicus Marine Service Information, 2020). This is a level 4 (L4) analysis product (Donlon et al. 2004) with a horizontal resolution of 0.05° x 0.05°, which combines satellite SST data with in situ data from the HadIOD dataset (Fiedler, 2014) within an optimal interpolation system (Group for High Resolution Sea Surface Temperature). L4 products are gridded and processed to be gap free, with uncertainty estimates. Foundation SST values were used, which represent the mixed layer temperature (equivalent to 0.2 to 1 m below the surface measured just before sunrise) (Donlon et al. 2012) and therefore removes diurnal variations.

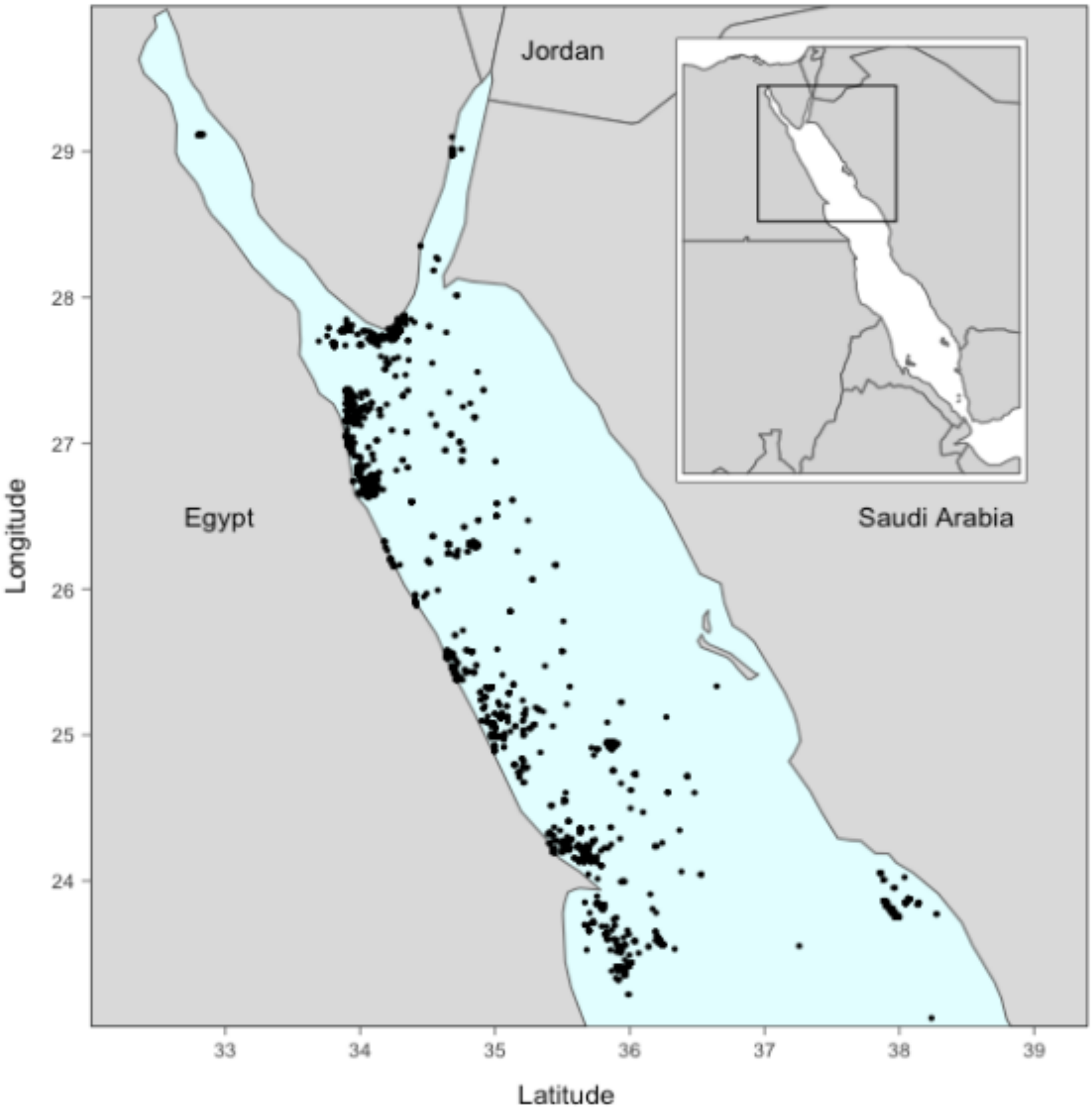


Fig. 3.2. Map of the study region with final selection of dives used in analyses. Inset map shows wider contextual area, with area of interest highlighted with a box.

The four nearest OSTIA grid cells by Haversine (or great circle) distance were identified, using the geosphere package in R (Hijmans et al. 2019). A cell is defined as land if greater than 50 % of the cell surface is land (Kara et al. 2007). Any returned grid cells with a land mask flag were excluded. An interpolated SST value, θ(sat), for the specified latitude and longitude was calculated from the four grid cells. As bilinear interpolation requires four surrounding data points and many dives were situated along the coastline, to calculate the interpolated value, the inverse distance weighted interpolation function from the Akima package (Gebhardt, 2020) was used.

'TEMPERSEA' (TSEA), a 3-D gridded monthly mean 0.25° by 0.25° in situ data product utilising an optimal interpolation algorithm was used as a reference in situ dataset (Agulles et al. 2020). TSEA has 23 vertical (depth) levels, two within the recreational diving depths of interest in this study (15 and 30 m), plus another one just below, at 50 m. Dive computer data were matched to the TSEA spatial grid at the closest TSEA level below the maximum dive depth, i.e., dive computer data at depths of between 7 and 15 m ($\theta(DC_{15})$) were compared with 15 m TSEA data ($\theta(TSEA_{15})$), from 15 m to 30 m ($\theta(DC_{30})$) were compared with 30 m TSEA data ($\theta(TSEA_{30})$), and between 30 m and 40 m ($\theta(DC_{40})$) with TSEA 50 m ($\theta(TSEA_{50})$). Values did not exist for all grid cell/depth level combinations. If present, the value (mean monthly temperature at that location/depth) was selected for in situ comparison. Plots of θ(DC) vs. θ(sat), θ(DC) vs. θ(TSEA) and θ(sat) vs. θ(TSEA) were created. Bias was calculated as θ(DC) – θ(sat), θ(DC) – θ(TSEA), or θ(sat) – θ(TSEA).

Monthly and weekly (based on day of year) climatologies of the whole region were produced encompassing the entire temporal and geospatial extent of the study ($\overline{\theta}(region)$). For example, to create a monthly climatology, all daily OSTIA data from all years were aggregated by month and average temperatures produced. These provided baseline seasonal patterns. Mean annual, monthly and weekly values were calculated for each data source for comparison. Anomalies from annual means were calculated for each year and data source (DC, sat, TSEA), to ascertain interannual variation. Amplitudes for each dataset were calculated by year, and each depth band by year, by taking the difference between maximum and minimum mean temperature for each subset. Temporal and spatial resolutions for each data source are summarised in Table 3.1.

Table 3.1. Temporal and spatial resolution by data source.

Data source	Temporal resolution	Spatial resolution
θ(DC)	Point	Point
θ(sat)	Daily	0.05° x 0.05°
θ(TSEA)	Monthly mean	0.25° x 0.25°
$\overline{\theta}$(region)	Mean daily	Whole study region

Coastal satellite SST has been found to have poorer agreement with insitu data (Brewin et al. 2017a). Therefore, we investigated whether dive computer temperature correlated better with satellite data away from the coast. We extracted a 10 m resolution shapefile for the Red Sea coastline from a global coastline shapefile (ne_10m_coastline.shp) (Natural Earth). The shortest distance from dive locations to the coastline were calculated using the sf package in R (Pebesma). As the OSTIA data are on a 0.05° grid, approximating 5.5 km at these latitudes, all dive computer points within 11 km of the coast were categorised as coastal and beyond 11 km as offshore, allowing comparisons to be made between biases based on distance from shore.

3.3.4 Statistical approach

The lm function in R (Carchedi et al.) was used to calculate a simple linear regression between each combination of θ(DC), θ(TSEA) and θ(sat). As uncertainty was present in both variables, York regression was applied to subsetted data at monthly and weekly resolutions, using the yorkregression function in R (Lichter and Delgado) and using σ_x and σ_y for each subset as the error value.

Adjusted R^2 ($\hat{R}^2$)(was calculated using the Wherry formula 1 as defined by Yin and Fan (Yin and Fan, 2010) (Eq.1) where N is the sample size, p is the number of predictor variables and R is the sample multiple correlation coefficient:

$$\hat{R}^2 = 1 - \frac{N-1}{N-p-1}\,(1 - R^2) \quad (1)$$

3.4 Results

A total of 9310 records with co-located values for θ(DC), θ(TSEA) and θ(sat) were identified (Fig. 2). Simple linear regression of θ(sat) vs. θ(DC) (intercept= 1.33, slope = 0.93, $\hat{R}^2$= 0.78, p = <0.001), θ(TSEA) vs. θ(DC) (intercept= -0.5, slope = 1.01, $\hat{R}^2$= 0.65, p = <0.001) and θ(sat) vs. θ(TSEA) (intercept= 6.99, slope = 0.72, $\hat{R}^2$= 0.74, p = <0.001) (Fig. 3) found θ(sat) and θ(TSEA) respectively explained 78 % and 65 % of the variation in θ(DC). Mean timeseries bias was (-0.5±1.1) °C for θ(DC) – θ(sat), (–0.2±1.4) °C for θ(DC) – θ(TSEA), and (0.3±1.1) °C for θ(sat) – θ(TSEA).

Dive computer resolution is limited to integers in many models. This is seen in the predominance of dive computer temperatures at integer values in Fig. 3.3. Mean annual SST amplitude was (6.5±1.0) °C for θ(sat). Annual temperature amplitude was comparable for $\theta(DC_{15})$ at (6.8±1.2) °C, and $\theta(TSEA_{15})$ (6.2±0.7) °C.

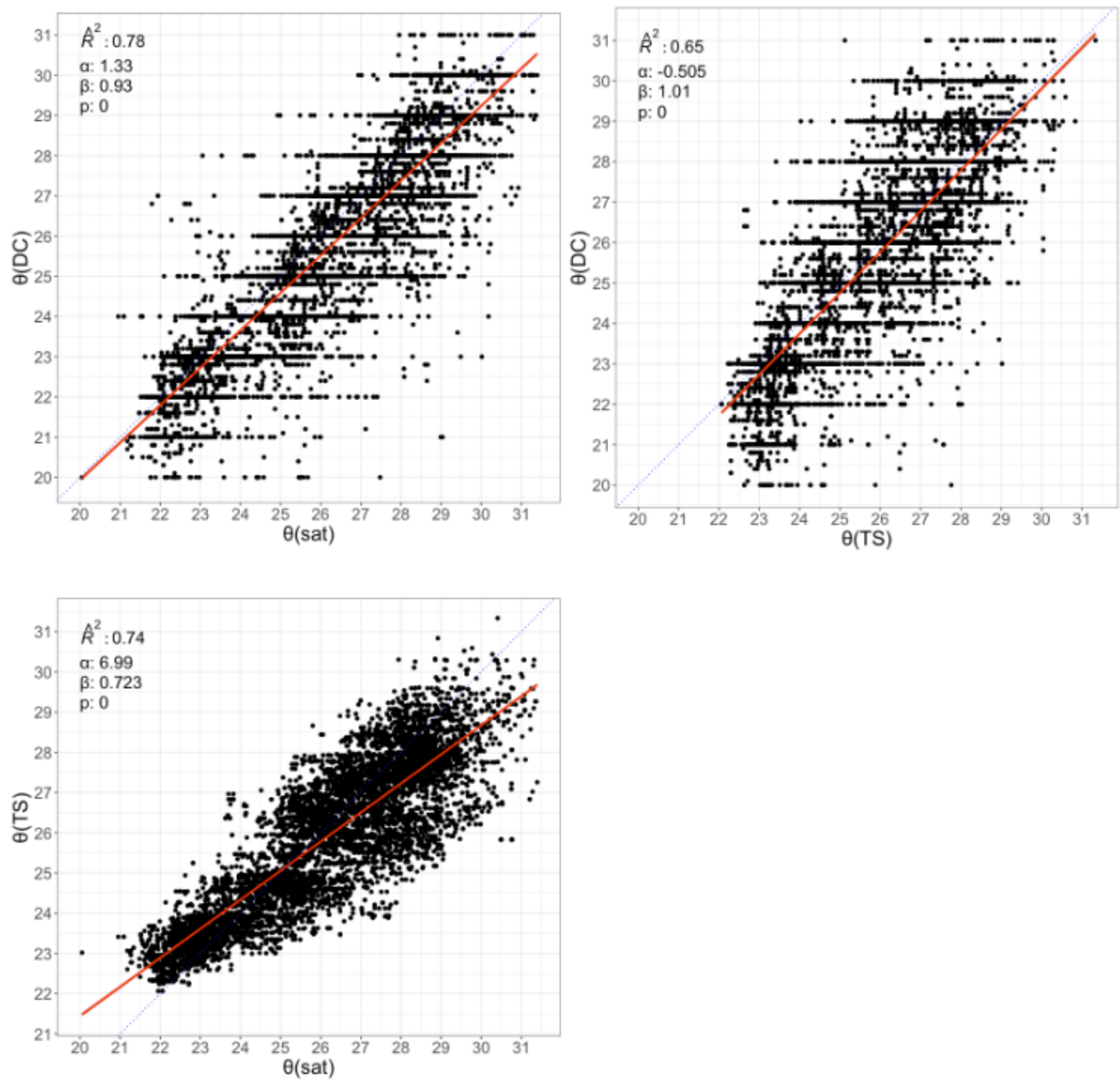


Fig. 3.3 Scatterplot of retained dives (n = 9310). a) θ(sat) vs. θ(DC), b) θ(TSEA) vs. θ(DC), c) θ(sat) vs. θ(TSEA). Linear regression is solid line, dotted line is 1:1 (included as a visual aid).

3.4.1 Monthly resolution

York regression on mean monthly bias found $\hat{R}^2$was comparable across all three comparison datasets (Fig. 3.4).

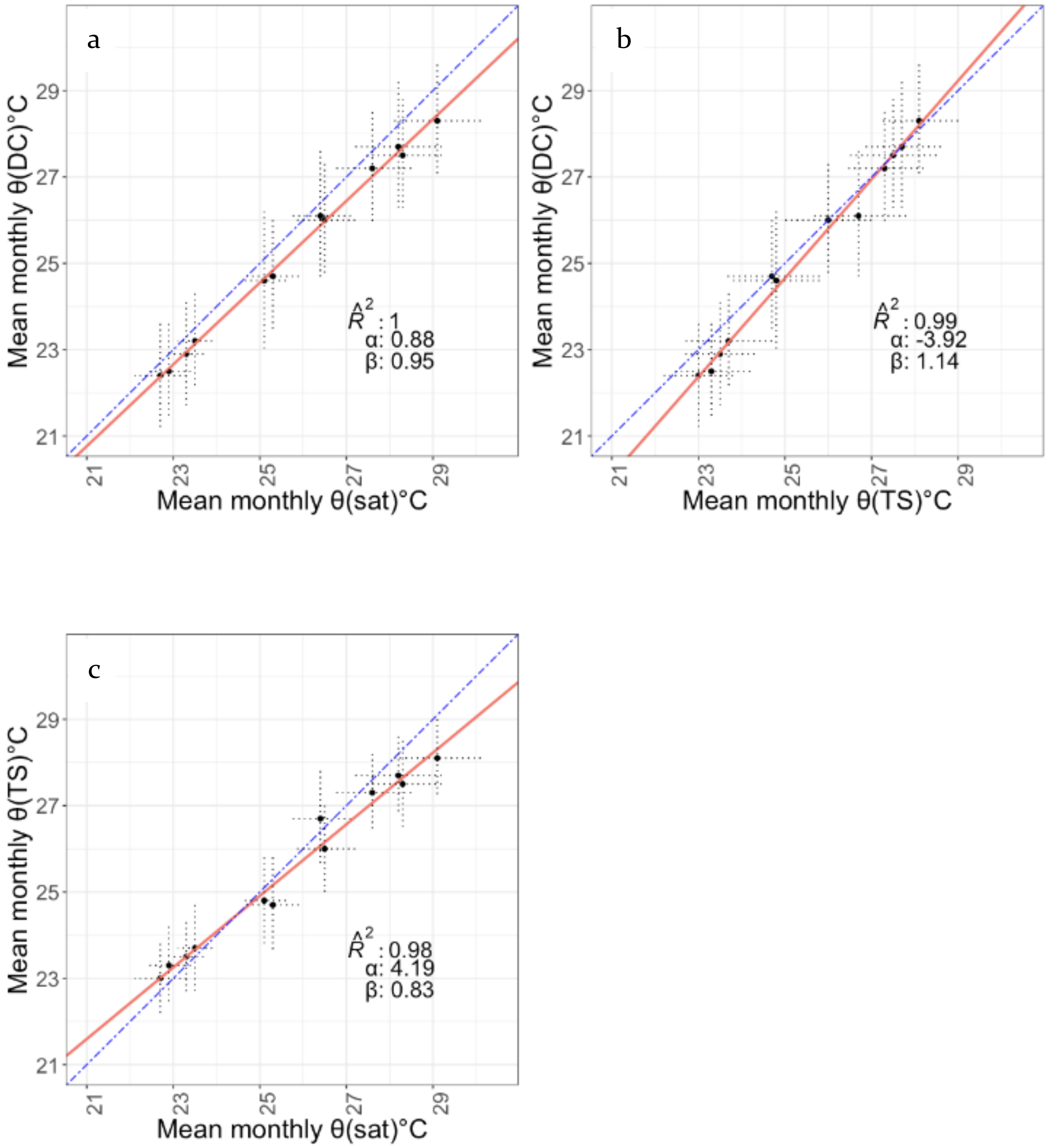


Fig. 3.4. Solid line shows York regression on mean monthly temperature for a) θ(sat) - θ(DC), b) θ(TSEA) - θ(DC) and c) θ(sat) - θ(TSEA), showing intercept α, slope β and $\hat{R}^2$. Dashed line is 1:1. Error bars are standard deviation for a given month / dataset, across all years.

Bias for all three monthly timeseries is shown in Fig. 3.5. The mean maximum depth across all months was consistent at (22.5±1.0) m. The highest biases for θ(DC) – θ(sat) and for θ(sat) – θ(TSEA) were seen in July and August (Fig's 3.5a and 3.5c). θ(DC) – θ(sat) bias ranged from (−0.2±1.0) °C in February to (−0.8±1.2) °C in July and August (Fig. 3.5a). θ(DC) – θ(TSEA) bias ranged from (-0.7±0.9) °C in March to

(0.0±1.2) °C in May. Absolute mean bias ≤ 0.1 °C was found between May and October (Fig. 3.5b). θ(sat) – θ(TSEA) bias ranged from (-0.4±0.7) °C in March to (1.0±1.3) °C in August, with absolute mean bias ≤ 0.4 °C found between October and April and in June (Fig. 3.5c). Mean monthly temperatures for all data sources show seasonal patterns consistent with those seen in the regional climatology. Seasonal patterns can be seen in overall mean monthly data for each data source, and also individual years (Fig. 3.6)

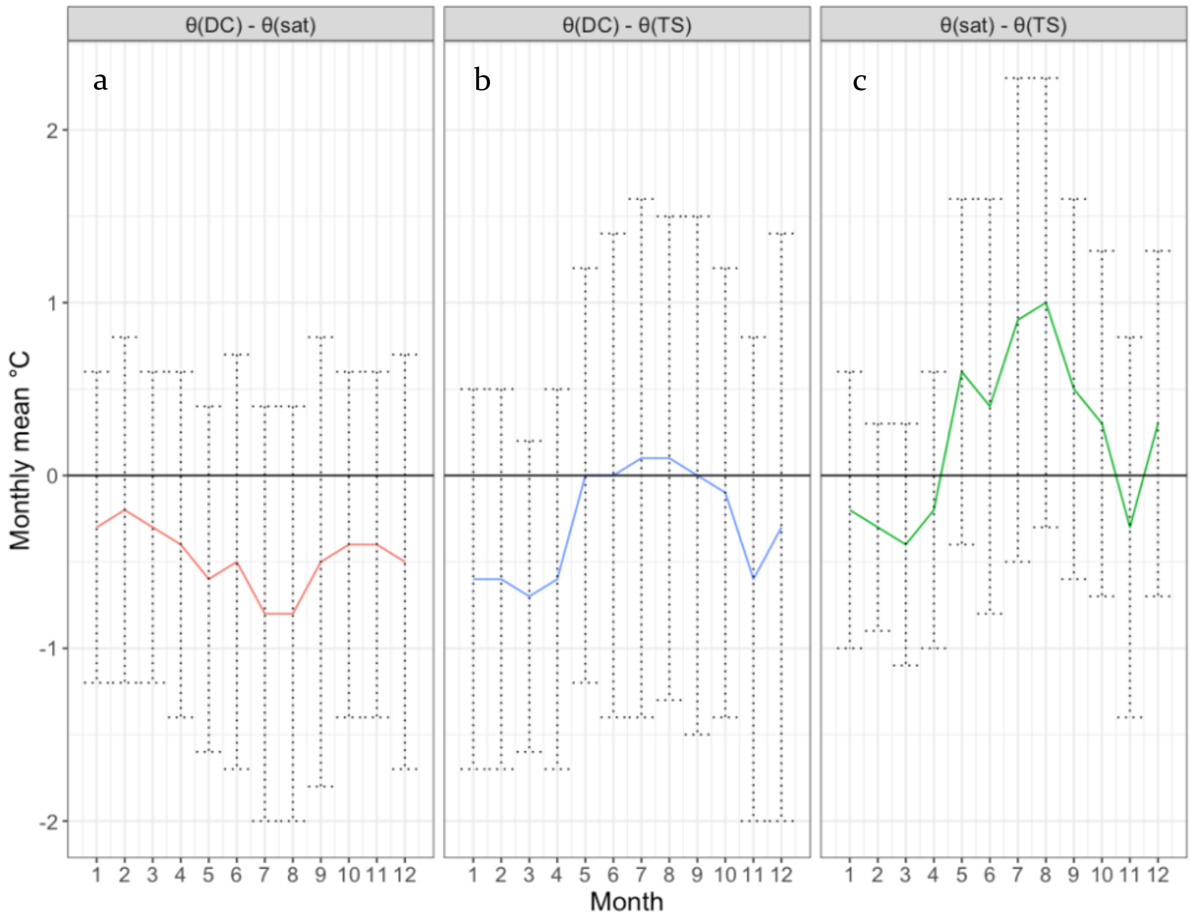


Fig. 3.5. a) θ(DC) - θ(sat), b) θ(DC) - θ(TSEA) and c) θ(sat) - θ(TSEA) bias by month. Error bars show standard deviation for a given month / dataset, across all years.

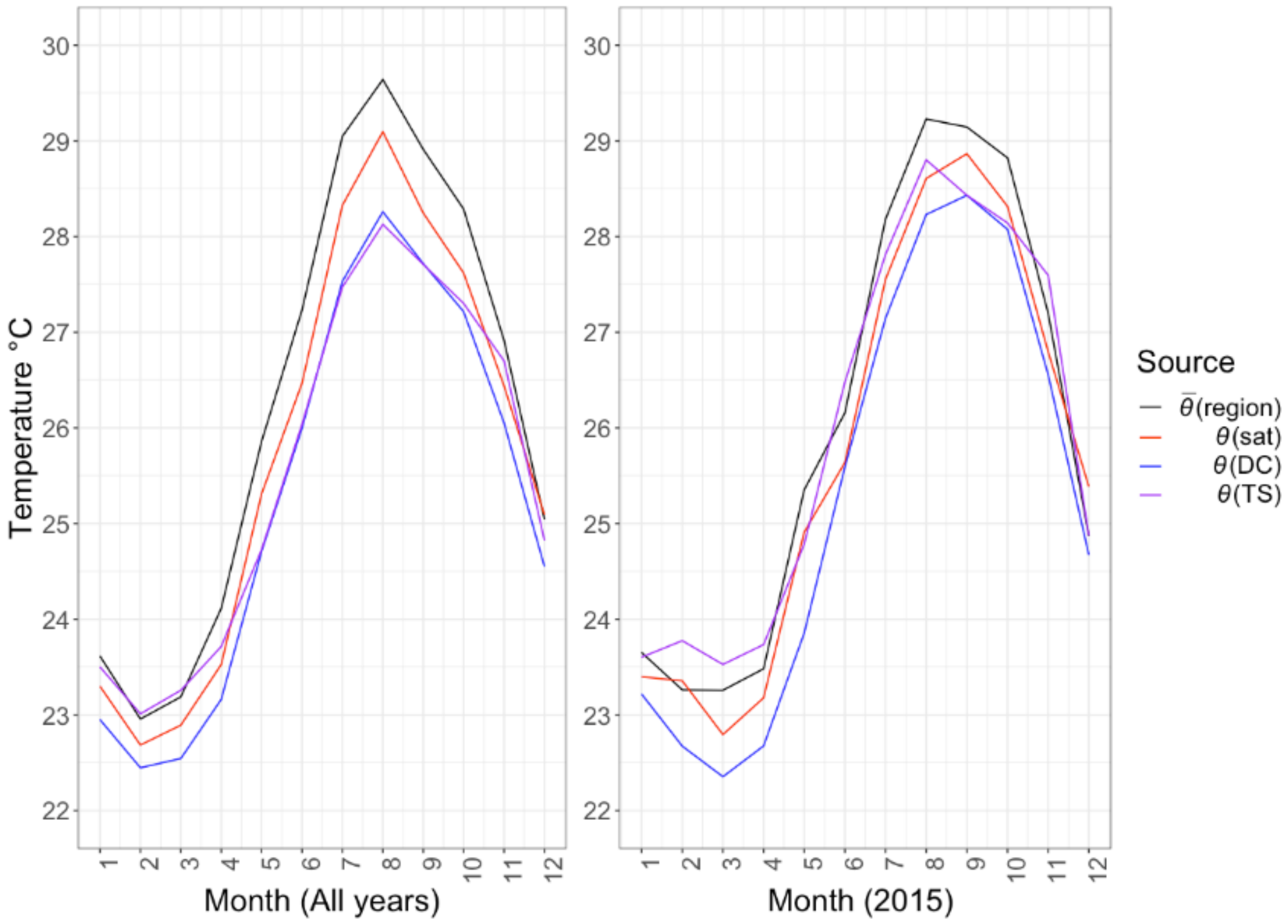


Fig. 3.6. Mean monthly temperatures for θ(DC), θ(sat) and θ(TSEA) with $\bar{\theta}$(region) for a) all years, b) for an example year (2015)

We also explored bias on a weekly basis, with the same patterns of relative differences observed (see supporting information).

3.4.2 Interannual variation

All-year mean temperatures were (25.1 ±2.2) °C (θ(DC)), (25.7±2.3) °C (θ(sat)) and (25.5±1.8) °C (θ(TSEA)). The annual mean temperature anomalies (annual mean data compared with all-year mean temperature) show consistency (Fig. 3.7). 2003, 2010 and 2016 were warm years across all three timeseries, with 2010 being the warmest ($\bar{\theta}(region)$) year of our study period at (27.1±2.3) °C. This is reflected in θ(DC) and θ(sat), where highest mean annual temperature is also seen for 2010 (θ(DC) = (26±2)

°C, θ(sat) = (26.0±2.1) °C). In contrast, although θ(TSEA) shows 2010 as a warm year at (25.6±1.7) ºC, it is only equal third warmest.

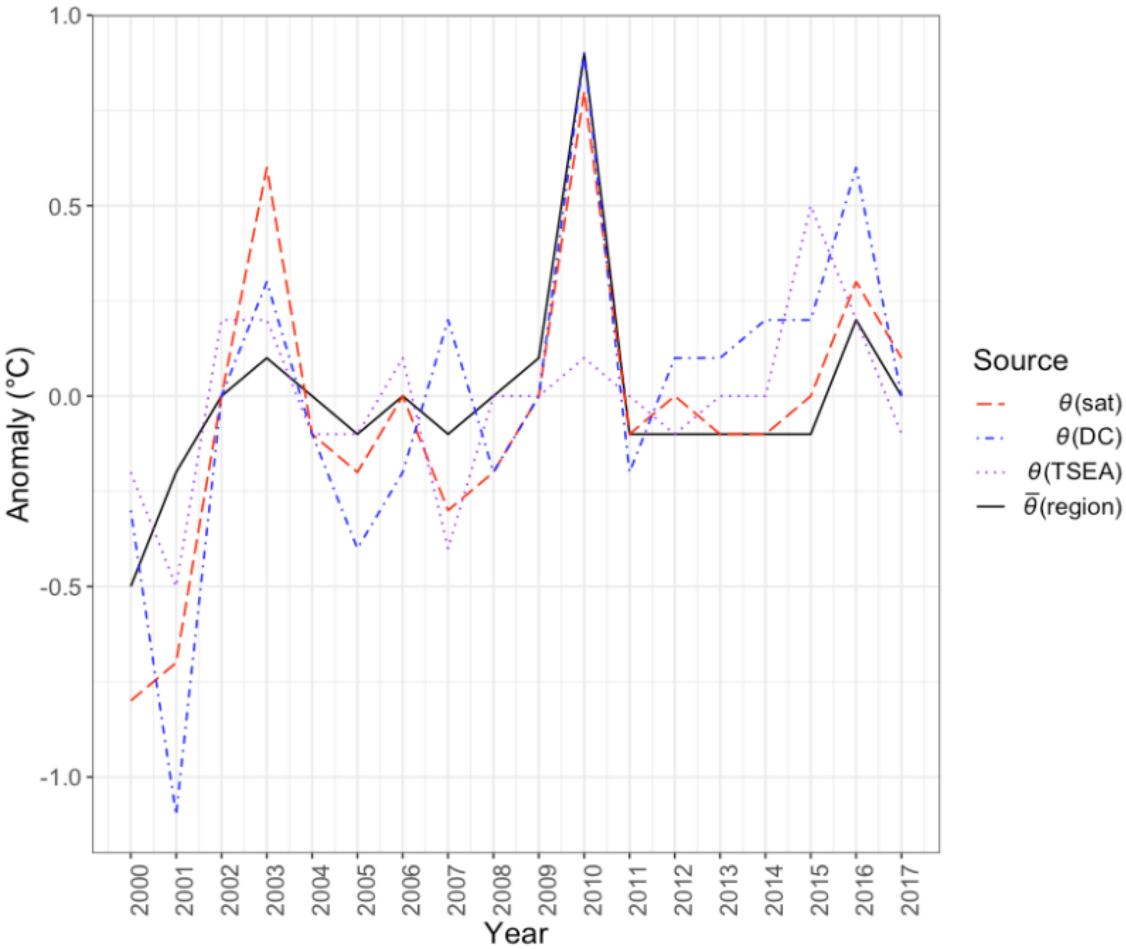


Fig. 3.7. Interannual variation in anomalies from mean θ(DC), θ(sat) and θ(TSEA). Red denotes years that are warmer than average (for the data source) and blue cooler than average.

Months with unusually large anomalies are also comparable across timeseries; for example, the warmest November is 2010 for both θ(sat) (1.5 °C anomaly) and θ(DC) (1.8 °C anomaly), but for θ(TSEA), November 2010 was equal third warmest, with no anomaly from average November temperature.

3.4.3 Latitude bands

In addition to assessing the representativeness of the dataset by comparison with the regional climatology, geospatial and depth effects were investigated. Mean θ(DC), θ(sat) and θ(TSEA) temperature all decreased northwards, except from 28–29° N to 29–30° N (Table 3.2). Mean θ(DC) – θ(sat) bias ranged from (-0.6±1.0) °C for 23–24° N to (1.1±0.8) °C for 29–30° N, but with bias of –0.6 °C or smaller in the five most southerly bands (Table 3.2). Mean θ(DC) – θ(TSEA) bias followed a similar pattern, turning increasingly negative northwards, except for the most northerly band (Table 3.2). Mean θ(sat) – θ(TSEA) bias ranged between (-1.2±0.8) °C for 29–30° N and (0.8±1.3) °C for 24–25° N, with smaller absolute bias in the 25–28° bands.

Table 3.2. Mean temperature and bias (θ(DC) - θ(sat), θ(DC) - θ(TSEA) and θ(sat) - θ(TSEA) by latitude band.

Latitude band	**θ(DC) / °C**	**θ(sat)/ °C**	**θ(TSEA) / °C**	**θ(DC) - θ(sat)**	**θ(DC) - θ(TSEA)**	**θ(sat) - θ(TSEA)**	**n**
				Bias / °C	**Bias / °C**	**Bias / °C**	
23–24° N	27.0±2.4	27.6±2.1	26.9±2.0	-0.6±1.0	0.1±1.4	0.7±1.2	602
24–25° N	26.3±2.4	26.9±2.3	26.2±1.9	-0.6±1.3	0.1±1.5	0.8±1.3	1287
25–26° N	25.9±2.5	26.0±2.3	26.2±2.0	-0.2±1.1	-0.3±1.3	-0.1±1.0	887
26–27° N	25.6±2.2	26.0±2.0	25.8±1.7	-0.5±1.1	-0.3±1.3	0.2±1.0	3292
27–28° N	25.2±2.2	25.7±2.1	25.6±1.8	-0.5±1.1	-0.4±1.3	0.1±1.0	3158
28–29° N	24.1±2.0	24.1±2.0	24.9±1.7	0.0±1.4	-0.8±1.3	-0.8±1.0	55
29–30° N	26.4±1.4	25.3±1.6	26.5±1.2	1.1±0.8	-0.1±0.5	-1.2±0.8	29

3.4.4 Distance from coast

When categorised into coastal (≤ 11 km) or offshore (>11 km) by distance from the coastline, θ(DC) – θ(sat) mean bias was similar for coast and offshore: (-0.6±1.1) vs (-0.5±1.1) °C. θ(DC) – θ(TSEA) bias was smaller offshore by 0.3 °C and θ(sat) – θ(TSEA) was 0.5 °C larger offshore (Table 3.3). When depth level is included in coastal comparisons, all three data sources showed consistent patterns in direction of temperature bias irrespective of the coastal/offshore category (Table 3.3). Mean DC depths in the levels (15, 30, 40) m were comparable: (12.6, 21.8, 33.4) m for the coastal dives and (12.7, 23.5, 34.7) m offshore. All biases were 0.1 to 0.3 °C greater offshore, with the exception of $\theta(DC_{30})$ - $\theta(TSEA_{30})$ which had a 0.2 °C smaller offshore bias.

Table 3.3. Mean bias by depth level and coastal grouping.

Measure	**Coast / °C**	**Offshore / °C**	**Difference / °C**
θ(DC) - θ(sat)	-0.5±1.1	-0.6±1.1	0.1
θ(DC) - θ(TSEA)	-0.3±1.3	-0.0±1.5	-0.3
θ(sat) - θ(TSEA)	-0.1±1.0	-0.6±1.3	0.5
$\theta(DC_{15})$ - θ(sat)	-0.3±1	-0.5±1.1	0.2
$\theta(DC_{30})$ - θ(sat)	-0.5±1.1	-0.5±1.1	0.0
$\theta(DC_{40})$ - θ(sat)	-0.7±1.2	-0.8±1.2	0.1
$\theta(DC_{15})$ - $\theta(TSEA_{15})$	-0.6±1.2	-0.9±1.4	0.3
$\theta(DC_{30})$ - $\theta(TSEA_{30})$	-0.4±1.3	-0.2±1.3	-0.2
$\theta(DC_{40})$ - $\theta(TSEA_{50})$	0.4±1.4	0.5±1.6	0.1
θ(sat) - $\theta(TSEA_{15})$	-0.3±0.8	-0.4±0.9	0.1
θ(sat) - $\theta(TSEA_{30})$	0.1±0.9	0.3±1	0.2
θ(sat) - $\theta(TSEA_{50})$	1.2±1.2	1.3±1.4	0.1

3.4.5 Vertical resolution

The mean DC depth was 12.6 m for $\theta(DC_{15})$, 22.2 m for $\theta(DC_{30})$, and 34.2 m for $\theta(DC_{40})$. When considered in isolation (not including temporal or spatial factors), mean θ(DC) was consistent irrespective of depth: (25.4±2.3) °C for $\theta(DC_{15})$, (25.7±2.3) °C for $\theta(DC_{30})$ and $\theta(DC_{40})$. Although θ(sat) is a foundation temperature and therefore does not have depth level variation, local temperature of the dives will be affected by spatial factors, so it is still a useful comparison, for example, mean comparison satellite temperature was 0.8 °C colder for $\theta(DC_{15})$ dives (θ(sat) = (25.7±2.2) °C) than $\theta(DC_{40})$ (θ(sat) = (26.5±2.2) °C). Mean $\theta(TSEA_{15})$ °C was (26.1±2.1) °C, reducing to (25.2±1.3) °C for $\theta(TSEA_{50})$. As depth increased, θ(DC) cooled compared with θ(sat) and both θ(DC) and θ(sat) became warmer in comparison with θ(TSEA)) (Table 3.4, Fig. 3.8).

Table 3.4. Mean DC depth, temperature and bias by depth band for θ(DC), θ(sat) & θ(TSEA).

Depth band	**Mean DC depth / m**	**Mean θ(DC) / °C**	**Mean θ(sat) °C**	**Mean θ(TSEA) °C**	**θ(DC) - θ(sat) °C**	**θ(DC) - θ(TSEA) °C**	**θ(sat) - θ(TSEA) / °C**
$\theta(DC_{15})$	12.6	25.4±2.3	25.7±2.2	26.1±2.1	-0.3±1	-0.7±1.2	-0.4±0.8
$\theta(DC_{30})$	22.2	25.7±2.3	26.2±2.2	26.0±1.9	-0.5±1.1	-0.3±1.3	0.1±0.9
$\theta(DC_{40})$	34.2	25.7±2.3	26.5±2.2	25.2±1.3	-0.8±1.2	0.5±1.5	1.2±1.3

When taking depth level into account in combination with month, the mean bias shows a clear impact of depth (Table S1, Fig. 3.8). θ(DC) – θ(sat) bias is negative across all θ(DC) depths. All θ(DC) – θ(TSEA) biases are negative except for $\theta(DC_{40})$ - $\theta(TSEA_{50})$ between May and October (Fig. 11). All θ(sat) – $\theta(TSEA_{15})$ and θ(sat) – $\theta(TSEA_{30})$ month biases are negative (θ(sat) < θ(TSEA) °C) except December (θ(sat) – $\theta(TSEA_{15|30})$), May and October (θ(sat) – $\theta(TSEA_{30})$). All θ(sat) – $\theta(TSEA_{50})$, biases are positive except February.

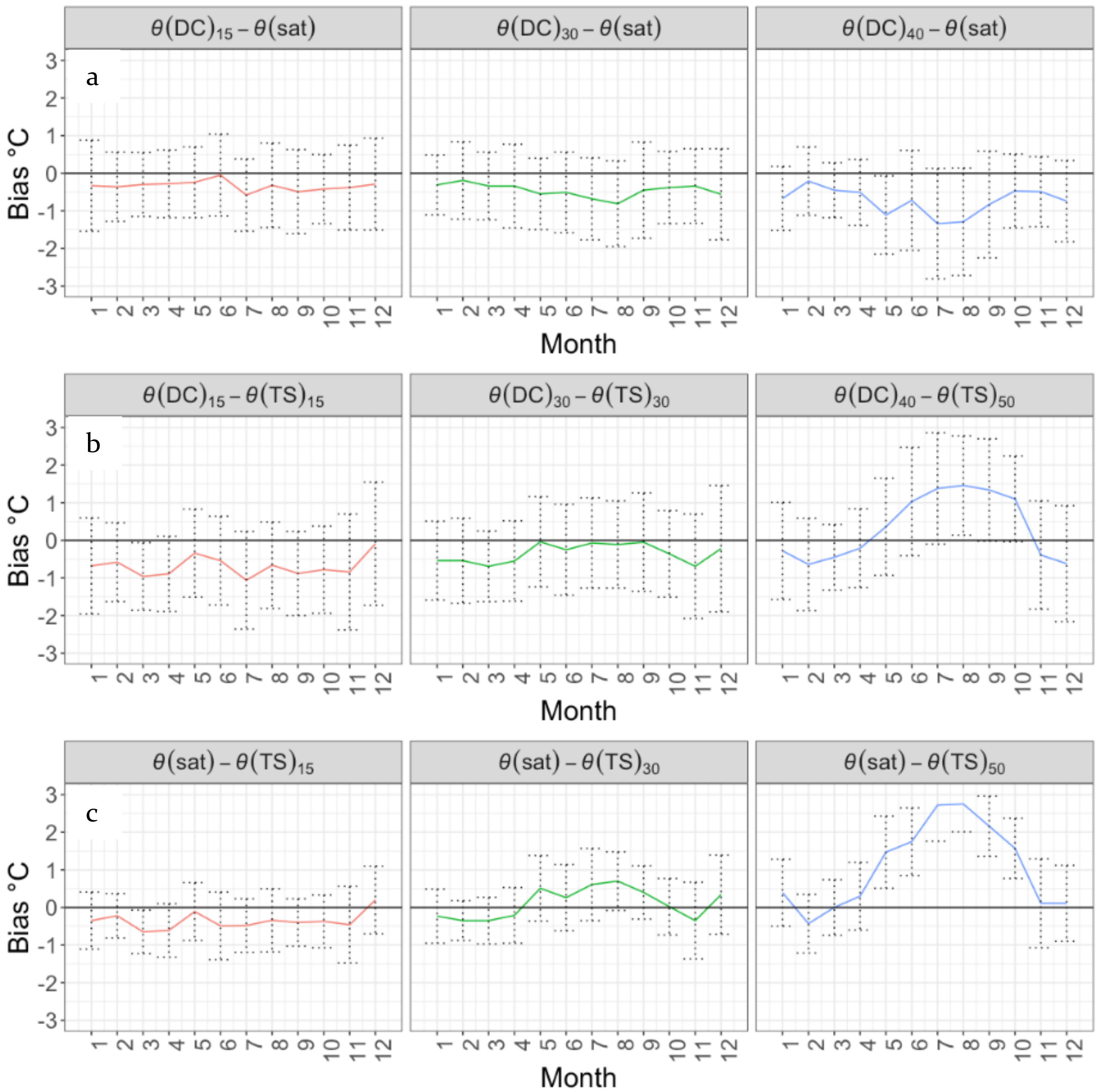


Fig. 3.8. Mean bias by depth and month for a) θ(DC) - θ(sat), b) θ(DC) - θ(TSEA), c) θ(sat) - θ(TSEA)

3.4.6 Group size

To ascertain the number of dive samples required for consistent results, an approach based on a random fraction of samples per year was used. Analysis was run on random samples of different sample fractions (75, 50, 25, 10 and 1 %). This generated sample sizes of 6982, 4655, 2328, 931 and 93, respectively. Mean θ(DC) vs. θ(sat) bias remained consistent at (-0.5±1.1) °C at all sample sizes down to 1 % (-0.8±1.2) °C. Similarly, θ(DC) vs. θ(TSEA) bias remained consistent with biases of (-0.2±1.4) °C at all sample sizes down to 1 % (-0.6±1.5) °C. To check for consistency, from a bootstrap of 50 iterations of 1 % (n_{dives} = 93), 36/50 absolute mean biases (θ(DC) - θ(sat)) were ≤0.5 °C, with the remaining 14/50 (≥ 0.5 ≤ 8) °C. 45/50 absolute mean biases (θ(DC) - θ(TSEA)) were ≤0.5 °C with 5/50 (≥ 0.6 ≤ 8) °C. For (θ(sat) - θ(TSEA)) 45/50 absolute mean biases were ≤0.5 °C with 5/50 (< 0.7) °C.

3.5 Discussion

The Red Sea has a pronounced seasonal temperature cycle (Al-Subhi and Al-Aqsum 2008). This study utilised a 17-year non-continuous timeseries of in situ and satellite sea temperature data, investigating the potential for temperature data from citizen science logged dives to contribute useful ocean temperatures. We found that temperature data from dive computers can be used to derive interannual patterns in temperature change, and seasonal temperature cycles at monthly and weekly resolutions. These patterns, in agreement with satellite-derived climatology, are consistently seen in timeseries of biases for θ(DC) - θ(sat), θ(DC) - θ(TSEA) and θ(sat) - θ(TSEA). The overall mean θ(DC) - θ(sat) bias of (−0.5±1.1) °C is comparable to the result of Woo and Park (Woo and Park, 2020) who found consistent warm bias in coastal SST of over 0.3 °C in coastal regions when compared with in situ data from buoys, but is in contrast to studies in other areas where a 0.3 °C cool bias in satellite SST was found (Baldock et al. 2014).

3.5.1 Temporal resolution

The overall mean maximum depth of dives was consistent across months at (22.5±1) m. The mixed layer depth (MLD) of the northern Red Sea shows monthly variations (Eladawy et al. 2017). In winter, surface cooling forces convection and a subsequent deepening of the MLD, leading to uniform temperatures around 22 °C (Yao et al. 2014). In summer, surface warming increases SST to over 28 °C, with a coincident reduction of MLD. When surface temperatures are warmest, poorest θ(sat) vs. θ(DC) and greater θ(DC) vs. θ(TSEA) agreement is seen, indicating shallower MLD and increased stratification leading to greater variation in water temperature. This agrees with the MLD climatology (Fig. 3.9); depending on month and latitude, MLD varies from < 20 m to > 80 m, with shallow mean MLDs (< 25 m) in our latitude range mainly observed between April and September (Abdulla et al. 2018). The difference in biases seen by month, in agreement with varying MLD values, demonstrates the importance of depth-resolved data and the potential value dive computers an bring by giving insight into local conditions at depth which is not possible to gather with just sea surface temperature or an interpolated monthly in situ value. Dive durations are unknown, but a likely contributing factor to increased variance in summer months is device heating due to solar radiation prior to the dive.

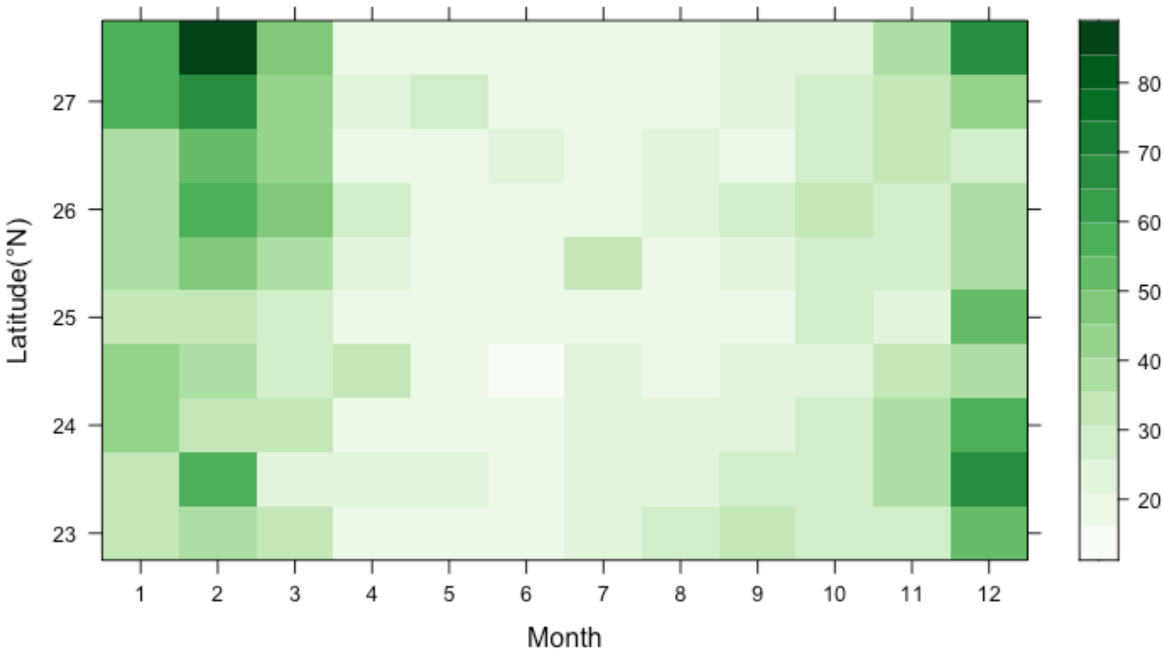


Fig. 3.9. Mixed layer depth by month and latitude (Abdulla 2018)

At a weekly resolution, comparable seasonal patterns are observed (Fig. S2). As with monthly comparisons, larger θ(DC) - θ(sat) biases are seen in the summer weeks when surface temperatures are higher and MLD shallower. The reduced consistency in θ(DC) - θ(TSEA) bias seen at weekly resolution is expected as θ(TSEA) has only monthly resolution. θ(sat) interannual variation was largely in agreement with Karnauskas and Jones (2018), with largest SST variations seen in winter. Berman et al. (2003) found a mean surface temperature summer-winter difference of 6 °C. We found amplitudes of 6.4 °C (θ(DC)), 6.5 °C (θ(sat)) and 5 °C (θ(TSEA), amplitude decreasing with increased depth). This consistency is another demonstrable instance of dive computers producing comparable data to that from more commonly used sources.

3.5.2 Spatial differences

$\overline{\theta}$*(region)* is composed of data across the entire spatial and temporal bounds of the study. Comparing the time series with climatology of the whole region gives insight into seasonal pattern expectations and agreement. The Red Sea is known to display a strong latitudinal temperature gradient from south to north (Chaidez et al., 2017), and a weaker zonal gradient in the north, with eastern monthly mean surface temperatures 0.3 °C higher than the western side (Al-Subhi and Taqi, 2014; Alraddadi et al. 2021). As most dives in our dataset are located near the western coast, this will contribute to the observed bias with the regional climatology (Fig. 3.6; Fig. 3.8). Inspecting latitude bands, we see good spatial agreement, with the latitudinal south – north cooling trend observable in the mean temperatures by latitude band in all datasets, with the consistent exception of the most northerly band. This inconsistency is likely attributable to the small n_{dives} in this band (n = 29).

Satellite SST is purported to have poorer accuracy close to coastlines (Ricciardulli and Wentz, 2004; Smit et al. 2013). As such we would expect to see greater deviation from θ(DC) in data categorised as coastal, but instead see a marginally greater negative bias (-0.1 °C) in the offshore data. However, a L4 analysis product was used as comparison SST, to provide a gap-free dataset. L4 products incorporate data from drifting buoys (E.U. Copernicus Marine Service Information, 2020), to compensate for satellite error, minimising coastal inaccuracies.

3.5.3 Group size

Reducing n_{dives} by random sampling to 1 % of the initial 9310 dives (i.e., 93 dives) did not affect mean bias, standard deviation or $\hat{R}^2$ values. However, when increasing the granularity by encompassing multiple categories (such as to week by depth level), the number of points reduce to low numbers and the relative importance of the different explanatory variables are less clear. Despite noisy data, significant information about trends is seen, therefore in areas where there are few in situ data alternatives available, small datasets may still offer trend information if care is taken.

3.5.4 Representativeness of data

Representativeness of data is not as simple as merely sample size; individual device factors need to be considered. Drift can occur in forecasting systems as well as citizen science datasets, but sensors utilised for monitoring are usually regularly recalibrated (Bell et al. 2013). Dive computers are not calibrated (after purchase) and use piezoelectric sensors, which are known to drift over time (Otmani et al. 2011). If large volumes of data are collected in a small area from an individual device which has drifted, or has a large systematic bias, overall bias may be seen in the data. In the dataset there are examples of a pattern of morning and afternoon dives, consistent with that of a diving holiday (for example, 10 dives over 5 days), all with a θ(DC) - θ(sat) bias (-5.1±0.2) °C. In the above example (10 dives in September 2001) a corresponding monthly bias is seen; September 2001 was the coldest September instance for θ(DC) (mean = 24.4) °C, in contrast to both θ(TSEA) and θ(sat) where it was not in the coolest 6 years, and had a mean temperature of 27.7 °C. If a diver is extremely active in logging dives in a particular area, care needs to be taken if there are only a small number of dives logged from other devices. By carrying out regular simple calibration in an ice bucket (Wright et al. 2016), an indication of device bias, and any change over time, could be collected.

3.5.5 Relevance for data usage: local monitoring

Between 1982 and 2006 the Red Sea experienced warming SST at 5.5 times the global change (Belkin, 2009), but temperature measurement is not straightforward. While Argo floats are commonly used to gather in situ temperature/depth profiles, there are few cycles recorded in the Red Sea, with only 1615 cycles recorded between 2001 and 2021 (Argo 2021), presumably as the single narrow entry point at the Strait of

Bab al Mandeb limits their ingress. Mean differences of 0.5 °C have been found between satellite-derived SST products in the Red Sea (Karnauskas and Jones, 2018). Regional variation in coral mortality is affected by local differences in physical parameters (Moore et al. 2012) and Davis et al. (2011) found daily variations ranging from 0.5 °C to >5 °C on shallow Red Sea reefs, depending on the level of protection from waves. As such, micro level data are essential to monitor ambient temperature variation, and its influence on corals and other ecosystem processes (Baldock et al. 2014). With consistent biases being seen between all three datasets at different depths, our findings agree with Colin and Shaun Johnston (2020), identifying depth-resolved temperature differences which are not captured by satellite data. Dive computers therefore are interesting for their potential to provide depth resolved data as they are not limited to nominal depths like sea-surface (satellite) or a fixed depth (in situ sensor). They can offer a valuable additional layer of information at a micro level, to complement data from other sources. Utilising the potential volumes of data that could be available in the highly dived areas of the Red Sea, long term time series could be collated to support monitoring of important corals and their surrounding ecosystems.

3.5.6 Practical considerations for dive computer accuracy

Most dive computer models do not have GPS functionality, which introduces potential error in any user recorded coordinates. If a position is recorded to the nearest 0.01° longitude/latitude, the accuracy will be approximately 1 km. The satellite SST grid used here is 0.05°, equivalent to 5.5 km. In addition, the coordinates of the most frequently dived sites are well documented online. Many divers will note the reef or wreck name at the time of dive, looking up coordinates later when back on dry land. In these instances, the potential risk for dive to be recorded at a location greater than 5 km from the actual location is considered small. In less well documented areas, GPS coordinates should be carefully recorded at the start or end of the dive using a GPS tracker or mobile.

Dive computers record time and date, but some require these to be changed manually. If divers travel into a different time zone, and divers do not do this, data are potentially recorded at the wrong time of day. For the purposes of this study, this should not cause an issue because the comparison foundation temperature reflects pre-dawn values. However, a citizen science project would need to consider this where daily variation in temperature is relevant, such as a reef ecosystem. With sufficient data and accurate metadata (such as time zone) from dive computers, in areas with sufficiently large diurnal variation, it could also be possible to gather insight into this variation. By collecting longer term time series of dive computer data, the demonstrated ability to identify anomalously hot or cold periods will become another a valuable source of historical data available for comparison with other biological datasets.

The MS5803-14BA pressure sensor (TE Connectivity, 2017), which is commonly used in dive computers, has sufficient resolution (<0.01) °C to offer improved temperature recording, especially in those models which currently only record temperature in integer intervals. Dive computer models have time constants (time to adjust to 63% total temperature change) ranging between 17 and 300 seconds (Marlowe et al. 2021), which affects the time taken to equilibrate to ambient temperature. In areas of high air temperature, this risks artificially high temperatures being recorded because of surface heating of the device. Knowing the duration of each dive would allow either removal of dives of less than 5 minutes (which is insufficient time to equilibrate to ambient water temperature for some models with slower response time) or based on a known time constant for the model.

Subject to data storage capacity, improving the recorded resolution and recording parameters such as the model and dive duration would ensure that bounce dives or known inaccurate models could be excluded, as features such housing material and pressure sensor location are known to be significant for bias (Marlowe et al. 2021). These would allow better quality control of a dataset and maximise future potential for using dive computers for temperature monitoring. Computers are not calibrated instruments and so sensor temperatures may also drift over time, further research would be required in this area.

3.5.7 Uncertainties and requirements for data

Both comparison datasets used in the study have been interpolated, spatially, using weighted algorithms and/or using background data for gap filling. Uncertainty estimates for individual comparison data points in this study are between 0.16 and 1.07 ºC for θ(sat) and between 0.04 and 1.0 °C for θ(TSEA), with the TEMPERSEA dataset having a formal error of 0.31 °C at the surface (Agulles et al. 2020). It is not possible to ascertain the proportion of systematic error in θ(DC) point data from the current dataset and therefore, ad hoc point data is of little use for temperature measurement in isolation. Devices with large bias should still correctly identify seasonal variation, albeit offset. Additionally, the overall absolute mean bias seen of 0.5 °C (θ(DC) - θ(sat)) and 0.2 °C (θ(DC) - θ(TSEA)) are within the specified uncertainty ranges of the comparison datasets, the proportion derived from each component indeterminable.

The requirements for accuracy, spatial and temporal resolution, and acceptable degree of uncertainty for ocean temperature data varies depending on the intended use (National Research Council, 2000). For example, requirements for monitoring of deep ocean sea temperature are stringent at 0.002 °C (Pawlowicz, 2013), but the World Meteorological Organization (World Meteorological Organization, 2020) only requires SST measurements to 0.1 °C. The three themes of the Global Ocean Observing System (GOOS) have requirements more within reach; climate change detection (0.1 °C on 500 km grid at monthly resolution), operational services (e.g., numerical weather prediction: 0.2 – 0.5 °C accuracy at 100 km grid and 3-day resolution) and ecosystem health (0.2 °C daily) (Needler et al., 1999; Kennedy, 2014; Moltmann et al. 2019). The observed biases indicate dive computers can offer data within the required range for numerical weather prediction and ecosystem health analyses. Observations from buoys stratified to weekly, monthly and seasonal resolutions have been used to identify seasonal patterns, interannual variability and climate signals related to ENSO (McPhaden et al. 2010). Buoys have SST resolution and accuracy (0.1±1.0) °C (National Data Buoy Centre) and while overall bias in data collected from unknown models is greater than that, the ability to identify seasonal patterns at different resolutions has clearly been demonstrated, and many dive computer models are known to have comparable resolution and accuracy (Marlowe et al. 2021). Thus, a dataset restricted to dive computers with higher accuracy could be used in comparable ways to buoys.

3.6 Conclusions

Our results clearly demonstrate that dive computers can resolve interannual variations and seasonal patterns of data comparable with OSTIA and insitu data. This can provide a layer of insight at varying depths on a local level, over and above that available from other sources. As depth resolved data is key to monitoring of ecosystem processes, we suggest that a database of temperature data derived from SCUBA diver citizen scientists can deliver viable data to complement existing datasets. The consistency between the bias found for subsamples of the total data demonstrate that the numbers of dives do not need to be in the thousands to be produce useful results, with only around 100 datapoints needed for consistency. Data will be most useful in commonly dived areas, giving greater spatial continuity, but in areas with fewer dives and limited or no other monitoring, patterns of data should still be visible from smaller datasets.

Retrospectively analysing data collected without a research question limits the possible analyses (Hochachka et al. 2012), and these limits were seen with the lack of useful metadata such as model of dive computer or dive duration, which could improve overall analyses. However, despite this lack of information our uncontrolled real-world example gave outputs with absolute bias of 0.5 °C and less, identification of months and years with large anomalies and consistent, comparable seasonal patterns at different scales.

Chapter 4. Diveintoscience.org: an interactive website for citizen science divers

4.1 Chapter summary

The crowdsourcing of data from sensors worn by the public, to inform research, is increasingly common. SCUBA divers commonly wear dive computers, which have been shown to have potential for contributing to ocean monitoring, but data are largely unavailable, or inaccessible, in the dive logs of individual divers. This chapter describes the current knowledge landscape in geospatial online citizen science and the development of an interactive citizen science website for collection of data from dive computers, using the Shiny package in R.

4.2 Introduction

Public participation in scientific research (Bonney et al. 2009a) (commonly referred to as citizen science), is increasingly recognised as a mechanism for gathering volumes of data at temporal and spatial scales that are not possible by other means (Dickinson et al. 2012). The benefits and potential of citizen science have been recognised by governments (Pocock et al. 2014a), the European Union (de Rijck et al. 2020) and the United Nations (Rogers 1995). In their White Paper on Citizen Science for Europe (2015), *Socientize* highlight the need for public engagement, trust and education in designing effective programmes for reform, and state that citizen science should be seen as an integral part of mainstream science activities. Datasets are often difficult to access, many being contained within distinct research projects, or dispersed in small quantities around many independent researchers (Reichman, Jones, and Schildhauer 2011). Data quality is a concern cited in the literature (Bonney et al. 2014; Lukyanenko, Parsons, and Wiersma 2016), but many case studies show that data gathered in a participatory manner can be of equally high-quality as that gathered in a more traditional manner (Vianna et al. 2014; Kosmala et al. 2016; Albus, Thompson, and Mitchell 2019).

4.3 Technology-driven citizen science

Citizen science projects can be contributory, collaborative or co-created (Bonney et al. 2009a), depending on the level and/or manner of public involvement. Most projects falling into the 'contributory' category (Science Communication Unit University of the West of England 2013). Using low-cost or non-traditional sensors (Strigaro, Cannata, and Antonovic 2019) as a complementary source of data for environmental monitoring is an example of a 'crowdsourced' approach (Haklay 2018) to contributory projects. Wearable biosensors (such as electrocardiogram monitors included in smart watches) which record continual time series of physiological parameters (Li et al. 2017) are on the increase. Our ability to gather, share and connect large quantities of data has been revolutionised by the smartphone (Roy et al. 2012; Katapally 2020). Fine scale atmospheric data from smartphones have been utilised to correct bias in surface meteorological-station measurements (Li et al. 2021). In contrast to citizen science projects requiring subject matter expertise such as capturing species presence data, the quality of the data output from crowdsourced sensor projects is largely a function of the underlying sensor capacity, not the capability, knowledge or experience of the wearer, although project design and metadata will play a part.

Environmental conservation is accessible to large groups of people via digital platforms (Sharma et al. 2019). With ever expanding use of and access to the internet, websites are an important communication mechanism (Garett et al. 2016). Projects which require web-based technology achieve this either by the development of their own website or web application (e.g., Birdwatch (RSPB n.d.)) or by hosting on a platform which brings multiple projects together, such as Zooniverse (Aristeidou, Scanlon, and Sharples 2020). There are also sites which collate links to interesting or related projects, such as Scotland's Environment Citizen Science Portal (Scotland's Environment n.d.). The danger of sites with a list of links, is that if not regularly checked, links go out of date and the referring page itself becomes out of date.

The development of geospatial technologies has increased the abundance of environmental data (Zhang 2019). Geo-located web-based activities may range from submission of photos of bees (University of Aberdeen n.d.) to logging roadkill (Projekt Roadkill n.d.). Combined with web technologies, with different degrees of automation, volunteers are able to submit large volumes of spatially defined ecological data from GIS-enabled devices, via the internet, to centralised databases (Dickinson et al. 2012), with data seen as analogous with remote sensing (Thiel et al. 2014). This offers potential in areas where a monitoring network would be prohibitively expensive, or there are other sampling challenges such as inaccessibility (for example the Caribbean or Pacific Islands) (Brewin et al. 2017b). Participants in environmental citizen science have been shown to make better environmental decisions, with citizen science having been described as 'a public good which supports environmental stewardship' by Dickinson et al. (2012). Motivations and personal benefits to participating such as empowerment, greater self-awareness, learning about science and positive mental health impacts have been well documented in the literature (Hartig et al. 2003; Koss and Kingsley 2010; Bratman, Hamilton, and Daily 2012).

4.3.1 Divers as citizen scientists

Dive computers are as ubiquitous as smartphones and biosensing watches in the diving world; the majority of the estimated 6 - 10 million SCUBA divers worldwide wearing one or more (Wright et al. 2016). With sufficient data, dive computers have been found to have an overall mean bias of (−0.2 ± 1.1) °C (Marlowe et al. 2021), offering huge opportunity to contribute to observational datasets, given the potential numbers of available data points worldwide. SCUBA divers are particularly keenly engaged with participating in conservation initiatives (Thiel et al. 2014; Hermoso et al. 2019). The greatest potential for SCUBA divers as citizen scientists is to gather depth-resolved information that is difficult to gather by traditional means (Marlowe et al. 2021), to support the shortfall in available data due to logistical and economic constraints of collection (Wright et al. 2016). Although SCUBA divers are already active in coastal areas, and in conservation projects, and dive computers have been shown to have the potential to contribute to ocean monitoring, most data remain undiscovered and inaccessible in divers' personal computers or logs.

Diver focused initiatives exist which aim to utilise recreational divers for collection of physical parameters, such as Project Baseline (Project Baseline n.d.), an online resource connecting divers and snorkellers with projects in their local areas. Projects include logging a range of underwater observations, which may include water temperature or quality. Paralenz make small diving cameras, which also record geo-located temperature profiles. When users upload their videos to the Paralenz app, the additional oceanographic data is shared, which can contribute to research (Paralenz.com n.d.). Project Hermes is a pilot stage project where recreational divers carry a small GPS enabled device, collecting temperature depth profiles, with the goal to add additional sensors in the future (Cousteau n.d.). However, there is currently no cohesive central database for data derived from citizen science divers. The ideal 'futurescape' would be a collaborative shared database fed into from multiple sources, allowing users to contribute to a local initiative they feel connected to, whilst contributing to a wider global effort.

4.3.2 Diveintoscience (DiS1)

A pre-existing Diveintoscience portal (DiS1) was developed alongside work carried out by Wright et al. (2016), providing simple visualisation of approximately 7500 records collected in 2012. There was no upload or interactivity option, but to contribute, users had to complete a spreadsheet template provided on the site with details of their dives, then email this to the project convenors. This was a barrier to uptake as to manually transfer their data from a logbook to a templated .csv file involved a significant effort on the part of the user.

4.3.3 R Shiny

Shiny is an R package designed to allow users to easily build interactive web apps using R knowledge rather than standard web technologies (Shiny). This can be advantageous to scientists who may already be comfortable working in R.

Shiny is commonly used as a tool for interactive visualisation and manipulation of data, with many apps, including citizen science data websites, easily findable online. The Centre for Ecology and Hydrology, for example, has a website displaying data collected through the Grasshoppers and Allied Species Recording Scheme map (UK Centre for Ecology and Hydrology n.d.) and the California Seagull Frequency and Distribution site (Blasco n.d.) visualises data collected via the eBird project (Cornell Lab of Ornithology n.d.). However, of the sites found, most do not allow direct import of data, but primarily support interactive visualisation of pre-existing data. The Community Water Data Analysis Tool (Anonymous, n.d.) is a free tool built using R and Shiny, providing visualisation tools allowing community-based water quality monitoring initiatives to explore their data. CWDAT includes functionality to upload .csv files but does not save to a data repository in the backend. To the best of our knowledge there are no Shiny based citizen science apps allowing not only visualisation, but collection of user data to add to a back-end database.

4.3.4 Diveintoscience2 (DiS2)

Diveintoscience2 (DiS2) is a website built with the aim to provide a mechanism for recreational divers around the world to anonymously upload temperature/depth profiles from their dive computers. It is developed functionally from a blank slate but is an expansion to the DiS1 website concept. All collected data is open access and freely available for download. By offering a mechanism to collate, store and process data, it is possible to extract information and build greater knowledge of the marine environment, supporting conservation and climate change initiatives.

The aims of DiS2 are to

- Provide a mechanism for people to easily share data from their dive computer profiles, making a meaningful contribution to conservation.
- Allow people to explore the collected data in a manner which is easy and understandable.
- Make data open for anyone to freely access and use.
- Increase the volume of depth resolved ocean temperature data.

This chapter does not aim to discuss in detail methods for developing web development processes or designing citizen science projects, as these are well documented elsewhere (e.g. Burdman 1999; Howcroft and Carroll 2000; Bonney et al. 2009b; Robinson et al. 2019). We describe using the Shiny package in R (RStudio n.d.) to develop a website with the defined purpose of collection of depth-resolved temperature data from SCUBA dive computers. We cover the project history, provide a background context in the use of web technologies, followed by a description of the developed website and under-pinning thought processes. We conclude by discussing benefits and limitations, offering improvements for future research.

4.4 Development of DiS2

4.4.1 Design goals

The original portal (DiS1) had achieved its purpose as a proof-of-concept exercise. However, it was built using code which formed part of a wider system. As such, much of the code was redundant, with no reason for inclusion in the project, making the site hard to interpret. The graphics were dated, with minimal interactivity. As such, the decision was made to develop the DiS2 from scratch. The revised website needed to improve on this in multiple ways; it should be intuitive and simple to use, catering to different audiences' needs (for example, citizen scientist, researcher, policy maker). Requirements were a clean user interface, interactivity (ability to filter and manipulate the data on display), meaningful and clear visualisations, alongside simple upload. Upload needed to allow the input of additional metadata, such as dive computer make and model, and geographic coordinates if these were not present in the dive logs.

Mass participation citizen science projects require simplicity. While websites are generally an example of low-effort participation (Garcia-Soto et al., 2017), as data upload was a feature, it was important to ensure the website was easy to use and accessible, with as few user experience barriers as practically possible. Usability is key, as not only do participants need to be attracted to the website and engaged once they arrive (Vicens, Duch, and Perelló 2018), but high levels of usability lead to improved rates of revisiting (Garett et al. 2016). For DiS2 to be a successful initiative, revisit rates will need to be high.

There are many definitions of web usability (Chen, Germain, and Rorissa 2009), but we consider it here to be an absence of difficulties that users may experience with achieving a particular website goal. Different factors contribute to usability (Lee and Kozar 2012) such as intuitiveness and ease of navigation, short page response times and high-quality, relevant content (Palmer 2002). The relative importance of the usability elements is dictated by the primary purpose of the site (Calongne 2001). Diveintoscience is interdisciplinary by nature, combining the collection elements of hands-on environmental data collection with use of website technology. To provide value to users, increased volumes of data need to be accessible (Iwamoto et al. 2019). Exploration of large datasets and insight into underlying data can be more easily achieved with interactive visualisations (Walker et al. 2020). Visualisation is therefore a key feature of DiS2, with large volumes of data being displayed concurrently, so page load speed is an important factor.

One of the European Citizen Science Association's 10 principles of citizen science is the importance of making project data publicly available (ECSA 2015). Open data are data made available by organisations or individuals for use/re-use or distribution by all, and bring innovation, productivity and economic value (Duvivier 2018). In addition, the more open data are, the greater the societal benefit (Molloy 2011). Easy access and inclusion of metadata is important, with prescribed specifications for comprehensive and consistent description of data (Reichman, Jones, and Schildhauer 2011), including collection mechanism and uncertainties.

4.4.2 Build

DiS2 is built using the Shiny package in R and published via RStudio Connect. R is a statistical programming language commonly used in the sciences. Benefits of using R based web-publishing is that it allows future development by scientists, who may not have web-development skills, to share their data using a language with which they may be more familiar. R also offers out-of-the box easy visualisation and interactivity. The Shiny system architecture separates code relating to the user interface (usually via a file named ui.R) and server logic (server.R) although these can be maintained in a single file should project simplicity allow it. Data or filtering options are primarily via user input into a browser. Shiny is built on a reactive programming model (RStudio n.d.). In simple terms, when the user does something in the browser, reactive sources are affected, and a response is returned in the browser, e.g., a plot is displayed. DiS2 is distinct from other Shiny based citizen science websites in its live file processing, in-line user addition and editing of metadata, and importation into a database.

Users expect websites which are not only usable and functional, but also look appealing. Although out of the box Shiny offers a clear, responsive user interface with intuitive interactivity features, to produce something more aesthetically pleasing in keeping with modern website design, additional Cascading Style Sheets (CSS) knowledge is required.

4.4.3 Landing pop-up

When a user arrives at the site, a pop-up lightbox is automatically displayed (Figure 4.1).

This fulfils multiple purposes:

a) Delivers a call to action, inspiring people with the message that we need their data
b) Quickly summarises why temperature data are important
c) Allows the page to continue loading in the background whilst the user is reading/closing the lightbox

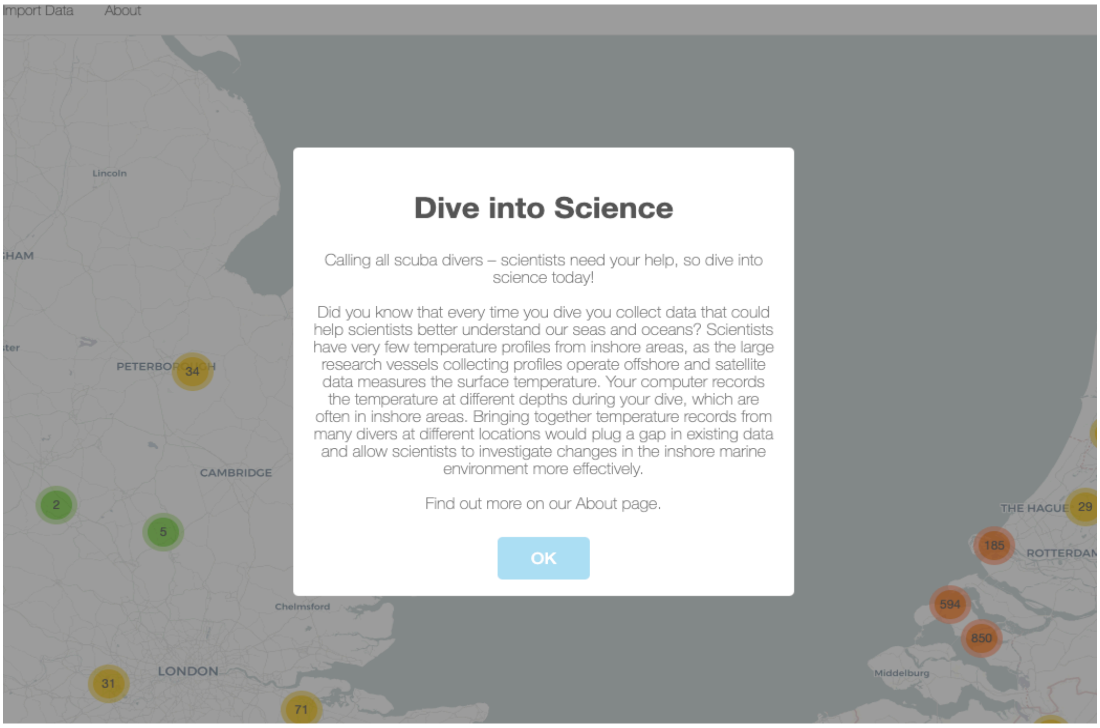


Figure 4.1. Pop-up lightbox displayed as a user arrives at diveintoscience.org.

4.4.4 Site map

Page titles were chosen to facilitate an intuitive understanding either of the underlying content of the page, or the task that can be fulfilled on the page (Dive Map, Import Data, Export Data, About)(Figure 4.2).

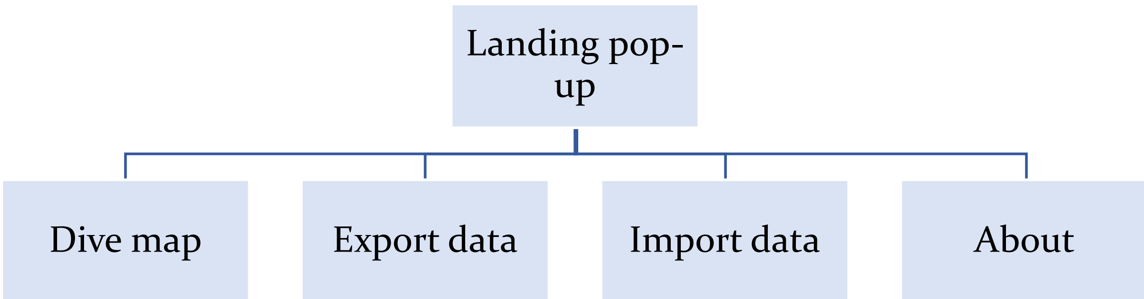


Figure 4.2. Diveintoscience site map

4.4.5 Data

Divelogs.de is a free open access online dive log application. Users can upload their dive logs and chose whether they are able to be seen publicly. Around 89 000 open access temperature data points (individual dives, with associated metadata) were sourced from divelogs.de and used to initially populate Diveintoscience.

4.4.6 Dive map

The landing page of the website consists of an interactive map (Figure 4.3) built using the leaflet package in R (RStudio n.d.). On initial load the map is seen greyed out in the background, behind the previously described popup. The map is centred at a zoom level which facilitates display of a number of dives that gives a usable page load speed. At time of writing this was just under 4000 dives (out of the original 89 000 dives uploaded). If more dives within the map bounds defined by the zoom level (area displayed on the screen) are uploaded by users, then this number will increase. Page load speed will also be impacted by the connectivity speed dictated by the broadband of the user.

In the bottom left-hand corner, multivariate filters enable the user to select which dives are plotted in the current bounds of the map. Filtering between inland and ocean dives, a date range of interest and/or selection of one or several months are allowed in any combination. The user can move the map or zoom to an area of interest using the mouse, trackpad or on screen zoom buttons. A dive is defined as 'Inland' based on intersection with a wrld_simpl spatial dataset (Bivand n.d.) in the R maptools package (Bivand and Lewin-Koh n.d.). wrld_simpl provides simplified country polygons and sf_intersects from the sf package (Pebesma n.d.) is used to ascertain intersection. If there is no intersection between a dive and a polygon, the dive is classified as 'Ocean'. The inland/ocean distinction allows separation of lakes (and potentially swimming pools) from ocean data to assist with analyses.

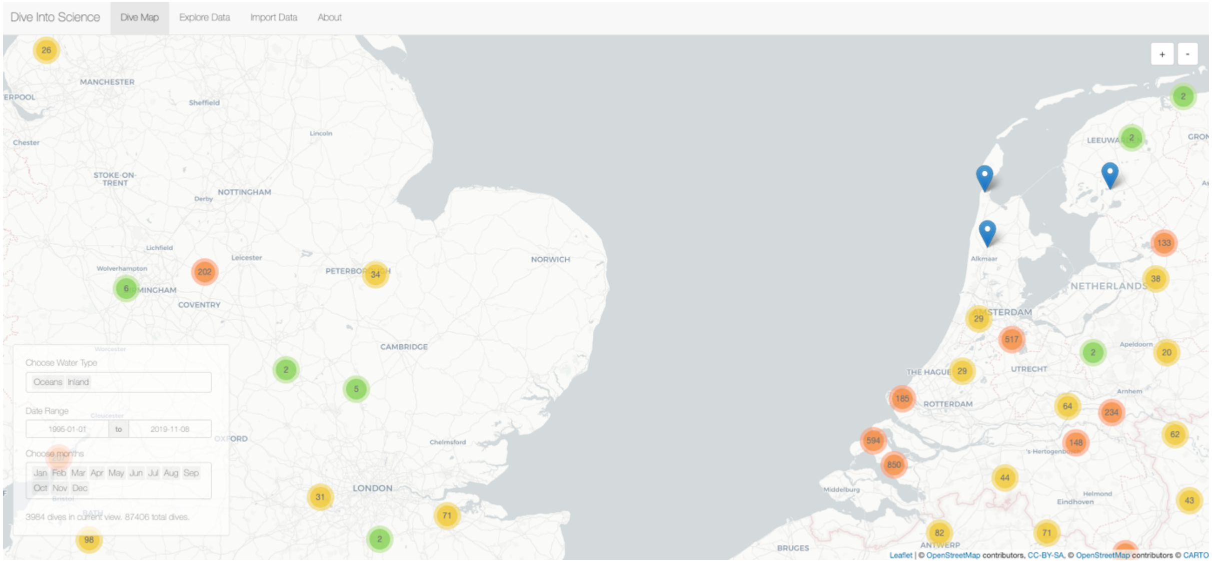


Figure 4.3. Diveintoscience 'Dive Map' page, showing clusters of dive points.

Contextual information is important in interactive visualisations (Rock Content Writer n.d.), to help the user get an accurate picture of the data. Diveintoscience provides context by displaying the total number of dives, along with the number of dives in view - which adjusts as the number of dives in the map bounds change with user filtering.

Dives are displayed in clusters, for ease of viewing, using markercluster options (RStudio n.d.). Clicking on a cluster will either zoom in and split into smaller clusters or expand the cluster into individual points. Clicking on an individual point gives additional detail of the dive such as date, model, temperature, latitude and longitude (Figure 4.4).

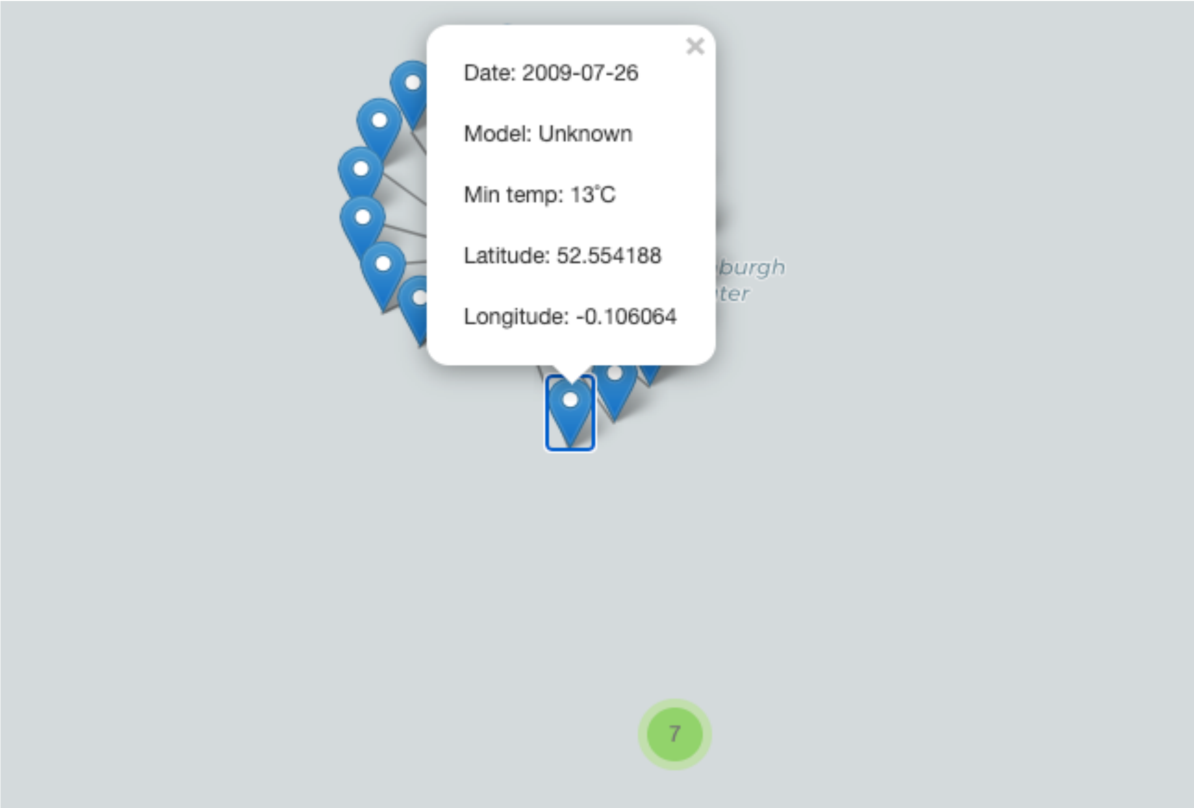


Figure 4.4. Detailed information for one dive, showing single dive metadata, markercluster and expansion

Innovative solutions for pre-processing, interactive analysis and intuitive visualisation have all been developed over the past decades, such as pattern recognition and interactive mining of datasets (Fayyad, Grinstein, and Wierse 2002). Good design is critical, as however good the underlying data or the statistical rigour, if the results are poorly displayed, they will not convince or encourage the tool to be used (Driscoll n.d.). Visualisation requirements of the data for a policy maker may be different to that telling the story to a wider audience, but the primary intended audience is citizen scientists.

The 'Explore Data' page provides interactive plots of the median temperature by month (Figure 4.5) and numbers of dives per year, for the data which is in view bounds on the Dive map. For example, if the data have been filtered to just show ocean dives for a specific year, only these are reflected in the plots. The timeline at the base of the plot adds an additional interactive layer, allowing selection of a smaller date range in the plot itself. Plots are built using ggplot2 (Wickham 2016) and dygraphs ("Dygraphs for R" n.d.).

The 'Filtered data' tab displays the source data in tabular form.

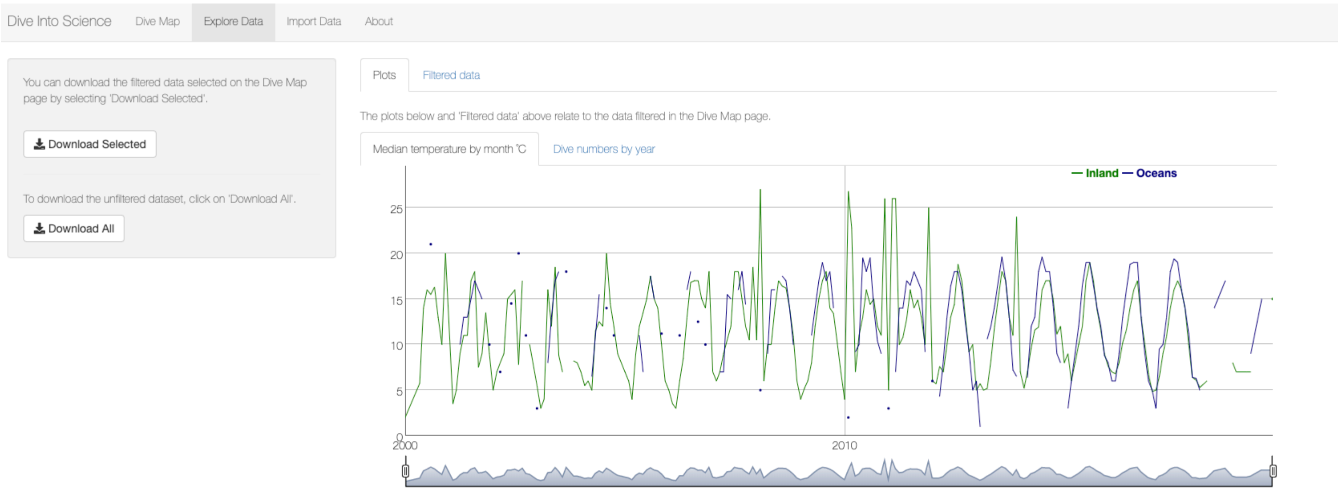


Figure 4.5. 'Plot' tab in Explore Data page, showing median temperature by month (°C). The range of the x axis is manipulatable by the user via the bottom bar.

A key principle for Diveintoscience is to ensure open access to all data collected. In the left-hand column, download buttons are provided for both the filtered data (Download Selection) and the entire dataset (Download All). Downloads contain the summary data for each dive in .csv format. This which allows easy individuals, researchers, or scientists to carry out their own complementary analyses.

4.4.7 Import data

Dive log applications allow users to upload depth/time profiles as a history of their dive locations. There are many levels of additional detail that may be recorded according to user preference, but commonly these include information on dive buddy (who they partnered with on the dive), equipment used or what they saw on a dive. Most modern dive computers also record changes in temperature during the dive as a function of depth and time, although some older models of dive computer record a single minimum temperature.

Dive computer export formats are not consistent. Whilst an XML based protocol (UDDF) exists, this is not universally used, and export formats are in the main proprietary to each manufacturer. To develop a website that allows upload of files directly exported from dive computers, it needs to be able to cater to these multiple formats. A cross-platform, open-source code library 'libdivecomputer' (Driesen n.d.) exists, providing a mechanism for communication across models. In addition, there are various third-party applications which use libdivecomputer to provide inter-model dive log applications. One example is Subsurface (Subsurface Divelog n.d.), a fully featured desktop/mobile dive logging app. Both libdivecomputer and Subsurface are actively maintained and new dive computer models are catered to as they are released.

DiS2 could be developed to use libdivecomputer and allow uploads directly from dive computers. However, developing this would involve significant coding expertise, which is contrary to one of the primary benefits of using Shiny, that of using knowledge of R rather than web technologies to develop online applications. It is common for users to import data from their dive computers using proprietary software and subsequently export data from that application into an additional dive logging application or website which may, for example, allow them to add photographs or share/ track their dives differently. This was the chosen approach for DiS2. A user has one-off task to install Subsurface, with its benefit of being compatible across all dive computers. Subsurface is then used to import data from their dive computer(s). Subsequently, a standardised XML export can be made from Subsurface which DiS2 has been developed to accept. This was considered the best compromise between user and coding effort.

On opening the 'Import Data' page a single tab with instructions is seen. The instructions cover the entire process in simple bullet points: from importing data into Subsurface, exporting in a format that DiS2 can consume, uploading the file to the site and the required steps to save to the database. The requirement to add latitude and longitude data is highlighted in bold text, also that any profiles without latitude and longitude will not be saved to the database. A note is made on the left-hand side that large files may take a little while to upload and process. In the left-hand column there is a short paragraph explaining the benefit of using Subsurface, along with a browse button to allow the user to locate a file for upload from their file system.

If the user attempts to upload an invalid file format, a user-friendly error message is shown (Figure 4.6). Often error messages seen on websites are system-generated, HTTP status codes ("Hypertext Transfer Protocol (HTTP) Status Code Registry" n.d.) (e.g., 500 is an Internal Server Error) which are uninformative to the uninitiated, leaving casual users unable to proceed. It is important to retain interest and motivation of the user, and the risk is that they lose interest if there are difficulties uploading the file. By providing a 'human' message, the user is encouraged to try again with a Subsurface file, rectifying a possible file issue, or to directly contact the team, who should be able to identify and solve issues more quickly. As this is rolled out to a global audience, it is better to have direct contact to solve problems as they arise. It would be unlikely for the site to explode into an unmanageable level of use at such an early stage. As the site becomes more widely used, more automated mechanisms will be developed.

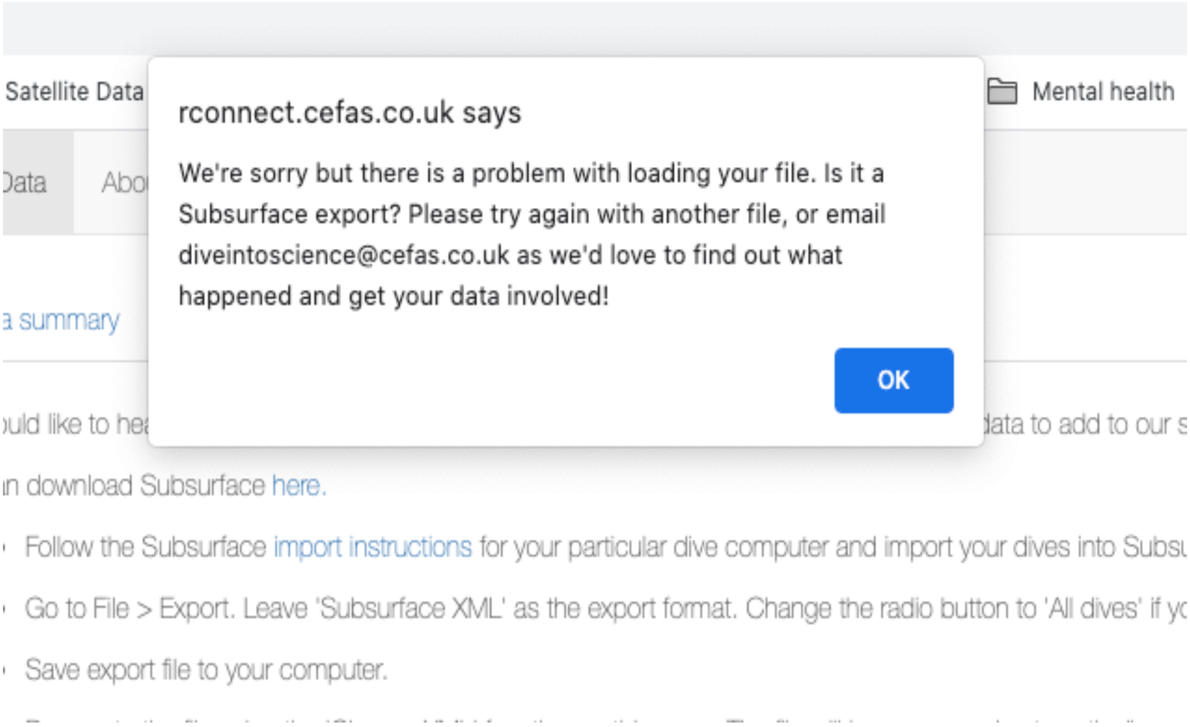


Figure 4.6. User readable error message seen on attempt to upload invalid file.

When a user selects a valid file to upload, a progress bar shows the time to completion, and states 'Upload complete' when processing has finished. Once the file has loaded, two new tabs are visible in the main body of the page: a 'Data summary' tab and a 'Profiles' tab, with the 'Data summary' being the area in view. The instruction tab is still available, should the user wish to clarify anything, but it is now behind the new tabs. 'Data summary' contains summary information for each uploaded dive in tabular form, including a dive number, site, date, time, model of dive computer, device identifier number, minimum recorded temperature, maximum depth, latitude and longitude. With a few exceptions, most dive computer models do not currently have GPS capability. If latitude and longitude data are present in the uploaded log file, these will be shown in the table; if not, the columns will be blank, and the user will need to add these manually. A message to input latitude and longitude in decimal degree format is shown at the top of the table.

As a user adds latitude and longitude to a row in the table (or there are geolocated dives in the import file) the site becomes aware of these dives, and the location appears on a small map on the bottom left-hand side of the page. This is updated in real time, for each row that is updated by the user. This also acts as a visual cue to the user of any errors in coordinates, for example, if they see a dive appear in the wrong continent. A user can also edit or add the dive computer model but is unable to edit any other fields. When the user has finished adding metadata, to send their geolocated data to the database they must click 'Save Data'. Any dives which do not have coordinates are ignored. Imported dives are not immediately visible on the site but are stored in the database with a status of 'New'. This is part of a user testing process and in future, dives will be automatically validated by the system and displayed in the main site.

4.4.8 About

'About' is a simple text-based page with longer information about the project than given in the loading pop-up box. The page also includes acknowledgments, logos of all the funding sources and partners, and primary contact details for the project. Citizen science projects should clearly convey the context in which data have been collected or created (Balázs et al. 2021). As the project evolves, and further data sources may become integrated, this information will be clearly disseminated here.

4.4.9 Data management

One concern with citizen science data is that quality may be impacted by experience, training or expertise of the contributors (Hunter, Alabri, and van Ingen 2012; Dickinson et al. 2012). Bias and noise can arise from uneven sampling, with local variation missed where data are reported nationally (Fritz et al. 2019). As in this instance volunteers are transporting instrumentation to collect temperature readings, bias based on user training should not be present. There will be heterogeneity caused by systematic errors in individual dive computers, and these have been explored in Chapter 2.

Assessing the quality of volunteered geographic information (VGI) such as georeferenced citizen science data is challenging (See et al. 2013) if the location is manually added. Smartphones can utilise GPS for automated location identification, but as most dive computers do not have this capability at present, there is a reliance on the user entering the correct coordinates. This adds a level of risk. Adding the visual cue of the display on the upload map which is displayed as the user adds co-ordinates aims to mitigate this risk.

Subsurface XML export only generates metric values, even where the user has preferences set to imperial, relieving the need to cater to both imperial and metric units. There are many different levels of data validation and cleaning, from manual verification through automated assessment and data mining (Balázs et al. 2021). Currently manual (expert) validation is carried out on dive computer data uploaded to the database, prior to display on the website. This is to allow review of imported data and build an assessment of the data landscape from citizen science divers and can be modified in the future once more user uploaded data is present. One driver for this step is that sensors may drift over time if they are not calibrated (Otmani, Benmoussa, and Benyoucef 2011). Dive computers are often used by divers for decades without calibration, and it is not known what level of drift occurs. If we automatically exclude data which are outside of realistic oceanographic bounds, we will lose insight into the percentage of dive computers which are producing impossible or unlikely output due to drift or inherent systematic bias. It is impossible to know in advance what dives users may upload, but over time this information will give us additional understanding in the possible placement of dive computer data in the overall monitoring realm.

4.4.10 Database schema

An underlying PostgreSQL database holds all live data available for plotting on the map and stores uploaded profiles. It has a simple schema, consisting of two tables (Figure 4.7).

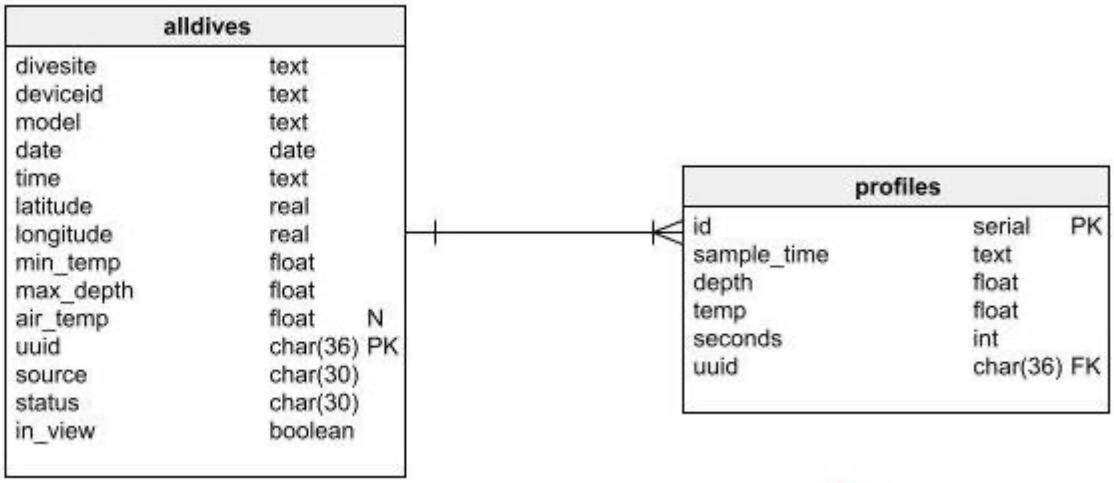


Figure 4.7. PostgreSQL database schema for Dive into Science.

The table 'alldives' has one row of summary information for each dive. The associated temp/depth/time profiles are stored in the 'profiles' table, with a uuid (universally unique identifier) linking the summary and profile.

4.4.11 Engagement

The goal was to develop a working proof of concept website, accessible as a beta to the outside world. Having been through a thought exercise of what considerations should be made, allowing ease of future development, it was to have visualisation features and upload capacity, but without necessarily being fully formed or fully scalable (for example). Following citizen science and human behaviour guidelines (Vicens, Duch, and Perelló 2018), DiS2 aims to motivate participation and engagement.

By involving stakeholders in the planning process, trust, collaboration and buy-in are enhanced (Cigliano et al. 2015). The needs of the varying stakeholders were considered in the design process, aiming to understand the motivations and goals of participants for data collection, but also for potential consumers of the data. Initial engagement was carried out via a survey which was shared on several diving related social media groups. This was a brief survey with a small number of questions such as 'What make and model is your primary dive computer?' and 'Do you regularly use more than one computer on each dive?'. This was intended as a quick finger in the air check to establish a starting point for the project and to allow interested parties to share their thoughts - rather than being a detailed analysis process. Approx. 90 responses were received. Many contributors wanted features which would have been out of the realistic scope of the project, for example, requesting photo uploading capability. These features would have functionally turned DiS2 into a general dive-logging software (of which there are many already). The decision was made to keep it simple, focused on collection of temperature data, but allowing open access to filter or download raw data for users to utilise freely.

Continued engagement and contribution is important for the success and longevity of online citizen science projects (Nov, Arazy, and Anderson 2014). In the context of DiS2, this means repeated visits and data uploads as more dives are completed, although as batches of dives can be uploaded at once, uploads can be periodical. Studies of motivation into engagement with online participatory studies have included exploration of projects with community and social network elements, along with reciprocity and increased knowledge (Aristeidou 2017).

Where the primary motivation for contributors to open-source software projects is a ‘desire to help for the greater good worldwide’ (Baytiyeh and Pfaffman 2010), along with work enjoyment, the main motivations for SCUBA divers partaking in citizen science projects are out of interest in the field under study, to be able to ‘contribute’ and for science (Lucrezi et al. 2018). Whilst DiS2 has online elements, they are secondary: the means for recording the data collected in the field. As such, it is considered that motivations are likely to be more aligned with other marine citizen science than fully online projects, with personal satisfaction, knowledge and recognition scoring highly (Thiel et al. 2014).

4.4.12 GDPR

It is important to consider wider ethical issues around collection of data, including legislation, sharing, rights and minimising negative impact. Protection of contributors’ privacy and anonymity is key (Garett et al. 2016; Katapally 2020). For the current iteration of DiS2, to ensure privacy and minimise potential harm or additional security complications, user logins and security were considered out of scope. The design decision was made to build DiS2 in a way where no personally identifiable information about participants is collected or recorded. This removed the need to develop login areas and adhere to GDPR (ICO 2021) legislation.

4.5 Discussion

4.5.1 R Shiny

A purported benefit of Shiny is the ability for R users to develop web applications via R, rather than with web technologies directly. Shiny removes a lot of the development load and simplifies interactive visualisations, by offering pre-existing functions. Out of the box, Shiny offers the ability to develop clear, responsive user interfaces with intuitive interactivity features for information visualisation. However, to produce something more aesthetically pleasing and appropriate for an external facing website, additional Cascading Style Sheets (CSS) knowledge is required to manage design elements. In addition, to develop a more complex site such as including a database connection, it is recommended that the developer has at least a basic understanding of programming.

A Shiny server instance, along with R, are required in the background. Publishing options exist, from a fully-fledged RStudio Connect publishing solution (RStudio n.d.) to simpler and cheaper cloud-based hosting options with shinyapps.io (RStudio n.d.). In an organisation where Shiny is heavily used such as Cefas ("Cefas Open Science" n.d.) the former may be an achievable option, but for many citizen science organisations the associated costs would be a barrier. Shinyapps.io basic solution is free and can be a good entry point.

While the underlying language is R, new packages and approaches, such as Shiny's reactive programming methodology, need to be learned initially. Page speed can be an issue where large datasets are being mined, so careful planning of development approach is important. Long calculations can freeze the user interface until they finish, although new packages are in development to address this (Appsilon 2020a).

Ensuring Shiny only interfaces between R and the browser, with computations managed in a database or browser (Appsilon 2020b) helps. These factors may require more advanced knowledge. IT departments also may not know how to support R Shiny, so there is a risk that 'if you built it - you maintain it', which can lead to a future drain on time.

4.5.2 Potential for DiS2

DiS2 has been developed with an aim to collect data on a global scale. As demonstrated in Chapter 3, as few as 100 records in the Red Sea can identify seasonal patterns, so huge numbers are not required to provide insight. Although larger volumes of data would be required in water bodies with more complex hydrodynamics, DiS2 dive computer data need not stand alone, or give a complete picture. With appropriate techniques for management of uncertainties, DiS2 data could be incorporated into wider datasets such as the International Comprehensive Ocean-Atmosphere Data Set ("ICOADS" 2021) to form one part of the solution.

Regions with limited subsurface monitoring, are often well populated by SCUBA sites (e.g., the South Pacific or Caribbean). Working with sentinel dive schools in such regions with little or no available ocean temperature data would move the project from a broad 'get as much data as possible from everywhere' to a more focused approach. Callaghan et al. (2019) suggest incentivising sampling at specific locations or times. A media drive to request data in a particular area, to support specific conservation or ecological requirements, would be akin to projects such as those on Project Baseline (Project Baseline n.d.), where individual divers are connected with scientists working on projects in a specific area. These two approaches, global and targeted, are not mutually exclusive - targeting specific areas does not preclude DiS2 being useful on a global scale.

DiS2 also offers an opportunity to engage the wider global SCUBA diving community with issues of environmental importance, and a mechanism could be provided on DiS2 to allow highlighting of calls for data in areas of particular interest. Additionally, building a project around, and relationship with, known dive centres would give us the opportunity to control the equipment that is used, such as using 'in-house' dive computers in the case of the Berwickshire Marine Reserve project (described in 5.2.1), and ensure dive computers are calibrated frequently. By frequent sampling in the same locations, a long-term time series and observation of local patterns would be possible.

4.5.3 Data considerations

When designing citizen science projects, it is important to be strategic in assigning any research tasks (Cigliano et al. 2015) such as considering participant comfort and experience levels. However, in this proof-of-concept project, contributing divers make decisions about dive locations, based on their own recreational requirements or limits. As the participants select their own dive locations, the project style is defined as semi-structured data collection (Kelling et al. 2019). This approach has been found to attract sufficiently large numbers of participants to reduce bias in data (Kelling et al. 2019). Dive site selection ultimately makes data collection an engagement exercise, facilitating the collection of data as a secondary benefit of individuals' leisure activity in which they would participate anyway. The challenge then lies in motivating participants to upload their logs.

As the data collection itself is automated (collected by the dive computer), but the profiles need to be manually uploaded, the process is defined as semi-automated (Muller et al. 2015). Contributors are able to collect data in a real-world context, but the addition of metadata on upload to the platform allows scientific rigour to be applied to the data (Vicens, Duch, and Perelló 2018). Three important elements of a citizen science project are to ensure the data are accessible, findings are shared, and contributors are acknowledged (de Vries, Land-Zandstra, and Smeets 2019). For data to be used, people need to know they exist, so an engagement approach for raising awareness needs to be considered, whether it be by publication, social media, or other mechanisms.

Spatial and temporal inconsistencies may be present in both traditional data sources and citizen science initiatives (Callaghan et al. 2019). As a global citizen science initiative, Diveintoscience is not a structured collection effort and as such has no control over these variations. There will always be clusters of data points in spatial and temporal dimensions, as more diving will happen in preferred locations and at certain times of year. This can be positive for research into changes on a micro (local) scale. To bring focus to an area of interest, a call to action from community or science organisations could lead a concerted push for data submission in a more targeted approach. Tiago (2012) suggests that combining different data sources might produce improved results. While there is currently no single centralised database for dive computer data, if data from the available sources were combined, numbers of dives would be optimised.

From a data output perspective, the longevity and value of a website which relies on participation depends on engagement, alongside the volume and quality of data collected (Nov, Arazy, and Anderson 2014; Waldispühl et al. 2020). Some initiatives have successfully encouraged several hundred of thousand participants (Waldispühl et al. 2020), but understanding the audience and developing retention mechanisms, longevity, scalability, encouraging repeated uploads or attracting a constant stream of new participants are essential. Feedback was gathered pre-development of DiS2, but stakeholder access was minimal due to COVID-19. The authors believe in the potential of dive computers and Diveintoscience to gather useful oceanographic information, but improved engagement will be required moving forward. It is also important to define the success criteria, and which parameters identify whether the website has been effective in its goals or demonstrating quality of data (Vicens, Duch, and Perelló 2018). Data quality of dive computer temperature is now more clearly understood, including the required number of datapoints for accuracy (Marlowe et al. 2021). The inclusion of metadata such as model and length of dive will allow further data cleaning and validation. DiS2 has achieved three of the aims stated in 4.3.4 by providing a mechanism for people to easily share and explore data and make a meaningful contribution to conservation, with data freely accessible for all. No quantification has been given to the final aim of increasing the volume of depth resolved ocean temperature data, but further user testing and engagement will establish any barriers or blocks to its use, and mitigation processes can be initiated.

4.5.4 Participant acknowledgement

Acknowledging participants for their involvement is important (Brewin et al. 2017b) and public recognition is an important motivator for marine science (Thiel et al. 2014). Acknowledgement should include citizen scientists who are involved at any time in the project. Journal authorship requirements often follow the International Committee of Medical Journal Editors ICMJE 4 step protocol, in which named authors need to have substantially contributed to the design, acquisition, analysis or interpretation of data, but this definition precludes the recognition of citizen scientist contributions. Ward-Fear et al. (2019) recommend group co-authorship as an approach to recognise contribution by non-professionals. However, citizen science datasets are in a state of constant expansion, with new contributions being added all the time. The Dynamic Data Citation Working Group within the Research Data Alliance propose dynamic data citation for subsets of data via time-stamped queries with persistent identifiers, allowing citation acknowledgement for contributors of the data subset (Hunter and Hsu 2015). As Diveintoscience does not record who has uploaded dives, it is also not currently possible to individually acknowledge contributors in the site, or any journal authorship, or develop a 'reward' system for their feedback, but an umbrella acknowledgement is included in the About page. In future if this functionality is extended, then individual/group acknowledgement will be implemented.

4.5.5 Limitations and future work

From a development perspective, relying on Subsurface to provide files for input is beneficial, tying into the requirement for low coding knowledge and imbuing the longevity and maintainability gains of using an actively updated software which caters to new dive computer models as they arise. However, from a user perspective this requires the download/installation of additional (open source) software, and extra steps to exporting a logfile which can be imported into DiS2. The future goal is to offer an automated upload process, integrating directly with libdivecomputer (Driesen n.d.).

As dive computers do not commonly have GPS functionality, there are potential risks of poorly entered coordinates, along with the user effort in adding these to each dive. As such, both scientific potential and user experience will be improved once it is more dive computer models commonly have GPS functionality. Locations will be recorded more accurately at source, and uploaded automatically into dive logs/DiS2, reducing user effort.

Maintenance of a website involves continuous investment over time to keep packages and libraries up to date and secure, evolving to meet new technological developments so that the site: a) remains functional; and b) is not seen as out of date or un-maintained by users. This is a consideration in any website project, not unique to Shiny, citizen science websites or DiS2. Many of the underlying processes could be easily adapted to suit other data collection goals, offering the potential for re-use/ adaptation of code, saving time on subsequent projects. The DiS2 code could be deployed as a standalone site on a local machine, should there be technical benefits to do so, for example in remote areas with poor internet connection. In this instance, it would be beneficial to agree sharing mechanisms to avoid the issue of discrete chunks of inaccessible data.

An additional feature which could improve the user experience and reduce risk of recording error in geolocation of dives is to provide a list of known dive sites, using pre-specified latitude and longitude. This would offer users the option to select from a list instead of manually adding coordinates. However, there is no comprehensive existing agreed list of dive site names and locations. Lists that exist from online dive logging software have language implications and site duplications with slightly different names. In DiS1, for example, dive site names were manually entered; from the 7500 records there were nearly 3200 unique dive site names, while the actual number of unique sites was much smaller. To implement this in DiS2, design decisions would need to be made such as whether to allow users to manually input a name for a dive site that does not currently exist, and how to allow selection from a list of possibly hundreds of thousands of names. These issues are a significant challenge to implement, given the numbers of possible global dive sites.

Currently, full profiles of temperature and depth against time are downloaded and stored in the database, along with the summary data. This will allow future display of profiles against an individual dive, but also the ability to collect insight into temperature patterns at depth such as thermocline depth/strength, depending on the shape of the dive profile and model of origin.

By not having login functionality, code development to cater to security considerations was minimised. However, this also removed the potential to allow users to store a collection of their own dives, and view these and the associated data analysis in the wider context of all site dives. These could be a barrier to engagement and is a question to be asked when further user testing occurs. Communication of findings is important for participants' motivation, especially in contributory projects (de Vries, Land-Zandstra, and Smeets 2019). If a login mechanism were added, it would open the door to customisation (as opposed to interactivity), allowing a user to see their own individual dive logs in the context of the greater whole, along with in-site feedback, communication and dissemination of information. A sign-in mechanism would also allow development of a 'reward' system for contributions (Gerovasileiou et al. 2016), such as giving users a grading based on number of contributions made, by uploads or number of dives.

Once DiS2 is fully encompassed in a system of engagement and being used by divers, the impact of DiS2 should be assessed. As citizen science data may be combined with other datasets as a gap filling exercise (Sprinks et al. 2021), impacts are often cumulative and not easily separable. Wiggins et al. (2018) have developed a list of 18 science 'product' metrics for citizen science projects, to help with project evaluation from a science perspective. Product output categories are 'written', 'data', 'management and policy', and 'communication', with example products being inclusion or use of data in theses and/or peer-reviewed publications, availability of data visualisations and metadata, direct actions and social media coverage.

4.5.6 Project ownership

Whilst DiS2 is a fully functioning working site, with the ability to be scaled according to levels of usage, the work does not end with delivery of a website. For any citizen science project to be successful, appropriate ownership and management processes need to be put in place, such as mechanisms to raise awareness, ongoing communication with users and, in this case, technical trouble shooting. For DiS2 to reach its potential, attracting and retaining users will be key.

4.6 Conclusion

I have demonstrated that tools are available to researchers to facilitate visualisation and sharing of their research for engagement along with collection of additional data, with minimal coding knowledge. Giving users the means to contribute data they have collected simply by doing the thing they love can provide data to support local and global monitoring efforts, improving our ability to connect the effect of temperature changes to climate, ecosystem and biological changes. DiS2 demonstrates the flexibility of R Shiny to deliver a web-based citizen science offering, with an upload facility, built with minimal web development knowledge (or none if default styling is used), but suggest that some level of prior knowledge is required for more advanced projects. In isolation, R Shiny is not a complete solution to developing an online citizen science project, as clear project ownership and engagement mechanisms will always be required, but it can deliver the building blocks of a flexible, scalable, interactive and engaging website.

DiS2 aims to increase the availability of long-term data, with potential as a broad spread global data collection mechanism, as a push for data in specific areas, or as a stand-alone offline site. However, the development effort does not end with delivery of a website; continued user engagement and maintenance are required. Citizen scientists can form part of the answer to the lack of marine data, but ongoing engagement is essential to keep motivating people to submit data, to ensure code is kept functioning and up to date, or to scale up or down depending on usage.

Chapter 5. Thesis summary and conclusion

5.1 Summary

This chapter summarises the aims of the thesis and contribution to advancement of knowledge. The overall objective of the thesis was to investigate the potential of citizen science SCUBA divers as novel source of oceanographic data, focusing on temperature data from dive computers. I have established the accuracy, precision, and response to temperature change of dive computers, demonstrated the real-world potential of a citizen science dataset to identify seasonal patterns comparable with those generated from satellite and in situ datasets, and delivered a website for interactive visualisation and collection of data, exploring the potential of R Shiny as a development tool.

5.1.1 SCUBA divers as citizen scientists

To address the first thesis objective, the within and between-model bias and uncertainty of 28 dive computers and 3 underwater cameras were quantified. In contrast to Azzopardi and Sayer (2012) and Egi et al. (2018), and in agreement with Wright et al. (2016) I conclude that some models of dive computer do offer potential as a source of data for oceanographic monitoring. I have found that some models produce data at an accuracy and precision comparable to existing tools and therefore can form part of the solution to the data shortage in coastal areas. With sufficient data, overall accuracy was good, irrespective of model. In addition, there is within-model consistency, and significance in model features such as material and pressure sensor location. I have demonstrated that data from recreational divers' computers can be of value without needing to know the model. However, with collection of metadata, additional insight into potential data quality either directly (such as data from a model with known response characteristics) or indirectly (indicative data quality based on pressure sensor location and material) can be gathered. Further work will offer the potential for development of bias compensating algorithms.

5.1.2 Satellite and in situ data comparison

The 2nd objective was to compare dive computer generated data against known sea surface temperatures from satellites and depth resolved in situ datasets. In doing so, I have shown that seasonal patterns are identifiable at annual, monthly and weekly resolutions in dive computers, well correlated with those seen in related satellite SST and in-situ data at depth. Interannual anomalies were also identifiable. Temperature-depth differences between dive computer, satellite and in situ data, in agreement with MLD reported in the literature (Abdulla et al. 2018) were seen. Divers (and thus dive computers) differ from in situ monitoring platforms such as buoys, as they are not restricted to specified nominal depths (outside of training and qualification limitations). This highlights potential benefits for dive computer data to offer depth related information to complement existing datasets, offering insight at a micro scale, which may be beneficial for ecosystem data discovery.

In agreement with Jones (2016), I found that groupings of approximately 100 dives were sufficient to identify seasonal patterns, irrespective of dive computer model. As this held true in an area the size of the Red Sea, given 100 dives in a smaller area, where less temperature variation might be expected, improved values may be seen. With smaller quantities of data, inclusion should be considered on a case-by-case basis (Hyder et al. 2015). Callaghan et al. (2019) discuss the idea of the leverage and/or value of a sample based on the scientific question, such as species distribution modelling or phenology. Although devices with large biases may contribute to bias in small datasets, an advantage of citizen science divers is their access to areas with little pre-existing data. Therefore, data from areas with few existing data points, similarly to other spatially focused analyses, may be of higher value, and should still be considered.

5.1.3 Citizen science website design

A website was developed in fulfilment of objective 3, as a mechanism to allow upload and visualisation of dive computer data primarily using R skills, and demonstrating the capability, advantages and challenges of the Shiny package in R for doing so.

Long-term time series are a powerful tool to investigate patterns and changes in environmental data over time. By offering a solution for bringing together temperature data in one place, under open data principles, this capitalises on the potential of SCUBA divers as citizen scientists, but also improves access to data for scientists, marine managers and community groups. Data can also be collected in discrete areas to support environmental campaigns, or local versions of the website can be implemented in areas where internet connectivity is poor. In future, it could be possible to correct temperature based on depth and known model and time constant (Daunt et al. 2003) along with dive profile shape.

5.1.4 Potential for use

The environment is consistently in the top three most pressing issue of concern to the public (YouGov 2021) and is especially important to young adults (YouGov 2021; Uba 2021). The mean age of SCUBA divers in the US is 29.7 years (median = 26 years) (DEMA 2021), so the 18 – 24-year-old demographic, who are currently most concerned about environmental issues (YouGov 2021), are the potential SCUBA divers of tomorrow. A pan-European study exploring public awareness and concerns around marine environmental impacts found the >10 000 respondents had most concerns around ocean acidification, pollution and habitat destruction (Gelcich et al. 2014).

Previous studies define high-quality citizen science data as having comparable accuracy and bias to that gathered by experts (Bonney et al. 2009b; Kosmala et al. 2016). In this instance we assessed uncalibrated sensors, so it follows that a reasonable comparison would be with sensors with a similar purpose. An individual ship-borne SST measurement has measurement uncertainty of 1 – 1.5 K (Kennedy 2014) and models of depth-resolved in situ data with accuracy of ± 1 °C, 78% of the time have been used for MPA monitoring purposes (Baldock et al. 2014). These examples show there are precedents for usage of data with comparable accuracy. GOOS recognises that observations exist that meet the required specifications but are not currently part of the integrated system. As part of the UN Decade of Ocean Science for Sustainable Development GOOS aims to support integration of these observations into end-products (Fischer et al. 2021). A recent example of this is the addition of data from animal-borne ocean sensors into the GOOS in 2020 (AniBOS, 2020). Data from appropriate models of dive computer could be integrated into GOOS in a similar way, with the requisite statement of data assurance (Schläppy et al. 2017).

As the vast majority of citizen science projects focus on life sciences (van Hee, Seldenrath, and Seys 2020; Garcia-Soto et al. 2021), with physical parameters such as temperature only contributing to a small number of projects (11 % when grouped in with projects such as fish stock counts, archaeology and maritime history (Garcia-Soto et al. 2021)), there is an opportunity to capitalise on the rising interest in citizen science and recent government research into opportunities for and barriers to UK marine citizen science (Defra 2021).

Whilst existing satellite and in situ SST data combined offer a broad reach, there are fewer subsurface observations. Citizen scientist divers to fill some of the shortfall, adding an extra dimension of information in areas that otherwise have poor in situ sampling. Targeting areas of specific community interest could be approached in two ways: 1. a call for data could be put out through social media engagement avenues to all associated recreational divers, for data to be collected in a specific area; or 2. subject to available funding, a more formally created citizen science project could be initiated to manage a requirement for local data. With a local on-the-ground presence, support could be given with simple ice bucket calibration of individual devices prior to diving, and collection of data directly post. This would not only build understanding of wider variation in models such as due to sensor drift, allow compensation for systematic bias to be incorporated, but also ensure correct coordinates are logged (assuming known dive sites have been visited) and reduce the likelihood of people forgetting or being distracted from to upload data after the event.

Although intense research has been carried out on ocean fluctuations with relation to El Niño Southern Oscillation (ENSO) since the 1950s (Cravatte et al. 2016), it is still not fully understood (Smith et al. 2015). Degree heating weeks (DHW) are measures of accumulated heat stress for corals related to ENSO and can be used to predict bleaching events. Hot spots (50 x 50 km areas) with anomalies greater than 1 °C are of interest (McClanahan et al. 2007), but increased ocean temperature time series are needed (Cravatte et al. 2016) to support understanding and to improve models (Kessler et al. 2014). This offers an opportunity for dive computer temperature data on a broader scale. Temperature anomalies at this resolution are identifiable with dive computers, and there are many regions spanning areas of this size where sufficient dives would take place to produce temperature time series.

One potential for dive computer data use in hindcast/reanalysis and forecasting models. Modellers commonly incorporate data of lesser quality into models and have procedures for managing the associated uncertainties (Atkinson 2021). One such example is the use of historical data from ship logbooks, which are being transcribed and made available for use in climate research and modelling (ICOADS RECLAIM n.d.; “Old Weather” n.d.), including incorporation into the International Comprehensive Ocean-Atmosphere Data Set (ICOADS). Dive computer data could be assimilated using similar processes to ensure appropriate uncertainty measures are in place.

Year on year, engagement with citizen science is increasing, not only raising awareness of environmental issues, but there is also positive feedback; the more engaged people are, the more they are likely to change behaviour (Jones et al. 2013), and the greater the awareness, the greater likelihood of participation (Kragh 2016). The most successful initiatives are those with the least barriers to participation in terms of effort and knowledge (Garcia-Soto et al. 2021). As divers are enthusiastic citizen scientists willing to collect several days of data annually (Martin, Christidis, and Pecl 2016), and divers will be diving recreationally, the largest barrier to potential for these data could be the mechanism for collection of data from the divers themselves. I have offered a potential solution to this, with the development of DiS2 as a platform to increase the available data for science and monitoring purposes. However, availability does not equate to usage. While providing open access to data increases citation rate, increased volumes of data do not inevitably lead to better science; the data need to be used (Molloy 2011). One barrier to use is perception of data quality. Quantification of the variability and evaluation of limitations of temperature data from dive computers carried out in this doctorate should positively influence this. Schlappy et al. (2017) recommend provision of documentation covering data quality assurance, which could be added to DiS2 in future iterations. Provision of metadata in downloads from the DiS2 database will allow additional filtering, validation and processing of data, as required by the scientific question being addressed. Demonstration of applied use of the data to solve ocean problems and identification of possible opportunities for data use may initially be required to ensure uptake by policy makers and scientists. The greater awareness and usage of the data, the increased likelihood of future expanded usage. As dive computer temperature has been proven to identify seasonal and interannual patterns of temperature change, with positive engagement mechanisms maximising the number of participants in marine citizen science, these data can become part of an integrated observation platform.

5.2 Additional work

The 4th and 5th objectives were to carry out engagement with dive schools and to investigate and marine reserves, delivering talks and exploring the enthusiasm for citizen science projects collecting temperature data from dive computers and investigate the potential for identification of thermoclines. These were both hampered by the arrival of the global pandemic.

5.2.1 Engagement

Dickinson et al. (2012) state that the mantra "easy, fun and social" is what is required to recruit large numbers of volunteers, but for ongoing commitment, targeting specific audiences may be more effective. The original aim of working with sentinel dive schools largely had to be put on hold because of the obvious constraints of the pandemic. An engagement exercise was carried out over a period of 3 months with dive schools in Cape Town, although data was not collected as DiS2 was not built at that point. Conversations were held with recreational SCUBA divers, dive centres and marine conservation organisations, assessing motivation to get involved with citizen science, but especially Dive into Science. Without exception, every individual spoken to was enthusiastic about getting involved.

Understanding the motivations for citizen science will be key to harnessing the available data moving forwards. This applies to both volunteers' desire to share data they have collected on SCUBA trips, but also minimising any barriers to the upload of that data and having a good understanding of website user experience. Participants begin to develop questions whilst taking part in field observations (Hyder et al. 2015) but also when interacting with data via mapping tools (Conceição, Samuel, and Biniecki 2017). This agrees with personal experience; having engaged with divers prior to a dive, they became attentive to the temperature responses of their dive computers during a dive and had increased likelihood to re-engage and raise questions after the dive.

Contacts were made with headquarters of the two major dive organisations in the UK: BSAC and PADI, but to no response (NB. however, as of July 2021, I have been co-opted onto the BSAC Council (a volunteer directorship role), with an aim to support the new environmental/conservation strand of their 3-year strategy, so forward movement may now be possible). Positive relationships were also built with Project Baseline, PADI Project Aware (which has since become the PADI Project AWARE Foundation) and Paralenz. There are other dive organisations and citizen science projects with slightly different diving focus, such as GUE, SSI, TDI, Divers against Debris and the Community Seagrass Initiative who may also be open to collaborations. In addition, it may be more productive to contact dive shops and clubs directly to establish interest and work on a local scale, as club engagement and enthusiasm seems high. Working with clubs and dive schools is a means of not only gathering data, but also building engagement directly with scuba divers who are diving in these areas, whether it be on a regular or one-off basis.

Other engagement included provision of advice and support in project approach and selection of appropriate dive computers to St Helena Government, which aims to address a shortage of temperature data around its coast by using dive computers. A project was also initiated with the Berwickshire Voluntary Marine Reserve (BVMR) (formerly St. Abbs and Eyemouth Voluntary Marine Reserve), which covers 8 km of coastline from around Eyemouth. The reserve spans 1030 hectares, extending offshore to the 50m depth contour, which is an average distance of 1.5 km (St. Abbs & Eyemouth Voluntary Marine Reserve n.d.). The reserve is a base for offshore fishery and has many recreational SCUBA dive sites because of particularly clear water. There is a small finger of the North Atlantic drift extending over the northern tip of Scotland, which brings warmer water species than would be expected in the North Sea (St. Abbs & Eyemouth Voluntary Marine Reserve n.d.). Wolf-fish are also unusually found here, at much shallower depths than elsewhere and BVMR has an existing wolf-fish identification project and were keen to engage with further citizen science projects.

BVMR is working with Blue Marine Foundation and local fishers in a baseline survey project, collecting data to build knowledge of species and commercial fishing practices inside the BVMR. The aim is to understand key stocks, temporal changes, and inform efficiency, to improve the sustainability of local fishery. A citizen science SCUBA diving project was scoped and planned with BVMR. The scope was to include the impact of temperature on species distribution and abundance, utilising temperature data from loggers on the seabed, on creels & by collection of data from citizen science SCUBA divers' dive computers. With contributions from the (then) BVMR Manager and a local dive boat captain, who has in depth local knowledge of the underwater landscape and insight into commonly dived areas, 6 sites of different depths were proposed as potential logger locations. The intention was to place in situ loggers at commonly dived sites, which could be used for comparison with dive computer temperatures. Advice was given to the BVMR Manager on suitable dive computers for the project, which were purchased, Subsurface was downloaded to BVMR machines, and training given. Early trials by BVMR volunteers found temperature differences between dive computer and a positioned logger of +0.3 °C at the closest sample point, and at a steady depth a difference of +0.2 °C, which is consistent with an offset found in our research into dive computer accuracy discussed in Chapter 2. The proposed approach was to hand out the BVMR dive computers to divers on dive boats on a dive-by-dive basis, as positive relationships exist between BVMR and dive boat captains. Post-dive, the computers would be recovered by BVMR volunteers, the data uploaded to Subsurface, and subsequently to DiS when live. This would have the benefit of gathering data for the BVMR projects while removing the data upload effort from the divers. Additionally, by handing out and retrieving dive computers an engagement opportunity was seen. It would be a chance to excite divers about the wider BVMR activities whilst piquing their interest in the wider DiS project, hopefully to then go on and submit additional data from their own computers. With the exit of the then manager, a succession of further volunteers in the role, and little seeming project handover, project energy was intermittent, and the project stalled. I was recently contacted by a new Project Officer at the BVMR, who was interested in finding out about the project, and who may progress things.

5.2.2 Thermocline

Other aspects of utilising temperature data from dive computers were also explored, such as identification of thermoclines. Due to the pandemic, field work was not allowed, preventing the planned collection of dive computer and CTD data in areas with known thermoclines. Coincidentally, two dives with thermoclines had been carried out alongside Castaway CTDs in Cape Town in early 2019. As insufficient data was available to fully unpick the factors involved, a full description has not been given as further data are required. The following section gives a brief overview of results and is provided to suggest the potential for future investigation.

Three simple approaches were explored: one-sided differentiation, where

$$Gradient(n) = \frac{T(n)-T(n-1)}{Z(n)-Z(n-1)}; \tag{2}$$

two-sided differentiation, where

$$Gradient(n) = \frac{T(n+1)-T(n-1)}{Z(n+1)-Z(n-1)}; \tag{3}$$

and a binned approach, where

$$Gradient(bin) = \frac{T_{mean}(bin) - T_{mean}(bin-1)}{\Delta z}; \tag{4}$$

2 m depth bins were found to have the most successful results in early trials.

Early results showed potential with all three methods, however, each method returned a different thermocline depth for the Castaway itself, likely due to subtle gradient changes in different dives. One dive, which had a square profile (a descent to the maximum dive depth was followed by a consistent period at that depth, followed by an ascent to the surface) had better agreement with the Castaway results. For this dive, a suggested depth for the maximum temperature gradient within ± 1 m of the Castaway was returned for 14 out of a possible 26 dive computers following the one-sided approach. 21/26 were within ± 1 m using two-sided differentiation, and 20 dive computers registered the largest temperature change in a bin with depth ± 1 m of the Castaway bin depths. For the second dive, 14/26 dive computers were within ± 1 m using one-sided differentiation, 14/26 with a binned approach, but none with two-sided differentiation. The dives were not carried out with the intention of collecting thermocline data, so profiles were not consistent, and there was a highly variable depth profile through the course of the latter dive. This dive did not follow a square profile (square profile: descend to maximum depth, retain a consistent depth before ascending at a safe speed), but passed through the subjective thermocline layer multiple times. With the varying time constants, the dive computers, this type of profile would be hard to map. It is suggested that in this dive, one-sided differentiation also captured minor gradient changes in the CTDs that were not identifiable within dive computer resolutions, as there were two distinct dive computer depth groups: eight dive computers were within 1 m of each other, and a further 16 in another 1 m spread group. For both dives, several computers returned multiple bins with the same maximum change in temperature (dT) when using a binned approach. The rate of ascent through the thermocline as well as profile shape and dive time will all have an effect, but the results seen here show promise for further investigation.

Egi et. al. (2018) proposed a dive plan (including pausing for 3 min at subjective depth of thermocline) which would 'mark' the thermocline in the profile, although no research has been presented demonstrating its effectiveness. As time constant has been found to range between 18 and 300 s, a citizen scientist diver could target their dive to include marking a perceived thermocline, stopping for a duration based on knowledge of their dive computer model's temperature response characteristics. These stops would need to be carried out without endangering divers' health or contravening decompression limits. For this reason, and to allow dive computers to acclimatise from potential surface temperature affects, it would be recommended to mark the thermocline on the ascent if following this approach. Further conclusions will be possible in the future, with greater access to a wider range of dive computer and thermocline profiles.

5.3 Limitations

The doctorate as a whole was affected by the pandemic, including the inability to carry out field data collection which impacted on the intended scope of work.

Limitations of dive computers themselves have been discussed in section 2.5.3, and of potential user error in section 3.5.6. Lack of spatial and temporal consistency is a feature of citizen science data (Callaghan et al. 2019). As with many geo-referenced citizen science datasets, the spatial and temporal density in data collected from dive computers is incidental and therefore will be inconsistent. However, a comprehensive monitoring network is not suggested, but gap-filling, or increased volumes of, data in areas where there is little or no existing in situ monitoring. Rather than using interpolation to fill large gaps, calls for data in specific areas can be made.

Feedback from scientists is important to all groups of citizen scientists (Martin et al. 2016). It was a bureaucratic challenge in getting diveintoscience live, which minimised available time to carry out necessary engagement. With the reduction in diving in 2020 and 2021 due to lockdowns and lack of travel, the site has not yet been well used, but also no comprehensive engagement programme has been carried out.

User testing needs to be widened and increased volumes of feedback need gathered to identify whether there are issues with site usability, effort to upload, lack of awareness or other barriers to participation.

5.4 Final thoughts

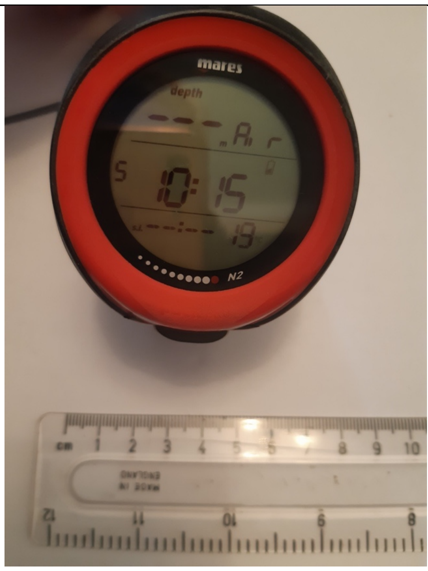
The pandemic has highlighted the importance to expand our methods for data collection, with key mooring arrays at risk and 10 % of real-time data distribution lost in 2020 – 2021 (IOC-UNESCO n.d.). The environment and conservation are increasingly part of key diving agencies' focus. PADI AWARE Foundation is the conservation arm of PADI, one of the leading training agencies worldwide. For the first time, 'Environment' is a strand in the 2021 – 2023 strategic plan for BSAC (the national governing body for diving in the UK). Importantly, this study has strengthened our understanding of the potential of SCUBA divers as citizen scientists, particularly with regards to ocean temperature. Further studies with specific depth/time points in profiles would develop our understanding further. We should consider the potential for SCUBA diver citizen scientists to collect measurements of physical parameters in the ocean is in their spatiotemporal reach. With the increasing miniaturisation and decreasing costs of sensors, the potential to expand to other physical and chemical parameters, such as pH, is likely imminent.

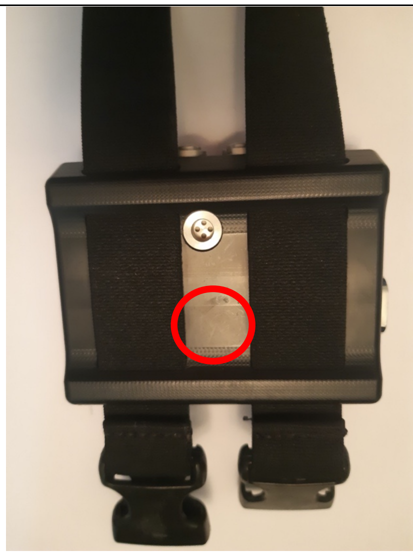
Now that dive computer temperature responses and uncertainties are better understood, the possibilities are extensive. Although with a resolution that is not appropriate for climate monitoring, dive computers provide information on patterns and local temperature variability, which, in some areas, are not available by other means. If feature mapping is important (such as thermocline identification) then actual accuracy is less important than the ability to detect change. While it is not suggested that dive computers are the sole answer to the data shortage, they can form part of the solution. When multiple organisations start to investigate the same issue from different angles, I believe it is an indication that there is value in the idea. Over the duration of this PhD, new projects have arisen investigating this issue in a similar way, such as DORIS (Diver carried Oceanographic Recording InstrumentS), a small autonomous CTD which can be carried by divers (Sayer et al. 2021); Sonic kayaks, low cost open source hardware for collecting marine data such as temperature and turbidity (Action 2021) and ECOTag, a low cost, open source, 3d printable device for collecting marine temperature, pressure and light (pers. comm. Mark James; University of St Andrews n.d.). Existing initiatives such as the Smartfin project (collecting temperature data from surfboard fins)(Brewin et al. 2021) and Project Hermes (GPS and Wi-Fi enabled device for collection of temperature and depth, designed to attach to SCUBA divers' tanks) (Cousteau n.d.) have been further refined and/or evaluated. A single source of citizen science temperature data can contribute to an integrated observation platform, but, assuming data source and quality measures are clearly stated, combining these data sources offers the greatest opportunity. All data would not need to be collected via one initiative, or technology solution, but open data sharing and collaboration will be key. Sustained observations have struggled because of lack of funding or stopped completely (Mieszkowska et al. 2014) despite the importance of long-term time-series in advancing our understanding of ecosystems and ocean processes (Brander, Dickson, and Edwards 2003; Harvey et al. 2020). As a result of this study, a potential mechanism to develop a long-term time series has been delivered, and results which can underpin further work into areas such as more detailed thermocline investigations. With an engaged community of citizen scientist divers, advanced sensors and tools could be developed to measure additional parameters, allowing us to take better care of our oceans.

Appendix

Table A.1: Device sizes and pressure sensor locations

Model	**Front view**	**Pressure sensor location**
Aqualung i750TC		
Garmin Descent Mk1		

Mares Matrix		
Mares Puck Pro		
Paralenz Dive Camera+		Underneath pull 

Ratio iX3M GPS Deep		
Scubapro G2		
Shearwater Perdix		

Suunto D4i		
Suunto D6i		
Suunto EON Steel		

Suunto Vyper		

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