SUPERVISED IMAGE CLASSIFICATION MODEL FOR CORAL BLEACHING DETECTION USING A BI-TEMPORAL SENTINEL-2 IMAGE STACK

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ABSTRACT:

Coral reefs are among the most vulnerable ecosystems to coastal and land-based anthropogenic factors. Aside from sudden increase in sea temperatures, external factors such as local and regional disturbances are found to influence coral reef environments which often lead to bleaching events. According to the Status of Coral Reefs of the World: 2020 report, from 2009 to 2018, there has been a progressive loss of live corals at the global level which may be attributed to the increasing anthropogenic activities (Souter et al., 2021). Due to coral's sensitivity to environmental stressors, it is significantly considered as an indicator for global climate conditions. In this regard, this study developed a remote sensing change detection technique to segment coral bleaching from satellite images. Using a bi-temporal image stack composed of Sentinel-2 images showing pre and post bleaching, a machine learning classification model was developed to capture typologies of changes visible between the two images which included bleaching. Random Forest (RF) algorithm was employed to classify changes. This model obtained overall accuracies and kappa statistics of 0.97 and 0.94 respectively with minimum consumer and producer accuracy of 0.91. Moreover, the identified changes showed 78% agreement with the *in-situ* data composed of 31 monitoring stations distributed around Sekisei Lagoon, Okinawa, Japan. This study demonstrated a promising potential of machine learning for change detection for coral bleaching monitoring.

1. INTRODUCTION

In 1998, a mass coral bleaching occurred and killed approximately 8% of the world's corals and from 2009 to 2018; there was a progressive loss of coral reefs resulting in a 14% loss of world's coral reefs (Souter et al., 2021). This study uses the case of Japan, specifically the coastal regions of Iriomote and Ishigaki islands which can be found at the south western tip of the country. Between these two islands is the Sekisei lagoon which is considered as the largest coral lagoon in the country which helped in maintaining the coral reef ecosystem across the archipelago by being a major source of coral spawn and larvae (Takeda et al., 2021). This area however has been severely affected in both the 1998 and 2009 to 2018 global-scale coral bleaching event resulting in a 98% death rate for 10 of the 11 major coral species in the lagoon. In 2022, another coral bleaching was observed which affected more than 90% of the corals in the area (Takeda et al., 2021; Shimbun, 2022).

Coral reef ecosystems play an important role in supporting marine life. Despite covering only 0.2% of the seafloor, approximately 25% of marine species are being supported by coral reefs, which also provides coastal protection, well-being, and food security to millions of people (Souter et al., 2021). This underscores the importance of rehabilitation to induce regrowth of corals.

Key to effective management and monitoring of coral reef environments is information about their spatial and temporal distributions which allow experts and the authority to identify effective decisions and measures to maintain its condition (Mora, 2008; Hedley et al., 2012). Thus, in the case of coral bleaching, spatial and temporal information about such events is all the more necessary not just to support strategic rehabilitation efforts but also to help experts gain other insights significant to related studies.

While there are monitoring methods implemented on the ground such as actual ground surveys or airborne image capture, satellite remote sensing is now becoming a viable option which offers a cost-effective and efficient data acquisition process for coastal applications such as coral reef monitoring. Having the capability to capture information at large spatial extents and at an almost real-time rate, remote sensing technology can help researchers and experts better obtain relevant information about such environments (Hedley et al., 2012). Several studies have already explored the capability of remote sensing to such applications establishing baseline data for satellite data obtained using either Landsat ETM+ or SPOT Earth observation satellites (Andréfouët et al., 2001, Caplosini et al., 2003, Mumby et al., 1997).

This study therefore aims to further support the viability of remote sensing technology for coastal applications, specifically for coral reef environments, by developing a remote sensing-based monitoring tool to detect coral bleaching events. Unlike other studies, Sentinel-2 data was used in this study for its higher spatial and temporal resolution and narrower spectral bands (Hedley et al., 2012).

With that, this study presents a time series change detection technique for coral bleaching events using the visible bands of pre and post event Sentinel-2 data. Train and test data were obtained and a bi-temporal supervised image classification was implemented using Random Forest classifier to delineate bleached corals. To test this proposed method, the coral

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bleaching incident recorded in Sekisei Lagoon, Japan in 2022 was used as a case study.

2. RELATED STUDIES

2.1 Coral bleaching

The main objective of this study is to capture coral bleaching events using satellite remote sensing techniques. This phenomenon can be described as the loss in colour of coral reefs due to the loss of zooxanthellae and pigments resulting in the change of colour from something greenish or darkish to white, thus being called 'bleaching' (Call et al., 2003; Li et al., 2011). This is mainly caused by the upwelling of sea surface temperatures, but it can also be attributed to diseases and environmental pressures brought about by land-based and coastal anthropogenic factors (Call et al., 2003; Souter et al., 2021).

Monitoring this kind of phenomena using visible satellite imagery can be detected depending on the severity of coral bleaching and the specifications of satellite data. Accordingly, if a coral undergoes bleaching, its color will transition to white which can be translated as an increase in spectral reflectance in the visible region (Call et al., 2003). Thus, this should be visible in a satellite image, depending on the severity of the bleaching, specifications of the satellite's sensor specifications and the percent cover of corals in a pixel of the image (Call et al., 2003; Yamano & Tamura, 2004). The difference in spectral response between a live coral and a bleached coral are significant, making the two types of corals sufficiently separable.

2.2 Preprocessing of Satellite Data

In the context of coastal and marine applications, various remote sensing methodologies were developed to model its environments such as benthic habitat modelling which segments benthic features from satellite data, depth estimation, water quality modelling and even the detection of coral bleaching. While most of the studies have shown sufficient performances in achieving their goals, there seems to be an agreement that while remote sensing is capable, coastal mapping is a challenging application mainly due to the environment's characteristics which hinders satellite-based sensors to effectively capture sub-water features. Aside from the heterogeneity of benthic features which is not really captured by satellite sensors primarily because of their limited spatial resolution, effects of water attenuation, its temporal variability and the effects from atmosphere also play major roles to remote sensing technology's success in coastal mapping applications (Hedley et al., 2018; Call et al., 2003; Nurdin et al., 2019). In this regard, preprocessing of satellite data has been of great importance.

Among these challenges, reduction of the effects due to water column attenuation has contributed to improve the accuracy of remote sensing-based coastal applications thus its importance in the process (Minghelli-Roman & Dupouy, 2014; Siregar et al., 2018). In most studies, the Depth Invariant Indices (DII) following the Lyzenga algorithm is being adopted in which it estimates an attenuation coefficient for every 2 bands of the visible spectrum producing three DII from the combination of red, green and blue bands of most remote sensing data (Nurdin et al., 2019; Siregar et al., 2018; Tamondong et al., 2013). However, the study of Tamondong et al. (2013), suggests that the Simple Radiative Transfer model (SRTM) and bathymetric models derived from the satellite data can be considered as alternatives to water column correction. Based on their study which compared SRTM, SRM and DII, SRTM performed best, followed by SRM and then by DII in terms of producing accurate benthic maps from satellite data (Tamondong et al., 2013). It was also argued that while DII can remove effects of water column, the process would require producing DIIs for each substrate therefore resulting in an expensive processing approach to the study (Tamondong et al., 2013).

Aside from water column corrections, the study of Watanabe et al. (1993) was able to improve separability of benthic substrates such as red soil, turbid water, corals and clear water using ratios of the visible bands of Landsat TM obtaining an overall accuracy of 80% for their time series analysis. This suggests the use of the band ratios of red, green and blue bands for coastal remote sensing applications.

2.3 Change detection techniques

In detecting cases of coral bleaching, a general methodology is the use of sea surface temperature often derived thermal bands from satellite images. However, with the development of the Sentinel-2 optical imagery, optical data have now been considered in various studies mainly due to its relatively high spatial resolution of 10m and its narrow band widths making it an additional alternative data for coastal and marine applications (Xu, et al., 2021; Wouthuyzen, et al., 2019; Liu, et al., 2021; Collin, et al., 2016; Hedley et al., 2012; Hedley et al., 2018)

This study explores the implementation of a change detection process in order to segment bleached corals from optical satellite imagery. In relation to that, there are different change detection techniques which have been utilised to detect coral bleaching in an area. One of the techniques is the post-classification change detection technique in which an image classification process is separately implemented on both pre and post image processing and after which, a change image is produced by differencing the classified images (Nurdin et al., 2019; Collin et al., 2016; Gapper et al., 2019, Mishra et al., 2017). This approach however requires a supervised process to classify the images, moreover, after image differencing, the typologies of the detected changes will have to be strategically identified, unless the analysis of changes is mainly visual (Nurdin et al., 2019; Fargas et al., 2021).

Another approach to detect changes, not just in the case of coral bleaching, are automated techniques such as straight-forward image differencing and image ratios in which the post image is either subtracted from or divided by the pre- image (Mishra et al., 2017). These techniques however, despite being automated in nature, require threshold values to accept changed areas and additionally, these methods are usually implemented on single-band images or indices which are supposed to be describing the surface (Mishra et al., 2017). Moreover, these techniques are also susceptible to atmospheric variability between the two images (Mishra et al., 2017).

Change vector analysis such as the Spectral Correlation Mapper and Spectral Angle Mapper, is another technique to detect changes in which vectors using the spectral response of pre and post image at pixel level are computed resulting in a magnitude and direction of the change describing the nature of change which occurred at pixel level (Carvalho et al., 2013; Mishra et al., 2017). However, while this method could provide directionality of the change, its value is still lacking in order to help the users classify the detected change (Carvalho et al., 2013; Mishra et al., 2017).

Lastly, direct multi-date classification is another change detection alternative in which it employs image classification of a straightforward stack of multi-temporal images into one dataset (Mishra et al., 2017; Fargas et al., 2021). The multi-temporal image stack is supposed to capture the phenological patterns of surface features such as in the case of mapping agricultural resources, which may be extended to surface changes (Fargas et al., 2021). This method however requires selection of train and test data in a multi-temporal sense which may be a challenge in most cases due to the added dimension for the analysis.

3. MATERIALS AND METHODS

3.1 Study area

The areas of interest of this study are the coastal regions of the islands of Ishigaki and Iriomote, Japan, and the Sekisei lagoon located in between the two islands (Figure 1). This has been selected as the study area due to the recent observed coral bleaching incident in September 2022 in which 90% of the largest reef has been affected (Shimbun T. Y., 2022).

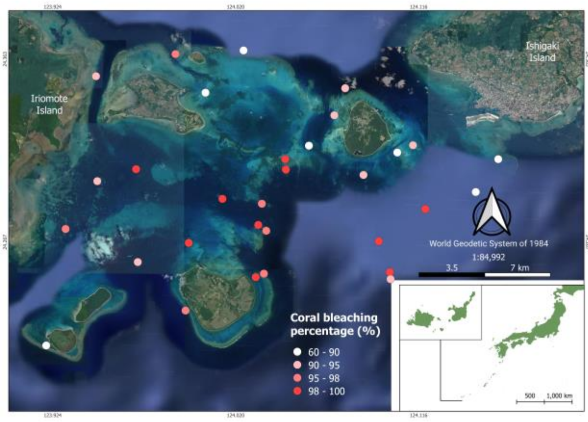

Figure 1. Cloud-free Google Earth satellite image of Sekisei lagoon overlaid with the September 2022 coral bleaching monitoring report of the Ministry of Environment of Japan.

3.2 Data processing

The bulk of the processing of this study was implemented in Google Earth Engine using the GEEMAP library in Python (Wu, 2020). Google Earth Engine (GEE) is a cloud computing, open-source, and code based remote sensing visualisation platform developed by Google which offers various processing tools and functions (Gorelick et al., 2017). This platform has access to petabytes worth of Radar-based and open-source Earth-Observation (EO) data such as those obtained by Landsat, Sentinel and MODIS (Gorelick et al., 2017). Moreover, it also has a repository of derivatives of said satellite data developed by various contributors, researchers and developers around the world (Gorelick et al., 2017).

By default, GEE uses Javascript to automate its tasks and functions, but with the use of GEEMAP, Python can be used to develop remote sensing scripts using GEE together with its data visualisation and analytics features (Wu, Q., 2020)

3.3 Satellite Data

For this study, satellite data obtained by Sentinel 2 were used. Landsat 8 image can also be used for coastal applications, however, Sentinel 2's spatial and temporal resolution offers a better option. For coral bleaching, the capability of Landsat 8 to detect changes in benthic habitats is mainly limited to cases of drastic changes such as severe coral bleaching and as for Sentinel 2, the narrowness of its spectral bands is more capable of detecting variabilities while its spatial resolution is more capable of approximating the heterogeneous characteristics of benthic features (Hedley et al., 2012; Hedley et al., 2018)

Using GEE, Sentinel 2 images for the year 2022 were inspected and filtered based on cloud-cover percentage and cloud-free and glint-free images over the study area were selected. It is important to select glint-free images as they may have effects on the quality of the data, else a sun-glint correction must be implemented to preprocess your satellite data (Hedley et al., 2018).

To capture the coral bleaching incident in the study area in 2022, Sentinel 2 images in March and in September were obtained since the coral bleaching incident occurred progressively since the start of the year until September (Shimbun T. Y., 2022).

Although the Sentinel 2 image is composed of 12 bands spanning from the visible to short wave infrared (SWIR), for this study, only the visible bands were used since the infrared bands are being absorbed by water (McFeeters, S.K., 1996). Additionally, band ratios between the visible bands were included producing 3 new data to the stack consisting of the band ratios of blue-red, green-red, and green-blue to further increase separability of benthic features (Watanabe et al., 1993).

3.4 Selection of train and test

Through visual inspection and image interpretation, 3 types of change and no change cases were identified. First is bleaching which is characterised by the visible change in colour from dark green or grey to white of supposed coral features from the pre- to post-bleaching images. Second case is for evidence of algal or seagrass growth in the seabed which can be described as change in colour from white to green of some benthic features, mostly found on areas which can be interpreted as mud-bottom, sand or rubble surfaces.

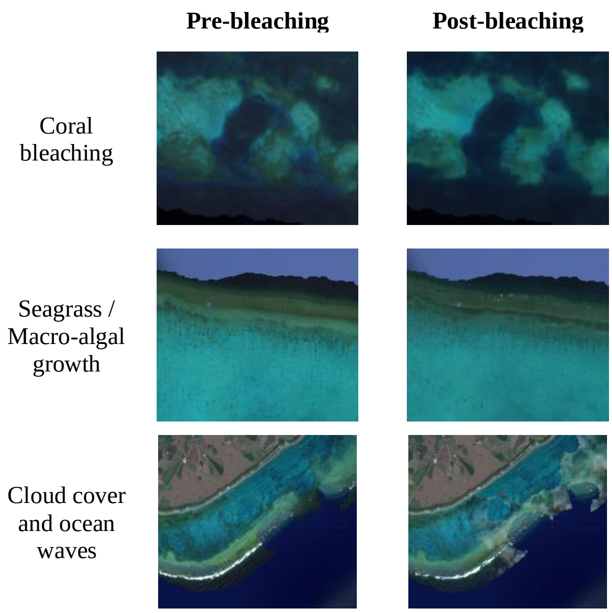

Figure 2. Pre and post bleaching Sentinel-2 snapshot of each change detection class identified for this study.

Cases for change due to cloud covers and ocean waves were also identified. There were observable changes in which there was an initial presence of cloud-cover or ocean waves in the initial image and were not found in the second image. And there were also observed changes in which there were no cloud cover and ocean waves in the initial image.

For each class of change case, at least 50 train pixels were selected and 20 pixels were selected for the validation. A no-change train and test data were also selected which included cases of shadows. Figure 2 shows samples of change for each case.

3.5 Methods

The methodology of this study as shown in Figure 3 follows a general supervised image classification workflow for remote sensing. The Random Forest image classification algorithm, a non-parametric ensemble learning classifier based on decision trees, was used in this study due to its robustness and flexibility in terms of handling high dimensional and non-normalized datasets while obtaining consistent accuracies compared to other algorithms (Fargas et al., 2021; Torbick et al., 2016; Pelletier et al., 2016). The input to this process is a multi-temporal stack composed of the Sentinel 2 visible bands and band ratio derivatives of the pre- and post-bleaching images. The land mask from the Hansen global forest cover change in Google Earth Engine repository was used to mask out the land features from the multi-temporal Sentinel 2 stack (Hansen et al., 2013).

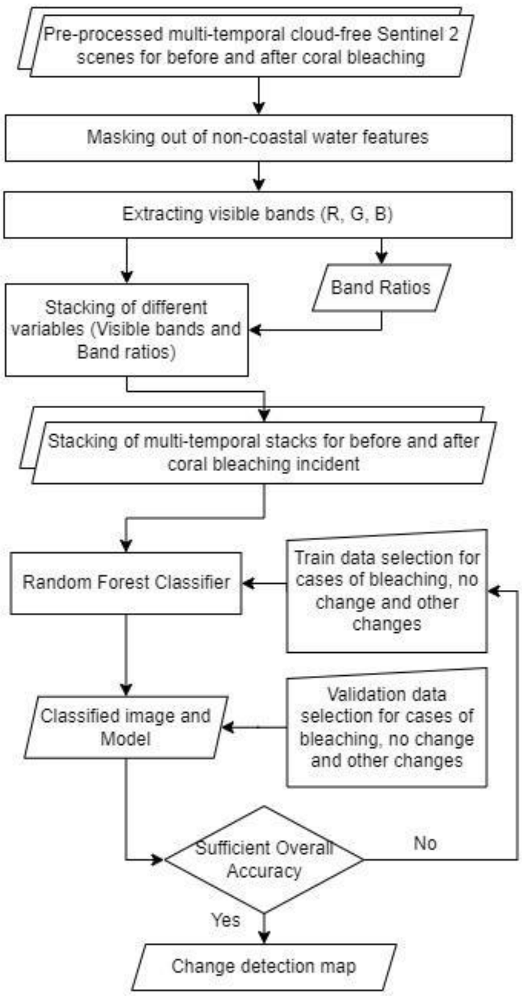

Figure 3. General workflow for change detection time series image classification.

For accuracy assessment, a confusion matrix was produced using the output classified change detection image and the test dataset to compute for the overall, Kappa, producer and consumer accuracies. This followed an iterative process to fine tune the change detection model until sufficient accuracy is achieved. After which, the output change detection map was then compared with the results of the coral bleaching spot survey implemented by the Ministry of the Environment of Japan done in September 2022. The data is composed of bleaching percentage results at 31 monitoring stations distributed over Sekisei Lagoon. Using this data, a binary comparison was implemented in this study.

4. RESULTS AND DISCUSSION

4.1 Variable importance

Using the Random Forest image classifier, variable importance can be computed from the model which provides information about which variable has the most contribution to the classification model. Figure 4 shows the level of importance, in ascending order, of the different variables used for the classification. Combining the pre- and post-bleaching images into a single image stack produced a total of 12 variables which are supposed to capture the temporal trends of the different cases of changes observed. The blue and red bands, B2 and B4 respectively, and the ratio of blue and green have contributed the most to the classification model while the green band contributed the least. The increase or decrease in reflectance for observed cases of change in the scene may explain this trend since the observable changes can generally be characterised by the shift of colour from dark to light in which there is significant change in reflectance for the red band. Although blue and green bands were considered to have better water column penetrating capability compared to the red band, in the classification process, the green band might have been considered as a redundant variable due to the presence of the blue band.

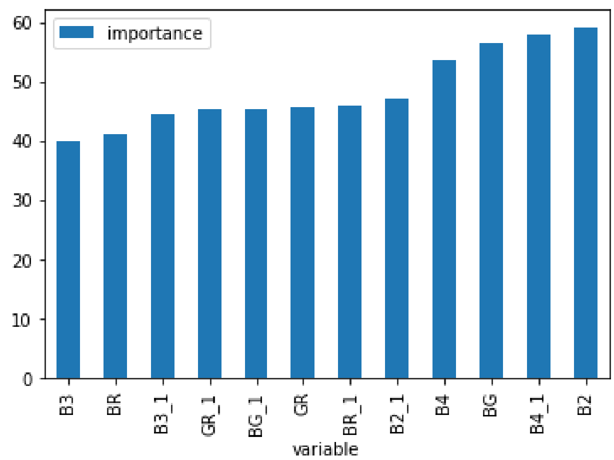

Figure 4. Variable importance produced using Random Forest image classification.

4.2 Separability of selected train and test data

To assess the selected train and test data, pre-bleaching values were subtracted from the post-bleaching values per change class. The box plots in Figure 5 provide a statistical summary of the sampled reflectance values for the train and test data.

For cases of coral bleaching, the most observable characteristic is the change from dark to light colour. Based on its

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corresponding box plots, there is significant increase in reflectance values for the blue and green bands from pre to post bleaching image. Although there are observed outliers which have contradicting values, the majority lie in the positive range. As for the red band, although it may be expected to also have positive difference values, the box plots show otherwise which implies how corals have better interaction with blue and green bands. It may also be attributed to the red band's high absorption characteristic for water surfaces since its energy approaches the infrared region already making it susceptible to underwater attenuation.

Using the band ratios however, difference values were dominantly in the positive ranges especially for Blue/Red (BR) and Green/Red (GR) implying how coral's response to the red band is very minimal. For Blue/Green (BG), since their penetration capabilities are very similar, their ratios tend to be equal to 1 thus resulting in difference values close to 0.

Changes due to growth of seagrass or seaweeds on the other hand shows almost the opposite of the trends produced for bleached corals most especially for the blue and green bands. For the box plots of the band ratios however, detected change in reflectance values are found to be less than the magnitude of change for observed cases of bleaching. And for cases of no changes, obtained differences in reflectance tend to range close to 0 implying that if there are variations in reflectance values, they are very minimal.

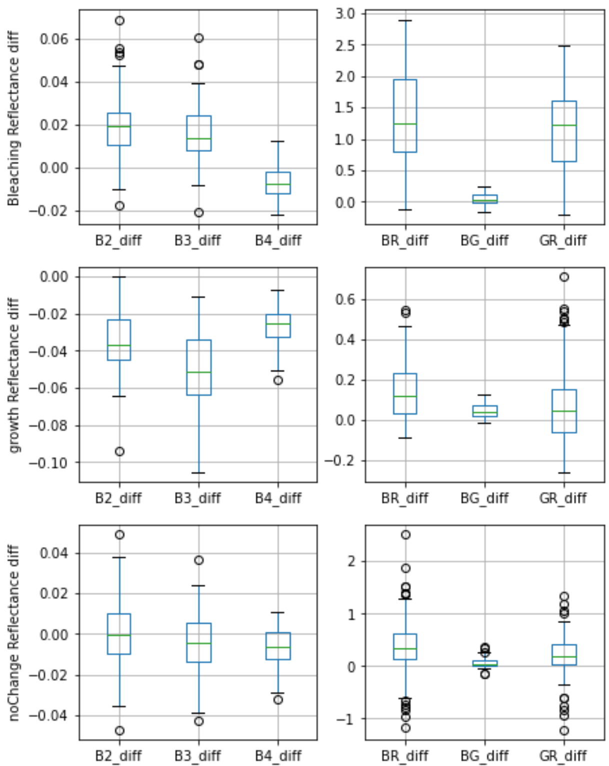

Figure 5. Comparison of boxplots for bleaching, seagrass or macroalgal growth and unchanged features.

Figure 6 show the boxplots for changes due to presence of clouds or waves in either the post or pre-bleaching image using box plots. These covers are mainly characterised by their white colour, thus whenever there are clouds or wave foams, reflectance values approach max values. Therefore, the presence of such covers in the pre would result in negative trends whereas for post image, positive trends.

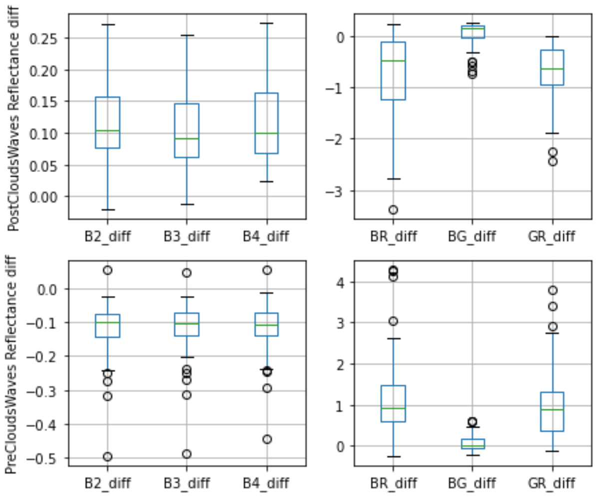

Figure 6. Comparison of boxplots for clouds and waves visible in the post- and pre-bleaching images.

Using the band ratios however, difference values tend to lie in the positive range for changes due to clouds and waves in the pre-bleaching image, whereas, for the post-bleaching image, the difference ranges from 0 to the negative.

Although the use of band ratios is highly suggested, using it in a multitemporal approach may not necessarily produce significant results as evidenced in the boxplots (Watanabe et al., 1993).

4.3 Change detection using supervised image classification

Finally, as for the model's capability to detect changes, Table 1 shows the model's confusion matrix showing sufficiently high accuracies with 0.91 as minimum. Misclassification is mainly between bleaching and change due to presence of clouds and wave foams in the pre- image. This either may be due to incorrect selection of training points or due to atmospheric haze. Nevertheless, the model produced high classification accuracy. This produces overall accuracies and kappa statistic values of 0.97 and 0.94 respectively.

	B	CW2	CW1	G	NC	Producers
B	49	0	5	0	0	0.91
CW2	0	50	0	0	0	1
CW1	0	0	86	0	0	1
G	0	0	0	60	0	1
NC	0	0	0	0	60	1
Consumers	1	1	0.95	1	1	

Table 1. Confusion matrix of the time series image classification where B is for bleaching, G is for seagrass/macroalgal growth, NC is for cases of no change, CW1 and CW2 are for presence of cloud and wave foams in the pre- and post-bleaching images respectively.

4.4 In situ data validation

The coral bleaching monitoring report of the Ministry of Environment of Japan showed an average of 92% bleaching for the 31 monitoring stations which translated to an average of 19% bleaching incidence when adjusted using coral cover percentage in the monitoring sites. Out of these monitoring stations however, 4 stations were not included in the comparison since they were not covered by the Sentinel-2 scenes used in this study due the cloud mask. In total, only 27 stations were used. Out of these stations, 21 showed agreements with the change detection map

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which is approximately 78% agreement. This indicates that the model performed well in terms of segmenting bleaching incidence from a time series image stack. For the other 6 stations, although they did not overlap with any bleaching-classified pixels, they still showed proximity to bleaching-classified pixels suggesting that the change detection map can be used to indicate possible bleaching in nearby regions.

5. CONCLUSION AND RECOMMENDATIONS

Although the coral bleaching is visually evident from the bi-temporal image, a limitation of this study can be attributed to the lacking *in situ* samples. While the coral bleaching report provided for 31 monitoring stations allowed binary comparison with the change detection map, the sample size is still limited to enable comprehensive accuracy assessment of the model. If sufficient sampling for ground data is available, better modelling may be produced. Aside from that, the methodology also lacked relative radiometric calibration assuming that GEE's repository already calibrates data relatively similar to the Landsat collections (Gorelick et al., 2017). With these, it would be recommended to have ground truth data for better validation process, and as for relative calibration, to implement calibration techniques to ensure that the bi-temporal data do not have shifted or skewed histograms which may result in erroneous results. With regards the change detection performance, most of the misclassification were due to bleaching and change because of the presence of clouds and wave foams in the pre-image. To mitigate this kind, a possible strategy to consider is the removal of clouds and wave foams from the pre- and post- images before performing the change detection process. In that case, classification will be constrained to bleaching and non-bleaching cases only.

Additionally, even though this study showed good classification results, a consideration for application of this model to other cases would be the intensity and magnitude of the bleaching. In this case, the bleaching is significantly visible in the satellite hence the good results but for cases where the bleaching is minimal, this model may not perform accurately.

Nevertheless, the researchers were able to develop a methodology that has the capability to detect changes in benthic habitats using the coral bleaching case of the coastal area of the Iriomote and Ishigaki, Japan islands in 2022. Detected changes include those due to coral bleaching and seagrass or macroalgal growth and other changes which were observed from the bi-temporal scenes, primarily other covers such as cloud covers and wave foams. This also demonstrated the applicability of Sentinel 2 data for coastal applications. Moreover, through this study, the use of Random Forest classifier on multi-temporal dataset can be said to have effective performance therefore having the capability to recognize temporal patterns.

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