1 **Title:** Reconstructing past thermal conditions in microclimates 2 **Authors:** Jacques-Olivier Laloë¹, William J. Chivers², Nicole Esteban^{3*}, Graeme C. Hays¹ 3 4 5 Author affiliations: ¹School of Life and Environmental Sciences, Deakin University, 6 Geelong, Victoria, Australia 7 ²School of Electrical Engineering and Computing, University of Newcastle, Callaghan, New 8 South Wales, Australia 9 ³Faculty of Science and Engineering, Swansea University, Swansea, Wales, United Kingdom 10 *corresponding author: n.esteban@swansea.ac.uk 11 12 Running headline: Modelling temperatures in unique microhabitats 13 14 **Journal:** Global Change Biology 15 16 Abstract 17 Reconstruction of past conditions provides important information on how ecosystems 18 have been impacted by climate change, but generally for microhabitats worldwide there are 19 no long-term empirical measurements. In these cases, there has been protracted debate about 20 how various large-scale environmental proxies can best be used to reconstruct local 21 temperatures. Here we help resolve this debate using sand temperature data at nest depths for 22 sea turtle nesting sites across the world. We examine how well environmental proxies 23 hindcast sand temperatures at nest depths at five sea turtle nesting sites across the world. We 24 link instrumental air temperature and sea surface temperature records with empirical sand 25 temperatures observations in the Atlantic (Ascension Island and Cape Verde), the Indian 26 Ocean (Chagos Archipelago), the Caribbean (St Eustatius) and the Pacific (French 27 Polynesia). We found strong correlations between sea surface temperatures, air temperatures 28 and sand temperatures at all our study sites. Furthermore, Granger causality testing shows 29 variations in sea surface temperature and air temperature precede variations in sand 30 temperatures. We found that different proxies (air or sea temperature or a combination of 31 both) predicted mean monthly sand temperatures within < 0.5°C of empirical observations. 32 Reconstructions of sand temperatures over the last 170 years reveal a slight warming of 33 temperatures (maximum 0.5°C per century). An analysis of 36 published datasets revealed 34 that the gradient of the relationship between sand temperature and air temperature is

relatively constant, suggesting long-term changes in sand temperature could be extended around the world to include nesting sites where there are no empirical measurements of sand temperature. Our approaches are likely to have utility for a range of micro-habitats where there is interest in long-term changes in temperature.

Key words: microhabitat modelling, Granger causality testing, Hadley SST, temperature-dependent sex determination, climate change

1 | Introduction

Reconstructing past environmental conditions offers valuable information on the rate of climate change. Since the distribution of plant and animals is closely linked with the climate, reconstructing past climates also allows modelling of the past distributions of species as well as exploring processes behind distribution range shifts (Melo-Merino et al., 2020). Different components of the past climate can be inferred using different proxies. For example, coral cores provide reliable information on sea temperatures over several centuries, as well as giving indications of the rates of sea level change and salinity variations (Corrège, 2006). For terrestrial ecosystems, dendroecological techniques help reconstruct the climate over several millennia by studying tree rings (Touchan et al., 2008). To extend further back in time, paleoclimatologists rely on oxygen isotope ratios found in ice cores (Steiger et al., 2017) and pollen diversity preserved in sediment layers (Davis et al., 2003). Taken together, these techniques enable the reconstruction of past climates on regional and global scales, and for time frames ranging several decades to several 100s of millions of years.

To estimate recent global temperatures climatologists can rely on the instrumental record, which extends as far back as the mid-nineteenth century in some locations. For example, air temperatures, sea surface temperatures and precipitation data are monitored daily at countless locations around the world and are compiled in datasets that are widely made available (e.g. the Bureau of Meteorology in Australia, the Meteorological Office in the United Kingdom, the National Oceanic and Atmospheric Administration in the United States of America). In some cases, these data can be used to directly assess how climate change may have impacted taxa, for example marine species whose range is influenced by sea surface temperature (e.g. McMahon & Hays, 2006; Chivers et al., 2017; Richardson & Schoeman, 2004). For species that live in particular microhabitats (i.e. very small and localized habitats) correlative models that use large-scale environmental proxies to predict local environmental conditions can be used (Kearney et al., 2010; Pacifici et al., 2015). For example, for species

that live in the soil, soil temperatures can be modelled using proxies such as land surface temperatures (Huang et al., 2020).

For sea turtles, the correlative approach using either air temperature (AT) and/or sea surface temperature (SST) has been widely used to reconstruct sand temperatures at nesting sites (Hays et al., 2003; Fuentes et al., 2009; Jensen et al., 2018; Bentley et al., 2020a; Chatting et al., 2021). However, there has been debate about whether AT or SST provides the best proxy for these sand temperature reconstructions (Fuentes et al. 2009; Bentley et al. 2020a; Hays et al. 2021). Here we set out to resolve this debate using sand temperature data at nest depths for sea turtle nesting sites across the world. In addition to simple correlative models, we further explored the potential causal pathways between AT, SST and sand temperature by using Granger causality testing which provides a measure of forecasting over and above that provided simply by temporal correlations and helps point towards causal links (Thurman & Fisher, 1988). Combining our best models with historical environmental datasets, we then reconstruct sand temperatures at nest depths for > 100 years at each study site and show the utility of our approach for both other sea turtle nesting sites around the world as well as other micro-habitats where there are no long-term local temperature measurements. In this way we demonstrate how our approach may have broad utility for those studying a range of habitats where there is interest in assessing how temperatures have changed over the past century and identifying those sites that are most likely to have been strongly impacted by recent climate change.

8990

69

70

71

72

73

74

75

76

77

78

79

80

81

82

83

84

85

86

87

88

2 | Materials and methods

- 91 2.1 | Sand temperatures
- We used sand temperature records published from six sea turtle nesting beaches from five
- 93 island locations (Figure 1). Data were obtained for Long Beach and North East Bay on
- 94 Ascension Island (South Atlantic) (Hays et al., 2003), Cape Verde (North Atlantic) (Laloë et
- 95 al., 2017), the Chagos Archipelago (Indian Ocean) (Esteban et al., 2016), French Polynesia
- 96 (East Pacific) (Laloë et al., 2020a), and St Eustatius (Caribbean) (Laloë et al., 2016). In these
- 97 studies, sand temperatures were recorded using loggers deployed at nest depth on sea turtle
- 98 nesting beaches. Loggers were deployed at different sites along the nesting beach to capture
- 99 the range of different thermal habitats in which the turtles nest. In all studies temperatures
- loggers were deployed adjacent to nests and at typical depths reported for each site. So
- although the depth of loggers varied between studies, changes in the recorded sand

temperatures from month to month reflected the temporal change in incubation conditions.

Details of each dataset can be found in Supplemental table 1.

We calculated monthly means from these sand temperature records to capture broad changes in sand temperatures as well as make these measurements directly comparable with the environmental datasets that are supplied as monthly means.

2.2 | Environmental datasets

We obtained air temperature records for our study sites from the International Comprehensive Ocean-Atmosphere Data Set (ICOADS) from the National Center for Atmospheric Research (https://ncar.ucar.edu). The ICOADS is an extensive set of surface marine data that extends as far back as 1854 and covers all oceans. Recent measurements (i.e. since the 1970s) are compiled from extensive arrays of drifting and moored buoys (Woodruff, 2001). We used the Enhanced ICOADS Monthly Summary Release 2.5 at the 2° spatial resolution. We used the same geographic area as defined in the original publications, which ranged from a 2° by 2° area (i.e. St Eustatius; Laloë et al., 2016) to a 10° by 10° area (i.e. the Chagos Archipelago; Esteban et al., 2016). We restricted the dataset to months with > 30 observations. We did not interpolate the data between months with missing data, so some gaps exist in these datasets.

We obtained Hadley sea surface temperature (SST) data for the same geographic areas from the United Kingdom Meteorological Office (www.metoffice.gov.uk). In this dataset, SSTs are reconstructed from *in situ* and remote-sensed measurements using reduced space optimal interpolation.

To examine if local AT is a better predictor for sand temperature than regional (i.e. ICOADS) AT, we obtained AT records from the Amílcar Cabral International Airport in Espargos, Cape Verde, from Weather Underground (www.wunderground.com). Local AT records were not available for our other study sites.

2.3 | Literature review

To explore if the relationship between sand temperature and air temperature is consistent at different sites across the world, we searched the literature for publications that present the relationship between sand temperature at nest depth and air temperature and/or sea surface temperature at sea turtle nesting sites. We entered the search terms "temperature" and "sea turtle" as TOPIC in Web of Science (apps.webofknowledge.com) for articles published between 1960 and 2021. We did a backward and a forward citation search on relevant articles to find further publications.

136 In some publications, relationships were not given but the data were available in figures or tables. For these cases, we digitized the data from the figures or tables using 137 138 WebPlotDigitizer 4.4 (automeris.io/WebPlotDigitizer) and subsequently established the relationships ourselves. 139 140 It is important to note that although the depth at which loggers were buried might vary 141 between studies, all studies present sand temperatures at nest depth. So regardless of specific 142 depths at which loggers were deployed in each study, relationships are always given relative 143 to sand temperature at nest depth. 144 145 2.4 | Statistical analyses 146 We investigated the relationship between sand temperature, ICOADS AT, and Hadley SST 147 using a stepwise multiple regression. We further explored the time series using a Granger 148 causality test. The Granger analysis was implemented using the "grangertest" function in the 149 R library "Imtest" and with a lag = 1. 150 We also explored the relationships between sand temperature and AT found in the 151 literature. We investigated whether the gradients and intercept of each relationship were 152 different for different sites using an analysis of covariance. All statistical analyses were done 153 in R version 4.0.3 (R Core Team, 2020). 154 155 3 | Results 156 3.1 | Best predictors for sand temperatures 157 Both ICOADS AT and Hadley SST were very good predictors for sand temperatures at our study sites, with R^2 values > 0.80 at all sites except in French Polynesia (Table 1; Figure 1). 158 159 When we entered AT and SST in a stepwise regression, AT was found to be the best 160 predictor for sand temperature for Ascension Island Long Beach, Ascension Island North 161 East Bay, and Cape Verde. SST was the best predictor for sand temperature for the Chagos Archipelago and French Polynesia. Only at one study site, i.e. St Eustatius, using AT in 162 163 combination with SST resulted in the best model fit (Table 1). We also found a strong 164 relationship between air temperatures recorded at the airport on Cape Verde and sand temperatures ($R^2 = 0.88$, p < 0.001; Table 1). 165 166 To further examine the differences between model outputs we calculated the mean 167 absolute difference between modelled sand temperatures and observed sand temperatures. 168 For example, for Ascension Island Long Beach the model with the best fit (i.e. using AT as 169

predictor; Table 1) modelled sand temperatures that were on average 0.36 °C from the

observed sand temperature. The next best model (i.e. using both AT and SST as predictors; Table 1) modelled sand temperatures that were on average 0.37 °C from the observed sand temperature. Using SST alone as a predictor produced results that were on average 0.47°C from the observed sand temperature. Similarly, for Cape Verde, using local air temperatures or regional air temperatures produced results that were within 0.1 °C of each other (Table 1; Supplemental figure 1). In short, all examined models produced results that were on average within fractions of a degree of the recorded mean monthly sand temperatures, i.e. there were only marginal differences in whether either AT or SST or a combination of both was used to predict sand temperature.

We used Granger causality tests to further explore the relationships between our predictor variables and sand temperatures. We found significant Granger causality between air temperature and sand temperature (p < 0.05) at all study sites except Cape Verde, i.e. when past values of AT were used in a regression model to predict future values of sand temperature (with a lag of 1 month) after adjusting for past values of sand temperature. We also found significant Granger causality between SST and sand temperature (p < 0.05) at all study sites except Cape Verde and St Eustatius.

3.2 | Long term reconstructions

We reconstructed sand temperatures at our study sites using the historic instrumental records (i.e. ICOADS and Hadley datasets) and the relationships highlighted in Table 1. In two cases (i.e. both beaches on Ascension Island), we were able to reconstruct sand temperature as far back as 1805 (Supplemental figure 2). In general, our times series extend from the late 19th century to the present.

To explore if there has been a warming trend over the last centuries, we examined mean monthly sand temperatures during peak nesting season at each site (Figure 2). We found that there has been a warming trend at all our study sites bar one (i.e. St Eustatius). Sand temperatures during peak nesting month increased by up to 0.5 °C per century (minimum = 0.15 °C per century, maximum = 0.5 °C per century).

3.3 | Sand vs air relationships

We found a total of 36 relationships between sand temperature and AT published for 23 different sea turtle nesting sites (Figure 3; Supplemental table 2). While the intercepts of the relationships found for different study sites vary (mean = 6.35, standard deviation = 7.40, n = 36), the gradient for all relationships remains relatively constant (mean = 0.86, standard

deviation = 0.26, n = 36; Figure 3). In other words, for every 1°C increase in air temperature, sand temperatures increase by an average 0.86 °C.

For 13 of these 23 sites, data were available in the publication either in tables or figures. For these sites, we investigated the relationships between sand temperatures and AT using an analysis of covariance. AT was modelled as the dependent variable with site as the factor and sand temperature as the covariate. We found a significant effect of AT on sand temperature ($F_{1,706} = 241.5$, p < 0.01) but no significant interaction ($F_{1,706} = 2.5$, p = 0.111), indicating that the slopes of the regression between sand temperature and AT is similar at all sites (Supplemental figure 3). This analysis confirms the above result that the gradient for all relationships remains relatively constant at all sites (Figure 3). At these 13 sites, a 1°C increase in air temperature resulted in mean monthly sand temperatures increasing by an average 0.84° C (95% confidence interval = [0.79; 0.90], n = 13 sites). Site had a significant effect on sand temperature ($F_{1,706} = 71.8$, p < 0.01) indicating that different sites have different intercepts, i.e. that some sites are warmer than others. For example, sand temperatures at nest depths recorded on two beaches on Ascension Island were very different: Long Beach was an average 3.0° C warmer than North East Bay beach.

Site	n	Variable	AIC	R²	р	Equation	Mean absolute difference
Ascension Island	29	AT	-44.64	0.80	< 0.001	10.38 + 0.67 x AT	0.35 °C
Long Beach		AT+SST	-42.64	0.80	< 0.001	10.42 + 0.68 x AT - 0.01 SST	0.34 °C
		SST	-29.86	0.67	< 0.001	9.81 + 0.68 x SST	0.47 °C
Ascension Island	25	AT	-33.15	0.82	< 0.001	11.22 + 0.75 x AT	0.36 °C
North East Bay		AT+SST	-32.36	0.83	< 0.001	10.15 + 0.58 x AT + 0.21 x SST	0.37 °C
		SST	-24.56	0.74	< 0.001	9.70 + 0.80 x SST	0.47 °C
Cape Verde	24	AT	-41.31	0.84	< 0.001	11.04 + 0.69 x AT	0.30 °C
		AT+SST	-39.94	0.85	< 0.001	10.47 + 0.55 x AT + 0.17 x SST	0.31 °C
		SST	-35.17	0.80	< 0.001	9.93 + 0.73 x AT	0.36 °C
		local AT	NA	0.88	< 0.001	10.44 + 0.73 x local AT	0.28 °C
Chagos Archipelago	15	SST	-33.93	0.82	< 0.001	3.65 + 0.86 x AT	0.23 °C
		AT+SST	-32.13	0.82	< 0.001	3.54 + 0.15 x AT + 0.71 x SST	0.23 °C
		AT	-30.36	0.77	< 0.001	4.86 + 0.84 x AT	0.25 °C
French Polynesia	23	SST	-35.77	0.58	< 0.001	13.32 + 0.52 x SST	0.31 °C
		AT+SST	-33.85	0.58	< 0.001	13.15 + 0.06 x AT + 0.46 x SST	0.31 °C
		AT	-31.3	0.49	< 0.001	14.48 + 0.49 x AT	0.38 °C
St Eustatius	14	AT+SST	-6.55	0.82	< 0.001	8.87 + 4.09 x AT -3.21 x SST	0.55 °C
		AT	0.44	0.70	< 0.001	-5.09 + 1.31 x AT	0.65 °C
		SST	6.32	0.49	0.005	-6.12 + 1.31 x SST	0.85 °C

TABLE 1 We found strong relationships between sand temperature (ST), air temperature (AT) and sea surface temperature (SST). For each site, the model with the best fit (lowest Akaike's information criterion) is indicated in bold. For Cape Verde, we additionally examined the relationship between sand temperature (ST) and air temperature from the international airport found on Sal (local AT; in italics). The sample size (n) is the number of months for which sand temperatures are available.

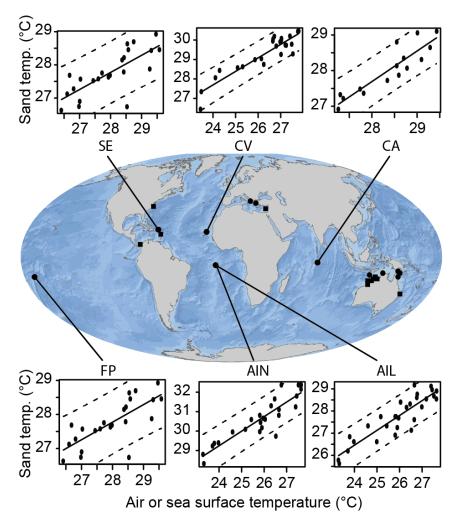


FIGURE 1 Location of sites used in our study. Relationships between sand temperature, air temperature and sea surface temperatures were given in the literature for all sites. Sites that gave the relationship as well as provided the data are indicated with circles. Sites which gave only the relationship are indicated by squares. We highlight the relationships presented in bold in Table 1. AIL: Ascension Island Long Beach; AIN: Ascension Island North East Beach; CA: Chagos Archipelago; CV: Cape Verde; FP: French Polynesia; SE: St Eustatius. The solid line in the regression line; the dashed lines define the 95% prediction interval.

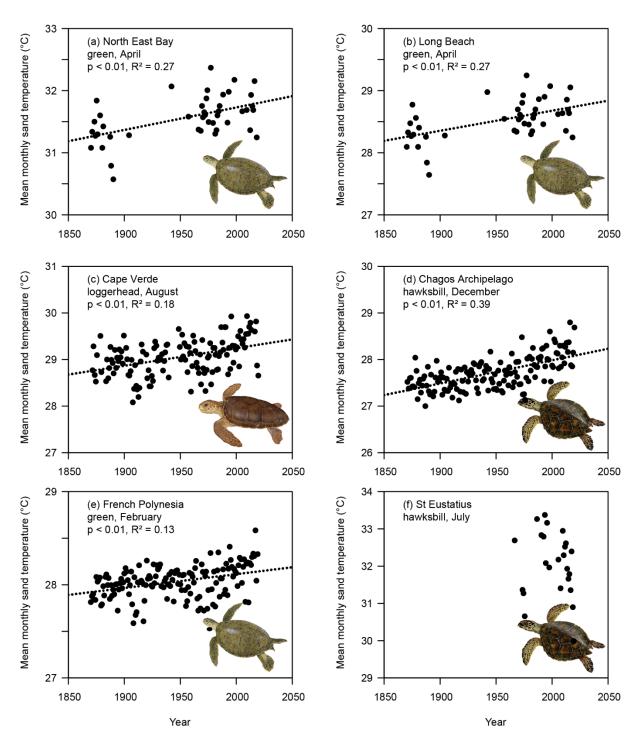


FIGURE 2 Mean monthly sand temperatures during peak nesting season have increased at the majority of our study sites. Sea turtle species and the month during peak nesting season shown are detailed in each sub-panel. For example, mean monthly sand temperature during December, a month during peak hawksbill nesting season in the Chagos Archipelago, has increased at an average rate of 0.5 °C per century since 1870 (subpanel b). There are gaps in our time series due to gaps in the historical records. Least squares fit regressions (dotted lines) are shown when significant.

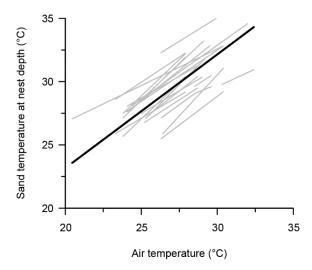


FIGURE 3 Warmer air temperatures consistently lead to warmer sand temperatures at sea turtle nesting beaches across the world. We found 36 relationships for 13 study sites (grey lines; Supplemental table 2). The black line represents the generic linear relationship defined by the mean intercept and the mean gradient of all relationships in grey (sand temperature = $0.86 \times \text{air}$ temperature + 6.35).

4 | Discussion

250

251

252

253

254

255

256

257

258

259

260

261

262

263

264

265

266

267

268

269270

271

272

273

274

275

276

277

278

279

280

281

282

283

Our findings highlight how environmental proxies can be used to accurately reconstruct temperatures in specific microclimates and so this approach may have wide utility across habitats, allowing current conditions to be placed into the context of likely conditions over the last century. So, for example, our approach could equally be applied to other coastal ecosystems such as mangroves, salt-marshes and coral reefs where there is intense interest in the impacts of climate change (Duarte, 2017). The same approach we used could also be applied to terrestrial habitats where there is interest in reconstructing past conditions but where local in-situ temperature records are lacking. In this way, this approach would allow an assessment of the extent to which climate change may already have impacted species and habitats.

For sea turtles, there are specific reasons why understanding past nest conditions is important. Sea turtles exhibit temperature-dependent sex determination (TSD), with females being produced from eggs incubating at high incubation temperatures (Standora & Spotila, 1985; Santidrián Tomillo, 2020; Bentley et al., 2020b). Hence there is concern that warming temperatures as a part of climate change may raise temperatures sufficiently to produce single-sex (female-only) hatchling cohorts and so ultimately population extinctions. In addition, high incubation temperatures cause embryonic mortality (Howard et al., 2014). For this reason, recording sand temperatures at sea turtle nesting beaches has become routine across the world (e.g. Hays et al., 1999; Rees and Margaritoulis, 2004; Fuentes et al., 2009; Bentley et al., 2020a). Set against this backdrop, our findings suggest that historic sea surface temperature or air temperature – both of which are freely available across the globe – can be used to accurately predict historic sand temperatures at nest depths. This conclusion in itself is not new, since reconstructing sand temperatures at sea turtle nesting sites has been widely done using the correlative approach (e.g. Hays et al., 2003; Hawkes et al., 2007; Fuentes et al., 2009; Chatting et al., 2021). However, there has been debate about which environmental variables are the best predictors of sand temperature and here our work adds value by showing there is little difference in the predictions made by using either sand or air temperature. For some sites air temperatures have previously been used to predict sand temperature (e.g. Laloë et al., 2017) while for other sites sea surface temperatures are better predictors (e.g. Fuentes et al., 2009). For yet other sites using both air and sea surface temperatures produce best results (Bentley et al., 2020a; Chatting et al., 2021). We show here that for sites across the globe all these approaches give good predictions of sand temperatures. So if air temperatures are not available for a specific nesting site, sea surface

temperatures can be readily used as a reliable substitute for sand temperatures reconstructions and vice-versa. It is likely that the applicability of air temperatures and/or sea surface temperatures for predicting sand temperatures are locally variable. In general, it is expected that at island sites sea surface temperatures will play a greater role in influencing sand temperatures than at mainland sites. Additionally, we show that predictions of sand temperature using large-scale records agree with those using local air temperature records at one of our study sites, i.e. large-scale proxies give a good indication of local conditions. This result agrees with the recent finding that broad-scale environmental measurements can reflect local measurements (Hays et al., 2021). However, one important point to note is that the more local records – such as the air temperature records obtained from the airport used in our study – may not extend as far back in time as other large-scale records, and so reconstruction of past sand temperatures will be limited.

284

285

286

287

288

289

290

291

292

293

294

295

296

297

298

299

300

301

302

303

304

305

306

307

308

309

310

311

312

313

314

315

316

317

Our demonstration that either large scale air or sea temperature measurements can be used to reconstruct local temperatures, will help a number of important questions to be addressed. It is well established that female-skewed hatchling sex ratios predominate at rookeries around the world (e.g. Cuong et al., 2008; Hays et al., 2014; Booth et al., 2020). For instance, the largest green sea turtle rookery in the world was recently shown to be extremely female-biased (Jensen et al., 2018) and for our study site in Cape Verde, primary sex ratios were estimated to be > 70% female (Laloë et al., 2014). An important question is whether these skewed sex ratios are a normal feature for sea turtles and have persisted for a long time, possibly being adaptive by allowing increased population growth rates (Santidrián Tomillo & Spotila, 2020), or whether these skews are a maladaptive consequence of climate warming. Reconstructing the last century or more of sand temperatures on nesting beaches across the globe will help answer this question. Interestingly, our long-term sand temperature reconstructions reveal that incubation conditions currently reported at our study sites are not very different to conditions for the several past decades, as temperatures have increased at a slow rate of < 0.5 °C per century. So, it is likely that sex ratio production at these sites will have stayed relatively stable over the last century. For example, the biased sex ratios estimated in Cape Verde (Laloë et al., 2014) are likely not a new occurrence. Similarly, on Ascension Island's North East Bay sand temperatures are well above the pivotal temperature for TSD (Figure 2a), so it is unlikely that sex ratios have changed drastically over the past 100 years. If similar results were found at other nesting sites, it might suggest that biased hatchling sex ratios, at least to a certain extent, may in fact be quite normal for sea turtles and might serve to increase hatchling production and population resilience by having more

breeding females (Hays et al., 2017). However, it is important to underline that because of the steepness of the relationship between incubation temperature and hatchling sex ratio at the pivotal temperature (Bentley et al., 2020b), a 0.3 °C change in temperature at or near the pivotal temperature can lead to a large change in hatchling sex ratio. Additionally, there is important variability in sand temperatures both at shorter time-scales (e.g. Staines et al. 2020) and also between sites on the same beach (Esteban et al. 2016). So to gain a full picture of the likely long-term changes in sand temperatures, these sources of variability need to be assessed in addition to long-term changes. For example, it may be that even when the mean sand temperature on a beach drives the production of one sex, that thermal variability within a beach or over short time-scales may help ensure at least some production of the other sex (e.g. Porter et al. 2021).

In recent years, elegant mechanistic microclimate modelling approaches that rely on a suite of environmental variables have been used to reconstruct sand temperatures at turtle nesting sites (Fuentes and Porter, 2013; Bentley et al., 2020a). Advantages of the mechanistic model include that it can be forced with novel combinations of environmental variables to explore the impacts of climate change on sea turtle nesting grounds (Patrício et al., 2021) and that it is also possible to model sand temperatures over fine temporal scales (e.g. days or hours). However, microclimate models often require locally-calibrated input parameters (e.g. sand and beach properties as well as meteorological variables). Furthermore, projections are equally difficult to parametrize due to a lack of information regarding future environmental regimes (Patrício et al., 2021). Regardless, when applied correctly, mechanistic microclimate models can predict sand temperatures at sea turtle rookeries accurately, which in turn can help explore the impacts of climate change on beach temperatures (Bentley et al., 2020a). As mechanistic models are becoming readily accessible (e.g. through different R packages) alongside vast volumes of gridded climate data, they provide a powerful tool for investigating climate impacts in particular microhabitats.

Thanks to accessible online climate data repositories, the correlative approach is also easy to implement. One advantage of the correlative model is that it requires fewer input parameters than typical mechanistic models and so is usually easier to implement. On the other hand the correlative method may not be as reliable as the mechanistic model when making projections that fall outside of the range of observed values. However this was not an issue in our study since we were able to record large intra- and inter-seasonal variation by having temperature loggers deployed year-round and over multiple nesting season at all our study sites, and hence had a wide range of observations upon which to base our model. This

is confirmed by the fact that very few hindcasted values fell outside the range of values used to inform our models (Supplemental figure 2). Finally, both the mechanistic approach and the correlative method were shown to produce very similar results (Kearney et al., 2010; Bentley et al., 2020a) and, as detailed above, each approach has its advantages and drawbacks (Patrício et al., 2021). Our work and that of others (Bentley et al. 2020a), suggests that, when used appropriately, both mechanistic and correlative models will have broad utility as approaches for assessing how thermal conditions have changed on turtle nesting beaches, and other habitats, over the last century.

Ideally, more *in situ* sand temperature data will become available for nesting sites around the world both as temperature loggers become more widely used and data availability improves in academic publishing (Alsheikh-Ali et al., 2011; Munafò et al., 2017; Shin et al., 2020). However, it is likely that there will remain a huge number of nesting sites where *in situ* data continues to be lacking and so it would be useful to be able to estimate trends in nest temperatures for such sites. While absolute sand temperatures at a site may be influenced by physical and environmental factors such as sand colour (i.e. dark beaches are warmer Hays et al., 2003; Laloë et al., 2014), extent of shading (Esteban et al., 2016) and rainfall (Houghton et al., 2007; Laloë et al., 2020b, Staines et al., 2020), we found that the gradient of the relationship between sand temperature at nest depth and air temperature was relatively constant across nesting sites. So, by knowing simply the change in air or sea temperature for the last century at a site where there are no *in situ* sand temperature measurements, it might be possible to make a fairly accurate prediction of the likely changes in sand temperature at nest depths. In this way our finding of little change in sand temperatures at nest depths for several nesting sites could be extended to many more sites globally.

In summary, we show the broad utility of how environmental proxies may be used to reconstruct past conditions and we highlight how this approach could be used, not only for sea turtle nesting sites around the globe, but also for other species and habitats where predictions of temperatures in specific microclimates are difficult. Furthermore, there is intense interest in how climate change is impacting a number of coastal environments, such as coral reefs, mangroves and salt-marshes. Given the strong links we show between local temperature measurements and large-scale environmental proxies, it is likely that historic temperatures can reliably be reconstructed across this broad range of coastal habitats, allowing current conditions to be placed into a longer-term perspective.

386	This work was supported by the Bertarelli Foundation as part of the Bertarelli Programme in
387	Marine Science (BPMS-2017-4). The turtle images used in Figure 2 were kindly provided by
388	NOAA Fisheries (www.fisheries.noaa.gov).
389	
390	Authors' contribution
391	G.C.H., JO.L. and N.E. conceived the ideas and designed the study. JO.L. and W.J.C.
392	developed the statistical methods and analysed the data. JO.L. and G.C.H. led the
393	manuscript writing. All authors contributed critically to manuscript drafts and gave final
394	approval for publication.
395	
396	Data availability statement
397	The data that support the findings of this study are available from the corresponding author
398	upon reasonable request.
399	
400	References
401	Alsheikh-Ali, A. A., Qureshi, W., Al-Mallah, M. H., & Ioannidis, J. P. (2011). Public
402	availability of published research data in high-impact journals. PloS One, 6, e24357.
403	https://doi.org/10.1371/journal.pone.0024357
404	Bentley, B. P., Kearney, M. R., Whiting, S. D., & Mitchell, N. J. (2020a). Microclimate
405	modelling of beach sand temperatures reveals high spatial and temporal variation at
406	sea turtle rookeries. Journal Thermal Biology, 88, 102522.
407	https://doi.org/10.1016/j.jtherbio.2020.102522
408	Bentley, B. P., Stubbs, J. L., Whiting, S. D., & Mitchell, N. J. (2020b). Variation in thermal
409	traits describing sex determination and development in Western Australian sea turtle
410	populations. Functional Ecology, 34, 2302-2314. https://doi.org/10.1111/1365-
411	<u>2435.13645</u>
412	Booth, D. T., Dunstan, A., Bell, I., Reina, R., & Tedeschi, J. (2020). Low male production at
413	the world's largest green turtle rookery. Marine Ecology Progress Series, 653, 181-
414	190. https://doi.org/10.3354/meps13500
415	Chatting, M., Hamza, S., Al-Khayat, J., Smyth, D., Husrevoglu, S., & Marshall, C. D. (2021).
416	Feminization of hawksbill turtle hatchlings in the twenty-first century at an important
417	regional nesting aggregation. Endangered Species Research, 44, 149-158.
418	https://doi.org/10.3354/esr01104

419	Chivers, W. J., Walne, A. W., & Hays, G. C. (2017). Mismatch between marine plankton
420	range movements and the velocity of climate change. Nature Communications, 8,
421	14434. https://doi.org/10.1038/ncomms14434
422	Corrège, T. (2006). Sea surface temperature and salinity reconstruction from coral
423	geochemical tracers. Palaeogeography, Palaeoclimatology, Palaeoecology, 232, 408-
424	428. https://doi.org/10.1016/j.palaeo.2005.10.014
425	Cuong, T. C., Booth, D. T., & Limpus, C. J. (2008). Estimating the sex ratio of loggerhead
426	turtle hatchlings at Mon Repos rookery (Australia) from nest temperatures. Australian
427	Journal of Zoology, 56, 57-64. https://doi.org/10.1071/ZO08004
428	Davis, B. A., Brewer, S., Stevenson, A. C., & Guiot, J. (2003). The temperature of Europe
429	during the Holocene reconstructed from pollen data. Quaternary Science Reviews, 22,
430	1701-1716. https://doi.org/10.1016/S0277-3791(03)00173-2
431	Duarte, C. M. (2017). Reviews and syntheses: Hidden forests, the role of vegetated coastal
432	habitats in the ocean carbon budget. Biogeosciences, 14, 301-310.
433	https://doi.org/10.5194/bg-14-301-2017
434	Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and
435	prediction across space and time. Annual Review of Ecology, Evolution, and
436	Systematics, 40, 677-697. https://doi.org/10.1146/annurev.ecolsys.110308.120159
437	Esteban, N., Laloë, J. O., Mortimer, J. A., Guzman, A. N., & Hays, G. C. (2016). Male
438	hatchling production in sea turtles from one of the world's largest marine protected
439	areas, the Chagos Archipelago. Scientific Reports, 6, 1-8.
440	https://doi.org/10.1038/srep20339
441	Fuentes, M. M. P. B., Maynard, J. A., Guinea, M., Bell, I. P., Werdell, P. J., & Hamann, M.
442	(2009). Proxy indicators of sand temperature help project impacts of global warming
443	on sea turtles in northern Australia. Endangered Species Research, 9, 33-40.
444	https://doi.org/10.3354/esr00224
445	Fuentes, M. M. P. B., & Porter, W. P. (2013). Using a microclimate model to evaluate
446	impacts of climate change on sea turtles. Ecological Modelling, 251, 150-157.
447	https://doi.org/10.1016/j.ecolmodel.2012.12.020
448	Fuentes, M. M., Monsinjon, J., Lopez, M., Lara, P., Santos, A., dei Marcovaldi, M. A., &
449	Girondot, M. (2017). Sex ratio estimates for species with temperature-dependent sex
450	determination differ according to the proxy used. Ecological Modelling, 365, 55-67.
451	https://doi.org/10.1016/j.ecolmodel.2017.09.022

452	Glen, F., & Mrosovsky, N. (2004). Antigua revisited: the impact of climate change on sand
453	and nest temperatures at a hawksbill turtle (Eretmochelys imbricata) nesting beach.
454	Global Change Biology, 10, 2036-2045. https://doi.org/10.1111/j.1529-
455	<u>8817.2003.00865.x</u>
456	Godley, B. J., Broderick, A. C., Downie, J. R., Glen, F., Houghton, J. D., Kirkwood, I.,
457	Reece, S., & Hays, G. C. (2001). Thermal conditions in nests of loggerhead turtles:
458	further evidence suggesting female skewed sex ratios of hatchling production in the
459	Mediterranean. Journal of Experimental Marine Biology and Ecology, 263, 45-63.
460	https://doi.org/10.1016/S0022-0981(01)00269-6
461	Guisan, A., & Thuiller, W. (2005). Predicting species distribution: offering more than simple
462	habitat models. <i>Ecology Letters</i> , 8, 993-1009. https://doi.org/10.1111/j.1461-
463	<u>0248.2005.00792.x</u>
464	Hawkes, L. A., Broderick, A. C., Godfrey, M. H., & Godley, B. J. (2007). Investigating the
465	potential impacts of climate change on a marine turtle population. Global Change
466	Biology, 13, 923-932. https://doi.org/10.1111/j.1365-2486.2007.01320.x
467	Hawkes, L. A., Broderick, A. C., Godfrey, M. H., Godley, B. J., & Witt, M. J. (2014). The
468	impacts of climate change on marine turtle reproductive success. Coastal
469	Conservation. Cambridge University Press, Cambridge, 287-310.
470	Hays, G. C., Godley, B. J., & Broderick, A. C. (1999). Long-term thermal conditions on the
471	nesting beaches of green turtles on Ascension Island. Marine Ecology Progress
472	Series, 185, 297-299. http://www.jstor.org/stable/24853219
473	Hays, G. C., Broderick, A. C., Glen, F., & Godley, B. J. (2003). Climate change and sea
474	turtles: a 150-year reconstruction of incubation temperatures at a major marine turtle
475	rookery. Global Change Biology, 9, 642-646. https://doi.org/10.1046/j.1365-
476	2486.2003.00606.x
477	Hays, G. C., Mazaris, A. D., & Schofield, G. (2014). Different male vs. female breeding
478	periodicity helps mitigate offspring sex ratio skews in sea turtles. Frontiers in Marine
479	Science, 1, 43. https://doi.org/10.3389/fmars.2014.00043
480	Hays, G. C., Mazaris, A. D., Schofield, G., & Laloë, J. O. (2017). Population viability at
481	extreme sex-ratio skews produced by temperature-dependent sex determination.
482	Proceedings of the Royal Society B: Biological Sciences, 284, 20162576.
483	https://doi.org/10.1098/rspb.2016.2576

484	Hays, G. C., Chivers, W. J., Laloë, J. O., Sheppard, C., & Esteban, N. (2021). Impact of
485	marine heatwaves for sea turtle nest temperatures. Biology Letters, 17, 20210038.
486	https://doi.org/10.1098/rsb1.2021.0038
487	Houghton, J. D. R., Myers, A. E., Lloyd, C., King, R. S., Isaacs, C., & Hays, G. C. (2007).
488	Protracted rainfall decreases temperature within leatherback turtle (Dermochelys
489	coriacea) clutches in Grenada, West Indies: Ecological implications for a species
490	displaying temperature dependent sex determination. Journal of Experimental Marine
491	Biology and Ecology, 345, 71-77. https://doi.org/10.1016/j.jembe.2007.02.001
492	Howard, R., Bell, I., & Pike, D. A. (2014). Thermal tolerances of sea turtle embryos: current
493	understanding and future directions. Endangered Species Research, 26, 75-86.
494	https://doi.org/10.3354/esr00636
495	Huang, R., Huang, JX., Zhang, C., Ma, H.Y., Zhuo, W., Chen, YY., Zhu, DH., Wu, Q.,
496	& Mansaray, L. R. (2020). Soil temperature estimation at different depths, using
497	remotely-sensed data. Journal of Integrative Agriculture, 19, 277-290.
498	https://doi.org/10.1016/S2095-3119(19)62657-2
499	Jensen, M. P., Allen, C. D., Eguchi, T., Bell, I. P., LaCasella, E. L., Hilton, W. A., Hof, & C.
500	A., Dutton, P. H. (2018). Environmental warming and feminization of one of the
501	largest sea turtle populations in the world. Current Biology, 28, 154-159.
502	https://doi.org/10.1016/j.cub.2017.11.057
503	Katselidis, K. A., Schofield, G., Stamou, G., Dimopoulos, P., & Pantis, J. D. (2012). Females
504	first? Past, present and future variability in offspring sex ratio at a temperate sea turtle
505	breeding area. Animal Conservation, 15, 508-518. https://doi.org/10.1111/j.1469-
506	<u>1795.2012.00543.x</u>
507	Kearney, M. R., Wintle, B. A., & Porter, W. P. (2010). Correlative and mechanistic models
508	of species distribution provide congruent forecasts under climate change.
509	Conservation Letters, 3, 203-213. https://doi.org/10.1111/j.1755-263X.2010.00097.x
510	Laloë, J. O., Cozens, J., Renom, B., Taxonera, A., & Hays, G. C. (2014). Effects of rising
511	temperature on the viability of an important sea turtle rookery. Nature Climate
512	Change, 4, 513-518 (2014). https://doi.org/10.1038/nclimate2236
513	Laloë, J. O., Esteban, N., Berkel, J., & Hays, G. C. (2016). Sand temperatures for nesting sea
514	turtles in the Caribbean: Implications for hatchling sex ratios in the face of climate
515	change. Journal of Experimental Marine Biology and Ecology, 474, 92-99.
516	https://doi.org/10.1016/j.jembe.2015.09.015

517	Laloë, J. O., Cozens, J., Renom, B., Taxonera, A., & Hays, G. C. (2017). Climate change and
518	temperature-linked hatchling mortality at a globally important sea turtle nesting site.
519	Global Change Biology, 23, 4922-4931. https://doi.org/10.1111/gcb.13765
520	Laloë, J. O., Monsinjon, J., Gaspar, C., Touron, M., Genet, Q., Stubbs, J., Girondot, M., &
521	Hays, G. C. (2020a). Production of male hatchlings at a remote South Pacific green
522	sea turtle rookery: Conservation implications in a female-dominated world. Marine
523	Biology, 167, 1-13. https://doi.org/10.1007/s00227-020-03686-x
524	Laloë, J. O., Tedeschi, J. N., Booth, D. T., Bell, I., Dunstan, A., Reina, R. D., & Hays, G. C.
525	(2020b). Extreme rainfall events and cooling of sea turtle clutches: Implications in the
526	face of climate warming. Ecology and Evolution, 11, 560-565.
527	https://doi.org/10.1002/ece3.7076
528	McMahon, C. R., & Hays, G. C. (2006). Thermal niche, large scale movements and
529	implications of climate change for a critically endangered marine vertebrate. Global
530	Change Biology, 12, 1330-1338. https://doi.org/10.1111/j.1365-2486.2006.01174.x
531	Melo-Merino, S. M., Reyes-Bonilla, H., & Lira-Noriega, A. (2020). Ecological niche models
532	and species distribution models in marine environments: A literature review and
533	spatial analysis of evidence. Ecological Modelling, 415, 108837.
534	https://doi.org/10.1016/j.ecolmodel.2019.108837
535	Munafò, M. R., Nosek, B. A., Bishop, D. V., Button, K. S., Chambers, C. D., Du Sert, N. P.,
536	Simonsohn, U., Wagenmakers, E J., Ware, J. J., & Ioannidis, J. P. (2017). A
537	manifesto for reproducible science. Nature Human Behaviour, 1, 1-9.
538	https://doi.org/10.1038/s41562-016-0021
539	Patino-Martinez, J., Marco, A., Quiñones, L., & Hawkes, L. (2012). A potential tool to
540	mitigate the impacts of climate change to the Caribbean leatherback sea turtle. Global
541	Change Biology, 18, 401-411. https://doi.org/10.1111/j.1365-2486.2011.02532.x
542	Patrício, A. R., Hawkes, L. A., Monsinjon, J. R., Godley, B. J., & Fuentes, M. M. (2021).
543	Climate change and marine turtles: recent advances and future directions. Endangered
544	Species Research, 44, 363-395. https://doi.org/10.3354/esr01110
545	Pacifici, M., Foden, W. B., Visconti, P., Watson, J. E., Butchart, S. H., Kovacs, K. M.,
546	Scheffers, B. R., Hole, D. G., Martin, T. G., Akçakaya, H. R., & Corlett, R. T. (2015).
547	Assessing species vulnerability to climate change. Nature Climate Change, 5, 215-
548	224. https://doi.org/10.1038/nclimate2448
549	R Core Team (2020). R: A language and environment for statistical computing. R Foundation
550	for Statistical Computing, Vienna, Austria. https://www.R-project.org

551	Santidrián Tomillo, P., & Spotila, J. R. (2020). Temperature-dependent sex determination in
552	sea turtles in the context of climate change: uncovering the adaptive significance.
553	BioEssays, 42, 2000146. https://doi.org/10.1002/bies.202000146
554	Shin, N., Shibata, H., Osawa, T., Yamakita, T., Nakamura, M., & Kenta, T. (2020). Toward
555	more data publication of long-term ecological observations. Ecological Research, 35,
556	700-707. https://doi.org/10.1111/1440-1703.12115
557	Standora, E. A., & Spotila, J. R. (1985). Temperature dependent sex determination in sea
558	turtles. Copeia, 711-722. https://doi.org/10.2307/1444765
559	Rees, A. F., & Margaritoulis, D. (2004). Beach temperatures, incubation durations and
560	estimated hatchling sex ratio for loggerhead sea turtle nests in southern Kyparissia
561	Bay, Greece. Testudo, 6, 23-36.
562	Richardson, A. J., & Schoeman, D. S. (2004). Climate impact on plankton ecosystems in the
563	Northeast Atlantic. Science, 305, 1609-1612. https://doi.org/10.1126/science.1100958
564	Staines, M. N., Booth, D. T., Hof, C. A. M., & Hays, G. C. (2020). Impact of heavy rainfall
565	events and shading on the temperature of sea turtle nests. Marine Biology, 167, 1-11.
566	https://doi.org/10.14264/c90b3d0
567	Steiger, N. J., Steig, E. J., Dee, S. G., Roe, G. H., & Hakim, G. J. (2017). Climate
568	reconstruction using data assimilation of water isotope ratios from ice cores. Journal
569	of Geophysical Research: Atmospheres, 122, 1545-1568.
570	https://doi.org/10.1002/2016JD026011
571	Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J., Collingham, Y.
572	C., Erasmus, B. F. N., de Siqueira, M. F., Grainger, A., Hannah, L., Hughes, L.,
573	Huntley, B., van Jaarsveld, A. S., Midgley, G. F., Miles, L., Ortega-Huerta, M. A.,
574	Townsend Peterson, A., Phillips, O. L., & Williams, S. E. (2004). Extinction risk
575	from climate change. <i>Nature</i> , 427, 145-148. https://doi.org/10.1038/nature02121
576	Thurman, W. N, & Fisher, M. E. (1988). Chickens, eggs, and causality, or which came first.
577	American Journal of Agricultural Economics, 70, 237-238.
578	https://doi.org/10.2307/1242062
579	Touchan, R., Meko, D. M., & Aloui, A. (2008). Precipitation reconstruction for Northwestern
580	Tunisia from tree rings. <i>Journal of Arid Environments</i> , 72, 1887-1896.
581	https://doi.org/10.1016/j.jaridenv.2008.05.010
582	Woodruff, S. D. (2001). COADS updates including newly digitized data and the blend with
583	UK Meteorological Office Marine Data Bank and Quality control in recent COADS
584	updates. In: Proceedings of Workshop on Preparation, Processing and Use of

Historical Marine Meteorological Data, 28-29 November 2000, Tokyo, Japan. Japan Meteorological Agency and the Ship and Ocean Foundation, pp. 9-13.