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Algal turf productivity on coral reefs: a meta-analysis

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26 **Abstract**

27 Algal turfs are an abundant and highly productive component of coral reef ecosystems.
28 However, our understanding of the drivers that shape algal turf productivity across studies
29 and among reefs is limited. Based on published studies we considered how different factors
30 may shape turf productivity and turnover rates. Of the factors considered, depth was the
31 primary driver of turf productivity rates, while turnover was predominantly related to turf
32 biomass. We also highlight shortcomings in the available data collected on turf productivity
33 to-date; most data were collected prior to global coral bleaching events, within a limited
34 geographic range, and were largely from experimental substrata. Despite the fact turfs are a
35 widespread benthic covering on most coral reefs, and one of the major sources of benthic
36 productivity, our understanding of their productivity is constrained by both a paucity of data
37 and methodological limitations. We offer a potential way forward to address these challenges.

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39

40 **Keywords**

41 Algal turfs; Coral reef; Ecosystem function; Herbivory; Productivity; Sediment

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48 **1.0 Introduction**

49 Globally, millions of people directly rely on highly productive, shallow-water coral
50 reef ecosystems (Moberg and Folke 1999; Woodhead et al. 2019). This productivity is
51 harnessed by people in the form of fishable biomass (Teh et al. 2013; Samoilyis et al. 2017;
52 Lau et al. 2019; Robinson et al. 2019b), with fishes acting as conduits that shunt primary
53 productivity up the food chain (Russ and St. John 1988; Rogers et al. 2018; Morais et al.
54 2020). It is posited that primary productivity and its utilisation by herbivorous fishes are two
55 of the eight core ecosystem processes that are fundamental to the functioning of coral reefs
56 (Brandl et al. 2019). If the goal of coral reef scientists and managers is to sustain the
57 functioning of coral reef ecosystems into the future, especially in productive states that
58 continue to provide key services to people (Hughes et al. 2017; Bellwood et al. 2019a), then
59 understanding the nature of primary productivity in these ecosystems is clearly important.

60 The highly productive nature of coral reefs is epitomised by the diminutive algal turfs,
61 small <2 cm tall multispecies assemblages of algae (Fig. 1b), that cover the hard substratum
62 in these ecosystems (Adey 1998; Connell et al. 2014; Tebbett and Bellwood 2019). Indeed, it
63 has been widely suggested that these algal turfs are the major contributors to benthic
64 productivity on coral reefs (e.g. Adey and Steneck 1985; Carpenter 1985; Hatcher 1988;
65 Klumpp and McKinnon 1989). Productivity is considered herein as the biomass (g Carbon)
66 produced by algal turfs in a given area over a given time ($\text{m}^{-2} \text{day}^{-1}$). This contribution of
67 algal turfs to productivity is set to increase as global climate change, and a suite of other
68 stressors, reduce coral cover on reefs, leading to an inevitable increase in algal turf cover
69 (Holbrook et al. 2016; Brown et al. 2017; Ellis et al. 2019; Koester et al. 2020; Vercelloni et
70 al. 2020). However, while the highly productive nature of algal turfs piqued the interest of
71 formative reef scientists (e.g. Odum and Odum 1955; Wanders 1976; Hatcher 1981; Adey

72 and Steneck 1985; Carpenter 1985; Russ 1987), we currently lack a full understanding of
73 how algal turf productivity varies across previous studies and different coral reefs.

74 A broad suite of drivers have been linked to the productivity of algal turfs (Klumpp
75 and McKinnon 1989; Hatcher 1990). These potential regulators of algal turf productivity are
76 likely to include light availability (Carpenter 1985; Klumpp and McKinnon 1989),
77 hydrodynamic activity (Roff et al. 2019), nutrients (Williams and Carpenter 1988; Sura et al.
78 2019) and sediment loads (Tebbett et al. 2018a). All such drivers vary among reefs. In
79 addition to these drivers, the methods employed for quantifying algal turf productivity (e.g.
80 the substratum algal turfs were grown on) may also shape our understanding of this process.
81 However, to-date, the studies that have quantified algal turf productivity on coral reefs have
82 not been considered together in a comparative framework, limiting our understanding of how
83 and why algal turf productivity varies across studies and among coral reefs. This comes at a
84 time when anthropogenic activity is altering the strength of many biophysical drivers on the
85 world's reefs (Harborne et al. 2017; Hughes et al. 2017; Williams et al. 2019; França et al.
86 2020), with algal turfs set to play an ever more central role in the functioning of coral reef
87 ecosystems into the future (Bellwood et al. 2019b; Tebbett and Bellwood 2019).

88 Considering the rapidly changing nature of reefs, it is surprising that we currently lack
89 a clear understanding of how and why the productivity of a core group of benthic primary
90 producers varies among reefs and across past studies. The aim of this study, therefore, is to
91 gather available data on coral reef algal turf productivity and assess how it varies among
92 coral reef locations. In doing so, we will explicitly consider how the available data in this
93 research field, and the methods employed to quantify algal turf productivity to-date, may
94 have shaped our understanding of algal turf productivity. To achieve these aims, this study
95 will utilise a robust analytical framework to bring together data from disparate studies and
96 provide an insight into the cross-study drivers of algal turf productivity on coral reefs.

97 **2.0 Methods**

98 **2.1 *Productivity database compilation***

99 To assess how algal turf productivity varies across coral reefs we first had to compile
100 a database of productivity measurements from previous studies. This was achieved by
101 undertaking an extensive search of the literature. Initially, we undertook a formal search in
102 Google Scholar using the search terms ‘("algal turf" OR "epilithic algal") AND (production
103 OR productivity OR growth) AND "coral reef"’. This search yielded 4010 results in April
104 2020 (not including patents or citations). To check how comprehensive Google Scholar was
105 we also ran this search through Scopus and Web of Science. These two search engines only
106 yielded a total of 1945 and 78 results, respectively. We initially filtered the 4010 studies
107 returned by Google Scholar for any potentially relevant studies based on the title and abstract,
108 yielding a pool of 105 potentially relevant studies. To ensure that our search was
109 comprehensive, and that we did not overlook any, more cryptic, studies, we also undertook
110 two general searches of the literature in Google Scholar using the search terms ‘algal turf
111 productivity’ and ‘algal turf productivity coral reefs’ and filtered the 1000 most relevant
112 studies in each case. This process yielded an additional 26 potentially relevant studies. Based
113 on our prior knowledge in this research field there were also 5 additional studies that we were
114 aware of and thought may contain relevant information on algal turf productivity. These 5
115 additional studies were added to the pool of potentially relevant studies for a total of 136
116 studies. It is important to note that these 5 additional studies were not found in the searches
117 because they were relatively old and published in unusual journals, conference proceedings
118 or in a PhD thesis. These studies would have been overlooked without extensively reading
119 the relevant literature.

120 Each of the potentially relevant studies was then evaluated against a specific set of
121 criteria to determine if it could be included in our analysis. These criteria were: a) that
122 quantification of productivity was performed in-situ on the reef; b) details of the sampling
123 month/depth/specific location were provided; c) the study quantified ‘productivity’ directly
124 (N.B. data on ‘yield to herbivores’ [i.e. the amount of algal biomass removed by herbivores]
125 was not included; see Russ, [1987] for details of how productivity and yield to herbivores
126 differ) in g Carbon m⁻² day⁻¹ (or in a form that could be converted into this unit of measure);
127 d) the substratum that turfs were grown on had been conditioned to some extent on the reef;
128 and e) the algal community examined fell within the general definition of small <2 cm tall
129 multispecies assemblages of algae on a hard benthic substratum, i.e. algal turfs (Steneck and
130 Dethier 1994; Connell et al. 2014; Tebbett and Bellwood 2019).

131 We applied the above criteria to ensure that: a) algal turf productivity was reflective
132 of natural conditions on the reef and the relevant drivers at the study location (i.e.
133 productivity was not measured under laboratory conditions where these drivers were altered);
134 b) suitable information was available to assess potential drivers underpinning the productivity
135 values recorded (especially depth and sampling month); c) we did not confuse ‘yield to
136 herbivore’ measurements as ‘productivity’ measurements; d) we focused on the units most
137 widely used for primary productivity on coral reefs (Hatcher 1988; Klumpp and McKinnon
138 1992; Russ and McCook 1999); e) values were not biased by initial algal turf settlement
139 dynamics (Diaz-Pulido and McCook 2002; Fricke et al. 2011); and f) we only examined
140 ‘algal turfs’ rather than macroalgae or productivity of entire reef communities. It should be
141 noted that our definition of ‘algal turfs’ includes non-algal cyanobacteria (see Borowitzka et
142 al. 1978; Diaz-Pulido and McCook 2002) and the methods commonly used to quantify algal
143 turf productivity (e.g. scraping algal biomass from coral blocks) is likely to include
144 contributions from endolithic algae and cyanobacteria in the surficial layers of the substratum

145 matrix (e.g. Odum and Odum 1955; Tribollet et al. 2002). After this filtering process we were
146 left with a pool of just 17 studies (14 were derived from the initial formal search, 2 from the
147 general search and 1 study that we were aware of). Our search and filtering procedures were
148 based on PRISMA protocols (Moher et al. 2009) with a flow-diagram provided in the
149 supplementary material (Fig. S1).

150 From our pool of relevant studies, we then extracted data on algal turf net primary
151 production ($\text{g Carbon m}^{-2} \text{ day}^{-1}$). Where possible we also extracted data on turnover or
152 calculated this based on standing biomass estimates provided in the studies. Here turnover
153 was considered as the ratio of production ($\text{g C m}^{-2} \text{ day}^{-1}$) to standing biomass (g C m^{-2})
154 measured in $\% \text{ day}^{-1}$ (Odum and Odum 1955). From each study, data were sourced from
155 tables or, where necessary, extracted from graphs using webplot digitizer (Rohatgi 2019) (full
156 details of data extraction procedures for each study are reported in supplemental Table S1). In
157 addition, all mean \pm SE values used in the dataset are provided in Table S3 and the raw data
158 extracted from each study is presented in Figure S2.

159

160 **2.2 Explanatory variable compilation**

161 In addition to extracting productivity and turnover data from each study, we also
162 extracted information on available, relevant, variables to assess why and how productivity
163 data vary. Firstly, we extracted information on the water depth in which each observation was
164 quantified. Water depth was considered because it is a key environmental gradient that is
165 strongly correlated with light availability (Roberts et al. 2019), hydrodynamic exposure
166 (Fulton and Bellwood 2005), sediment loads (Purcell 2000) and herbivory (Cooper et al.
167 2019), all of which have been linked to algal turf productivity levels (Carpenter 1985, 1986;
168 Tebbett et al. 2018a; Roff et al. 2019).

169 Secondly, seasonal influences were considered by quantifying the sampling month for
170 each observation reported in the study. Seasonal influences were standardised between
171 northern and southern hemispheres as the month since first winter month (i.e. December = 1
172 in northern hemisphere locations, June = 1 in southern hemisphere locations). The yearly
173 seasonal cycle has previously been related to algal turf productivity as both temperature and
174 day length (light availability), vary during this cycle which influences productivity (Carpenter
175 1985) as well as herbivory (Van Rooij et al. 1998; Longo et al. 2019).

176 Thirdly, hydrodynamic exposure of the study location (windward, leeward or
177 protected [lagoonal]) was noted based on information reported in each study. Again,
178 hydrodynamic exposure has previously been linked to algal turf productivity (Roff et al.
179 2019), and it influences other factors such as algal turf sediment loads (Tebbett et al. 2017a),
180 herbivory (Bejarano et al. 2017), turbidity/light availability (Whinney et al. 2017) and mass
181 transfer to algal turfs (Carpenter and Williams 2007).

182 Fourthly, the reef identity was recorded. This reef identity factor accounted for the
183 lack of spatial independence present in the dataset due to multiple measurements coming
184 from the same reefs. This reef identity factor also concatenated the range of broader-scale
185 drivers (e.g. sea surface temperature, water clarity, proximity to land, sediment loads,
186 herbivore abundance, hydrodynamic exposure and light availability) that vary among reefs
187 (e.g. Cheal et al. 2012; Fabricius et al. 2014; Assis et al. 2018; Tebbett et al. 2018b; Heenan
188 et al. 2020) and could influence algal turf productivity levels over broader spatial scales.
189 While concatenating these variables into a single categorical factor loses information on what
190 specific variables may be important, it can effectively account for the lack of spatial
191 independence in the database. In addition, limitations with the data, and the high degree of
192 co-linearity among explanatory variables, precluded the consideration of these broader scale
193 factors in more detail.

194 Fifthly, the study identity was recorded. As above, this study identity factor accounted
195 for the lack of independence present in the dataset due to multiple observations from the
196 same studies. In addition, the study identity factor concatenated the potential effects of a
197 range of ‘study-level’ factors (e.g. the quantification method, study substratum, and the
198 conditioning time of substrata) that could influence productivity values. Notably, different
199 methods have been used to quantify algal turf productivity including respirometry techniques
200 and caging techniques, therefore, differences between these techniques, may have shaped
201 productivity estimates. The surfaces algal turfs are grown on, as well as how long
202 experimental surfaces are conditioned for, can also substantially influence their community
203 composition (Harlin and Lindbergh 1977; Borowitzka et al. 1978; Hixon and Brostoff 1985)
204 with potential impacts on the community’s productivity. While noting this factor, we also
205 specifically recorded the year each observation was taken, as well we the substratum (natural
206 coral reef benthos, block/tile cut from a dead coral skeleton, or artificial tile) from which
207 algal turf productivity was quantified, to facilitate more nuanced insights into the algal turf
208 productivity research conducted to-date.

209 Finally, standing biomass of the algal turfs in g C m^{-2} was extracted for each
210 observation (details of how are provided in Table S1). Unfortunately, this factor could only
211 be quantified for turnover data because it was not available for all productivity observations.
212 While standing biomass is inextricably linked to turnover estimates it represents an important
213 explanatory variable because it provides information on the efficiency of algal turf
214 productivity as biomass increases. Essentially, if turnover is related in some way to algal turf
215 biomass this suggests that the factors associated with changes in algal turf biomass impact the
216 productivity efficiency of turfs.

217

218 **2.3 Boosted regression trees**

219 To examine the relative importance of each explanatory factor in predicting algal turf
220 productivity or turnover, as well as to examine the nature of the relationship between key
221 explanatory variables and productivity/turnover, we used XGBoost (Chen and Guestrin
222 2016), an Extreme Gradient Boosted Regression Tree. We used this method because Gradient
223 Boosted Regression Trees are a machine learning technique that can yield fast, accurate,
224 predictions while efficiently modelling nonlinearity and multilevel interactions in data that
225 may not be suitable for more traditional analysis (Elith et al. 2008). XGBoost in particular,
226 utilises an algorithm that has been specifically designed to be efficient, flexible and robust,
227 outperforming algorithms used by other Gradient Boosted Regression Trees (Chen and
228 Guestrin 2016). For the XGBoost models we used Gamma distributions and treated algal turf
229 productivity estimates ($\text{g C m}^{-2} \text{ day}^{-1}$) or turnover ($\% \text{ day}^{-1}$) as the dependent variable and
230 examined these against the potential explanatory variables.

231 Prior to running the XGBoost models to make predictions, two tuning steps were
232 performed following Morais and Bellwood (2018). Firstly, the models were fitted repeatedly
233 with combinations of model parameters (learning rate, maximum tree depth, gamma and
234 subsampling rate) that were varied systematically. The combination of parameters that
235 yielded the minimum root mean square error (rmse) was subsequently recorded (productivity
236 model: learning rate = 0.4, maximum tree depth = 7, gamma = 0.1, and subsampling = 0.5;
237 turnover model: learning rate = 0.2, maximum tree depth = 7, gamma = 0, and subsampling =
238 0.5), while all other parameters were kept at their default values. During the second round of
239 tuning, we fitted the models repeatedly with combinations of parameters drawn randomly
240 from a uniform distribution bounded by the recorded parameters from the first tuning round \pm
241 10 %. Again, we recorded the parameters that resulted in the lowest rmse (productivity
242 model: learning rate = 0.413, maximum tree depth = 8, gamma = 0.093, and subsampling =

243 0.543; turnover model: learning rate = 0.188, maximum tree depth = 6, gamma = 0.003, and
244 subsampling = 0.493), however, the second tuning step did not improve rmse substantially in
245 either case as it only changed from 0.329 to 0.333 and from 2.288 to 2.172 for the
246 productivity and turnover models, respectively.

247 The accuracy and precision of our tuned XGBoost models were subsequently
248 evaluated using a cross-validation procedure. To do this, the productivity and turnover
249 datasets were randomly split into training and testing datasets. The training datasets were
250 used to refit the models to generate coefficients for prediction and were based on 80 % of the
251 data. The testing datasets were used to contrast with predictions from the training dataset and
252 were based on the remaining 20 % of the data. We calculated a bias metric by subtracting
253 each algal turf productivity/turnover value predicted by the respective XGBoost model from
254 its actual value (an accurate model has a bias value at or close to zero). Precision of the
255 models was assessed using prediction R^2 values which were calculated by fitting a linear
256 regression model between the raw data values and the predicted values and recording the R^2
257 from this regression. These cross-validation steps were repeated 1000 times in each case.

258 Finally, predictions of algal turf productivity as well as turnover were calculated using
259 our tuned and cross-validated XGBoost models across all explanatory variables. To generate
260 a distribution of algal turf productivity and turnover predictions we bootstrapped the models
261 for 1000 iterations and subsequently sampled the median predicted value \pm 95 % highest
262 density intervals. The relative importance of different predictor variables, in accounting for
263 variation of algal turf productivity and turnover estimates, were assessed against the expected
264 importance of variables given chance alone (i.e. if all variables were equally involved in
265 explaining variation within the dataset then each variable would account for 20 % or 16.7 %
266 of the variability explained by the productivity or turnover XGBoost models, respectively).

267 All XGBoost modelling was performed in the software R (R Core Team 2019) using the
268 *XGBoost* (Chen et al. 2019) package.

269 **2.4 Methodological considerations**

270 In addition to assessing how and why algal turf productivity observations vary among
271 coral reefs, we wanted to further consider how the methods used to quantify algal turf
272 productivity could have shaped our understanding. Specifically, we wanted to consider the
273 implications of quantifying algal turf productivity on experimental tiles/coral blocks, rather
274 than natural reef substrata. Especially, considering recent research that has linked the
275 accumulation of sediment in algal turfs to the growth of turfs (Clausing et al. 2014; Tebbett et
276 al. 2018a; Tebbett and Bellwood 2020). We initially sourced data on sediment accumulation
277 in natural algal turfs (n = 20) and in algal turfs on conditioned coral blocks (n = 43) from
278 Tebbett et al. (2018a). Note the data contained within this previous study represented a direct
279 comparison between natural reef substrata and coral blocks as all sediments were collected
280 from the same location (Lizard Island), in the same habitats (the reef flat between Palfrey and
281 South Island), at the same sites (two sites), during the same sampling period.

282 Initially, we specifically tested for differences in sediment loads in algal turfs on
283 natural substrata versus coral blocks using a Bayesian generalised linear model (GLM) with a
284 Gamma distribution and log link. Substratum identity (natural or block) and site identity were
285 fitted as interacting fixed effects. The GLM was based on weakly informative priors, 3
286 chains, a warmup of 500 iterations, a thinning value of 3 and 3000 iterations. Model
287 convergence, fit and assumptions were assessed using trace plots, autocorrelation plots, rhat
288 plots, posterior predictive checks, effective sample sizes and residual plots. These tests
289 suggested the chains were well mixed and had converged on a stable posterior, and that no
290 patterns were present in the residuals. We then predicted potential algal turf productivity (mm

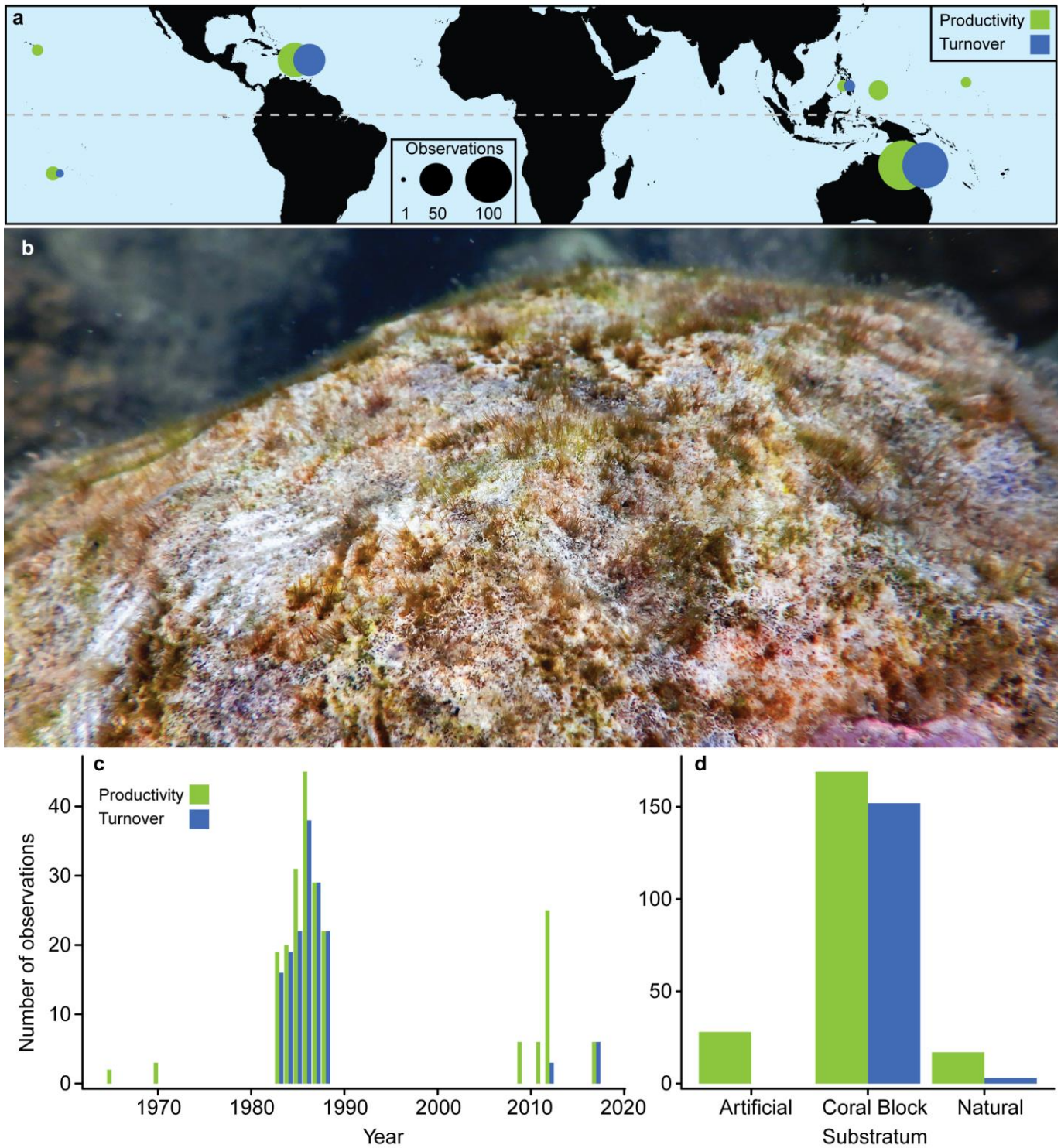
291 growth day⁻¹), as a function of sediment load, on coral blocks and natural reef substrata. To
292 do this we utilised a Bayesian model, relating potential algal turf productivity to sediment
293 loads, formulated in Tebbett and Bellwood (2020), and fed each sampled sediment load to
294 this model to estimate productivity (mm growth day⁻¹) for that specific sediment load. It
295 should be noted that the term ‘productivity’ applies to increases in mass, however, in the case
296 of this model the term ‘productivity’ is applied to increases in turf length. All statistical
297 analyses were performed in the software R (R Core Team, 2019) using the *rstan* (Stan
298 Development Team 2018) and *rstanarm* (Goodrich et al. 2018) packages.

299

300 **3.0 Results**

301 **3.1 Dataset**

302 After examining the relevant literature on coral reef algal turf productivity our final
303 dataset consisted of 214 productivity estimates and 155 turnover estimates from 17 and 11
304 studies, respectively. While we placed no spatial or temporal limitations on the inclusion of
305 studies in this dataset there were some noticeable patterns. Firstly, despite observations being
306 distributed around several of the world’s coral reef regions, the vast majority (54 % and 63 %
307 of productivity and turnover observations, respectively) were from the Great Barrier Reef
308 (Fig. 1a). Secondly, the restricted temporal distribution of these observations was marked,
309 with 80 % and 94 % of productivity and turnover data, respectively, collected prior to 1990
310 (Fig. 1c). Finally, most of the productivity and turnover observations (92% and 98 %,
311 respectively) were based on experimental substrata (coral blocks or artificial tiles), rather
312 than studying natural reef substrata (Fig. 1d).



313

314 **Figure 1** a) The distribution of algal turf productivity and turnover observations from coral

315 reefs around the world in our dataset. b) A short productive algal turf community on a

316 shallow-water coral reef at Orpheus Island on the Great Barrier Reef (photograph: CHR

317 Goatley). c) The temporal distribution of algal turf productivity and turnover observations in

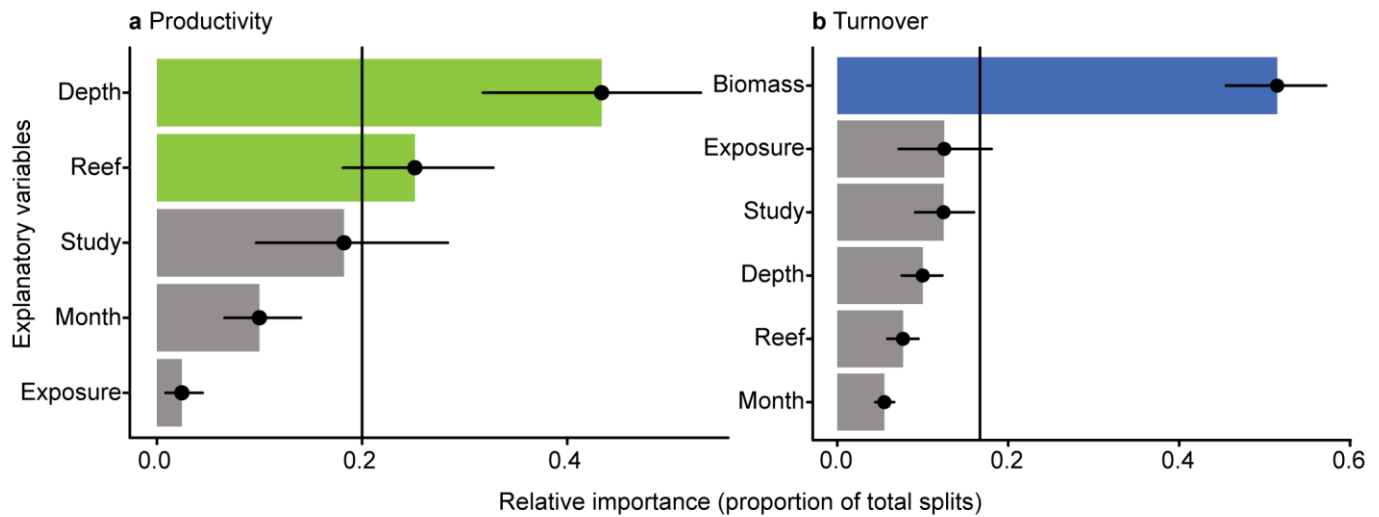
318 our dataset. d) The frequency by which algal turf productivity and turnover were examined
319 on different substrata in our dataset.

320

321 ***3.2 Drivers of algal turf productivity and turnover***

322 The formulated XGBoost models resulted in a median bias that was close to zero
323 (0.26 and 0.349 for the productivity and turnover models, respectively) suggesting that the
324 models were relatively accurate. Furthermore, the median R^2 of the final models were 0.69
325 and 0.87 (for the productivity and turnover models, respectively), suggesting that the models
326 were relatively precise. These XGBoost models revealed that some of the explanatory
327 variables were far more important than others in accounting for patterns in algal turf
328 productivity and turnover. In terms of productivity, depth was the single most important
329 variable and explained 47.0 % (median) (39.2 % - 55.0 %; upper and lower 95 % highest
330 density intervals) of the variation in productivity accounted for in the XGBoost model (Fig.
331 2a). In addition, study site (reef) explained more variation in algal turf productivity than
332 expected by chance, accounting for 24.1 % (19.3 % - 30.3 %) of the variation explained.
333 Standing algal turf biomass was the single most important variable for explaining turnover
334 patterns, with this variable accounting for 51.5 % (46.3 % - 58.1 %) of the variation in
335 turnover explained by the XGBoost model (Fig. 2b). The remaining explanatory variables all
336 remained below the relative importance level expected by chance in both productivity and
337 turnover models.

338



339

340 **Figure 2** The relative importance of potential explanatory variables in accounting for a) algal
 341 turf productivity and b) turnover estimates from coral reefs. Black dots indicate the median
 342 relative importance value, while the range presented represents the 95% highest density
 343 intervals based on bootstrapping predictions 1000 times. The vertical black line indicates the
 344 relative importance expected for each variable by chance.

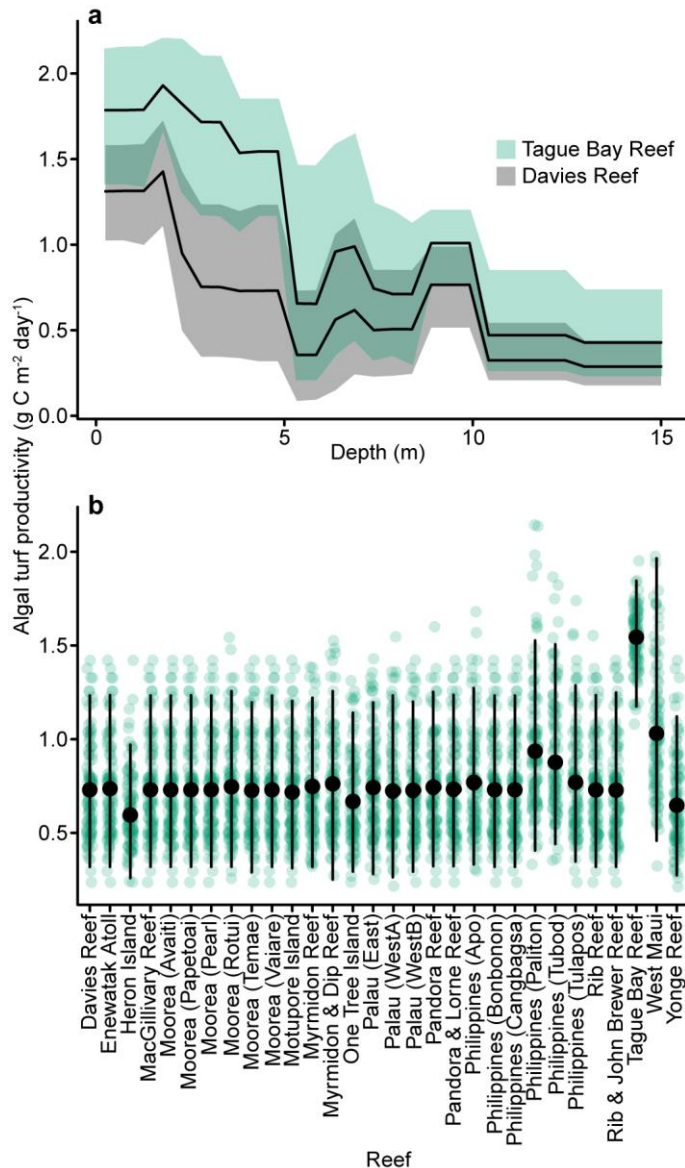
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347 With the key explanatory variables identified, partial dependency plots provided an
 348 insight into how these variables related to algal turf productivity and turnover (Figs. 3, 4). In
 349 terms of the relationship between productivity and the key explanatory variables there was a
 350 clear decrease in algal turf productivity as depth increased. Notably, productivity remained
 351 relatively high down to 5 m, a depth which aligns well with the end of the reef crest habitat
 352 and the beginning of the reef slope habitat, before decreasing sharply and remaining
 353 relatively low down to 15 m (Fig. 3a). While the general nature of this relationship between
 354 depth and productivity appeared to be similar across sites (e.g. Fig. 3a), there was a distinct
 355 difference in the magnitude of productivity levels among sites (Fig. 3). Specifically, predicted
 356 productivity values from the reef in Tague Bay, St Croix (the only Caribbean site in this
 357 dataset) were approximately twice the productivity values from all other reef sites, which

358 were generally very similar (Fig. 3b). Therefore, while decreases in algal turf productivity
 359 with depth appear to be a universal pattern, the magnitude of the productivity values may be
 360 dependent on the site in question.

361



362

363

364 **Figure 3** Partial dependency plots of the relationship between algal turf productivity and the
 365 key explanatory variables that accounted for more variability than expected: a) water depth
 366 and b) study site. All other variables were kept at their mean values and the most common
 367 category of categorical variables were used for plots (note in panel (a) that Davies Reef and

368 Tague Bay Reef were both equally common in the dataset [n = 55]). The black line (a) and
369 the black points (b) represent the median predicted values, the coloured ribbons (a) and the
370 point ranges (b) denote the 95% highest density intervals, and the green points (b) represent
371 100 randomly selected predicted values for each reef based on an extreme gradient boosted
372 regression tree model (n = 1000 model iterations).

373

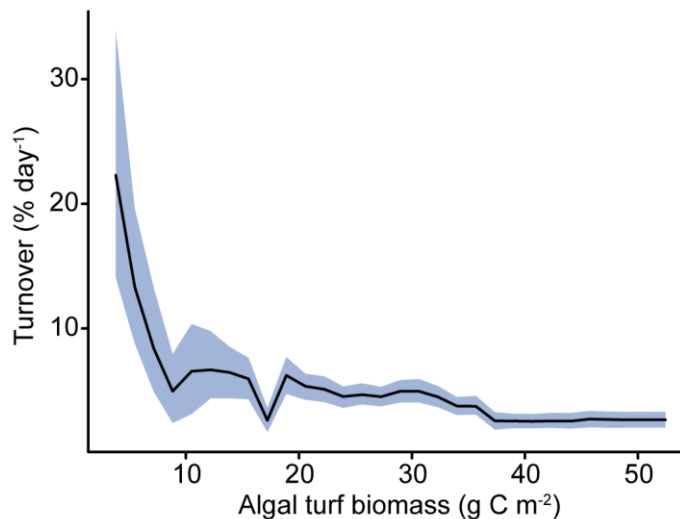
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376 The relationship between algal turf turnover rates and standing biomass was inverse in
377 nature. Turnover rates appear to be very high at low standing biomass levels but decreased
378 markedly across the range of algal turf biomass levels examined (Fig. 4). However, the most
379 precipitous decrease occurred at the lowest algal turf biomass levels ($<10 \text{ g C m}^{-2}$), with
380 turnover rates decreasing by more than half across this range alone (Fig. 4). This pattern
381 suggests that algal turf productivity rates and standing biomass levels do not scale linearly,
382 with a marked decrease in the ability of turfs to replace existing biomass as standing biomass
383 increases.

384

385



386

387 **Figure 4** Partial dependency plot of the relationship between algal turf turnover and the key
 388 explanatory variable (standing algal turf biomass). All other variables were kept at their mean
 389 values and the most common category of categorical variables were used for the plot. The
 390 black line denotes the median predicted values, while the coloured ribbon denotes the 95%
 391 highest density intervals, based on an extreme gradient boosted regression tree model (n =
 392 1000 model iterations).

393

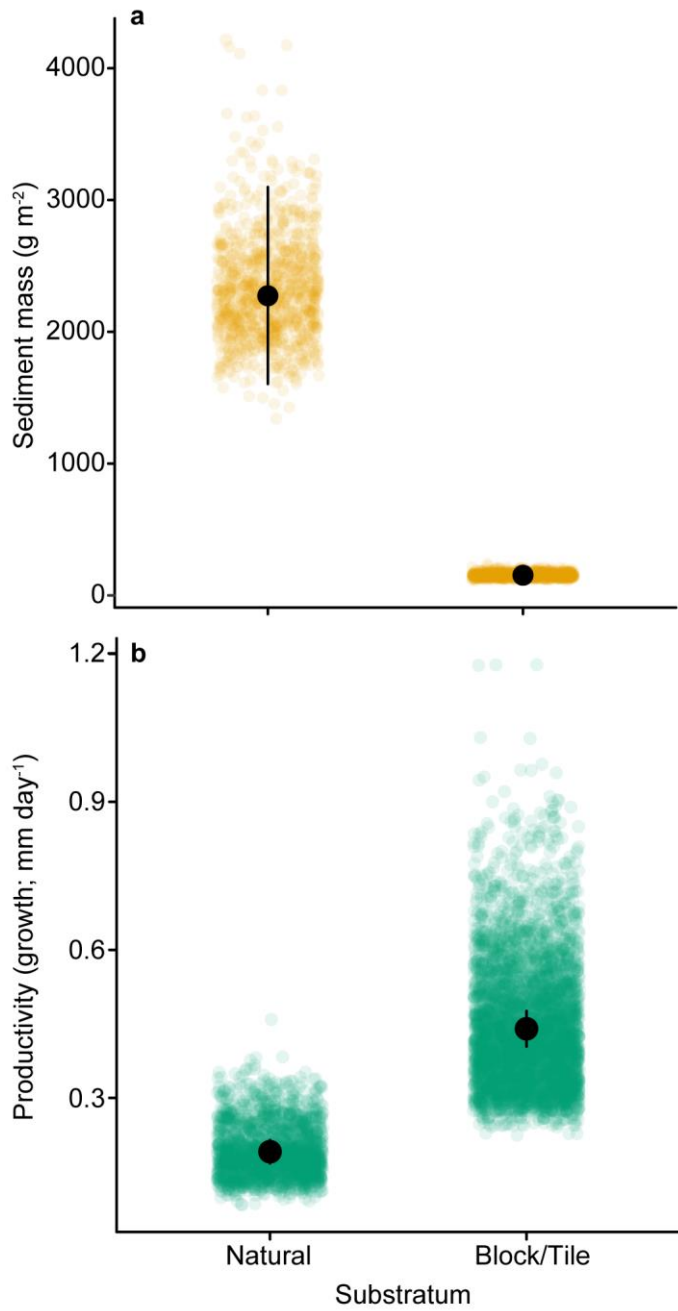
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395 **3.3 Methodological considerations**

396 There were marked differences in the sediment loads accumulated in algal turfs on
 397 natural substrata compared to conditioned algal turf-covered coral blocks (Fig. 5a). Sediment
 398 loads were more than 10-fold higher in natural algal turfs (2031.1 [1292.9 – 3238.4] g m⁻²;
 399 median ± 95% highest posterior density intervals) relative to algal turfs on coral blocks
 400 (188.9 [68.5 – 527.9] g m⁻²) (Fig. 5a; Table S2). The Bayesian model used to test these
 401 differences revealed that substratum type did influence sediment load as the 95 % credibility
 402 intervals did not overlap one (Table S2). There was no evidence that site had any effect on

403 these sediment loads (Table S2). The differences in accumulated sediment loads translated to
404 clear differences in algal turf productivity when we used a second Bayesian model to predict
405 potential algal turf productivity on each substratum (Fig. 5b). Predicted potential algal turf
406 productivity was more than two-fold higher on conditioned coral blocks (0.44 ± 0.02 mm
407 day^{-1}) relative to natural substrata (0.19 ± 0.01 mm day^{-1}). Together, these results suggest that
408 algal turfs grown on coral blocks/tiles accumulate lower sediment loads, potentially yielding
409 higher algal turf productivity rates.

410



411

412 **Figure 5** Differences in a) sediment loads, and b) estimated productivity, of algal turfs
 413 growing on natural substrata and coral blocks. Black points and range represent the mean
 414 predicted values and 95% credibility intervals; coloured dots represent 1000 random draws
 415 from the posterior distribution of Bayesian models to show the uncertainty around the
 416 estimates. The sediment data was sourced from (Tebbett et al., 2018a).

417

418

419 **4.0 Discussion**

420 Algal turfs are a key component of coral reef ecosystems and can underpin their high
421 productivity (Adey and Goertemiller 1986; Hatcher 1988; Steneck 1997) and fuel
422 herbivorous trophic pathways (Russ and St. John 1988; Kelly et al. 2017; Morillo-Velarde et
423 al. 2018). While algal turf productivity may be shaped by a range of factors (e.g. Carpenter
424 1985; Klumpp and McKinnon 1989; Roff et al. 2019), of the factors we considered, water
425 depth was by far the most important in structuring this productivity on coral reefs. Moreover,
426 our consideration of algal turf turnover revealed that algal turf productivity and standing
427 biomass do not scale linearly together in a one-to-one relationship. This suggests that the
428 efficiency of algal turf productivity decreases as standing biomass increases, i.e. higher
429 biomass reduces the capacity of algal turfs to replace existing biomass. However, it is
430 important to note that in undertaking this meta-analysis we also revealed a distinct paucity of
431 data on algal turf productivity rates from many coral reef regions around the world.
432 Furthermore, we highlighted that the methods employed to assess algal turf productivity on
433 reefs may have shaped our understanding of this process. The implications of these
434 methodological limitations need to be carefully considered when quantifying algal turf
435 productivity on coral reefs in the future.

436 **4.1 Productivity**

437 *4.1.1 Depth*

438 The depth at which algal turfs exist on coral reefs clearly has a marked influence on
439 their productivity. In this respect, our meta-analysis strongly supports the conclusion of
440 previous studies that have highlighted a decrease in turf productivity with depth (e.g. Klumpp
441 and McKinnon 1989; Carpenter 1990; Russ 2003), as well as variation in other qualities of
442 algal turf communities such as turf yield-to-herbivores, cover and community composition

443 (Brokovich et al. 2010; Fricke et al. 2014; Magalhães et al. 2015). The clear decline in algal
444 turf productivity as water depth increases is likely to be driven by a variety of key factors
445 including light availability (Brokovich et al. 2014; Fricke et al. 2014; Roberts et al. 2019),
446 wave-driven hydrodynamic activity (Fulton and Bellwood 2005), herbivory rates (Cooper et
447 al. 2019) and algal turf sediment loads (Purcell 2000), that all correlate with water depth on
448 coral reefs to varying extents. Of these factors, light availability is likely to be one of the
449 most important. This is because, the rate of algal turf productivity is constrained as light
450 levels decrease because algal turf photosynthesis rates are closely tied to irradiance levels
451 (Carpenter 1985; Klumpp and McKinnon 1989). Interestingly, previous studies have
452 highlighted that algal turfs are well adapted to high light intensity as rates of photosynthesis
453 increase steadily with irradiance levels, showing few signs of photo-inhibition (Carpenter
454 1985; Klumpp and McKinnon 1989). This lack of photo-inhibition may underpin how algal
455 turf communities maintain their highest productivity levels at the shallowest water depths.

456 While depth mediated light availability appears to shape algal turf productivity rates
457 directly (Carpenter 1985; Klumpp and McKinnon 1989), it may also influence productivity
458 rates indirectly by shaping the community composition of algal turfs. Specifically, different
459 algal species make up the algal turf community across depth gradients, potentially due to
460 different tolerances for light levels (Anderson et al. 2005; Fricke et al. 2014; Magalhães et al.
461 2015). In addition, herbivory is known to decrease substantially as depth increases
462 (Brokovich et al. 2010; Cooper et al. 2010), and this factor can also shape the community
463 composition of algal turfs (Scott and Russ 1987; Hixon and Brostoff 1996; McClanahan
464 1997). This is important because the nature of algal turf communities, in terms of the species
465 that inhabit them, as well their structure and diversity, is likely to influence biomass and
466 productivity levels, as per-unit biomass and productivity differs between algal species and
467 functional groups (Rogers and Salesky 1981; Steneck and Dethier 1994; Bruno et al. 2006;

468 but see Williams and Carpenter 1990). As such, variation in algal turf community
469 composition across depth/light gradients could also influence net productivity rates.

470

471 4.1.2 *Site effects*

472 Apart from factors associated with the depth at which algal turfs exist, there was some
473 variability in productivity among sites. There are two notable points that can be drawn from
474 these results. Firstly, there appeared to be remarkably little variation in algal turf productivity
475 among the vast majority of reef sites. This suggests that the broader scale factors that vary
476 among reefs such as temperature, light intensity and nutrient inputs may not have a
477 substantial influence on algal turf productivity for many reefs. However, secondly, algal turf
478 productivity from the Tague Bay Reef site was approximately two-fold higher than all other
479 sites. These data suggest that a factor, or factors, operating at Tague Bay Reef led to far
480 higher productivity levels at this site. Tague Bay, is located on Saint Croix in the Caribbean,
481 and it has been suggested that Caribbean reefs function quite differently from other reef
482 systems due to factors such as lower species and functional diversity, geographic isolation,
483 and more severe anthropogenic impacts (Bellwood et al. 2004; Roff and Mumby 2012; Bruno
484 et al. 2019; Siqueira et al. 2019). Unfortunately, determining which factors may be
485 accounting for these higher productivity levels is difficult, as Tague Bay is the only site from
486 the Caribbean in our dataset, and all productivity values at this location were quantified on
487 the same experimental substrata, using the same methods. Therefore, it is unclear if these
488 productivity estimates were driven by a methodological difference between the studies at this
489 site vs other studies, a factor associated with the reef in Tague Bay, or a broader Caribbean
490 phenomenon.

491

492 **4.2 Turnover**

493 Turnover was clearly related to algal turf biomass, highlighting a loss of productivity
494 efficiency as biomass increased. Importantly, variation in algal turf biomass is associated
495 with variation in the length and density of turf filaments (i.e. an alteration of the algal turf
496 canopy structure) (Purcell 2000; Tebbett and Bellwood 2020), as well as the community
497 composition of algal turfs (Scott and Russ 1987; Hixon and Brostoff 1996; Harris et al.
498 2015). Essentially, algal turfs exist on a gradient from short productive algal turfs (SPATs) to
499 long sediment-laden algal turfs (LSATs) (Goatley et al. 2016; Tebbett and Bellwood 2020).
500 SPATs are maintained by the constant grazing pressure of herbivorous fishes, as well as other
501 herbivorous organisms, which remove algae, reduce sediment loads (Carpenter 1986; Steneck
502 1997; Goatley et al. 2016; Steneck et al. 2018; Humphries et al. 2020), and constrain the
503 community of algal species to ones that tolerate high grazing (Sammarco 1983; Scott and
504 Russ 1987; Hixon and Brostoff 1996; McClanahan 1997). However, when the strength of
505 herbivory is reduced, through factors such as herbivore removal (Heenan et al. 2016; Steneck
506 et al. 2018), or the accumulation of sediments that weaken herbivore feeding pressure
507 (Tebbett et al. 2017b; McAndrews et al. 2019), this can result in an increase in algal turf
508 length/biomass (Goatley and Bellwood 2013; Fong et al. 2018; Humphries et al. 2020) and/or
509 changes in algal taxonomic composition (Scott and Russ 1987; Hixon and Brostoff 1996),
510 resulting in LSATs.

511 Across this gradient in algal turf condition from SPATs to LSATs, a number of
512 abiotic factors within the turf canopy varies, including flow speeds and mass transfer
513 (Carpenter and Williams 1993, 2007), light levels available for photosynthesis via self-
514 shading (Williams and Carpenter 1990) and sediment loads (Purcell 2000; Latrille et al.
515 2019). As turf biomass increases this suite of factors may act together to reduce productivity
516 in the basal portion of the turf community because these factors limit light and the exchange

517 of nutrients. This results in a turf community that is reliant on the apical portion of filaments
518 for most of the production, i.e. the filament sections that are above the sediment layer and
519 exposed to high water flow and light. As such, reductions in algal turf turnover rates may be
520 driven by changes in the conditions within the turf community as biomass increases.

521 In addition to the abiotic factors described above, the community composition of the
522 algal turf may be related to the productivity efficiency of the entire turf community as per-
523 unit productivity rates can differ between algal species (Rogers and Salesky 1981; Steneck
524 and Dethier 1994; Bruno et al. 2006; but see Williams and Carpenter 1990). However,
525 unfortunately, our understanding of the specific nature of the relationships between sediment
526 accumulation, canopy structure, productivity and algal turf community composition are
527 currently limited (reviewed in Tebbett and Bellwood [2019]), making it difficult to determine
528 the relative importance of community composition changes, compared to abiotic conditions
529 within the turf canopy, in driving variation in turnover. However, exploring these
530 relationships in more detail offers fertile ground for further future research.

531 ***4.3 Methodological considerations and future studies***

532 Despite evidence that algal turf coverage has increased on coral reefs in recent
533 decades (Toth et al. 2014; Holbrook et al. 2016; Ellis et al. 2019; Kennedy et al. 2020;
534 Koester et al. 2020), and algal turfs are likely to be an abundant benthic covering on coral
535 reefs in the future (Bellwood et al. 2019a; Tebbett and Bellwood 2019), the paucity of
536 available data on their productivity is concerning. Unfortunately, beyond the foundations laid
537 by the pioneering research of formative reef scientists (e.g. Carpenter 1986; Klumpp and
538 McKinnon 1992; Steneck 1997; Russ and McCook 1999) there appears to have been
539 remarkably little quantification of algal turf productivity in-situ on coral reefs within the last
540 three decades, within the scope of our meta-analysis. It is important to note that this result is

541 not because of our search parameters and paper filtering methods, as the same units of
542 measure ($\text{g C m}^{-2} \text{ day}^{-1}$) are just as applicable to studies of productivity today as they were
543 historically. Unfortunately, the exact reason behind the limited quantification of algal turf
544 productivity in-situ on coral reefs in recent decades is unclear. It may be due to logistics
545 (limited access to respirometry chambers or field time/access). However, it probably reflects
546 a shift in emphasis, with attention focussed on documenting declines rather than
547 understanding the system.

548 Regardless of the reasons behind the limited quantification of algal turf productivity,
549 the amount of available data is sobering. Especially, considering the extent to which coral
550 reef research has grown recently, the technological advances that have assisted this research,
551 the strength and frequency of environmental disturbances (e.g. global coral bleaching events)
552 that are now shaping this ecosystem (Cheal et al. 2017; Hughes et al. 2018; Williams et al.
553 2019), and the inevitable increase in algal turf area on reefs (Bellwood et al. 2019a; Tebbett
554 and Bellwood 2019; Vercelloni et al. 2020). If we are to understand the functioning of coral
555 reef systems into the future, it appears to be a logical imperative to enhance our knowledge
556 about the productivity of one of the most widespread primary producers; algal turfs. To
557 stimulate further research into the quantification of algal turf productivity on coral reefs, this
558 may require the development of new technologies that are both relatively cheap and easy to
559 use in the field (see below for further discussion), as well as greater collaboration between
560 research groups with access to such technologies, or with access to areas where turf
561 productivity has not been quantified. In addition, exploring potential links between algal turf
562 productivity and other reef processes, that are viewed as inherently valuable (e.g. fishable
563 biomass [Lau et al. 2019; Woodhead et al. 2019]), may help highlight the importance of turfs
564 on coral reefs, and in-turn, encourage the study of turfs in other research fields.

565 Furthermore, it must be noted that our understanding of algal turf productivity to-date
566 appears to have been shaped substantially by the methods used, especially the use of
567 experimental substrata, and their interactions with sediments. Overwhelmingly, artificial tiles
568 or coral blocks have been used to quantify in-situ algal turf productivity (>92 % of
569 observations in our dataset used these methods). Such tiles or blocks can be readily deployed,
570 removed and quantified, and offer exact replicate units. However, these surfaces only
571 represent ‘potential productivity’ at a location as they are not natural. Indeed, experimental
572 surfaces such as coral blocks accumulate far lower sediment loads than the natural
573 surrounding reef substratum (Fig. 5). This may be due to: 1) the elevation of tiles/blocks
574 above the substratum making them more exposed to hydrodynamic activity, 2) ‘edge effects’
575 and/or 3) enhanced fish grazing (Duran et al. 2018; Latrille et al. 2019; Tebbett et al. 2020).
576 The influence of these factors is likely to be relatively consistent across tiles, meaning that
577 the patterns of algal turf productivity reported in prior studies are valid in relative terms.
578 However, in terms of absolute productivity levels, we may have systematically overestimated
579 productivity values for coral reef algal turfs. There is a clear need to estimate algal turf
580 productivity on natural reef substrata more widely.

581 In terms of estimating algal turf productivity in-situ on natural reef substrata this may
582 involve the use of specially designed incubation chambers (e.g. Miller et al. 2009; Tait and
583 Schiel 2010; Murphy et al. 2012; Dellisanti et al. 2020), boundary layer approaches (McGillis
584 et al. 2011; Takeshita et al. 2016), or PAMs (Silveira et al. 2015). Indeed, the use of the
585 Community In Situ Metabolism ‘CISME’ units appears to offer a particularly promising
586 avenue for future research (Murphy et al. 2012; Dellisanti et al. 2020). However, it must be
587 noted that the methods outlined above can be limited by constraints associated with expense,
588 technical difficulties, and time. All would hamper our ability to quantify productivity
589 efficiently across broader spatial scales. To address this issue, and expand this research field

590 further, such methods may be used to establish relationships between easily measured
591 universal traits (sensu Bellwood et al. 2019b), such as algal turf length/density or
592 accumulated sediment load, and algal turf productivity rates. Essentially, mechanistic
593 relationships could be established between these traits and algal turf productivity, allowing
594 for the estimation of productivity from more-easily, and cheaply, measured universal traits
595 (as for the length and biomass production relationships established in reef fishes e.g. Morais
596 and Bellwood [2020]). If such relationships were established, this would allow productivity
597 on natural reef substrata to be widely estimated and studied, allowing more nuanced insights
598 into the functioning of coral reefs going forward.

599

600 **5.0 Conclusions**

601 In this study we identified water depth and standing algal turf biomass as important
602 drivers that shape algal turf productivity and turnover on coral reefs, respectively. This
603 strongly supports the conclusions of past studies (e.g. Klumpp and McKinnon 1989;
604 Carpenter 1990; Russ 2003). However, we also uncovered potential limitations in our
605 understanding of these ecosystem processes, and our approaches to measuring them. This
606 comes at a time when climate change is changing the status-quo for coral reefs (Hughes et al.
607 2017; Williams et al. 2019), and when more people than ever before are depending directly
608 on the productivity that coral reefs provide (Newton et al. 2007; Teh et al. 2013; Hicks et al.
609 2019). Into the future it appears likely that people will have to increasingly depend on algal
610 turf-covered reefs (Bellwood et al. 2018; Tebbett and Bellwood 2019), particularly as many
611 reefs already support algal turf cover of >50% (Vroom 2011; Harris 2015; Aued et al. 2018;
612 Bierwagen et al. 2018; Emslie et al. 2019). As such, renewed research into the quantification
613 of algal turf productivity, particularly on natural reef substratum, will be important. This

614 research will help us to understand how coral reefs will function in the future and the extent
615 to which they can continue to provide the services that people require.

616

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623

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