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Reviewer 2

COMMENT 1

In their response authors write that “As such, there are multiple adaptations (that are described in the text) that make the manuscript novel and of use to a wide audience.” At the same time in the manuscript (page 4, line 141) they say that: „The methodology described in [13] was followed with some minor adjustments for seagrass habitats.“ I would suggest to define more specifically (point by point list), what were the methodological adaptation used in the current manuscript compared to the paper by Lyons et al. 2020.

RESPONSE:

The methods section has been adjusted to make the specific changes to the methodology more apparent by indicating the changes in italicized text.

Text was:

“2.3 Mapping Method

A cloud-based processing methodology developed for mapping coral reef habitat [13] was adapted in this study for seagrass environments (workflow shown in Figure 2(b)). Here adaptations are indicated in italicized text. Bathymetry (30 m resolution; [30]), a coral reef mask [26], and spot check field data (georeferenced, distributed across the study area and assigned one of two classes: substrate or $\geq 25\%$ seagrass cover), were ingested into the Google Earth Engine (GEE) cloud processing environment [31] from which Landsat 8 Operational Land Imager (OLI) imagery (June 4, 2015) was imported directly through GEE from the United States Geological Survey (USGS; surface reflectance, Tier 1; ee.'LANDSAT/LC08/C01/T1_SR/LC08_089079_20150604'). This imagery is geometrically and radiometrically corrected and further corrected to surface reflectance using the Land Surface Reflectance Code (LaSRC) [32].

The processing methodology described in [13] was also followed with some minor adjustments for seagrass habitats (indicated in italicized text). Briefly, input data sets were first ingested (Figure 2(b), Module 1a) and the area to be mapped was segmented into pixel-based objects, consisting of relatively homogeneous pixels based on color and texture [33]. This was done via ‘simple non-iterative clustering’ [34] using the blue, green and red bands of the satellite imagery, with the bathymetry layer, and slope as a derivative of depth. A depth limit for analysis was set at 5 m (Figure 1(a)). The mean value for each input layer was extracted for each pixel within an object.

Module 1b of the workflow randomly assigned the point-based input field data, which was relatively evenly distributed across the study area, to either training or validation data. The training data, representing known occurrences of bottom type, was used to sample the data created in Module 1a, and train a random forest algorithm (Figure 2(b), Module 2) [35]. The random forest classifier was trained with 50 trees per class, a minimum leaf population of one and the square root of the total number of co-variables as the number chosen at each node split. The random forest prediction was then used to predict the class membership (seagrass or substrate) of each individual pixel across the full extent of the mapping area. In this instance, only slope and depth auxiliary data was utilized. Mapping depth was limited to 5 m, as this represents the depth range of most seagrass in Moreton Bay [28].

The seagrass map was refined via smoothing using a kernel size of three (Figure 2(b), Module 3), a coral reef mask [26] was applied to remove known areas of coral reef from the output, while a

manual mask was used to remove inland waterways. Finally, the output map was validated, and the map accuracy determined (Figure 2(b), Module 4)."

Text has been changed to:

"2.3 Mapping Method

A cloud-based processing methodology developed for mapping coral reef habitat [13] was adapted in this study for seagrass environments (workflow shown in Figure 2(b); ***Adaptations are indicated in italicized text.***).

Bathymetry (***30 m resolution***; [30]), a ***coral reef mask*** [26], and spot check field data (georeferenced, distributed across the study area and ***assigned one of two classes: substrate or $\geq 25\%$ seagrass cover***), were ingested into the Google Earth Engine (GEE) cloud processing environment [31] from which ***Landsat 8 Operational Land Imager (OLI) imagery (June 4, 2015) was imported directly through GEE from the United States Geological Survey*** (USGS; surface reflectance, Tier 1; ee.'LANDSAT/LC08/C01/T1_SR/LC08_089079_20150604'). This imagery is geometrically and radiometrically corrected and further corrected to surface reflectance using the Land Surface Reflectance Code (LaSRC) [32].

Input data sets were ingested into GEE (Figure 2(b), Module 1a) and the area to be mapped was segmented into pixel-based objects, consisting of relatively homogeneous pixels based on color and texture [33]. This was done via 'simple non-iterative clustering' [34] using the blue, green and ***red*** bands of the satellite imagery, with the bathymetry layer, and ***slope as a derivative of depth. A depth limit for analysis was set at 5 m (Figure 1(a)).*** The mean value for each input layer was extracted for each pixel within an object.

Module 1b of the workflow randomly assigned the point-based input field data, which was relatively evenly distributed across the study area, to either training or validation data. The training data, representing known occurrences of bottom type, was used to sample the data created in Module 1a, and train a random forest algorithm (Figure 2(b), Module 2) [35]. The random forest classifier was trained with 50 trees per class, a minimum leaf population of one and the square root of the total number of covariates as the number chosen at each node split. The random forest prediction was then used to predict the class membership (***seagrass or substrate***) of each individual pixel across the full extent of the mapping area. ***In this instance, only slope and depth auxiliary data was utilized. Mapping depth was limited to 5 m, as this represents the depth range of most seagrasses in Moreton Bay [28].***

The seagrass map was refined via smoothing using a kernel size of three (Figure 2(b), Module 3), ***a coral reef mask [26] was applied to remove known areas of coral reef from the output, while a manual mask was used to remove inland waterways.*** Finally, the output map was validated, and the map accuracy determined (Figure 2(b), Module 4)."

COMMENT 2

I would suggest to remove the entire sentence (page 4, line 158): „Mapping depth was limited to 5 m, as at depths of ~10 m it becomes unreasonable to view seagrass via satellite imagery [36].“ This sentence is irrelevant and confusing. If you set your depth limit to 5 m, then it becomes unnecessary to talk about 10 m depth limit.

RESPONSE:

This sentence was amended as follows.

Text was:

"Mapping depth was limited to 5 m, as at depths of ~10 m it becomes unreasonable to view seagrass via satellite imagery [36]."

Text has been changed to:

"Mapping depth was limited to 5 m, **as this represents the depth range of most seagrasses in Moreton Bay [28].**"

COMMENT 3

As I understand the mapping depth limit was set to 5 m based on the bathymetry layers? Still in my mind it would be necessary to delineate optically shallow and optically deep pixels within that 5 m layer. According to your Secchi measurements it could be assumed that in areas of lower water quality, the depth of substrate detection was considerable shallower than 5 m and it is very confusing if you show that you retrieved bottom maps from the areas, which cannot be mapped (or can be mapped to optically deep water) due to the decreased water quality. I would suggest to address this issue at least in your discussion.

RESPONSE:

We agree with the reviewer's comments. Ideally you would separate optically deep water from optically shallow water within the area mapped (above 5 m). However, this is currently not feasible other than doing it manually which is time consuming and negates the objective of this study, as well as highly being highly subjective.

The following text has been added to the Discussion:

"It must be considered that in the mapped area there will be regions where one cannot see the bottom due to decreased water clarity. There are currently no automated approaches to remove these areas, and although manual delineation could be used to remove areas of less clear water, this is subjective. We ensured that the field data used represented a range of tidal stages and were in locations where water quality ranged from very clear to lower clarity [38, 39]. A random forest classifier as used in this study, is well suited to this scenario. In contrast to a parametric classifier for example that may average spectral signatures across training samples, a random forest classifier uses each individual training point to inform the classification based on the specific tidal stage and water quality captured in the imagery [35]. This accounts for the clarity, or lack thereof, of the water at the time of observation, enabling assignment of a bottom class to all pixels in the mapping area - clear and less clear. Nevertheless, there is still likely to be some error associated with training points that fall in very low-quality water and future users may wish to consider dealing with this more systematically, perhaps by adding a low visibility water class."