1 Tracing the influence of land-use change on water quality and coral reefs using a Bayesian
2 model

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23

24 Abstract

25 Coastal ecosystems can be degraded by poor water quality. Tracing the causes of poor water
26 quality back to land-use change is necessary to target catchment management for coastal zone
27 management. However, existing models for tracing the sources of pollution require extensive
28 data-sets which are not available for many of the world's coral reef regions that may have
29 severe water quality issues. Here we develop a hierarchical Bayesian model that uses freely
30 available satellite data to infer the connection between land-uses in catchments and water
31 clarity in coastal oceans. We apply the model to estimate the influence of land-use change on
32 water clarity in Fiji. We tested the model's predictions against underwater surveys, finding
33 that predictions of poor water quality are consistent with observations of high siltation and
34 low coverage of sediment-sensitive coral genera. The model thus provides a means to link
35 land-use change to declines in coastal water quality.

36

37 **Keywords:** Remote sensing, coral reefs, Fiji, water quality, sediment, ridge to reef planning.

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Introduction

40 The management of activities on land to avoid pollution run-off to the ocean is important for
41 the conservation of many coastal marine ecosystems [1-3]. Deforestation and farming increase
42 run-off of nutrients and sediment that can flow out to the ocean [4]. In the ocean, sediment and
43 nutrient pollutants can decrease water clarity and shade or smother habitats, reducing
44 diversity of benthic organisms [5], habitat complexity and fish diversity [6,7]. Thus, in places
45 where coastal waters are strongly influenced by freshwater run-off the management of
46 marine ecosystems requires actions in connected terrestrial and freshwater habitats.

47 Management of run-off to coastal marine ecosystems requires identifying the source of
48 impacts to ecosystems, so that appropriate actions can be taken to reduce threats. Between
49 the land-use change and changes in marine ecosystems, multiple processes are operating
50 across space and time that affect marine sediment concentrations: for instance, deforestation
51 causes increased sedimentation in rivers and floodplains e.g. [4,8,9], rivers transport sediments
52 to the ocean e.g. [10] and in the ocean sediments are dispersed to reefs e.g. [11]. Given that the
53 ocean can disperse sediments widely, water quality at a single location in the marine
54 environment may be influenced by rivers that drain multiple catchments. Thus, attributing
55 declines in coastal water quality to its cause on land is difficult, which hinders identifying
56 priorities for management actions on land, like the best locations for re-vegetation [4].

57 The methods used to trace the source of water quality issues to their causes on land are
58 generally data-intensive. For instance, on the Great Barrier reef, millions of dollars and years
59 of research have been in invested to trace the source of poor water quality [12]. Satellite remote
60 sensing products, *in situ* water quality measurements and river discharge measurements have
61 been used to trace the extent of influence of river flood plumes [13] and estimate potential
62 improvements in water clarity from acting to reduce river sediment loads [14]. However, the
63 investment of time and resources required to implement these approaches is not feasible in
64 many developing countries, where run-off can have severe negative impacts on the
65 livelihoods of people that rely on coastal ecosystems [15]. For instance, people in Fiji are reliant
66 upon coral reefs for fisheries and tourism, an ecosystem that is threatened by land-use change
67 [16]. There is limited historical data, funding and capacity to undertake additional science to
68 support a new government initiative for integrated coastal zone management. Capitalizing on
69 political opportunities for coastal planning requires methods that can be implemented with
70 existing and freely available data-sets [17].

71 Three approaches offer hope for data limited regions. The first uses soil erosion equations,
72 such as in those in the INVEST toolbox [18], to inform land areas contributing the greatest
73 sediment and nutrient loads to river mouths. The second approach relies on simple models of
74 reef exposure to river flood plumes based on Geographic Information Systems analysis (GIS)
75 e.g. [11,19,20]. A weakness of these modeling approaches is that they are not quantitatively
76 validated against local datasets, and parameters are estimated using expert opinion or
77 extrapolated from other study areas, often with very different climates and soil conditions [8]. A
78 third approach, the analysis of satellite data for indices of water quality offers a way to obtain
79 quantitative measurements even in data-limited regions e.g. [13]. However, satellite
80 measurements should be corrected locally for biases, for instance from benthic reflectance [21].
81 Further, satellite measurements cannot be used on their own to trace the source of poor
82 water quality back to land. An appropriate statistical modeling framework could integrate
83 these three approaches, drawing strengths from each, is required.

84 Here we combined satellite measurements with GIS models and catchment models to resolve
85 the contributions of different catchments to water quality, specifically turbidity, at coral reefs
86 using a hierarchical Bayesian model. We applied our model to estimate catchment
87 contributions to turbidity around Vanua Levu, Fiji, where information on sediment run-off is

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88   needed to inform coastal planning [22]. Because field data are often poorly controlled and there
89   are inherent errors in satellite measurements of water quality [13,14], we further tested our
90   model under idealistic conditions to suggest further scope for improvement in the model and
91   priorities for collecting empirical data. Our approach required freely available data on water
92   quality and land-use (from satellite imagery) and rainfall, making it broadly applicable for
93   linking catchments to water quality, even in data-limited regions, for use in integrated land-
94   sea management plans.

95
96   **Methods**

97   *Overview*

98   We approach the problem of determining the contribution of different catchments to satellite
99   measurements of turbidity in the ocean by developing a Bayesian hierarchical model. The
100 model simultaneously estimates the dispersion of sediments from sources (e.g. river mouths)
101 and the relative influence of different sources on ocean turbidity. The model was hierarchical
102 because the influence parameters were scaled by independently derived estimates of
103 sediment loadings. Sediment loadings themselves were calculated from catchment land-use
104 and rainfall data using a simple model of sediment run-off. To test Bayesian model's
105 predictions of turbidity, we related model estimated turbidity values to observed benthic
106 habitat data. Finally, we perform a power analysis where we test the Bayesian model's ability
107 to recover known parameter values for a simulated coastline.

108 *Bayesian model*

109 The core of our model was a function that described the influence of different sediment
110 sources on ocean turbidity at different distances from each source. In all equations below we
111 use Greek letters to represent parameters that were estimated. The likelihood of the satellite
112 observing turbidity value y_i at location i was specified:

113 $$y_i = \left(\sum_{j}^{m} z_{i,j} \right) e^{\varepsilon_i} \qquad\qquad \text{Equation 1}$$

114 where the summation is over m sediment sources, j, ε_i are normally distributed error terms
115 with precision τ_y and $z_{i,j}$ was a latent variable representing the influence of source j (e.g. a
116 river mouth) on ocean location i. We rescaled the turbidity measurements by subtracting the
117 minimum value then adding a small number so that estimation of an intercept parameter was
118 unnecessary [23].

119 The model described the declining influence of a source j on turbidity at an ocean site ($z_{i,j}$)
120 using a power function:

121 $$z_{i,j} = \beta_j d_{i,j}^{\alpha_j} \qquad\qquad \text{Equation 2}$$

122 where β_j was the influence of source j on turbidity at a distance of zero (e.g. at a river mouth),
123 α_j was a scaling parameter that controls the dispersion of sediment, and $d_{i,j}$ was a matrix of
124 distances (in kilometres) from ocean sites to sources. The parameters α_j were expected to be
125 negative if turbidity declines at greater distance from sources. We let the dispersion
126 parameter vary by sources, however, in practice allowing each source to have a unique α
127 would result in issues with parameter identification. Thus we suggest that α values are
128 restricted to one or just a few values. We also tested the model by replacing equation 2 with
129 an exponential function, which assumes diffusion of sediments across space. However, model
130 fits from the exponential function were poor, so we proceeded with the power function.

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131 We included a second hierarchical level in the model to allow for source influences (β_j) to
132 scale with estimates of sediment yield from catchments:

133 $$\beta_j = \theta S_j e^{\upsilon_j} \hspace{4cm} \text{Equation 3}$$

134 Where the parameter θ can take values >0 and rescaled estimates of sediment loadings
135 coming from rivers, S_j, into the units of the satellite measurement and υ_j were normally
136 distributed errors with precision τ_υ. Sediment loadings themselves are estimated according to
137 land use and rainfall patterns within each catchment, outlined below.

138 The hierarchical level was an important strength of this modeling approach. The problem of
139 attributing the contribution of multiple catchments to ocean turbidity is underdetermined,
140 because there is no one unique solution. Constraining catchment influences to scale with their
141 sediment loadings effectively requires the relative order of catchment influences to remain
142 similar to the order of their sediment loadings. This constraint helps constrain the plausible
143 parameter space .

144 We used vague priors for all parameters and priors were specified as follows: τ_y, τ_υ and α_j had
145 uninformative gamma priors, and θ had an uninformative log-normal prior (See appendix B
146 for further details).

147 We used Markov-Chain-Monte-Carlo (MCMC) sampling to numerically simulate posterior
148 distributions of the modeled parameters [23]. To implement numerical simulations, we used
149 JAGS version 3.3.0 [24], controlled from the R programming language [25], using the Coda package
150 [26] to evaluate model fits (Supplementary Material Appendix A). For all model runs, we used
151 the Gelman-Rubin statistic [27] to evaluate convergence and only accepted models where this
152 statistic was <1.05 for all variables.

153 The model could be applied to different water quality variables (e.g. turbidity, salinity) over
154 different time-scales, provided the estimates of catchment size and the water quality variables
155 are measured at consistent time-scales. For instance, the model could be applied to a pulse
156 event, such as a tropical storm, to estimate the contribution of different rivers to sediment
157 pollution in the ocean. The model could also be applied to time-integrated measures of
158 pollutant exposure e.g. [19], which is the approach we take here.

159 *Case-study*

160 We estimated catchment influences on ocean turbidity in the waters around Vanua Levu, the
161 second largest island of Fiji. Integrated Coastal Management (ICM) plans are currently being
162 developed at the provincial level for Vanua Levu. In Vanua Levu, there is concern from
163 government and communities that accelerating economic development on land, including
164 mining agriculture, road building and forestry will impact fisheries, tourism and the ecological
165 integrity of marine protected areas [28]. To address these concerns, coastal communities in
166 Vanua Levu's Bua province are currently working with government and a non-governmental
167 organization (The Wildlife Conservation Society, WCS) to design and implement an ICM plan
168 based on national ICM frameworks for Fiji [22]. The ICM plan will aim to balance terrestrial
169 economies, marine economies and ecological health. Therefore, the ICM plan requires
170 information on where development on land can have minimal impacts to marine ecosystems
171 and economies. However, there are limited data on the influence of land-use change on
172 coastal water quality to support this decision process and limited funding and time to support
173 further data collection. Thus, the ICM process would benefit from rapid advice on where
174 development may have the greatest impact on water quality.

175 *Data for Vanua Levu*

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176   We fitted the Bayesian model to remotely sensed turbidity measurements from the coastal
177   waters around Vanua Levu. We used satellite data from the Medium Resolution Imaging
178   Spectrometer (MERIS), part of the European Space Agency's Envisat platform [29]. We
179   downloaded images for the Level 2 products for turbidity for the years 2003-2011 (data
180   provided in Formazin Turbidity Units). The turbidity product has been empirically validated
181   for other regions with similar water types [13,30]. The satellite pixels were summarized onto a
182   standardized grid of 402 by 402 metres, removing any pixels with a low quality reading
183   (quality flag <0.01). We also masked pixels on reefs, in shallow water and all pixels next to
184   reefs or shallow water to minimize the confounding influence of benthic reflectance [21]. Reefs
185   were identified using a global reef database [31].

186   Turbidity measurements were summarized as the geometric mean of values across all years
187   in the wet season (119 images, November to April) and standardized by the mean value.
188   Standardization was performed because turbidity has not been validated against local in situ
189   data, and we were interested in the spatial patterns, not the absolute values. We also created
190   summaries using the maximum, minimum and frequency of high (>2SD) turbidity events,
191   however these all had similar spatial patterns, so we focus our analyses on the means
192   summary. The summary was resampled to a resolution of 3.12km by 3.14 km, resulting in
193   1250 pixels with turbidity measurements in the study region. Resampling was performed
194   because convergence of the MCMC algorithm was slow using the full resolution data.
195   Resampling to a lower resolution preserved spatial patterns in turbidity and exploratory
196   analysis indicated there was little bias in parameter estimates when resolution was reduced.
197   The pixels that were not used in model fitting were retained for evaluating model fit. Model fit
198   was evaluated using the residual mean square error. Parameters, priors and model code are
199   provided in Supplementary Material Appendix B.

200   Sediment yield from each river mouth was estimated for each catchment as:

201    $$S_k = \sum_l s_l p_{l,k} r_k f_{l,k} \hspace{4cm} \text{Equation 4}$$

202   Where S_k in mg is the summed product over the landuses l, s_l is the sediment yield of a land-
203   use (per mg/L of rainfall), $p_{l,k}$ is the proportion of rainfall that runs off a landuse (L^{-1}), r_k is the
204   total rainfall (L) in a catchment in the wet-season and $f_{l,k}$ is the proportion of area under a
205   landuse in a catchment ($\sum f_{l,k} = 1$). The proportion of rainfall that ran off a given catchment
206   increased with increases in that catchments spatially averaged wet season rainfall [32].

207   We consider two land-uses: forested versus deforested (including farmland, bare soil and
208   settlements). There were 74 catchments in the study region and for model fitting we scale the
209   S_k relative to the largest catchment. Delineation of catchment boundaries and data to calculate
210   source sediment contributions (Equation 4) were derived using freely available GIS products
211   and programming routines (Supplementary Material Appendix C).

212   Catchments with river mouths within 5km of each other were aggregated together before
213   fitting the Bayesian model. Aggregation was necessary because the influence of nearby river
214   mouths on turbidity was not identifiable by the model. For aggregated river mouths distance
215   from the rivers to each ocean pixel was taken as the mean distance from the river mouths.
216   River sediment loadings, S_k were summed over the groups to obtain 28 grouped river mouths,
217   S_j. Aggregation of river mouths meant we could only discriminate sediment contributions
218   from groups of neighboring catchments, however simulating testing indicated that the
219   aggregation procedure significantly reduced bias in parameter estimates (see below).

220   Initially we fit the model with a single dispersion parameter (α) for all sources. However,
221   examination of model fits indicated that this model tended to under-predict turbidity on the
222   north-west facing coast of Vanua Levu and over-predict turbidity on the south-east coast.

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223 Winds in Fiji are predominantly easterlies [33], suggesting that sediment dispersion might vary
224 on the two coasts. Therefore we re-fitted the model allowing unique dispersion parameters
225 for southern and northern coasts. We report results from both models, including statistics for
226 model selection: the predictive loss and the deviance information criteria [23,24]. Lower values
227 of predictive loss and deviance information criteria indicate a more parsimonious model.

228 *Impact of poor water quality on benthic habitats*

229 We conducted an independent verification of water quality predictions by assessing whether
230 the composition of benthic habitats was consistent with the Bayesian model's predicted
231 gradient in turbidity. We used mean turbidity as predicted by the model with two dispersion
232 parameters. Surveys of coral reef benthic habitats were conducted by WCS at 168 sites
233 around Vanua Levu. Point intercept surveys were performed using 2-6 replicates of 50 metre
234 long transects at each site, recording benthic habitat categories at 0.5 metre intervals
235 according to a standard classification adapted from Hill and Wilkinson [34].

236 For each site we calculated change in percent cover of three benthic habitat types that are
237 most likely to respond to high turbidity: silt, sediment sensitive scleractinian coral genera
238 (genera and justification are in Supplementary Material Appendix D) and algae. Silt cover and
239 percent cover of algae (which included macro algae and cyanobacteria) were expected to
240 increase with increased turbidity, cover of sediment sensitive coral genera was expected to
241 decline with increased turbidity. For the three habitat types (silt, algae and coral), we fitted
242 linear models to test for a relationship between predicted turbidity and the cover of each
243 habitat. For each habitat type, we used linear models and transformations appropriate to the
244 distribution of residuals (Supplementary Material Appendix D).

245 *Simulation testing*

246 We used a simulation study to test the model's ability to estimate source contributions to
247 pollution accurately and precisely for different geographies and data types. We simulated a
248 100 km long linear coastline with three river mouths. The ocean environment extended out to
249 100 km from shore and contained 300 (30 by 10) ocean pixels. For each simulation test we
250 used the power functional form (equation 2) to simulate 25 water quality data-sets with
251 random measurement errors. We then fit equations 2-3 to each simulated data-set to see if it
252 could recover the original parameters (see Supplementary Material Appendix E for details of
253 the MCMC algorithm).

254 We were particularly interested in the model's ability to predict turbidity at ocean pixels and
255 estimate the contribution of each source to water quality. We used two statistics to evaluate
256 the model's performance to estimate the source contributions [35]. The first was the mean
257 relative error (MRE), which is a measure of bias in parameter estimation. The second was the
258 mean coefficient of variation, which quantifies precision. We also evaluated bias in estimation
259 of ocean turbidity using the residual mean square error comparing model predicted turbidity
260 to simulation turbidity without observation error (Supplementary Material Appendix E).

261 Initially, we assumed the source contributions to turbidity were equal and they were position
262 at 100km, 200km and 300km along the coastline. In the first simulation test, we varied the
263 standard deviation of the observation error and ocean dispersal a (Supplementary Material
264 Appendix E). Based on these initial tests, we fixed the error and a at 0.5 and 1.25 for further
265 testing.

266 The second simulation test was to explore the model's ability to partition the contribution of
267 the sources to water quality. We then ran crossed trials where the southern-most source was
268 iteratively moved towards the center of the coast. We also iteratively increased the magnitude
269 of one source's contribution to water quality.

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Results

Case-study for Fiji

Satellite measurements of turbidity indicated a gradient in the geometric mean of wet-season turbidity with high values near to river mouths (Fig. 1). Values tended to be higher on the north-coast of Vanua Levu, where there has been extensive land-clearing.
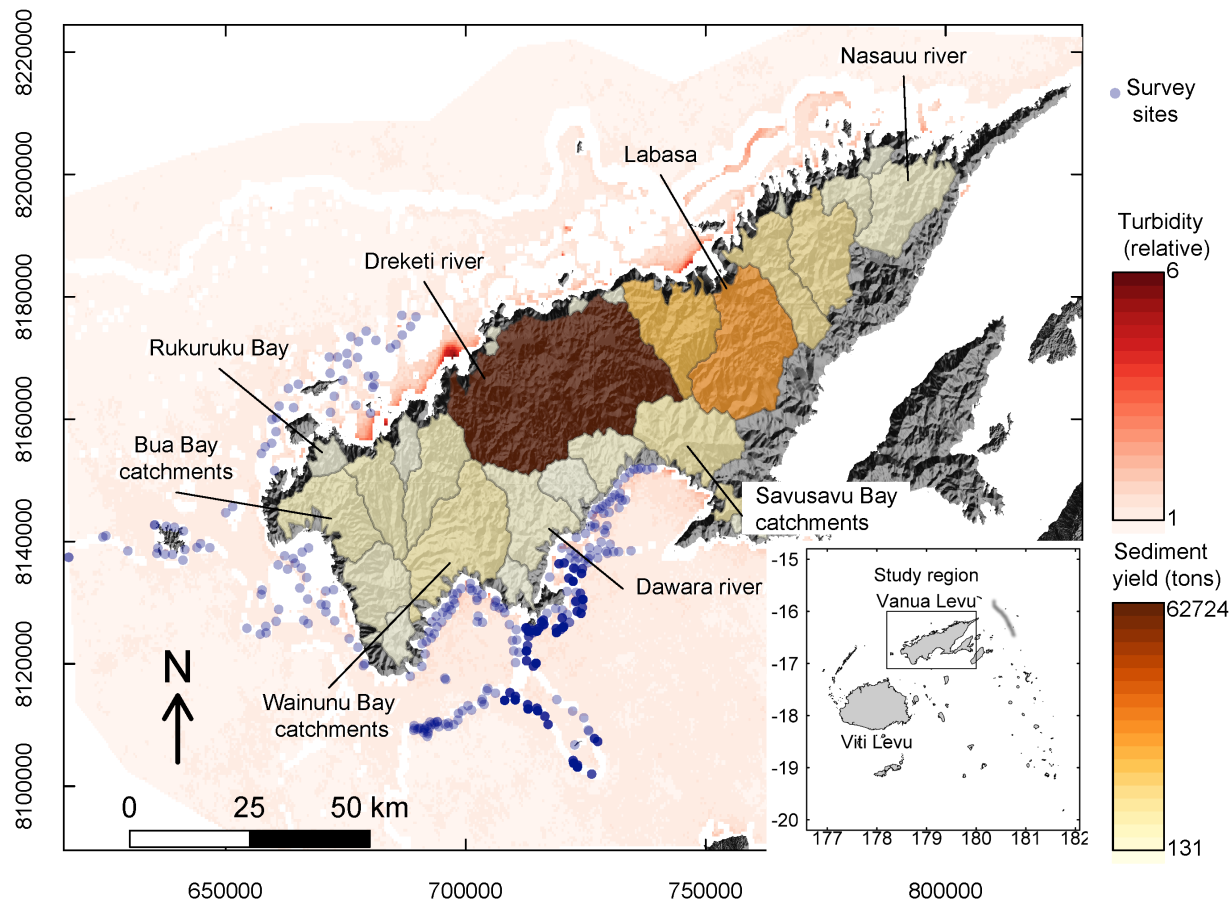

Fig 1 Map of the study region, showing grouped catchments (coloured polygons, overlaid on a hillshade map) with their estimated sediment yield (tons per wet season) and reef survey sites. White areas were excluded from analysis due to shallow water or being too far from the catchments. Ocean colour scale shows mean turbidity estimated from satellites. Inset shows the study region's location in relation to Fiji's largest islands.

Comparing the two model fits, the model with unique dispersion parameters for each coast provided a more accurate fit (lower root-mean square error) and was more parsimonious despite the extra parameter (lower DIC, Table 1). The estimates of the dispersion parameters also suggested that the dispersion parameter was significantly different on north and south coasts (compare overlap of 95% credibility intervals in Table 1). For further analysis we proceed with the two dispersion parameter model.

Table 1 Fit statistics from the two Vanua Levu models. North coast includes Bua Bay.

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Model	Estimate(s) of dispersion parameter (95% Credibility interval)	Root-mean square error on data not used in fitting	Predictive loss	Deviance information criteria
Single dispersion parameter	1.28 (1.22, 1.33)	0.14	217	1327
Unique dispersion parameters for each coasts	South coast: 0.77 (0.70, 0.83) North coast: 2.30 (2.14, 2.47)	0.13	191	927

289

290 The model provided accurate estimates of turbidity. Visualization of modeled turbidity
291 indicated that the large catchments on the north coast contributed to high turbidity in nearby
292 coastal waters (Fig. 2A). On the south-coast the degraded catchments around Savusavu,
293 contributed to moderate levels of turbidity. The moderately sized catchments around western
294 Bua also had a large influence on coastal waters. In comparison the catchments with high
295 forest cover on the south-west coast had little influence on south-west coastal waters. There
296 was some spatial bias in predictions of turbidity when compared to satellite measurements
297 (Fig. 2B). Turbidity was underestimated in inshore areas of the far north coast, particularly
298 near the mouth of the Nasauu River.

299 Estimates of source contributions were generally consistent with the estimates of sediment
300 loadings (Fig. 3), although the estimates for source contributions deviated significantly from
301 the linear relationship with sediment loads for several catchments. In particular, the Bua Bay
302 catchments and Nasauu river and Rukuruku bay catchments were estimated to have a far
303 greater influence on ocean turbidity than the estimates of their sediment loadings suggested.

304
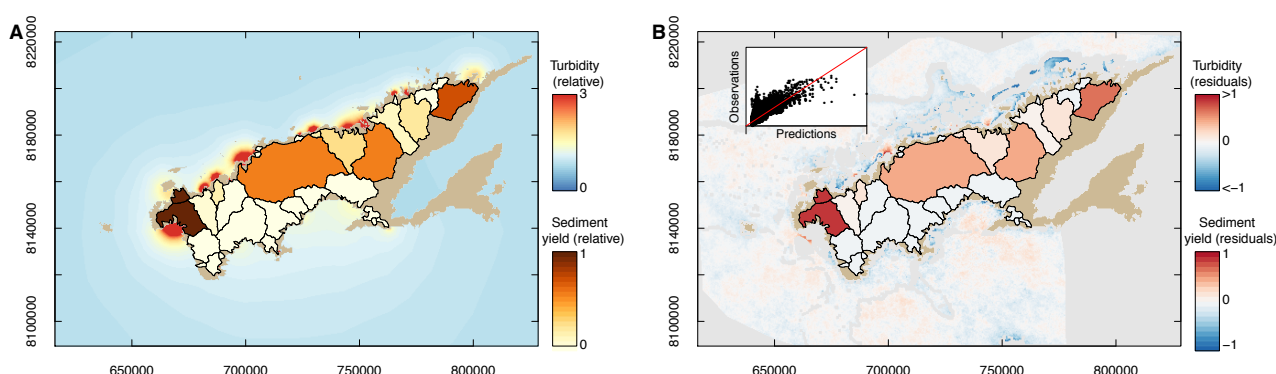
305

306 **Figure 2** Predicted (A) and residual (B) catchment yields and turbidity values from the model
307 fit for Vanua Levu. The inset on B show a plot of predicted versus residual values. Sediment
308 yields in (A) and residual yields in (B) are scaled relative to the maximum yield value.
309 Residuals for turbidity in (B) are constrained in [-1, 1] to aid visualization, because there were
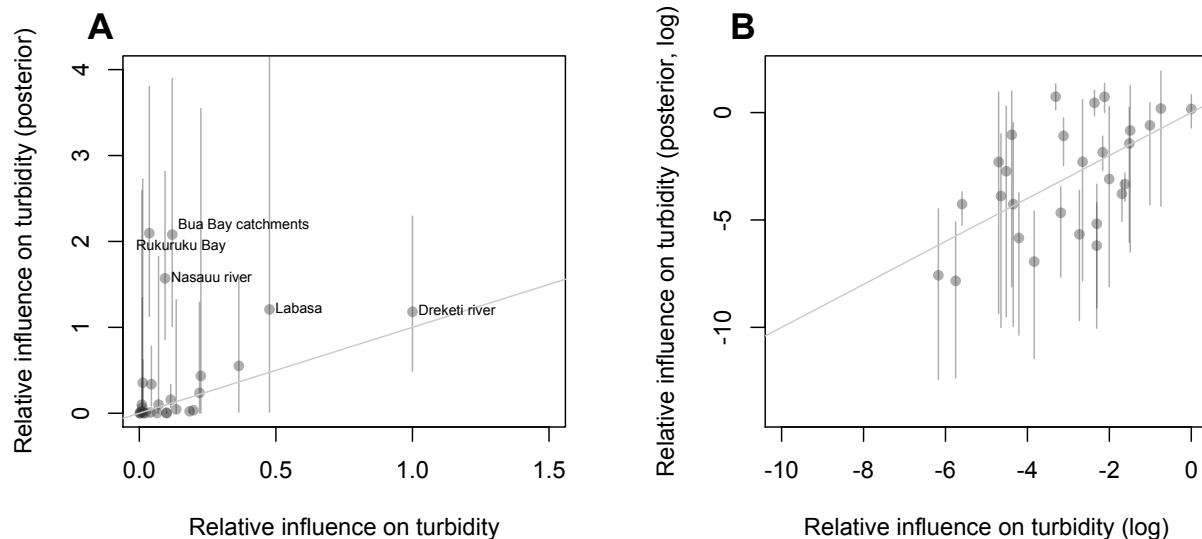310 more negative residuals (-4) at the mouth of the Dreketi river.

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312

Figure 3 Relative influence of sources on ocean turbidity (A) and logged influence values (B) estimated from the GIS analysis plotted against posterior estimates for relative influence. The x and y axis are scaled to the same units by dividing the x-axis by the slope from the mean estimate of the yield-influence parameter (θ). Error bars show 95% credibility intervals.

317

The verification analyses relating our predicted turbidity values to observed benthic habitat observations showed some statistically significant relationships, albeit with some uncertainty (Fig. 4). Modeled turbidity was consistent with spatial variation in cover of silt, which was estimated to increase from 2% to 19% from the clearest to most turbid water (Fig 4a, $p < 0.05$). The cover of sediment sensitive corals declined from an average of 21% to an average of 0.4% with estimated turbidity (Fig 4b, $p < 0.05$). Algal cover decreased slightly with turbidity, but the relationship was not statistically significant (Fig 4c, $p > 0.05$). Note that change in silt cover and coral cover was greater if sites with extreme turbidity values (>1.3) were removed from analysis.
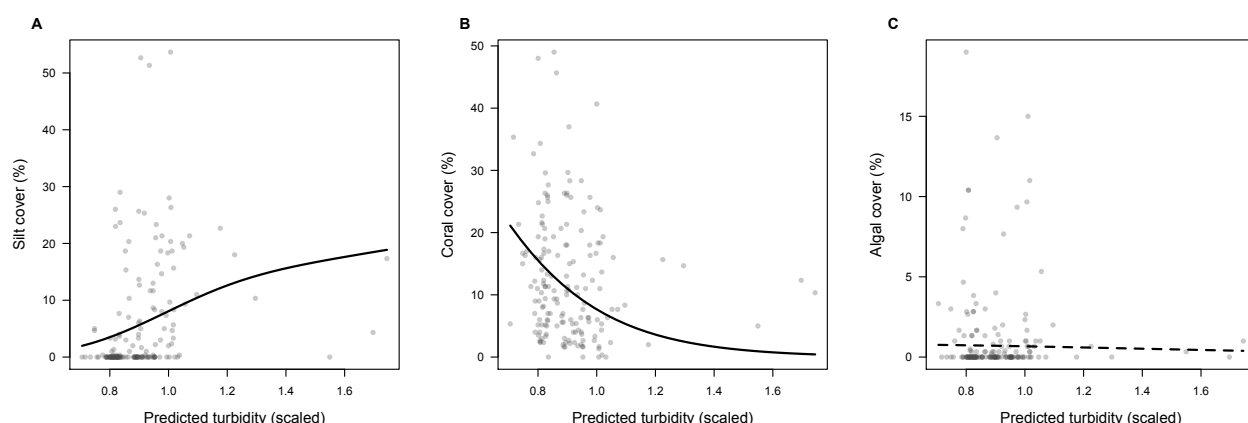
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328

Figure 4 Turbidity estimates from the Bayesian model predict (A) silt cover (zero inflated log-linear model), (B) cover of sediment-sensitive scleractinian coral genera (linear model fit with logit transform) and (C) algal cover (zero inflated logit model). Lines show model fits, where a solid line is statistically significant ($p < 0.05$).

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334 *Simulation tests for the power functional form*

335 Overall, simulation tests indicated that the model's estimates of dispersion, source
336 contributions and predictions of water quality had negligible bias across a broad range of
337 parameter and catchment configurations settings (Table 2). The primary cause of bias in
338 estimates was catchment configurations that reduced spatial contrasts in source
339 contributions to water quality. Weak spatial contrasts occurred in two types of data. First, if
340 the observation error on the satellite images was large and the gradient of turbidity from
341 inshore to offshore very weak, the model's estimates had high bias (>10% difference from the
342 true value) and predictions of turbidity had a large error. Second, if two sources were close
343 together, the contribution of the source with the smaller yield was generally over-estimated,
344 whereas the contribution of the source with the larger yield was underestimated.

345 The simulation tests also indicated caution must be taken when interpreting the model's fit. If
346 rivers differed greatly in their contributions, estimates of water quality were accurate (low
347 root-mean square error), but estimates of source contributions were likely to be biased,
348 particularly if the rivers were close together. Accurate water quality predictions may lead to a
349 false sense of security in extrapolating predictions to other run-off conditions.

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351 **Table 2** Summary of results from varying parameters for simulating testing of the Bayesian
352 model.

Test	Bias in estimate of alpha	Variance in estimate of alpha	Bias in source contributions	Variance in source contributions	Root mean square error for water quality predictions
More negative values of α	<1% for all values	<1% for all values	<1% for all values	<1% for all values	<1% for all values
Greater sd obs (sd of ε_i)	Negative bias if the sd was large and α low	High variance if the sd was large and α low	Negative bias if the sd was large and α low	High variance if the sd was large and α low	High if the sd was large and α low
Sources are closer together	<1% for all values	<1% for all values	Over-predicts smaller source and under-predicts larger source	Higher variance for sources that are closer together	
One source contributes more than the others	<1% for all values	<1% for all values	Bias low, but over-predicts smaller source and under-predicts larger source	Negligible, but increases if sources are close together.	<1% of mean turbidity value for all parameters

353

Discussion

355 Our model provides a rapid and effective tool for estimating the influence of multiple
356 catchments on coastal water quality. The data required to build this model are freely
357 available, making this model useful for regions with limited funding for development of more
358 sophisticated models of pollutant sources that rely on detailed *in situ* data. Further, the model
359 can be rapidly implemented, so can be used to inform development of environmental policy
360 during times of political opportunity [17]. Model outputs for influence of catchments on water
361 clarity could be used by planners directly, or integrated into simulation models to evaluate
362 different future scenarios of land-use change e.g. [3,36]. For example, the results from the model
363 for Fiji have provided input into the design of the Bua Province ICM plan for the next 5-10
364 years. Our modeling was incorporated into the consultation process by informing provincial
365 government and communities which catchments have had the greatest influence on coral reef
366 ecosystems, and therefore need to have sound strategies in place to manage those
367 catchments.

368 Results indicated that several catchments had a large influence on turbidity. These
369 catchments are some of the most degraded in the region, with native vegetation removed to
370 build towns and grow sugar cane, which has resulted in high erosion rates [9]. Similar high
371 erosion in other parts of the world has been documented to have substantial impacts on
372 ocean water quality and marine benthic communities [6,37]. Verification of the model against
373 benthic habitats also demonstrated that turbidity is likely affecting marine benthic habitats,
374 through an increased cover of silt, the stress and eventual loss of sediment-sensitive coral

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375   species. Algal cover was not related to turbidity. Multiple processes may drive algal cover,
376   resulting in non-linear response to turbidity, for instance algae may be excluded at low light,
377   and outcompeted by corals in very clear waters. Similarly other studies have also found that
378   algae does not necessarily replace corals on highly turbid reefs [38,39]. Degradation of fish
379   habitat and turbid waters over coral reefs are of concern to local communities because
380   fisheries and tourism are major sources of livelihoods in the region. Actions reduce
381   deforestation and target catchment restoration in the most degraded catchments may
382   therefore have the greatest benefits for local coastal marine livelihoods.

383   Our approach offers several advantages over other GIS models of catchment contributions e.g.
384   [19,20]. Using Bayesian estimation to fit parameter estimates to data enabled us estimate the
385   dispersal of pollutants in the ocean for a given region, rather than using fixed parameters that
386   have been obtained from other regions that may not be locally appropriate. Further, simple
387   GIS models rely on point estimates of catchment contributions to water quality, so do not
388   consider uncertainty in catchment contributions. The Bayesian model estimates uncertainty
389   in catchment contributions. Estimates of uncertainty are useful for decision-makers, because
390   they provide a range over which improvements in catchment land-use are expected to benefit
391   reefs.

392   There were some discrepancies between the estimates of catchment sediment loadings
393   derived from the GIS analysis and the Bayesian model's estimates of catchment contributions
394   to turbidity. Further, catchment influence parameters were highly uncertain for several
395   catchments. Such discrepancies may arise due to errors in the satellite measurement of
396   turbidity, processes of erosion that we did not consider in the simple catchment models, or
397   variation in the dispersal of sediment from across different river mouths. Estimates of
398   sediment loadings that were much greater than the GIS estimates may indicate erosion
399   processes we did not consider, such as significant stream bank erosion [4]. Likewise, where the
400   estimated contributions were much smaller than the estimated sediment loadings, sediment
401   capture and storage processes within hydrological networks may be important [40]. The
402   discrepancies could also result from oceanographic processes, for instance the effect of some
403   catchments on ocean turbidity may be low if plumes are rapidly dispersed offshore. Where
404   data on catchment processes are available, more detailed process models may provide better
405   estimates of sediment loadings e.g. [41]. These discrepancies thus indicate key catchments were
406   further empirical work to quantify sediment transport may have the greatest benefit for
407   improving predictions of source contributions to coastal turbidity.

408   One weakness of our approach is that it does not resolve sub-catchment processes of erosion,
409   so the model can only inform priorities for land-use management at the catchment scale. More
410   detailed catchment models have been used to successfully resolve sub-catchment erosion and
411   thus, can inform on priority areas for restoration within catchments [42]. However, the most
412   common models for sediment sourcing are based on temperate grasslands, so further work is
413   needed to develop their application to tropical catchments [8]. In particular, estimates of
414   catchment sediment yield could be improved by accounting for erosion of stream banks,
415   which can be the major source of sediment run-off [4,43]. The contribution of stream bank
416   erosion to sediment yield could be determined using chemical tracers of sediment sources [44]
417   and then catchment scale estimates could then be estimated by mapping streams and
418   remnant riparian vegetation e.g. [4]. Further development of the model to include stream bank
419   erosion could thus help managers achieve economic development targets for land-use change
420   while avoiding the areas that cause the greatest amount of sediment run-off.

421   Our model is a simplification of both catchment processes and oceanographic dynamics and
422   several steps could be taken to improve predictions of catchment influences on turbidity at
423   reefs. First, there were no available *in situ* measurements of water quality parameters. Ideally

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424 satellite images should be validated against in situ water quality data e.g. [13,39] or proxies from
425 coral reef cores e.g. [45]. To address this, we used satellite products that have previously been
426 validated for other similarly turbid water types [13] and verified our estimates against *in situ*
427 data of benthic habitats. Nonetheless, *in situ* water-quality data should be priority for further
428 testing of this model. An advantage of this Bayesian framework is its flexibility to incorporate
429 additional information. For instance, *in situ* measurements of turbidity and sediment
430 concentration could be used as prior information for the estimation of the scaling from
431 sediment loading to turbidity units.

432 A second caveat is the models of sediment dispersal were simplistic representations of
433 oceanographic processes, including dispersion, tidal transport and wind-driven transport.
434 The power function used to estimate turbidity is a phenomenological representation of
435 sediment dispersion. Thus, bridging the divide between numerical models of sediment
436 dispersion with sophisticated process descriptions e.g. [46] and the statistical approach we
437 employed requires further work. The inclusion of additional processes in Bayesian models
438 will require further development to improve the computational efficiency of the estimation
439 algorithm, such as employing customized MCMC algorithms [23]. One future improvement may
440 be to include the predominant direction of winds in the Bayesian model and allow sediments
441 to disperse further in the direction of winds e.g. [19]. For instance, we found that model fit was
442 improved considerably with different dispersion parameters for north and south coastlines.
443 The improvement in fit may be due to offshore versus onshore winds on the north versus
444 south coast. More specific parameterizations to account for bathymetric effects on currents
445 may help to resolve spatial auto-correlation in the model's residuals. Despite the model's
446 simplistic representation of oceanography, it still explained a large amount of the variance
447 (77%) in the satellite data, suggesting increasing model complexity will provide smaller
448 incremental gains in explanatory power.

449 We have developed a Bayesian model for estimating the influence of catchments on coastal
450 water quality. The model shows utility for rapidly assessing catchment contributions to water
451 quality in data limited regions and thus may be used to inform planning processes in a timely
452 and cost-effective manner. Building in sediment sourcing models into land-sea planning
453 processes is important to ensure that planners properly account for the downstream effects of
454 actions on land, many of which may impact the livelihoods of coastal people and degrade
455 ecological integrity.

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