SC: SDGs: Virtual Reef Diver: Enabling People to Help Protect the Great Barrier Reef

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Two Sustainable Development Goals are focused directly on combating the impacts of climate change on coral reef communities. These are: providing cost-effective and timely information to reef managers (SDG 13 - climate action) and sustaining healthy coral reefs in the future (SDG 14 - life below water). Citizen science (CS) features prominently in a range of programs that have been developed to address these goals. One such program is Virtual Reef Diver, which is designed to help monitor the health of the Great Barrier Reef in Australia. This program engages citizen scientists in two ways. Scuba-divers are asked to take geo-coded underwater images of the reef and upload them to an online virtual reef. Members of the public across the world are then asked to classify these images with respect to key reef indicators such as coral. Through the lens of a Virtual Reef Diver event held as part of 2021 Australia's National Science Week, we describe important features of this program that positively address common concerns about CS data, including the scientific trustworthiness of the data, the ability to incorporate these data with other more traditional data sources, and the quantifiable improvement in information about reef health using these data for management decisions. This demonstrates the important role that citizen science can play in achieving SDGs.

Keywords: Citizen science; Sustainable Development Goals; Great Barrier Reef; reef health; disturbances; management

INTRODUCTION

Coral reefs are one of the world's most highly valued natural treasures. As the 'rainforests of the sea', they sustain about 25% of the ocean's fish, provide food, income and protection for over one billion people, tens of billions of dollars in net economic value, and high cultural value to people globally (Cinner et al., 2014). However, coral reef ecosystems are under severe threat from increasing storms intensity and marine heatwaves induced by climate change with 99% of the world's coral reefs that may suffer from frequent marine heatwaves in the future (Dixon et al., 2022). Coral reefs also face increasing anthropogenic pressures such as overfishing, pollution, sedimentation and poor water quality. Management strategies are not able to cope with the acceleration of disturbance regimes resulting in unprecedented decline of coral reef communities across the globe (Hughes et al., 2018) and a slow-down in the implementation of the United Nations (UN) Sustainable Development Goals (SDGs) within these regions (Obura, 2020).

The Great Barrier Reef (GBR) is the largest coral reef system in the world and it is situated in Australia. Designated as a World Heritage Area in 1981, the GBR comprises over 3000 individual reefs, the GBR is 2300 km (1429 miles) long and encompasses almost 35 million hectares (133000 square miles). The GBR has suffered greatly from the impact of cumulative disturbances including back-to-back mass bleaching events in 2016 and 2017 that killed corals, the primary reef-building organisms, across hundreds of kilometers (Hughes et al., 2017). The broad-scale impacts of climate-driven disturbances increase uncertainty about how coral reef communities respond to climate change and our capability to predict the future status of coral reefs and manage them in the light of new environmental regimes (Vercelloni et al., 2017; Vercelloni et al., 2020).

The critical importance of coral reefs, and the international concern about their long-term viability, is reflected by two SDGs specifically dedicated to their protection. SDG 13 is to provide cost-effective and timely information to reef managers and SDG 14 is to sustain healthy coral reefs in the future. The progression toward these SDGs is informed by a range of coral reef monitoring programs across the globe. For example, the GBR Long Term Monitoring Program (LTMP), led by the Australian Institute for Marine Science, is based on biannual underwater surveys of coral cover and other key indicators of reef health. Since 1985, the program has surveyed hundreds of reefs, providing the most comprehensive record of coral status of a reef ecosystem in the world (Emslie et al., 2020). Despite this massive effort, the size and complexity of the GBR, the high cost of surveys and the accelerated decline in reef health mean that the LTMP alone cannot provide all the information required to address the SDGs (Anthony et al., 2017). Other reefs around the world are similarly challenged by the need for more, and more timely information including the sea-countries in the Pacific Ocean. Indeed, many reef ecosystems have no formal monitoring program to inform these SDGs (Obura et al., 2019; Obura, 2020). This has motivated the establishment of citizen science (CS) programs to fill the information gaps.

Virtual Reef Diver (VRD) is the premier online engagement platform for the GBR that enables citizen-science information to be combined with existing monitoring efforts to provide more comprehensive and up-to-date information on reef health (www.virtualreef.org.au). Established in July 2018, VRD was inspired by the following question: could we use photography from recreational divers, as well as international public interest in coral reefs, to help estimation of the health of the entire GBR? This inspired a second question: what if the scuba-divers could geo-tag their photos to an interactive web-based visualisation of the GBR, and what if other people across the world could access these photos and classify them with respect to key indicators of reef health such as presence/absence of coral to produce scientific information? The VRD program thus empowers citizen scientists across multiple communities to contribute to monitoring the GBR in three ways: 1) underwater divers and on-the-reef communities can upload geo-referenced reef photos taken from cameras or underwater drones, 2) citizens help classify benthic communities on uploaded photos, and 3) citizens receive education about GBR health and management efforts.

In addition to supporting the achievement of the Sustainable Development Goals (SDGs) 13 and 14, the VRD program also contributes to evaluation of the effectiveness of management actions as required by the Reef 2050 Long-Term Sustainability Plan of the Australian Federal and Queensland Governments. The CS program also supports the Global Coral Reef Monitoring Network (GCRMN), an official partner of the UN, that compiles global datasets on reef health to respond to the SDG 14 requirements.

VRD was featured during Australia's National Science Week 2021, challenging the online citizen community to classify as many images as possible during seven days. A total of 55,215 points were classified on the images by 195 participants. These data were then incorporated into spatio-temporal models of coral cover, accounting for people's abilities to classify corals on images as well as the associated difficulty in classification of the various images. This paper focuses on the delivery and outcomes of the National Science Week Challenge. Through this case study, we describe the dual roles that citizen scientists play in VRD. In particular, we discuss ways in which we have tried to address three common concerns about CS programs highlighted by Fritz et al. (2019): whether the CS data are scientifically trustworthy, how CS data can be formally integrated with other more accepted data sources, and whether the CS data quantifiably improves monitoring and predictions to help address the SDGs.

METHODS

Overview of Virtual Reef Diver

Dozens of publicly and privately funded programs have been established for monitoring the GBR. These are run by research institutions, government agencies, reef-based industries, citizen science groups and traditional owners. Virtual Reef Diver is a web-based, interactive platform that has three main features. First, it enables images of the reef to be uploaded to a specified location (latitude/longitude) on a digital image of the GBR. Second, it enables these images to be accessed and classified by citizen scientists. Specifically, an image is chosen randomly from the set of available images, and the participant is asked to classify 15 randomly generated points in the image as water, coral, algae, sand or other (Figure 1 a). These classifications are automatically extracted from the interface, coded and stored in a database. Third, as detailed in the following section, VRD combines these citizen science data (Figure 1b) with data from other monitoring programs to derive spatio-temporal estimates of coral cover across the GBR (Figure 1c and Figure 1d). The VRD site also includes help and training for citizen scientists through descriptions of these three features, guides on image capture and classification, frequently asked questions and links to other resources.

Coral cover was chosen as the key measure in VRD, since it is one of the most common indicators of reef health. Coral cover represents the proportion of the benthic zone covered in hard corals, without accounting for overlap in the three-dimensional coral structure. Hard corals build critical reef habitat.

VRD has received more than 255,000 image classifications, representing 3.8 million elicitation points. More than 1300 images have been contributed by recreational divers. In addition to internal logging of user activities, VRD uses Google Analytics (Google Analytics, 2022) to capture detailed technical, demographic and content data on a per user and per request basis. Since July 2018, 45,480 users (defined as a person who has visited the website) have visited the VRD platform with some substantive increase in online traffic associated with a number of public events in which the program was featured (Figure 2). These show the potential of the online platform to gather a large number of people for a specific purpose. The most visited page is the classification module with 61,547 views. Almost 75% of the users are based in Australia followed by the USA (13%), Asia and Europe (6%).

The VRD architecture ingests new classification contributions from citizens into a database. This information is then automatically combined with existing data to update spatio-temporal models of coral cover across the whole of the GBR. Changes in the health of the GBR can be monitored using the most up-to-date information about changes in coral cover.

The National Science Week Challenge 2021

The National Science Week citizen science Challenge invited participants to help classify images of the Great Barrier Reef via the Virtual Reef Diver platform (Figure 3).

The Challenge was promoted widely by the media, with multiple news articles, radio interviews, television broadcasts and social media posts on Twitter and Facebook. This attracted a diverse range of participants geographically across Australian and multiple demographics, including primary and secondary school students, teachers and other interested members of the community. Details are given in the Results section below.

Increasing Scientific Trust in CS Data

Classifications provided by citizen scientists differ with respect to accuracy and hence utility, primarily because of varying levels of expertise among the respondents (e.g., marine scientists are naturally more expert) and the difficulty of the images that the respondents were asked to classify (e.g., it is easier to classify an image comprising only sand than an image with a variety of coral and algae, and some cameras take better pictures than others).

In order to increase trust in these data, the ability of the participant can be estimated, adjusting for the image difficulty. This can be achieved via a Bayesian spatial item-response model (Santos-Fernandez and Mergensen, 2021). Let the binary response Y_{ijkl} represent whether a question associated with the *k*th point $(k = 1, \ldots, K)$ on the *j*th image $(j = 1, \ldots, J)$ taken by camera type *l* $(l = 1, \ldots, L)$ is correctly answered or not by the *i*th participant. Let Y_{ijk} follow a Bernoulli distribution with parameter $p_{ijkl} = \eta_k + (1 - \eta_k)/\ (1 + exp\ (-\alpha_k(\theta_i - \beta_k - \beta_l))$ where β_k and β_l are difficulties associated with the point and the camera, α_k gives the slope of the logistic curve and η_k adjusts for guessing. Then the parameter of most interest is θ_i, which depicts the ability of the *i*th participant after adjusting for these other factors.

Integrating CS Data with Other Data Sources

VRD employs a weighted likelihood method for combining data from disparate sources in order to obtain combined estimates of coral cover on the GBR. This approach, described by Peterson et al. (2020), involves two steps. In the first step, a set of mechanistic weights is determined for each input source, based on a pre-specified measure of their respective accuracy obtained using a gold standard dataset. In the second step, these weights are included in a spatio-temporal Bayesian model. These steps are described in more detail below.

In the mechanistic weighting approach, the weight w_{ijs} associated with the classification by participant *i* of image *j* within source *s* is calculated as the product of four separate weights characterising the physical extent of the image, the number of points used to elicit the coral cover in the image, the overall accuracy of the person classifying the image and a factor used to up- or down-weight an image depending on the source. The weights w_{ijs} were then used to calculate a spatially weighted mean estimate of coral cover at raster cell level for each source and year.

The proportion of coral cover y_{pts} within cell *p*, time *t* and source *s* was modelled as a random draw from a Beta distribution with mean μ_{pts} and a common precision parameter $\boldsymbol{\phi}$, with a logistic link function and a weighted log likelihood with four covariates, a temporal effect fitted as a first-order random walk and a spatial random effect modelled as a Gaussian Markov random field. The four covariates were binary measures of cyclone exposure (Matthews et al, 2019, Puotinen et al., 2016), anomalous sea surface temperature and bleaching (Liu et al., 2014), management zoning (Great Barrier Reef Marine Park Authority, 2014), and a categorical measure of the position of the reef shelf (Emslie et al., 2020).

Peterson et al. (2020) specifically investigated the impact of including different data sources in their models. In particular, they showed that data integration improved the predictive ability of the models and the uncertainty in predictions in areas with and without professional monitoring data.

In a later paper, Santos-Fernandez et al. (2021a) have proposed an alternative to the mechanistic weighting approach described above. The new method, based on a spatially dependent measurement error (SDME) model, avoids fixed, pre-specified weights of the data sources and instead adjusts for the quality of these data sources as part of the modelling process using the participants performance measures: sensitivity (correct classification of a point on an image as coral) and specificity (correct classification of a point as not coral). This approach has been shown by Santos-Fernandez et al. (2021a) to provide more accurate estimation of each participant's sensitivity and specificity, accuracy and precision of the resultant predictions and unbiased regression coefficients. The validity of the model was confirmed through a comprehensive simulation study, as well as a large crowdsourcing experiment via Amazon Mechanical Turk involving 212,910 classification points by 157 participants which were compared with classifications by expert marine scientists.

This approach uses a hierarchical structure and captures uncertainty around the participant's performance with the use of beta distributions for sensitivity (se) and specificity (sp). Sensitivity refers to the capacity of a participant to classify corals when they are truly present and specificity to classify non-corals when they are truly absent as (Santos-Fernandez et al., 2021b). Hence, for the participant *i*, $se_i \sim Beta(\boldsymbol{\alpha_{se}}, \boldsymbol{\beta_{se}})$ and $sp_i \sim Beta(\boldsymbol{\alpha_{sp}}, \boldsymbol{\beta_{sp}})$ where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are parameters of the respective beta distributions that are estimated as part of the analysis. These parameters are informative in their own right, and can also be used to derive the average sensitivity and specificity, and the corresponding variance of these averages, for the citizen scientist cohort.

Both of the above modelling approaches were implemented in R statistical software (R Core Team, 2017). Code is available in R-INLA (Rue et al., 2009) and Stan (Carpenter et al., 2017); see the respective papers.

RESULTS

The National Science Week Challenge 2021

Overall, 195 participants registered for the National Science Week Challenge, either individually (n=49) or as a team (n=146). A total of 3681 images and 55215 points in the images were classified during the week of 14-22 August 2021 (Figure 4). More than 20 schools, 7 universities and 7 community groups participated. Nine teams enrolled; eight of these registered between 2 and 11 members, and one team registered 102 participants and classified 1125 images. A composite team comprised 11 participants drawn from regional and remote areas of the State of NSW and classified 92 images.

During this week, a maximum of 220 users was recorded on Thursday 21/08 (Figure 5). Most of the website users came from Australia followed by USA and Europe. The page the most visited was about the classification page showing that people were interested in the classification module on which the event was supported.

Using the adjustment method proposed by Santos-Fernandez and Mergensen, (2021, see Methods section), the Challenge awarded 48 participants the category of ‘experienced’ and 49 the category of ‘super citizen scientists (experts)’. A similar number of participants were classified as beginners (49) and competent (49). The winner of the Challenge classified 18,195 number of points and belongs to the group of super citizen scientists. The first prize was a trip to the GBR, the Reef Today film showcased the Challenge and the winner can be seen at: https://www.youtube.com/watch?v=8F019Rl1Gds.

Increasing Scientific Trust in CS Data

The adjusted ability scores for each participant are shown in Figure 6. The vertical lines represent the 95% posterior highest density interval (HDI) with amplitude inversely proportional to the sample represented with the size of the dots. Participants were clustered into four groups based on their abilities. The smoothed line represents the model fit obtained using local polynomial regression.

These estimates of the abilities were used in a weighted consensus algorithm to obtain estimates of the true latent categories on each point in images. This approach weights the evidence of each participant based on their abilities penalizing for uncertainty.

We assessed the reliability of CS data and the effectiveness of the statistical model to correct for bias in CS datasets, by focusing on a subset of 514 underwater images for which the true labels were considered known based on classifications by marine science experts. These images (among others) were presented to the CS participants as part of the Challenge. Figure 7 shows empirical densities of the true proportion of coral cover based on this subset of images (in red), as well as the reported proportion of coral cover based on the participants’ classifications (in green), and the estimated proportion of coral cover after accounting for the abilities of the participants (in blue). It is obvious that the adjustments make a large difference to the accuracy of the CS data, thereby increasing trust in this data source.

Another aspect that we can derive from the model outcomes is the estimation of sensitivity (se) and specificity (sp) of the participants. Table 1 shows a sample of results from 3 representative participants and their performances. The columns mean and sd represent the posterior distribution mean and standard deviation of the parameters, while the 2.5-97.5% gives the uncertainty around these estimates. For example, participant 2 has high performance (with both se and sp above 90%) compared to subject 3. Hence, information produced by this subject 2 receives more weight in the item response model than from 3.

Table 1 Summary statistics of the posterior performance measures from a sample of 3 participants. Se and sp refer to the sensitivity and specificity measures of participant performances, sd stands for standard deviation and 2.5%-97.5% correspond to the measurement of uncertainty estimated by the model.

participant	variable	mean	sd	2.5%	97.5%
1	se	0.777	0.140	0.519	0.991
	sp	0.827	0.128	0.542	0.995
2	se	0.935	0.117	0.572	1.000
	sp	0.984	0.036	0.878	1.000
3	se	0.512	0.010	0.501	0.537
	sp	0.712	0.112	0.515	0.921

Integrating CS Data with Other Data Sources

As shown above, the CS data obtained through the National Science Week Challenge, and indeed through all of the VRD classifications, can be used to improve predictions of coral cover across the GBR. This relative benefit is demonstrated clearly in Figure 8, reproduced from the paper by Peterson et al. (2020), which shows the cross-validated predictions after including all existing data with the survey data from the gold-standard Long Term Monitoring Program (LTMP) survey data, compared with using the LTMP data alone.

The VRD statistical model can also be used to identify important features relevant to the SDGs. For example, the model was used to estimate the influences of various disturbances, management zoning and reef locations on coral cover changes between 2002-2020. Coral bleaching was the unique variable that contributed to the decline of coral cover at the scale of the GBR (Figure 9). The other variables are considered as non-substantive because the 95% credible interval includes zero.

The final output of VRD are predictive maps showing changes in coral cover across the entire GBR (https://www.virtualreef.org.au/explore/). This represents one of the most spatially and temporally extensive dataset available for research and management. Indeed, predicted values of coral cover are accessible at 500m^2 across the 3,000 reefs of the GBR from 2002-2020. These maps provide up-to-date knowledge to understand the impacts of disturbances on the reef health and inform decision-making about large-scale changes and efficiency of management interventions.

A total of 18 years of predictive values of coral cover along the entire GBR is freely accessible online. Uncertainty layers associated with these predictions are also available online. Predictions can be downloaded from the platform and instructions to perform various manipulation with the data are also available at

(https://www.virtualreef.org.au/resources/).

Discussion

This paper has focused on an exemplar event, the National Science Week in Australia in 2021, to highlight a variety of ways in which citizen science can help to meet the Sustainable Development Goals associated with conservation of coral reefs. The event employed the premier citizen science platform, Virtual Reef Diver, to facilitate wide public engagement in classifying images of the Great Barrier Reef. Overall, more than 55,000 new classifications were made, which contributed directly to improved spatial predictions of coral cover on the GBR. The high level of participation and interest in the Challenge demonstrated a broad interest by people of all ages, in particular young people, in contributing to citizen science programs in general, and to environmental conservation programs in particular.

One of the participants, an adult from an outback town in the desert area of New South Wales, responded after the event with the comment that although they had never seen the ocean, they now felt a strong connection with the GBR. This epitomized for us the power of citizen science and programs such as VRD to protect the largest World Heritage Area on Earth.

This paper has also focused attention on ways in which persistent concerns about citizen science data have been addressed in the VRD program. The first of these concerns is scientific trust in citizen science data. The solution adopted in VRD is to employ a form of item-response modeling to statistically quantify the ability of each participant, taking into account the difficulty of the images that they classified. Importantly, this approach can be translated to other CS projects for which there is concern about the quality of CS data. An example is the large class of more general species distribution studies in which species of interest may be missed or mistaken by untrained participants (indeed, even experts), thereby creating bias in estimated probabilities of presence unless such adjustments are made. Moreover, the proposed approach can be extended to include other important factors that may influence the ability of the participant, and can be oriented to more targeted aims such as preferring high sensitivity at the expense of lower specificity or selecting a group of citizen scientists with highest (or lowest) ability.

The second concern is how to aggregate the CS data with other data sources. As described above, two solutions have been employed in the VRD project. Under the first approach, a mechanistic weight is determined for each data source prior to the aggregated analysis, and these weights are used to adjust the relative influence of the data sources in a Bayesian spatio-temporal regression model. While this has been shown to effectively allow for combination of different data sources of varying quality, there is some concern about the weighting approach. A subsequent approach that we have developed overcomes this restriction by estimating the weights as part of the analysis. Through this process, estimates of sensitivity and specificity can be derived for each individual participant, providing much more nuanced information about their relative ability and facilitating more targeted use of these data as well as feedback and training. While the VRD platform currently includes the first of these approaches, the second solution is likely to be adopted in the next update of the VRD platform.

The third concern is whether CS data do, indeed, improve estimates and predictions relevant to SDGs. In this paper, we have demonstrated that the adjusted data contributed by CS participants through the VRD platform meaningfully improve predictions of coral cover on the GBR. These predictions can be employed to create indices to measure health and resilience of coral reef systems, as well as assess the effectiveness of reef restoration interventions, in line with the goals of major conservation policy and management strategies such as Reef 2050 and GCRMN. The outcomes of these major strategies in turn directly inform SDGs 13 (climate change) and 14 (life below water).

VRD is still evolving to better meet the needs of both its participant community and its user community. Future directions for the project include the following. The first is a focus on adding functionality into the platform, with improved feedback to close the loop for the CS participants. The second is a focus on data integration using both citizen science and artificial intelligence for image classification. This is the intention behind ReefCloud, a large international collaboration on coral reef monitoring, led by the Australian Institute for Marine Science (AIMS). The third is to explore broader directions with respect to other ecosystems to support additional SDG using the concepts of images, citizien science, data integration, modelling and informed decision making. More generally, the methods developed through VRD could be employed to facilitate more, and more trustworthy, use of CS data to succeed in the implementation of SDG 14 sustaining the use of the oceans and marine resources. By protecting the Great Barrier Reef, VRD indirectly contributes to achieve other SDGs that support the “blue economy” (Obura, 2020). These SDGs include: SDG 1 (no poverty), 2 (zero hunger), 3 (good health and well-being), 4 (quality education), 5 (gender equality) 8 (decent work and economic growth) and 10 (reducing inequality) and showcase the importance of protecting coral reefs for our socio-economic systems.

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Figure captions:

Figure 1 Main features of VRD platform with a) the classification module, b) map of the number of images contributed by the public, c) the total number of images used for the modeling and d) predicted coral cover for the Great Barrier Reef.

Figure 2 Number of users (defined as a person who has visited the website) that visited the VRD platform since its release in July 2018, with highlighted main events (Features – Google Analytics, 2022).

Figure 3 A citizen scientist classifying reef images as part of the Challenge.

Figure 4 Official results released to the media.

Figure 5 Overview of website activities during the National Science Week 14-08-21 to 22-08-21 (Google Analytics, 2022).

Figure 6 Ability scores of the VRD participants to classify corals from images. The size of the dots corresponds to the number of classifications made by a participant and colors to the groups allocated based on their abilities.

Figure 7 Density plot of the true coral cover (in red) in the images, the reported values from the participants (in green) and estimated proportion from the model after accounting for the participants abilities (in blue).

Figure 8 Model performance when integrating all the existing data versus using the long-term monitoring data only (reproduced with permission from Peterson et al., 2020).

Figure 9 Effects of model covariates. The dots show the estimated mean and error-bars associated 95% credible intervals.

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COMPETING INTERESTS

None

OVERVIEW OF ACEMS NATIONAL SCIENCE WEEK 2021 GREAT BARRIER REEF EVENT SERIES & CHALLENGE