A comparison of multispectral aerial and satellite imagery for mapping intertidal seaweed communities

Juliet Brodie[1], Lauren Ash[1*], Ian Tittley[1] & Chris Yesson[2]

[1] Natural History Museum, Department of Life Sciences, Cromwell Road, London, SW7 5BD, United Kingdom.

[2] Institute of Zoology, Zoological Society of London, Regent's Park, London, NW1 4RY, United Kingdom.

*Current address: University of Vermont, Department of Biology, Burlington, Vermont 05405, U.S.A.

Correspondence to: J Brodie, Natural History Museum, Department of Life Sciences, Cromwell Road, London, SW7 5BD, United Kingdom. Email: j.brodie@nhm.ac.uk

ABSTRACT

1. Habitat-forming seaweeds are vital components of marine ecosystems, supporting immense diversity and providing ecosystem services. Reports of major changes in the distribution and abundance of large brown seaweeds in the North-east Atlantic are an increasing cause for concern, but a lack of consistent monitoring over time is a key impediment in obtaining reliable evidence of change. There is an urgent need to recognize change rapidly and efficiently in marine communities which are increasingly impacted by pressures of human population growth, climate change and ocean acidification.

2. Here, the potential for remote monitoring of seaweed habitats is investigated using freely available, high resolution aerial and satellite imagery. Three sources of imagery were used: i) Channel Coastal Observatory (CCO) aerial imagery, ii) Aerial images from the Bing webmap server, and iii) RapidEye multispectral satellite data.

3. The study area, the Thanet Coast, is an area of chalk outcrop in South-east England of high conservation status and includes three Marine Conservation Zones. Eight habitat classes, including brown, red and green algal zones, were recognized based on ground-truthing surveys.

4. A multi-class classification model was developed to predict habitat classes based on the chromatic signature derived from the aerial images. The model based on the high resolution CCO imagery gave the best outcome (kappa value 0.89).

5. Comparing predictions for images in 2001 and 2013 revealed habitat changes, but it is unclear as to what extent these are natural variability or real trends. This study demonstrates the potential value for long term monitoring with remote sensing data. Repeated, standardised coastal aerial imaging surveys, such as performed by CCO, permit rapid assessment and re-assessment of habitat extent and change. This is of value to the conservation management of

protected areas, particularly those defined by the presence or extent of specific habitats.

KEY WORDS: aerial imagery; coastal habitats; *Fucus*; macroalgae; Marine Conservation Zones; remote sensing; satellite imagery

INTRODUCTION

Seaweed habitats have great economic value and provide ecosystem services globally worth billions of pounds annually (Beaumont, Austen, Mangi & Townsend, 2008; Smale et al., 2013). Large brown seaweeds (Phaeophyceae) are habitat-forming components of the littoral (fucoids – Fucales) and the shallow sub-littoral (kelps – Laminariales) of marine ecosystems (Smale et al., 2013; Steneck et al., 2002). These seaweeds are highly productive primary producers and important for carbon capture and transfer in coastal communities (Brodie, Wilbraham, Pottas & Guiry, 2014; Golléty, Migné & Davoult, 2008). They also protect shorelines by buffering currents and waves, and provide shelter for many other organisms (Yesson et al., 2015a). Canopy-forming macroalgae, such as kelp and fucoids, can increase the habitable surface area fourfold (Boaden 1996; Jueterbock et al., 2013), creating conditions for diverse understorey communities of flora and fauna (Golléty, Migné & Davoult, 2008).

There are many threats to these important and economically valuable seaweed habitats, but predominantly from human impacts including rising CO_2 levels and associated warming (Brodie, Wilbraham, Pottas & Guiry, 2014). Already there are a number of documented cases of kelp and fucoid species decline in abundance or loss attributed to ocean warming and a combination of other stressors (Brodie et al., 2014; Yesson et al., 2015b). Climate change can also facilitate the introduction of invasive species and there is evidence of an increasing rate of introductions of non-native algae in the north-east Atlantic (Brodie et al., 2016; Sorte et al., 2010). Despite the importance of seaweed communities, they have been afforded very little protection through statutory conservation measures (Brodie, John, Tittley, Holmes & Williamson, 2007; Brodie, Andersen, Kawachi & Millar, 2009). Although Marine Protected Areas (MPAs) cover around 23% of UK waters (as of December 2017 http://jncc.defra.gov.uk/default.aspx?page_4549), only a small proportion of these encompass seaweed communities, and the protection provided is highly variable and may have no bearing on seaweed communities.

A lack of knowledge of the distribution and abundance of seaweed habitats is a major impediment to understanding the impact of threats such as climate change. Fundamental information on species ranges, kelp forest biodiversity, and species interactions are included in this lack of knowledge (Harley et al., 2012; Smale et al., 2013). A limiting factor here is the difficulty of assessing seaweed-dominated areas. Many locations are remote or submerged, making sampling difficult and even dangerous. Scientific diving has been the traditional method for assessing and monitoring submerged macroalgal communities, but this can be logistically problematic and often impractical due to large time requirements as well as the expense of training, personnel and equipment (Pauly & De Clerck, 2010; Smale et al., 2013).

Remote Sensing

An alternative approach to direct, in-person surveys for documenting change in marine benthic habitats is the use of remote sensing. Images of the coastline taken from aeroplanes, drones or satellites can provide an overview of coastal habitats suitable for broad-scale habitat assessments and monitoring. This approach can be less time consuming, generally more cost-effective and requires less manpower than undertaking comprehensive shore work (Pauly & DeClerck, 2010). Quantitative analysis of coastal seaweed habitats also allows for an encompassing view of the area and provides clearer evidence for environmental change (Kuster et al., 2006).

Despite the wide range of remote sensing options, research using these techniques in the marine and coastal field lags far behind that for the terrestrial environment, and few published studies have used remote sensing to examine seaweed communities (Pauly & DeClerck, 2010). Nevertheless, a range of satellite imagery tools have been applied for mapping spatial and temporal distributions of macrolgae and associated habitats (Hoang, O'Leary & Fotedar, 2016 and references therein).

Mapping of three submerged macroalgal species was attempted in the Baltic Sea (Kutser Vahtmäe, & Martin, 2006) although they encountered difficulties with sensor penetration through the water column. A study to compare image-based and spectral library methods undertaken to classify shallow water habitats in the Baltic concluded that image-based methods were better (Vahtmäe & Kutser, 2013). Remote sensing was used in NW Spain to try to detect benthic macroalgae at the species level using the hyperspectral sensor CASI-2 (Casal, Kutser, Domínguez-Gómez, Sánchez-Carnero, & Freire, 2013) but only a few species were discernible. However, the authors reported that it was possible to discriminate between red, green and brown taxonomic groups in shallow water. Landsat images were used to assess spatial and temporal changes in seagrass-dominated submerged vegetation in Zanzibar (Gullström et al., 2006). Documenting temporal change in Caribbean coastal zones was undertaken using multispectral Landsat Thematic Mapper satellite data (Michalek, Wagner, Luczkovich, & Stoffle, 1993), although ground-truthing was required for verification of specific habitat changes. Mapping macroalgal communities in NW Spain was undertaken by Casal, Kutser, Domínguez-Gómez, Sánchez-Carnero & Freire (2011) using CHRIS-PROBA which gave good results for maximum likelihood classification, but mixed results for Spectral Angle Mapper where brown and red algae were not clearly distinguishable. Herkül, Kotta, Kutser & Vahtmäe, (2013) applied the spectral variation hypothesis in the Baltic Sea to successfully make biodiversity assessments. Identification and quantification of landscape scale algal populations were undertaken around Helgoland by Uhl et al., (2013) although they could not distinguish between species of the same genus or family due to strong spectral analogies. Uhl et al., (2016), who used hyperspectral data from AisaEAGLE to detect submerged kelp, developed a fully automated simple feature detection processor which was successful until a depth of 6 m.

Hennig, Cogan & Bartsch, (2007), who specifically focused on the intertidal zone, analysed hyperspectral imagery from the rocky intertidal of Helgoland. Their classification based on a spectral library allowed them to map the dominant intertidal macrophyte vegetation and general intertidal structures but found the separation of mixed vegetation types was limited.

Floating vegetation is challenging to classify because such rafts alter the spectral properties of the sea surface. In one of the first studies of its kind, Dierssen, Chlus & Russell, (2015) were able to discriminate spatial distribution of the floating macroalga *Sargassum* and seagrass mats in Greater Florida Bay, USA, using spectral measurements from the Portable Remote Sensing imaging Spectrophotometer (PRISM) imagery in conjunction with spectral measurements from experimental mesocosms, They were also able to discriminate the age of the wrack based on an increase in reflectance with time. Hoang, O'Leary & Fotedar, (2016), who were also working on *Sargassum* beds, achieved a highly accurate classification outcome using a combination of high spatial resolution WorldView-2 imagery and in-field observations around Rottnest Island, Western Australia.

Aims

A study was undertaken to determine whether intertidal seaweed habitats can be differentiated using (freely available) remote sensing images.

METHODS

Study area

The Thanet coast was chosen for this study because it is an area of chalk outcrop of high conservation importance in Kent, in the south-east of England. The Thanet Coast was designated a Marine Conservation Zone (MCZ – a statutory Marine Protected Area) in 2013, and Dover to Deal and Dover to Folkestone in 2016 (https://www.gov.uk/government/publications/marine-conservation-zones) under the UK's Marine and Coastal Access Act 2009 (www.jncc.gov). The Thanet coast was already afforded Special Area of Conservation (SAC) and Site of Special Scientific Interest (SSSI) status due to its chalk sea-caves and reefs (Tittley et al., 1998, 1999). The boundary of the MCZ runs from the east of Herne Bay around Thanet to the northern wall of Ramsgate harbour and the site protects an area of approx. 64 km^2 (Figure 1). The shores are gently sloping, uneven chalk reef incised by channels, with c. 100-140 m exposed at low tide. The upper shore consists of bare chalk, boulders and sand over chalk and supports green seaweeds consisting mainly of *Ulva* species. The middle and lower shore is chalk reef. The middle shore consists of a zone of large brown algae dominated by *Fucus vesiculosus* (predominantly higher up) and *F. serratus* (predominantly lower down). The lower shore consists of a zone of predominantly red algae, including *Corallina officinalis*, *Gelidium* spp., *Palmaria palmata* and *Rhodothamniella floridula*.

Remote sensing data

Image data were collected for North and East Kent, stretching from Herne Bay to Folkestone (Figure 1). Imagery came from three sources, ranging from high resolution aerial surveys, to lower resolution, multi-spectral satellite data: I) The Southeast Strategic Regional Coastal Monitoring Programme is one of six regional programmes that form the National Network of Regional Coastal Monitoring Programmes of England. This Network collects coastal monitoring data, including aerial and LiDAR surveys, to inform shoreline management plans. Data, metadata and survey reports are freely available to download from the Channel Coast Observatory website (www.channelcoast.org). The Channel Coastal Observatory (http://www.channelcoast.org/) is an England-wide project to collect coastal monitoring data, including regular aerial surveys (from twice yearly to every few years, depending on the region) conducted at low tides (Pixel resolution either 0.1x0.1m or 0.2x0.2m), data used in this study dates from May 2001 and May 2013. The 2001 CCO imagery was collected using a WILD RC 30 camera with 153.64 mm focal length at an average altitude of 762 metres. The 2013 imagery was collected using a Vexcel Ultracam Xp digital camera with a focal length of 100.5 mm at an average altitude of 1645 metres, II) Bing maps (http://www.bing.com/maps/) provide free access to aerial image data (resolution 0.6x0.6m) collected by Digital Globe via their representational state transfer (REST) interface (https://msdn.microsoft.com/en-us/library/ff701713.aspx), surveyed July-October 2011 (Walcher et al., 2012), and III) The RapidEye satellite data provides five spectral bands (blue, green, red, red edge, near infra-red) at 5 m x 5 m resolution, surveyed September 2013 (https://www.planet.com/products/satellite-imagery/rapid-eye-basic-product/), and has been used to detect invasive aquatic plants (Roessler, Wolf, Schneider, & Melzer, 2013). RapidEye data was freely provided by the Earthnet Online Website (http://earth.esa.int) after registration and submission of a brief project description. RapidEye data was provided orthorectified and corrected, so no pre-processing was required. Example images are presented in Figure 2, demonstrating the variety of pixel resolution and tidal state.

Ground-truthing

Ground-truthing surveys were undertaken in September 2011, January and June 2014. Transects were walked down or up the shore at low tide, sampling every 20-30 m. Habitats were photographed and dominant taxa were recorded along with GPS coordinates of the locations. Ground truth locations were classified into the following habitat types based on dominant taxa or substrata: i) Brown algae, ii) Red algae, iii) *Mytilus*, iv) Green algae, v) Sand, vi) Muddy-sand, vii) Bare Chalk, viii) Flint/Sand/Chalk.

Spatial error was recorded as approximately 3 m for GPS readings (Garmin eTrex 10/20 GPS units). The resolution of the imagery is more precise than this spatial ambiguity, so that a single pixel in the image data could not be matched to the ground truth locations. In order to associate pixel values with ground-truth sites, the set of pixels surrounding the recorded coordinates within a 3 m radius were collected and the combination of pixel values (Red, Green, Blue for CCO and Bing, plus Red Edge and Near Infra-Red for RapidEye imagery) occurring most frequently in this set were selected as the most representative of the ground-truth location. In the event of multiple combinations being equally represented, the combination closest to the mean was selected. The tidal state at the time of acquisition of the Bing and RapidEye images means that fewer ground-truth locations are valid (show an unsubmerged section of coastline). Therefore fewer ground-truth points are available for these images. See Table S1 for a breakdown of ground-truthing data available by habitat class, date of acquisition and image source.

Classification model

A habitat classification model was developed using a pixel-based approach. A model was trained using a chromatic profile based on the pixel values at the locations of ground-truthing samples. A pixel based approach has been used successfully to map coastal benthic habitats (Hennig, Cogan & Bartsch, 2007), and has been shown to be as effective as object-based methods for detecting small patches of vegetation (Castillejo-González, Pena-Barragán, Jurado-Expósito, Mesas-Carrascosa & López-Granados, 2014).

Ground truth sites were used as training data to create a multi-class classification model. A support vector machine model (SVM) was performed using the e1071 package of R statistical software program (Meyer, Dimitriadou, Hornik, Weingessel, & Leisch, 2014). SVMs are learning algorithms that are commonly used for supervised image classification (Mountrakis, Im, & Ogole, 2011), including benthic habitat mapping (e.g. Gougeon, Kemp, Blicher, & Yesson, 2016), and have been shown to perform well with small training datasets (Mountrakis, Im, & Ogole, 2011), and for multi-spectral imagery (RapidEye data) in terrestrial (Ustuner et al. 2015) and coastal environments (Adam, Mutanga, Odindi & Abdel-Rahman 2014). Data were partitioned by site into spatial cross validation replicates (Radosavljevic & Anderson, 2014). For each replicate, data for one site were kept as testing data, with the remaining data used for training. The gamma and cost parameters were tested in combination (gamma: 2^{-13}, 2^{-12}, ..., 2^{3}, cost: 2^{-5}, 2^{-6}, …, 2^{13}) for each spatial replicate and the kappa evaluation parameter was calculated based on predictions for the test data (following the recommendations of Chang and Lin, 2011). The parameter combination resulting in the highest combined kappa was chosen for the final model.

A model was calculated based on each imagery dataset (CCO, Bing and RapidEye). Models were projected back into the full images to predict habitat class in all areas not surveyed. Additionally, the model based on the CCO data was projected into CCO imagery taken in May 2001 to estimate change in habitat from May 2001 to May 2013. Areas of each predicted habitat class were calculated using the R package raster (Hijmans, 2015). The open source desktop GIS software QGIS was used for the manipulation of GIS layers (https://www.qgis.org/).

RESULTS

Comparison of model evaluation statistics

Model evaluation statistics are shown in Table 1, and a confusion matrix for each model is presented in Table S2. For all the parameters, the CCO imagery shows the best outcome. Notably, the kappa value for the CCO (0.89) is a much closer fit (a kappa value of 1 would equal an exact fit) of the model than either Bing (0.51) or RapidEye (0.48). The resolution is greater for CCO (0.1 m x 0.1 m) than Bing (0.6 m x 0.6 m) which is, in turn, greater than RapidEye (5 m x 5 m). Consequently the CCO imagery provides a higher number of pixels per unit area and thus shows greater detail (Figure 2).

Changing communities

The change in areas using the CCO imagery for 2001 and 2013 are shown in Table 2 and Figures 3 & 4a-d. Overall from 2001 to 2013, Flint/Sand/Chalk, Muddy-sand, Red algae and Sand cover have decreased, whereas *Mytilus* cover has stayed virtually the same, and Bare Chalk, Brown algae and Green algae cover have increased. A comparison of changes in cover for the individual MCZs between 2001 and 2013 showed that for Thanet there was an increase in Flint/Sand/Chalk and a decrease in Brown algae, *Mytilus* and Red algae, for

Dover to Deal there was a slight increase in Bare Chalk and a slight decrease in cover of Brown algae, and for Dover to Folkestone a slight decrease in Bare Chalk, and a decrease in Brown algae, *Mytilus* and Red algae.

Predicted areas

The modelled areas based on CCO 2013, Bing and RapidEye imagery, adjusted to compare only the shoreline observable in all three images, is shown in Table 3. The adjustment for the CCO reduces the shore line by 2/3rds (from 1163 ha to 389 ha). Bing and RapidEye models more or less fail to detect Chalk although RapidEye predicts Flint/Sand/Chalk. The model based on RapidEye data over-predicts Green algae whereas the model using Bing images under-predicts this group. Both sets of imagery fail to pick up Muddy Sand, which is a consequence of there being no valid (unsubmerged) ground-truth sites for Muddy Sand in these images. The Bing model is reasonable at predicting *Mytilus* but the RapidEye model fails completely to predict this category. The Bing model over-predicts Red algae, whereas the RapidEye model under-predicts them.

DISCUSSION

The value of coastal aerial surveys for conservation

This pilot project has demonstrated, using an SVM model, that intertidal seaweed communities can be differentiated using the freely available high resolution imagery of CCO and that it was possible to detect temporal and spatial changes for the habitat-forming species. There are direct conservation and management benefits to be able to produce widespread habitat maps (Medcalf, Parker, Turton, & Bell, 2013; Petchey, Brown, Hambidge, Porter, & Rees, 2011). For example, mapping UK habitats is essential for UK authorities to meet reporting and legal obligations, such as the EC habitats directive (Medcalf, Parker, Turton, & Bell, 2013). The standardised, repeated nature of many remote sensing surveys (including CCO) lends itself towards re-assessment of habitats, this creates an opportunity to assess variations in habitat coverage during a time of rapid environmental change (Secades, O'Connor, Brown, & Walpole, 2014). This is of great value to conservation management, particularly for protected areas which are defined by the presence of specific habitats, or those with the objective of protecting a particular habitat.

In comparison to this study, the majority of other studies that have used remote sensing to differentiate seaweed communities have concentrated on the shallow subtidal. A major problem with working in the subtidal is turbidity which can vary both spatially and seasonally such as was experienced in the Baltic (Kuster et al., 2006, Vahtmäe & Kuster, 2013). However, this can be much less of a problem in clear, tropical water such as was experienced in the study of seagrasses in Zanzibar (Gullström et al.,, 2006) and Michalek, Wagner, Luczkovich, & Stoffle, (1993) who worked in the Caribbean coastal zone.

As with our study, Vahtmäe & Kuster (2013) found that benthic habitat maps could be constructed from aerial images, but they point out the requirement for extensive fieldwork. This is dependent, in part, on the variability of the habitat. For the present study, we performed 2 days of ground-truthing and this permitted the construction of a habitat map covering more than 70km/1100ha of coastline. Our ground-truthing surveys were performed at different times to the image collection, both in a different year and month. It has been suggested that ground-truthing should be contemporaneous with imagery surveys to ensure results are not compounded by seasonal or annual changes (Vahtmäe & Kuster, 2013). However, our model produced good evaluation statistics (at least for the high-resolution imagery), although areas with less long-term stability may be less robust to asynchronous ground-truthing. This is likely to be an issue for many studies seeking to use freely available aerial/satellite imagery.

There are a number of advantages of the specialist low tide CCO imagery. The programme for coastal monitoring for the English coast (http://www.channelcoast.org/programme) collects tidally coordinated aerial imagery, thus significant coverage of intertidal seaweed communities are available, and this has recently been supplemented with near infra-red data which gives greater discriminatory powers. Furthermore, the very high resolution (0.1 m x 0.1 m) provides images with excellent differentiation of boundaries, making it more reliable to match with ground-truthing data. In contrast, using more sensors from hyperspectral satellite imagery can provide more information to discriminate habitats, but because the imagery is of a relatively coarse resolution, the relative gain from the additional sensors does not compensate the inability to detect smaller features. For example, Kuster et al., (2006), who used multispectral satellites, found that the sensors they used could only detect differences in brightness in one band which was insufficient to recognize different benthic types.

One of the few specifically intertidal studies which used hyperspectral remote sensing methods to classify rocky habitats on Helgoland (Hennig, Cogan & Bartsch, 2007) was able to map the dominant intertidal seaweed vegetation and general intertidal structures, although additional data were required to separate mixed vegetation types. In our study, the disadvantage of satellite data is that they are not specifically collected to capture the intertidal. The differences in the amount of shore exposed between images, combined with the coarseness of the resolution, do not provide the reliability of coverage and clarity of CCO.

Indeed one habitat class, Muddy Sand, is not observed in some images because of the tidal state. However, rapid advancement in technology and cost of image acquisition may change what is possible with satellite data (Hoang, O'Leary & Fotedar, 2016).

Changing communities

Observed changes in cover between 2001 and 2013 may represent natural variation that occurs in shore communities with time. There were pronounced differences between individual MCZs (Figures 4b-d), which showed local variations but a decrease in bare substrata (Flint/Sand/Chalk and Sand) and an increase in Red algae and *Mytilus* might indicate a general trend with time for an increase in the cover of these organisms. However, the increase observed in Bare Chalk in the Dover to Folkestone MCZ, in comparison with Thanet and Dover to Deal, could relate to the physical protection of chalk cliffs. Much of the chalk cliffs of Thanet and Dover to Deal (c. 80%) are incarcerated in concrete (Tittley et al., 1998), whereas Dover to Folkestone is a natural area of chalk and therefore subject to greater erosion. Smothering by chalk could explain the observed decrease in sand for Dover to Folkestone. However, sand cover changes rapidly and is reported locally to rise or fall by over a metre annually (I. Tittley, personal observation), so this change might be ephemeral in nature, rather than a sign of any long-term trend. Multi-year comparisons are possible with the repeated imaging surveys. Future work examining multiple years will help distinguish longer term trends from short term fluctuations. Detection of changing habitat cover could be an important monitoring tool within this protected area.

Fucus serratus and *F. vesiculosus* are the two main habitat-forming species of brown algae on the shores of this study. A slight but not significant decrease was reported for *F. serratus* for the Eastern English Channel between 1974 and 2010 and the trend for this species in other geographical regions around Britain was for a non-significant decrease in abundance, with the exception of the Western Channel and Celtic Sea where there was a significant increase in abundance (Yesson et al., 2015b). Furthermore, *Fucus vesiculosus* tended to show increases in abundance but only significantly so in the North Sea and warmer summer and winter temperatures appear favourable for this species (Yesson et al., 2015b).

Seasonality

An increase in Green algae may reflect differences in seasonal progression, although both 2001 and 2013 images were collected in May, this month in 2013 was unseasonably cold, while in 2001 it was closer to the long term average (http://www.metoffice.gov.uk/). Alternatively, variation in cover from year to year of *Ulva* species may influence observed patterns, which tend to be most abundant in the spring-summer (I. Tittley personal observation). A decrease in the Red algae overall may reflect the increase in Brown algae but it is possible that the red species are still present but inconspicuous underneath the fucoids at the time images were taken. Any image-based habitat classification will be biased in favour of the top-most layer of observed fauna/flora, as this is the layer picked up by the images. Ideally an assessment of understory taxa could be undertaken at the time of ground-truthing to assess the potential impact of this issue.

Modelling methods

The example classification presented herein employs a relatively simple pixel-based classification using a SVM model. There are a variety of models available to perform pixel-based classifications, and different methods may perform better on different datasets (Adam, Mutanga, Odindi & Abdel-Rahman, 2014; Mountrakis, Im, & Ogole, 2011). Object-oriented methods for classification are an alternative approach to pixel based assessment, the latter independently assesses the chromatic signature of each pixel, whereas the former examines local neighbourhoods to incorporate shape and texture features (Ouyang et al. 2011). Alternative methods might help produce better models for the coarser pixel resolutions.

Conclusions

The MCZs in Kent represent most of the rocky areas in the county, making them particularly crucial for the conservation and management of seaweed communities in the region. The high resolution habitat maps presented here form a baseline for future assessment. The problem of distinguishing natural variation between years and long term trends highlights the need for multiple year comparisons. The method we have piloted in this study would enable a periodic review of these communities and provide a tool for monitoring over the long term. As such, this could provide a valuable addition to the monitoring of SACs which have to be monitored by law under the EU habitats directive (Davies et al., 2001) every six years.

ACKNOWLEDGEMENTS

We are extremely grateful to Professor Mike Cowling (Chief Scientist, The Crown Estate) for his interest in this project. We thank Paula Lightfoot for her constructive review. The project was funded by The Crown Estate with additional support from the Natural History Museum Development Initiative Fund.

SUPPORTING INFORMATION

Table S1 – Summary of ground truthing observations by time of observation. The tide position in the Bing and RapidEye images mean that some observations cannot be tied to a valid (unsubmerged) section of image.

Table S2 – Confusion matrices evaluating predicted and observed habitat classes for ground-truth sites.

REFERENCES

Adam, E., Mutanga, O., Odindi, J., Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, 35(10), 3440-3458.

Beaumont, N. J., Austen, M. C., Mangi, S. C., Townsend, M. (2008). Economic valuation for the conservation of marine biodiversity. *Marine Pollution Bulletin,* 56, 386–396.

Boaden, P. J. S. (1996). Habitat provision for meiofauna by *Fucus serratus* epifauna with particular data on the flatworm *Monocelis lineata*. *Marine Ecology,* 17**,** 67–75.

Brodie, J., John, D., Tittley, I., Holmes, M. J., Williamson, D. (2007). *Important Plant Areas for algae: a provisional review of sites and areas of importance for algae in the United Kingdom*. Plantlife International, Salisbury, UK.

Brodie, J., Andersen, R., Kawachi, M., Millar, A. (2009). Endangered algae and approaches to their conservation. *Phycologia,* 48**,** 423–438.

Brodie, J., Wilbraham, J., Pottas, J., Guiry, M. D. (2016). A revised check-list of the seaweeds of Britain. *Journal of the Marine Biological Association,* 96, 1005-1029.

Brodie, J., Williamson, C. J., Smale, D. A., Kamenos, N. A., Mieszkowska, N., Santos, R., …, Hall-Spencer, J. M. (2014). The future of the NE Atlantic benthic flora in a high CO_2 world. *Ecology and Evolution,* 4, 2787–2798.

Casal, G., Kutser, T., Domínguez-Gómez, J. A., Sánchez-Carnero, N., Freire, J. (2011). Mapping benthic macroalgal communities in the coastal zone using CHRIS-PROBA mode 2 images. *Estuarine and Coastal Shelf Science,* 94**,** 281e290.

Casal, G,, Kutser, T., Domínguez-Gómez, J. A., Sánchez-Carnero, N., Freire, J. (2013). Assessment of the hyperspectral sensor CASI-2 for macroalgal discrimination on the Ría de Vigo coast (NW Spain) using field spectroscopy and modelled spectral libraries. *Continental Shelf Research,* 55**,** 129-140.

Castillejo-González, I. L., Pena-Barragán, J. M., Jurado-Expósito, M., Mesas-Carrascosa, F. J., López-Granados, F. (2014). Evaluation of pixel-and object-based approaches for mapping wild oat (*Avena sterilis*) weed patches in wheat fields using QuickBird imagery for site-specific management. *European Journal of Agronomy*, 59, 57-66.

Chang, C. C., & Lin, C. J.. (2011). LIBSVM: A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems Technology,* 2, 27.

Davies, J., Baxter, J., Bradley, M., Connor, D., Khan, J., Murray, E., … Vincent, M.. (2001). *Marine Monitoring Handbook*. JNCC. Retrieved from http://jncc.defra.gov.uk/PDF/MMH-mmh_0601.pdf.

Dierssen, H. M., Chlus, A., & Russell, B. (2015). Hyperspectral discrimination of floating mats of seagrass wrack and the macroalgae *Sargassum* in coastal waters of Greater Florida Bay using airborne remote sensing. *Remote Sensing of Environment,* 167, 247–258.

Harley, C. D. G., Anderson, K. M., Demes, K. W., Jorve, J. P., Kordas, R. L., Coyle, T. A., & Graham, M. H. (2012). Effects of climate change on global seaweed communities. *Journal of Phycology,* 48, 1064–1078.

Hennig, B. D., Cogan, B. C., & Bartsch, I. (2007). Hyperspectral remote sensing and analysis of intertidal zones: a contribution to monitor coastal biodiversity. In: Car, A., Griesebner, G., Strobl, J. (Eds.), *Geospatial Crossroads, GI Forum*. Wichmann, Heidelberg, pp. 62e73.

Herkül, K., Kotta, J., Kutser, T., & Vahtmäe, E. (2013). Relating Remotely Sensed Optical Variability to Marine Benthic Biodiversity. *PLOS ONE,* 8, e55624.

Hijmans, R. J. (2015). *raster: Geographic Data Analysis and Modeling*. R package version 2.3–33. https://cran.r-project.org/web/packages/raster/index.html

Hoang, T. C., O'Leary, M. J., & Fotedar, R. K. (2016). Remote-Sensed Mapping of *Sargassum* spp. Distribution around Rottnest Island, Western Australia, Using High-Spatial Resolution WorldView-2 Satellite Data. *Journal of Coastal Research,* 32, 1310-1321.

Jueterbock, A., Tyberghein, L., Verbruggen, H., Coyer, J. A., Olsen, J. L., & Hoarau, G. (2013). Climate change impact on seaweed meadow distribution in the North Atlantic rocky intertidal. *Ecology and Evolution,* 3, 1356–1373.

Golléty, C., Migné, A., & Davoult, D. (2008). Benthic metabolism on a sheltered rocky shore: role of the canopy in the carbon budget. *Journal of Phycology,* 44,: 1146–53.

Gougeon, S., Kemp, K. M., Blicher, M. E., & Yesson, C. (2017). Mapping and classifying the seabed of the West Greenland continental shelf. *Estuarine, Coastal and Shelf Science*, 187, 231-240.

Gullström, M., Lundén, B., Bodin, M., Kangwe, J., Öhman, M. C., Mtolera, M. S. P., & Bjork, M. (2006). Assessment of changes in the seagrass-dominated submerged vegetation of tropical Chwaka Bay (Zanzibar) using satellite remote sensing. *Estuarine and Coastal Shelf Science,* 67, 399–408.

Kutser, T., Vahtmäe, E., & Martin, G. (2006). Assessing suitability of multispectral satellites for mapping benthic macroalgal cover in turbid coastal waters by means of model simulations. *Estuarine and Coastal Shelf Science,* 67, 521–529.

Medcalf, K. A., Parker, J. A., Turton, N., & Bell, G. (2013). *Making Earth Observation Work for UK Biodiversity Conservation – Phase 2*. Report to the JNCC and Defra. Retrieved from http://jncc.defra.gov.uk/PDF/MEOW_Phase2Norfolk_Report_Draft_highres_web-2_p1_63.pdf

Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2014). *e1071: Misc Functions of the Department of Statistics (e1071), TU Wien*. R package version 1.6-4.

Michalek, J. L., Wagner, T. W., Luczkovich, J. J., & Stoffle, R. W. (1993). Multispectral Change Vector Analysis for monitoring coastal marine environments. *Photogrammetric Engineering and Remote Sensing,* 59**,** 381–384.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247-259.

Ouyang, Z. T., Zhang, M. Q., Xie, X., Shen, Q., Guo, H. Q., & Zhao, B. (2011). A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants. *Ecological informatics*, 6(2), 136-146.

Pauly, K., & De Clerck, O. (2010). GIS-Based environmental analysis, remote sensing, and niche modeling of seaweed communities. In Israel, A., Einav, R., Seckbach, J. (Eds.) S*eaweeds and their role in globally changing environments* (Vol. 15, pp. 93-+). Dordrecht: Springer.

Petchey, S., Brown, K., Hambidge, C., Porter K., & Rees, S. (2011). *Natural England/Environment Agency Collaboration: Operational Use of Remote Sensing for Environmental Monitoring*. Environment Agency Geomatics Group, Bath and Natural England, Peterborough. Retrieved from http://publications.naturalengland.org.uk/file/205029.

Radosavljevic, A., & Anderson, R. P. (2014). Making better Maxent models of species distributions: complexity, overfitting and evaluation. *Journal of Biogeography,* 41, 629–643.

Roessler, S., Wolf, P., Schneider, T., & Melzer, A. (2013). *Multispectral remote sensing of invasive aquatic plants using RapidEye.* In Earth Observation of Global Changes (pp. 109-123). Springer Berlin Heidelberg.

Secades, C., O'Connor, B., Brown, C., & Walpole, M. (2014). *Earth Observation for Biodiversity Monitoring: A review of current approaches and future opportunities for tracking progress towards the Aichi Biodiversity Targets.* Secretariat of the Convention on Biological Diversity, Montréal, Canada. Technical Series No. 72, 183 pages. Retrieved at https://www.cbd.int/doc/publications/cbd-ts-72-en.pdf

Smale, D. A., Burrows, M. T., Moore, P., O'Connor, N., Hawkins, S. J. (2013). Threats and knowledge gaps for ecosystem services provided by kelp forests: a northeast Atlantic perspective. *Ecology and Evolution,* 3, 4016–4038.

Sorte, C. J. B., Williams, S. L., Zerebecki, R. A. (2010). Ocean warming increases threat of invasive species in a marine fouling community. *Ecology,* 91, 2198–2204.

Steneck, R. S., Graham, M. H., Bourque, B. J., Corbett, D., Erlandson, J. M., Estes, J. A., et al. (2002). Kelp forest ecosystems: biodiversity, stability, resilience and future. *Environmental Conservation,* 29, 436–459.

Tittley, I., Spurrier, C. J. H., Chimonides, P. J., George, J. D., Moore, J. A., Evans, N. J., et al. (1998). *Survey of chalk cave, cliff, intertidal and subtidal reef biotopes in the Thanet coast cSAC.* English Nature, Peterborough, UK.

Tittley, I., Gilliland, P., Pound, D. (1999). Marine flora of the Thanet coast marine cSAC: A conservation and management perspective. In Scott, G. W., Tittley, I. (eds) *Changes in the marine flora of the North Sea*. CERCI, Scarborough. Pp 65-75.

Uhl, F., Bartsch, I., Oppelt, N. (2016). Submerged kelp detection with hyperspectral data. *Remote Sensing,* 8, 487.

Uhl, F., Oppelta, N., Bartsch, I. (2013). Spectral mixture of intertidal marine macroalgae around the island of Helgoland (Germany, North Sea). *Aquatic Botany,* 111, 112–24.

Ustuner, M., Sanli, F. B., Dixon, B. (2015). Application of support vector machines for landuse classification using high-resolution RapidEye images: a sensitivity analysis. *European Journal of Remote Sensing*, 48(1), 403-422.

Vahtmaë, E., Kuster, T. (2013). Classifying the Baltic Sea Shallow Water Habitats Using Image-Based and Spectral Library Methods. *Remote Sensing,* 5, 2451–2474.

Walcher, W., Leberl, F., Gruber, M. (2012) The Microsoft Global Ortho Program. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume 1-4, 53-58. https://doi.org/10.5194/isprsannals-I-4-53-2012

Yesson, C., Bush, L., Davies, A., Maggs, C. A., Brodie, J. (2015a). The distribution and environmental requirements of large brown seaweeds in the British Isles. *Journal of the Marine Biological Association,* 95, 669–680.

Yesson, C., Bush, L., Davies, A., Maggs, C. A., Brodie, J. (2015b). Large brown seaweeds of the British Isles: evidence of changes in abundance over four decades. *Estuarine and Coastal Shelf Science,* 155, 167–175.

Figures

Figure 1. Isle of Thanet and south Kent coast study area. The Thanet Coast Marine Conservation Zone (MCZ) was designated in 2013. Tranche 2 MCZs were designated in January 2016.

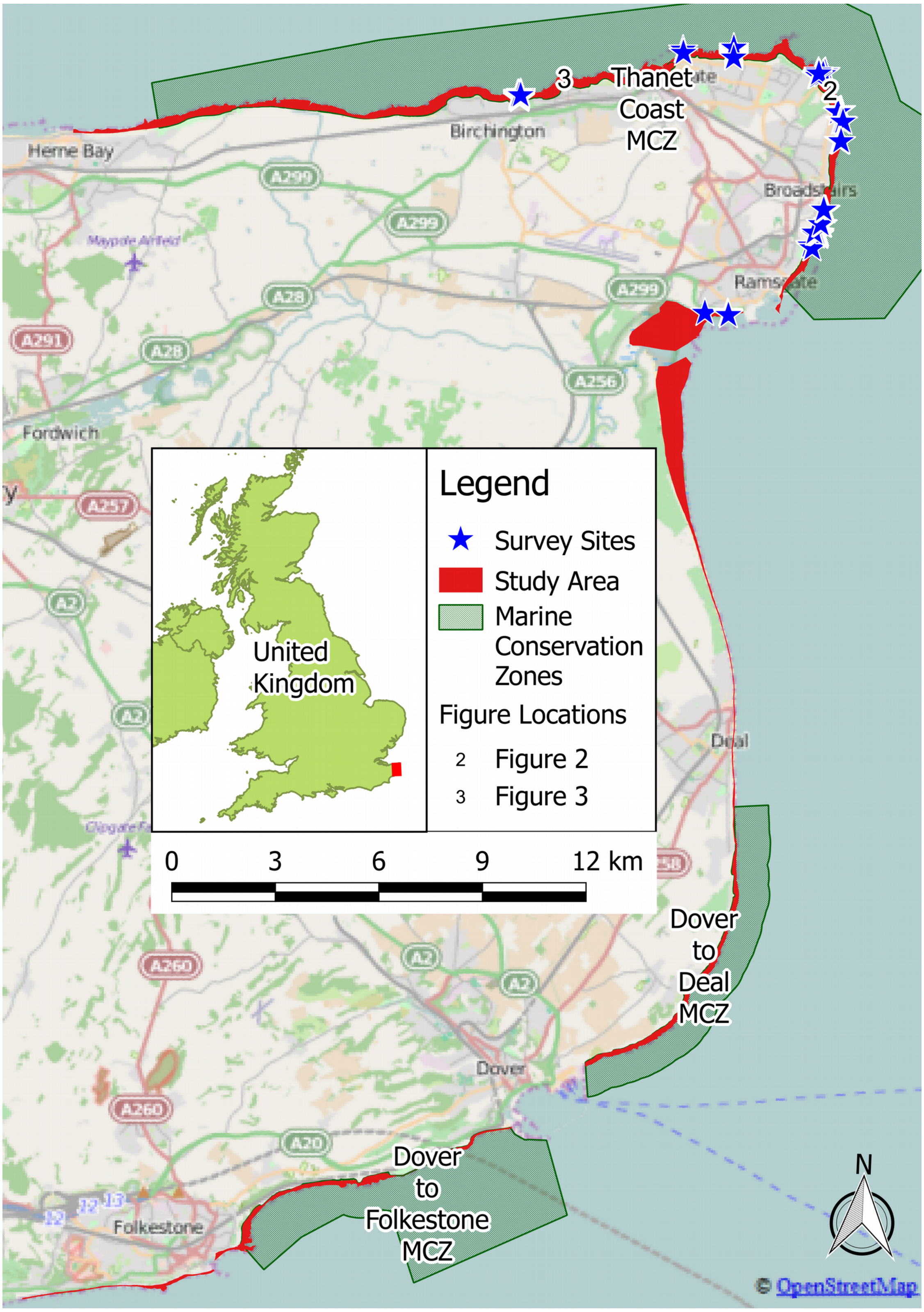

Figure 2. Sources of imagery. CCO = The Channel Coastal Observatory. Landsat data is not used in this analysis (the resolution is too coarse for useful modelling in this area), but is included for reference as this is a very popular remote sensing product.

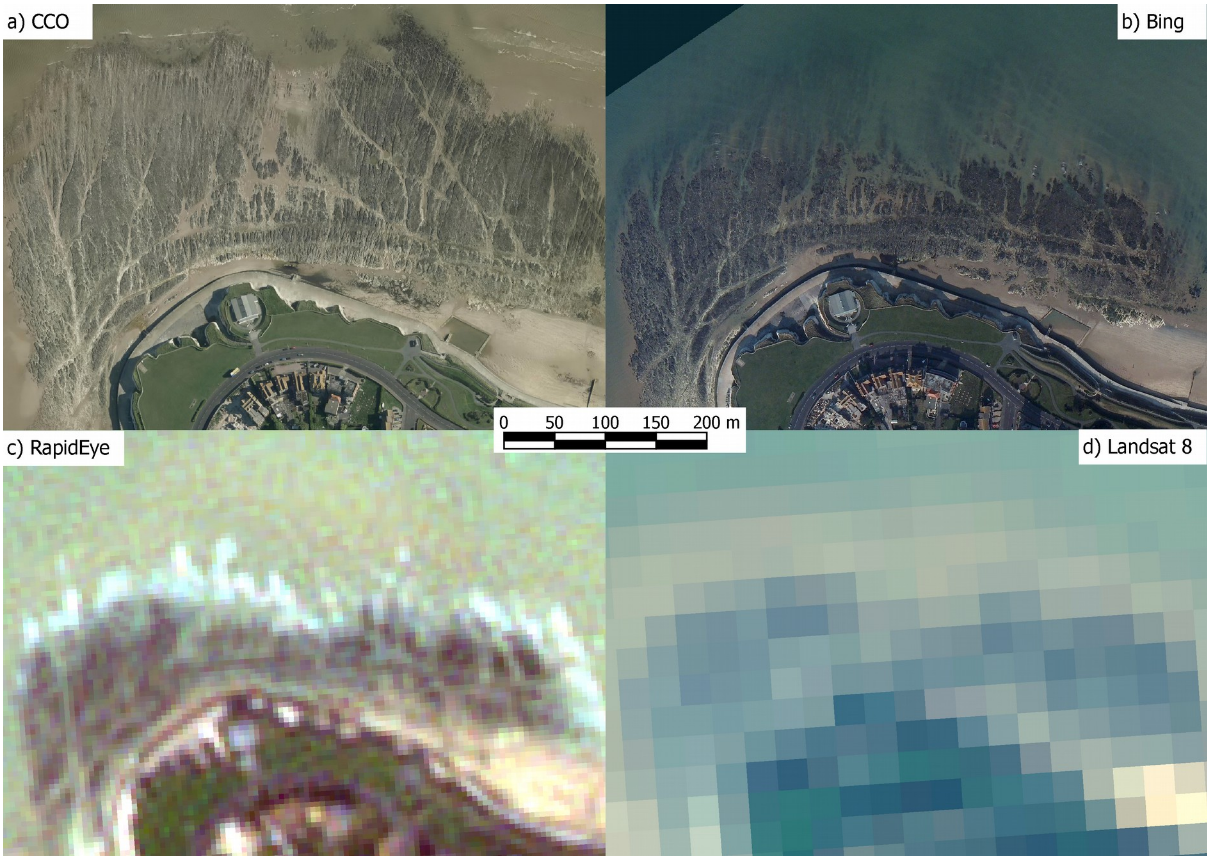

Figure 3. An example of a stretch of shore showing 2013 and 2001 imagery and predicted habitat. The shore is Hackemdown Point, the headland between Kinsgate Bay and Joss Bay, Kent, UK.

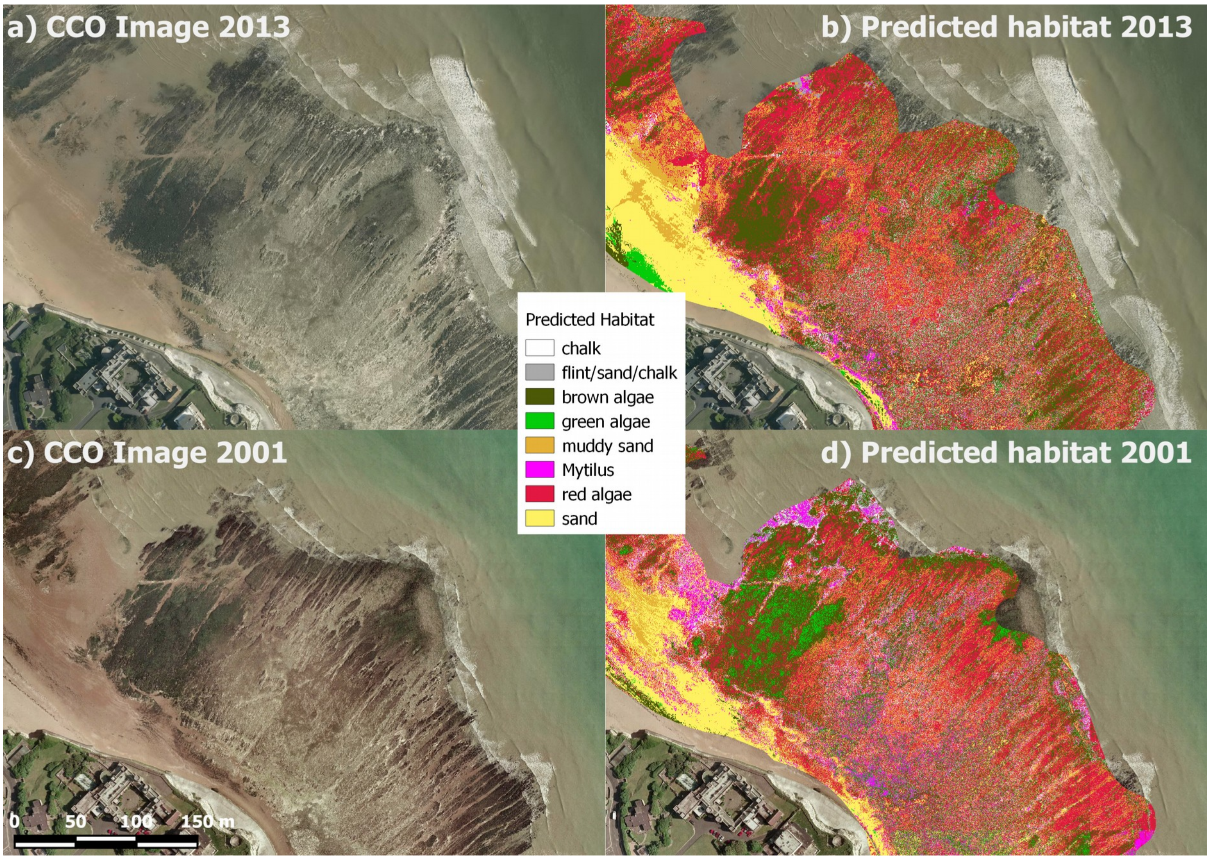

Figure 4a-d. Change in areas using the CCO imagery between 2001 and 2013. Figure 4a. Overall results. Figure 4b. Thanet MCZ. Figure 4c. Dover to Deal MCZ. Figure 4d. Dover to Folkestone.

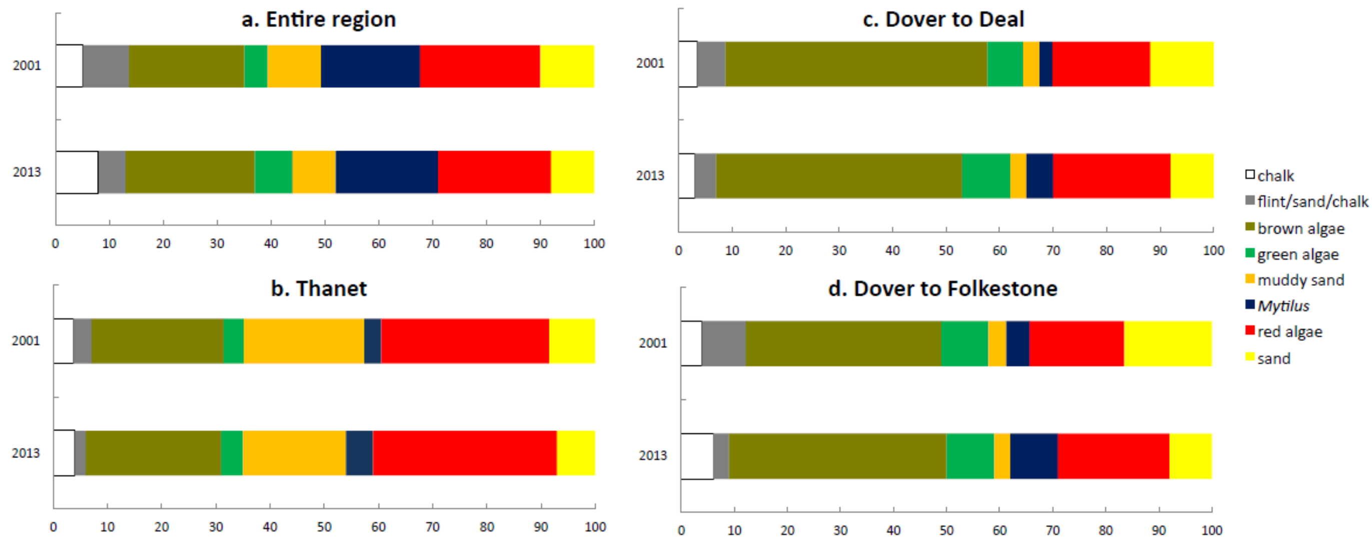

Table 1. Model evaluation statistics

Attributes	CCO	Bing	RapidEye
Resolution (m)	0.1 x 0.1*	0.6 x 0.6	5 x 5
Pixels within 3m radius	2833	79	4
Valid ground truth points	115	77	66
CV Kappa Range	-0.1-0.5	-0.1-0.4	0.0-0.4
Best gamma	0.5	0.03	0.0005
Best cost	2048	1024	4096
Diagonal %	0.91	0.65	0.62
Rand Index	0.94	0.73	0.75
Corrected Rand Index	0.83	0.35	0.40
Kappa	0.89	0.51	0.48
Bootstrap Kappa Range	0.2-0.6	0.0-0.6	0.0-0.8

* Resolution for 2013; resolution for 2001 = 0.2 x 0.2 m

Table 2

Areas (hectares) predicted using CCO images from 2001 and 2013 (proportions given in parentheses).

	Entire region			MCZ 2013			MCZ 2001		
Class	**2001**	**2013**	**Change**	**Thanet**	**Dover to Deal**	**Dover to Folkstone**	**Thanet**	**Dover to Deal**	**Dover to Folkstone**
Bare Chalk	58.85 (0.05)	93.54 (0.08)	34.69	22.67 (0.04)	2.73 (0.03)	4.85 (0.06)	17.78 (0.04)	3.67 (0.03)	2.47 (0.04)
Flint/Sand/Chalk	99.82 (0.09)	54.36 (0.05)	-45.45	8.93 (0.02)	4.08 (0.04)	2.90 (0.03)	16.37 (0.03)	5.66 (0.05)	5.27 (0.08)
Brown algae	248.77 (0.21)	275.38 (0.24)	26.61	131.61 (0.25)	46.15 (0.46)	33.92 (0.41)	116.57 (0.24)	52.07 (0.49)	23.41 (0.37)
Green algae	51.07 (0.04)	78.01 (0.07)	26.94	22.31 (0.04)	8.54 (0.09)	7.57 (0.09)	17.62 (0.04)	7.13 (0.07)	5.65 (0.09)
Muddy Sand	114.94 (0.10)	96.51 (0.08)	-18.44	100.80 (0.19)	2.85 (0.03)	2.35 (0.03)	106.90 (0.22)	3.24 (0.03)	2.14 (0.03)
Mytilus	214.19 (0.18)	215.29 (0.19)	1.11	25.05 (0.05)	4.93 (0.05)	7.46 (0.09)	15.15 (0.03)	2.53 (0.02)	2.83 (0.04)
Red algae	259.35 (0.22)	237.86 (0.21)	-21.48	179.38 (0.34)	22.21 (0.22)	17.68 (0.21)	148.36 (0.31)	19.51 (0.18)	11.35 (0.18)
Sand	116.14 (0.10)	87.71 (0.08)	-28.44	38.63 (0.07)	8.14 (0.08)	6.98 (0.08)	40.62 (0.08)	12.55 (0.12)	10.48 (0.16)
Total	1,163.13 (1.00)	1,138.66 (1.00)		529.38 (1.00)	99.63 (1.00)	83.71 (1.00)	479.38 (1.00)	106.36 (1.00)	63.61 (1.00)

Table 3

Predicted areas (hectares) based on three sets of images. Study area is the shoreline observable in all three images.

Classes	CCO 2013	Bing	Rapid Eye
Bare Chalk	30.49	2.45	0.00
Flint/Sand/Chalk	16.49	6.13	23.08
Brown algae	102.55	40.37	191.27
Green algae	30.68	60.73	94.76
Muddy Sand	17.02	0.00	0.00
Mytilus	68.56	50.21	2.54
Red algae	71.33	143.52	30.72
Sand	52.13	96.71	69.05
Total	389.24	400.11	411.43
Total no. of pixels	97302500	1111426	164572