Maritime Cliff and Slope

Yorkshire and Cornwall trial to map maritime cliff and slope habitats and characteristics and provide a cliff survey protocol.

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Contents

List of Abbreviations

AGL	*Above Ground Level*
AMSL	*Above Mean Sea Level*
CAA	*Civil Aviation Authority*
CHM	*Canopy Height Model*
CSM	*Common Standards Monitoring*
EO	*Earth Observation*
ES@S	*Environmental Sensing at the University of Southampton*
FCC	*False Colour Composite*
GCP	*Ground Control Point*
GIS	*Geographic Information Software*
GNSS	*Global Navigation Satellite System*
GPS	*Global Positioning System*
IMU	*Inertial Motion Unit*
LiDAR	*Light Detection And Ranging*
MCS	*Maritime Cliff and Slope*
NDVI	*Normalised Difference vegetation Index*
NE	*Natural England*
NN	*Nearest Neighbour*
NNRCMP	*National Network of Regional Coastal Monitoring Programmes*
NOTAM	*Notice to Airmen*
NVC	*National Vegetation Classification*
PHI	*Priority Habitat Inventory*
RGB	*Red, Green, Blue*
RF	*Random Forest*
RMSE	*Root Mean Square Error*
RINEX	*Receiver Independent Exchange Format*
RTK	*Real-Time Kinematic*
SfM	*Structure from Motion*
SVM	*Support Vector Machine*
UAV	*Uncrewed Aerial Vehicle*
UGCS	*Universal Ground Control Station*

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1 Background

Mapping Maritime Cliff and Slope (MCS) always presents a challenge both in terms of establishing the strong baseline (in terms of classification, boundary positions, function and habitat extents and habitat condition) and in monitoring change in relevant physical parameters and vegetation structure and composition. This is noted by the Coastal Margins project (Jones and others 2011) who comment on the lack of a comprehensive dataset for the MCS priority habitat inventory. Although those comments were related to the national ecosystem assessment and made fourteen years ago the general position is probably still true. Furthermore, there is a challenge in generating repeatable habitat mapping (in terms of accuracy (classificatory and locationally disparity) between surveyors / systems and over time that is capable of reliably detecting change (Hearn et. Al. 2011).

Although a collation of existing MCS surveys was undertaken in 2007 (Hill et al 2001, Hill et al 2006), this has not been maintained or incorporated in the PHI datasets despite several other cliff habitats sections having been surveyed in the intervening period. A further collation of the soft cliff surveys from 2001 – 2021 (Haycock and Jay Associates 2021) was conducted from sites from across England, but these different records are not consolidated.

There are also a series of further challenges related to the repeatability of the survey conducted using NVC (Hearne et al 2011), the high prevalence of habitat mosaics within the disturbed cliff environment and also the lack of NVC classes to describe some of the more complex cliff plant communities where a lack of NVC samples has meant that there are no NVC community types described and where various 'derived' classes have been used. This is particularly compounded by the underrepresentation of soft cliff assemblages by the NVC, with spatially limited data being used in their construction.

Furthermore, the extents of MCS surveys that have been undertaken are often inclusive of habitats that are not of PHI quality or community types, merely they are recorded within the extent of the mapping area of interest (i.e. within the 3 maritime cliff zones and based on maritime influence (Ratcliffe (1977) *Maritime, Sub-maritime and Para-maritime).* This is especially the case to cliff top habitats and cliff top grasslands where the transitions may be uncertain. This is the zone defined as 'cliff-top' which was determined by the Ratcliffe (1977) review should extend landward to at least the limit of maritime influence (i.e. limit of salt spray deposition), (Rees et al 2019). These three Ratcliffe's zones "Sub-maritime: (less direct effect of sea with soils still more saline than those inland) and Para-maritime: zone (in which special climatic conditions of sea coast are influential but soils not saline and halophytes not present)". Whilst the inclusions of these habitats may be for good reason, especially in terms of where coastal change may affect areas behind current cliff systems and transitions between vegetation types, they may not currently represent qualifying features of MCS as a semi-natural habitat of PHI status. This may not be an issue where there are other

PHI habitats and surveys that can recategorize these areas, but run the risk of over-estimating MCS where there are non-PHI or no effective habitat data. Therefore, being inclusive of adjacent areas in the habitat mapping becomes useful.

These survey challenges were reviewed within the earlier Maritime Cliff and Slope inventory undertaken by GeoData Institute, (ENR 426 2002) and the subsequent Inventory (GeoData 2007), but the source data survey method(s) for assessing extent and condition of maritime cliff habitat used predominantly ground-based surveys with aerial imagery, remote binocular based assessment of inaccessible sites and a protocol for integrating the data into the OS MasterMap parcel structure derived and PHI inventories. Since that report and inventory data (now 15 years old, and longer if one considers the dates of the secondary surveys incorporated into the inventory) the capability of Earth Observation (EO) sensors / Uncrewed Aerial Vehicles (UAV) sensors, remote airborne and UAV-based Light Detection and Ranging (LiDAR) has increased dramatically the potential to collect data from hard to survey locations, with greater spectral, spatial, and temporal resolution, and with the availability of related terrain data (LiDAR and Structure from Motion (SfM) processing). Furthermore, the advances in image processing and machine learning based capabilities to make best use of these data volumes has enhanced the ability to discriminate and map features of interest. A comparison of different survey methods and their spatial extents and resolutions, as well as barriers to implementation, can be seen in Figure 2 of Tomsett and Leyland (2019).

Cliff domains are often inaccessible, unstable and difficult to observe from land, making pervasive ground-based survey of the resource impractical. Their dynamic nature, both in relation to sea-level and wave-driven erosion, and cliff instability and seasonal to annual changes in ecology, means that there is a need for regular monitoring of cliff morphology and land cover (in relation to bare earth and flora) (Leyland and Darby 2008 and 2009). Whilst UAVs and other remote sensing techniques offer a potential solution in relation to the accessibility of these sites, other difficulties present themselves. For example, in relation to satellite and airborne imagery, the vertical nature of cliff features often mean that sites are not fully measured. Satellite imagery itself has the ability to identify changes at temporally relevant resolution, i.e. across seasonal and annual timescales. However, these are fixed intervals that cannot be modified and frequently suffer from cloud cover at both high and low levels. Typically, satellite imagery will struggle in coastal regions, not only due to the vertical nature of cliffs and slopes, but because of the small spatial extent they cover between sea and inland often meaning satellite imagery pixel sizes are not sufficient to capture the required detail. Newer constellations such as Planet and Airbus imagery allow for much higher resolution imagery, however there is a financial cost involved for acquiring such images.

These environments are also challenging for traditional UAV surveys, which rely on the operator being able to place and accurately survey (e.g., using GPS) Ground Control Points (GCPs) which are essential for accurate reconstruction of topography using SfM (Tonkin and Midgley, 2016). Furthermore, SfM techniques have been shown to be poor for accurately characterising vegetation structure (Cook, 2017; Dietrich, 2016). The fact that some cliff units will be heavily vegetated means that SfM alone will not be able to resolve vegetation or the underlying bare earth. This suggests that the use of standard UAV platforms may not be suitable for routine monitoring of cliff topography, leaving them only able to take images that may be useful for identification of species and/or habitat manually via an ecologist (e.g., Strumia et al., 2020). Nevertheless, other UAV mounted sensors may offer further survey potential.

2 Study Objectives

The objectives of this study were:

- **To assess ability to use EO / remote data to assess MCS condition.**
- **Evaluate a protocol for surveys of cliffs (process, costs and procedures)**
- **Secondarily, to generate products that can feed into the Priority Habitat Inventory of MCS**

These objectives were seen as complimentary to other work being undertaken to support the assessment of MCS habitats, and notably the move within Natural England to a Whole Feature Approach in determining favourable conditions (as a separate NE activity led by Louise Denning). The Whole Feature Approach has removed the unit divisions for condition monitoring in favour of reporting on special features across the whole SSSI. The study objectives were focused on using the historic, secondary, and current data to identify the procedures and practices to support priority habitat mapping and condition assessment on MCS.

In a related project, GeoData Institute (Hill, Leyland, Tomsett, 2025) is undertaking a literature review, evaluation and reporting to provide with recommendations as to how to take forward the monitoring of Maritime Cliff and Slope within the context of both the CSM; capitalising on the availability of new survey techniques using Earth Observation data / UAV, new processing techniques, environments, and technologies.

Together these projects should inform the development of the standard survey method(s) for assessing the condition and extent of maritime cliff habitat in England, rather than just the survey on its own. The development of any approaches also needs to be informed by the processing to develop Priority Habitat (PHI) data and update, which are also being undertaken by GeoData, so that emerging MCS approaches, and data outputs are compatible with the new PHI, update procedures and the geospatial data framework to be used for PHI datasets.

Furthermore, the field elements are split into survey in Cornwall and North Yorkshire; ostensibly on hard (Cornwall) and soft cliff (North Yorkshire). Both are needed if a single standard methodology is to be produced from this work, as the requirements for monitoring (via CSM attributes) differ. This will ensure consistency in approaches and to ground the survey in the context of the literature review and assessment.

The evaluation of the suitability of EO / UAV and remote sensed data relies on the ability to discriminate the relevant attributes of the CSM themes and attributes for both soft and hard cliffs (set out in Table 1).

Table 1 CSM Monitoring attributes requirements as the targets for the survey.

THEME	Attributes of cliff class	
	SOFT	HARD
Habitat	Habitat extent	Habitat Extent
Geomorphology	Geomorphological naturalness	-
Vegetation Structure	Zones and transitions	Vegetation, structure, zones and transitions
	Pioneer communities	Vegetation: pioneer communities
	-	Maritime grassland
Vegetation composition	-	Rock crevice and cliff ledge
	-	Maritime therophyte vegetation
	-	Species of grazed maritime grassland
	-	Species of ungrazed maritime grassland
	-	Negative indicator species
	-	Frequency of bracken and scrub
Indicators of local distinctiveness	Notable species	Notable species
	Maritime slope flush communities	-
	Extent and quality of cliff top grasslands	Extent and quality of cliff top grasslands
	Coastal scrub and woodland	Coastal scrub and woodland
	Coastal Heath	Coastal Heath

3 Methodology

To test the methodologies for survey of cliff and slope environments in this project we used three important recent advances in UAV platform and sensor technology to overcome the challenges:

i) use of the latest generation 'direct georeferencing' platforms, which make use of inertial sensors and differential GPS to resolve platform location down to centimetre accuracy, removing the need for a network of Ground Control Points (GCPs).

ii) use of a UAV Laser Scanner which is capable both of characterising vegetation structure and of penetrating through vegetation to measure ground points (Figure 15).

iii) use of multispectral imagery for deriving spectral indices (e.g., red-edge Normalised Difference Vegetation Indices (NDVI)) to aid detection and identification of vegetation

All drone surveys undertaken complied fully with Civil Aviation Authority (CAA) regulations see section 3.2 and Appendix A (typical risk assessment).

3.1 Survey Locations and base data

Site selection was undertaken in consultation with the project officer and reserve managers (and local teams, to secure permissions and to assess any constraints (e.g. overwintering birds etc). Criteria for site selection included availability of existing and recent geospatial habitat mapping, availability of images (aerial and airborne LiDAR data) and accessibility / permissions to survey the sites and the distinctive geology between locations. Additional considerations included the protected status.

Two sites of approximately 400m each were chosen in Yorkshire and Cornwall and extending up to c 50m inland. The coverage was to be sufficient to encompass a range of MCS habitats and cliff top areas to provide the basis for extrapolation of the survey requirements to English cliffs.

3.1.1 Yorkshire section: Reighton / Speeton Sands

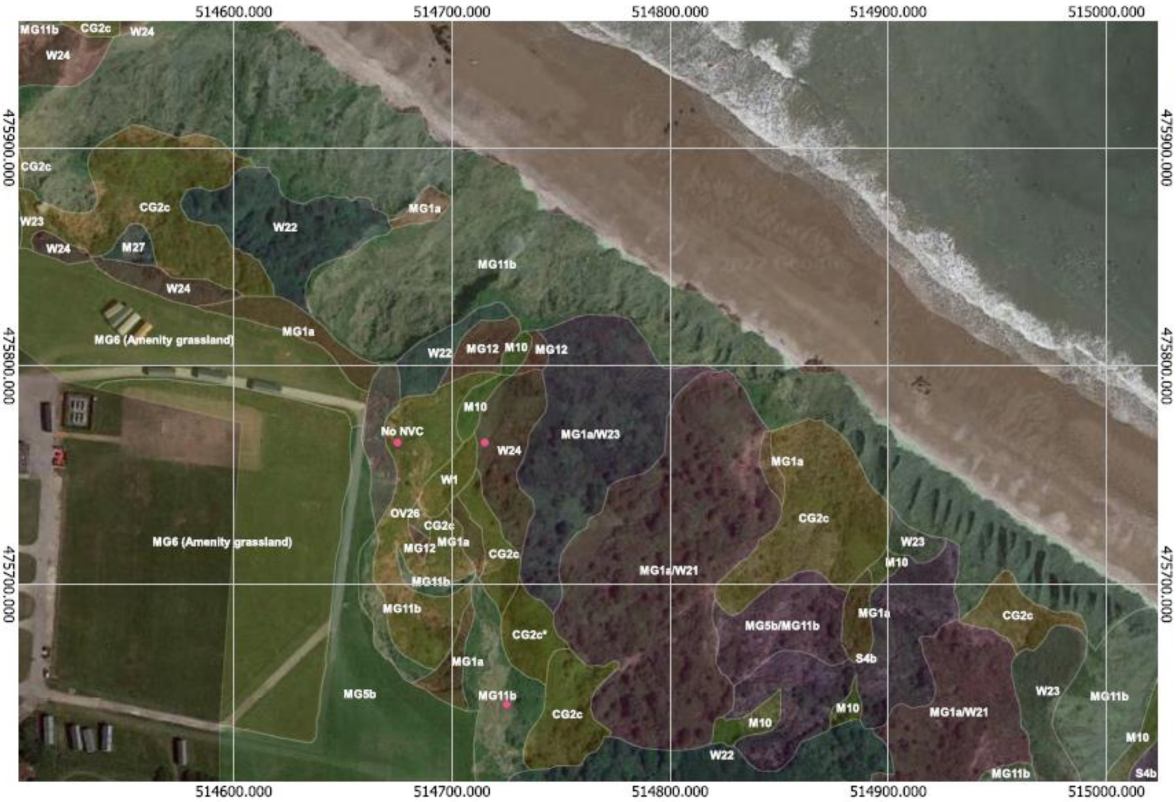
The sites selected include sections of eroding soft cliff that is a part-vegetated landslide complex developed in glacial tills. These cliffs are actively eroding through a series of relatively large rotational failures.

Natural England commissioned a vegetation survey (traditional visual condition assessment using aerial photography, remote viewing, and ground truthing) over the summer 2021 (Haycock and Jay Associates) as a repeat of previous survey carried out in 2012/13 (by the same surveyor) undertaken as part of SSSI extension assessment. Data were collected to NVC classes (Rodwell ed. 1991a,1991b, 1992) (where possible) and used a mixture of on-site and observation where access was impossible. These surveys do not mention the use of existing aerial photographic coverage within the survey area, but this is assumed although it is uncertain whether the aerial coverage used is contemporary with the survey – especially as some areas of cliff top vegetation transitions are not represented. Examination of the GIS data also showed a few misidentifications or misattributions of the habitat classes within the 2021 Reighton / Speeton survey.

There are earlier surveys of cliff vegetation and of coastal change prediction for the Flamborough to Scarborough cliffs from 2002 (Milliken and Pendry 2002) and surveys undertaken by Radley and Rogers 1995[1].

Figure 21 Presentation of the Haycock and Jay 2021 NVC data over the coastal monitoring orthorectified aerial photographic data from the National Programme of Regional Coastal Monitoring (coastamonitoring.org). These maps were used in the field to validate the coverage of the NVC geospatial datasets.

The vegetation of the Speeton Sands / Reighton Cliffs is characterised as a mosaic, and several of the mapped habitats are considered not to coincide with established NVC communities due to the poor representation of such sites within the original NVC sample datasets. Thus, areas are frequently mapped as community mosaics which "is compounded by the process of two-dimensional mapping of a three-dimensional surface upon which two or three vegetation types often intergrade (i.e. down the cliff) within a relatively small area" (Haycock and Jay Associates 2013). This is especially true in the early successional habitats of the Reighton / Speeton coast has been mapped as AG**: Agrostis successional vegetation – as not occurring in the NVC community classes. There are other communities that have



been mapped differently in the different surveyed dates, yet probably do not represent a change in habitat but rather a change in interpretation of the habitat (e.g. (Radley (1995) classified an area as CG6a *Avenula pubescens* grassland ￼￼Milliken and Pendry (2002). classified this as PB** Calcicolous grassland on slopes below the pillbox near Old Beck, which they considered poor fit to the established NVC classes.

The cliffs are a complex land slip (Lee 2014) and at Reighton the estimates of cliff top retreat over the 50 yr extrapolation are: Lower Bound Estimate: 10m Upper Bound Estimate: 20m, NCERM Estimate: 10-20m. Recent reporting (Lee 2025) indicates Scarborough Borough Council monitoring rates for 2008-2020 for Speeton was 0.01-0.11m/yr between 2008-2020. The Filey Strategy study (Halcrow 2002) undertook surveys of the long-term recession rates using historic map analysis and Profile 118, Reighton Cliffs

(1893-2000) gave cliff top recession rates of 0.17m/year. The North East Coastal Group cliff recession measurements: Scarborough to Filey (from Halcrow, 2013) undertook direct measurements of cliff top against a coastal baseline suggesting recession at Reighton (2008-2013) of 0.02 – 0.04 m/yr. These rates are for Reighton rather than directly at the Speeton Cliff surveyed so may differ but are on predominantly the same geology and alignments. The cliff slope is characterised by a series of rotational slips and recent failures, which are represented in the habitat mapping as bare ground or early successional vegetation communities.

The Haycock and Jay 2021 data includes a series of mosaic habitats.

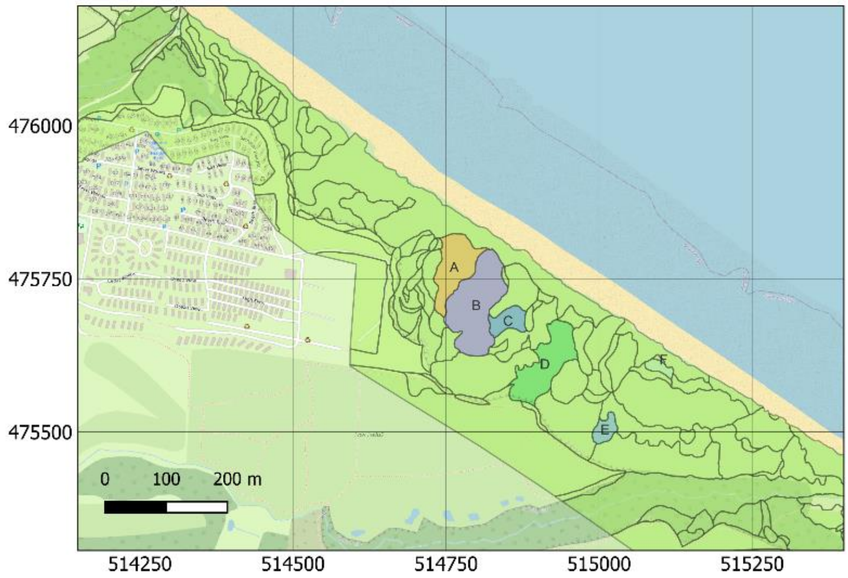


Figure 2 Map of habitat boundaries and mosaics within the Haycock and Jay 2021 survey datasets. NVC mosaics and percentage occurrence.

A: MG1a/W23 60/40
B: MG1a/W21 70/30
C: MG5b/MG11b 80/20
D: MG1a/W21 70/30
E: CG2c/W23 60/40
F: MG1a/W21 70/30

Within the context of mapping a site the first step may be the collation of the existing base data, existing classification, and habitat mapping. Table 2 highlights the datasets and mapping available for the Speeton site.

Table 2 Available imagery / data: Speeton, Yorkshire

Dataset	Date/s
Orthorectified aerial	2021, 2019, 2017, 2010, 2008
Lidar	2019, 2021, 2016, 2014, 2012, 2009
False-colour infrared imagery	2017, 2019, 2021
Habitat mapping (Regional Coastal Monitoring Programme Habitat surveys - RCMP)	2017-19

The RCMP habitat mapping data distinguishes maritime cliff and slope but separately identifies scrub that would form part of that mosaic within the MCS PHI as a separate class. This also occurs for other habitats mapping that uses the IHS classification system.

3.1.2 Cornwall Survey: Mullion Cove

A 400m stretch on the west side south of Mullion Cove was selected as a hard cliff geology and are listed as grade A/B SACs for H1230 Vegetated sea cliffs of the Atlantic and Baltic coasts ([The Lizard Cornwall and Isles of Scilly]() SSSI). The Mullion Cove cliffs are of magnesium-rich serpentine and hornblende schist hard rock geology and are part of the Lizard National Nature Reserve, managed by the National Trust. Lizard sites are also part of

Natural England's Long-term Monitoring Network (LTMN) and includes field survey data including vegetation quadrat data from 2013, 2017 and 2022, and supports a complex sequence of cliff vegetation with maritime heath and grassland. [LTMN The Lizard NNR - target habitat heathland - LTMNB40 (naturalengland.org.uk)] there is an excel file for 2022, 2017 and 2013 habitat quadrat data for 54 sites that covers both Mullion Cliff to Predannack Cliff SSSI and West Lizard SSSI.

Recent habitat survey of these sites is available as NVC (Bennallick, Ian and French Colin (2021) and available as GIS files. This is a novel approach to resurvey that uses the existing polygon structure from past surveys, added attributes to the GIS table to record the history of change and where necessary split and/or changed polygons to assign new NVC codes. This data builds on the earlier survey of the locations, basing its polygon structure at least partly on the structure of the features mapped previously by Byfield and Hopkins (1979) and Close (1990) and the structure of the data includes the earlier reference within mapped features.

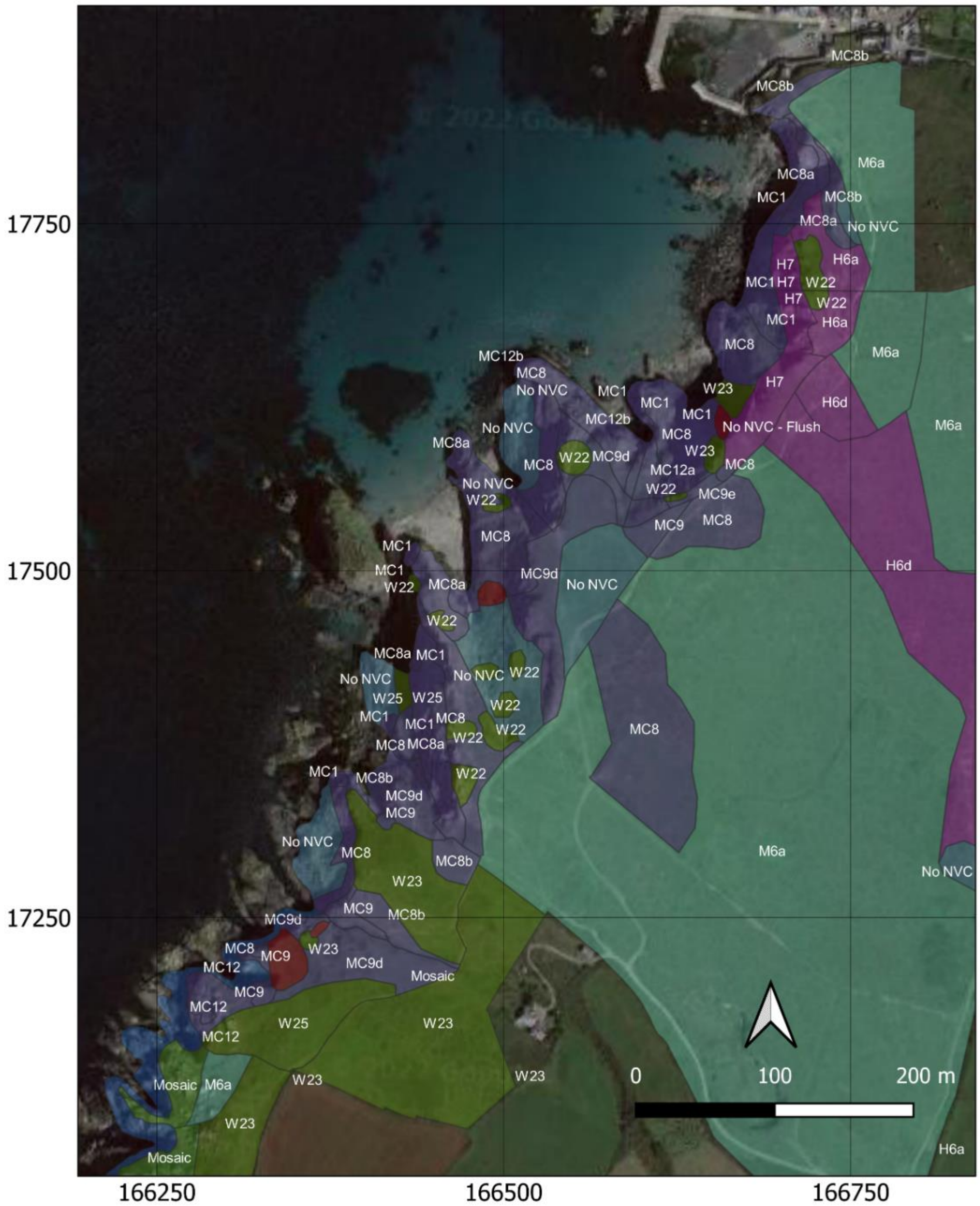


Figure 3 Habitat mapping to NVC (where possible) at Mullion cliff line, Cornwall, UK (Bennallick and French (2021))

The site is in Cornwall Area of Outstanding Natural Beauty, previously known as 'Mullion Cliffs to Predannack Head', partly a Biogenetic Reserve, partly within the Lizard National Nature Reserve, part owned by the National Trust. The site is a mix of heathland and maritime grasslands and with rock crevice communities lower down the cliff profile and coastal wetlands cliff flush communities.

Table 3 Available imagery / data Mullion Cove

Dataset	Date
Orthorectified aerial	2012, 2018
Lidar	2018 -19, 2010 -11, 2007 -08
False colour infrared imagery	2018, 2012
Coastal Vegetation Bennallick, Ian and French Colin (2021)	2017, 2021

Datasets from the National coastal monitoring programme also include a coastal vegetation mapping, but the results are very different from the NVC datasets and many MC communities and clifftop MCS habitats are missing from the survey. Access to the historic data would resolve this before undertaking the field surveys (including for the national monitoring).

The most recent surveys were conducted by remote view and field surveys. Similar to the Reighton surveys there are a number of polygons described as mosaics (two classes) and also habitats that do not correspond to NCV communities (classed as 'no NVC'). Inaccessible cliff was all classified as MC1 NCVC community but may include bare ground / bare rock. In addition, the survey noted that the were some transcription errors in converting the Byfield and Hopkins survey to digital form; some of the habitat polygons were attributed incorrectly and some deleted.

3.2 Pre-departure flight planning:

Environmental Sensing at Southampton (ES@S) flight planning protocol involves checking for flight restrictions and NOTAMs (NOTice To AirMen) ahead of the planned flights and incorporating any further information into a risk assessment for flying (see Appendix A for exemplar RA). In the case of Mullion Cove, restrictions due to the Navy airfield (RNAS Culdrose) meant that permissions were required from the airfield in order to unlock the built in DJI flight restrictions. This unlock procedure is carried out via a DJI web interface, whereby the permission letter is uploaded, and a polygon flight area defined for the required window of operation.

All equipment is checked, and batteries charged prior to departure for the field in accordance with our standard operations manual.

3.3 UAV aircraft and sensor packages used for these trials:

3.3.1 DJI M300 RTK with TopoLidar 100

This M300 RTK platform is an enterprise level quadcopter which is capable of >30 minutes flight time with the TopoLidar sensor payload attached. It has multiple failsafe features, including collision avoidance sensors. The TopoLidar sensor combines a Velodyne Puck Lite laser scanner with a high precision Inertial Motion Unit (IMU) and an L1/L2 GNSS receiver. It has a detection range of ~100 m and weighs less than 1 kg.

Figure 4: The DJI M300 RTK UAV with TopoLidar 100 sensor payload.

3.3.2 DJI INSPIRE II with modified X4S direct georeferenced camera

The Inspire II platform provides a fight time of around 27 minutes with the X4S camera attached. It is a very lightweight platform, suited to rapid deployments in remote areas. The X4S camera is a standard RGB (Red, Green, Blue) 1” CMOS sensor, with a mechanical shutter (which is preferable for the collection of aerial imagery for the purpose of creating high resolution models and orthomosaics).

Figure 5: The DJI INSPIRE II UAV with modified X4S direct georeferenced camera payload.

3.3.3 DJI M600 Pro with MicaSense RedEdge MX and Applanix APX15 INS.

The MicaSense RedEdge-MX is a five-band multispectral camera, with wavelengths ranging from blue to infra-red (see Table 4), including a red edge band designed to enhance separation between different vegetation characteristics. The post-processed positional and orientation accuracy is typically between 1-2 cm in the X and Y planes, 2-5 cm in the Z plane, and 0.1 degrees in orientation. This setup is mounted to a heavy lift, multirotor UAV, in this case a DJI M600 Pro. Although this is the current UAV being used, smaller UAVs with a lighter payload capacity could also be used. For a very detailed overview of the setup, see Tomsett and Leyland (2021).

Table 4: The waveband characteristics of the MicaSense RedEdge-MX multispectral sensor.

Band	Wavelength (nm)	Band Width (nm)
Blue	475	32
Green	560	27
Red	668	14
Red-Edge	717	12
Near Infra-Red	842	57

Figure 6: The DJI M600 Pro UAV with Micasense RedEdge MX (inset image) and Applanix APX15 INS payload.

3.3.4 GNSS equipment

In addition, raw RINEX GNSS data was recorded throughout all days of operation on a REACH RS2 unit and a Leica GS15 base station.

Figure 7: GNSS equipment consisting of a Leica GS15 (left) and Reach RS2 (right).

3.4 Mission planning and data collection:

3.4.1 DJI M300 and TopoLidar

All TopoLidar missions were planned using Universal Ground Control Station (UGCS), which is commercial software that is capable of planning and uploading missions to DJI aircraft (see Appendix B – Software). There are currently no freeware mission planning applications that have this level of functionality for UAV based LiDAR.

Mission planning in UGCS consists of using the area scan tool (Figure 8) in conjunction with take-off, landing and any inertial initialisation routines. For the TopoLidar sensor, a figure of eight (Figure 9) is flown prior to the survey to initialise the accelerometers ready for navigation.

Figure 8: UGCS mission planning for a flight at Mullion Cove.

Figure 9: Detail of the inertial navigation system (INS) initialisation procedure planned in UGCS, consisting of a clockwise and anticlockwise circular flight path (highlighted in the red box).

3.4.2 DJI Inspire and X4S

Mission planning for the DJI Inspire was undertaken in DJIs own surveying app, Ground Station Pro. This automatically detects the camera being used by the UAV, and for a given manually drawn survey area will calculate flight lines based on the front and side overlap specified. The flight height of the UAV can also be adjusted in order to match the desired ground resolution requested, enabling control over the survey design both pre-deployment and whilst in the field.

Once designed, the route can be uploaded to the UAV and flown autonomously, with the camera triggering automatically and the precise timestamp of each photo recorded in the on-board GNSS sensor for post-processing.

3.4.3 DJI M600 Pro and MicaSense RedEdge MX

Missions planning for the DJI M600 pro was again undertaken in DJIs Ground Station Pro. However, due to the camera not being integrated with the UAV, flight planning requires more manual involvement (note, recent advances in technology mean this is a more fluid and integrated process now). For this setup, manual flight lines are drawn with elevations relative to the take-off height set for each waypoint. The separation between these waypoints is determined by the user, with MicaSense providing an online calculator for identifying the flight line separation needed based on flight height and overlaps.

For each survey, a series of parallel lines were drawn with a separation of 20 m to ensure a minimum of 50% side overlap, and a flight speed set to allow at least 80% forward overlap based on a 1.5 second triggering interval from the camera. Flights were designed to capture imagery at the top of the cliffs, the cliff face, and the base of the cliffs, to get a good final model of the survey region. The flight height of the UAV was adjusted for each survey line to maintain as consistent ground resolution as possible. The flight heights varied between 30 – 50 m above ground level depending on the steepness of the cliff (a variation in pixel size of 1.3 – 2.1 cm).

Prior to survey, a sensor is connected to the camera which monitors incident light, so changes in lighting conditions can be accounted for in the image processing. In conjunction with this, a calibration panel is paced on the floor and a picture of the panel taken from the UAV when hovering above. This panel has factory calibrated reflectance values which can then be used to adjust the images so that any comparison made between different camera systems is consistent.

3.4.4 Comparison of flight parameters and outputted data

The various flight parameters used for each of the platform and sensor combinations can be seen in Table 5. Note, whilst RGB imagery and LiDAR data was obtained at both sites, Multispectral imagery was only obtained at Mullion due to weather constraints at Reighton.

Table 5: Flight parameters for each of the UAV and snsor combinations. Note that ground resoltuion for UAV LiDAR is not a pixel size, but the average seperation between two points on flat ground.

Location	Date	UAV and Sensor	Flight height (m, AGL)	Area (ha)	Flight speed (ms^{-1})	Ground Resolution
Reighton	10.03.22	M300 TopoLiDAR	50	35	5	
Reighton	11.03.22	Inspire X4S	45	8	5	1.2 cm pixel
Mullion	16.03.22	M300 TopoLiDAR	50	10	5	
Mullion	17.03.22	Inspire X4S	80	10	5	2.3 cm pixel
Mullion	17.03.22	M600 Multispec	50	15	5	5 cm pixel

Flight heights are set to optimise data collection and ensure enough overlap of images for post-processing and that each area of the ground is in view of two Lidar scans. All flight heights reported in Table 5 are Above Ground Level (AGL; as opposed to Above Mean Sea Level), see Figure 10.

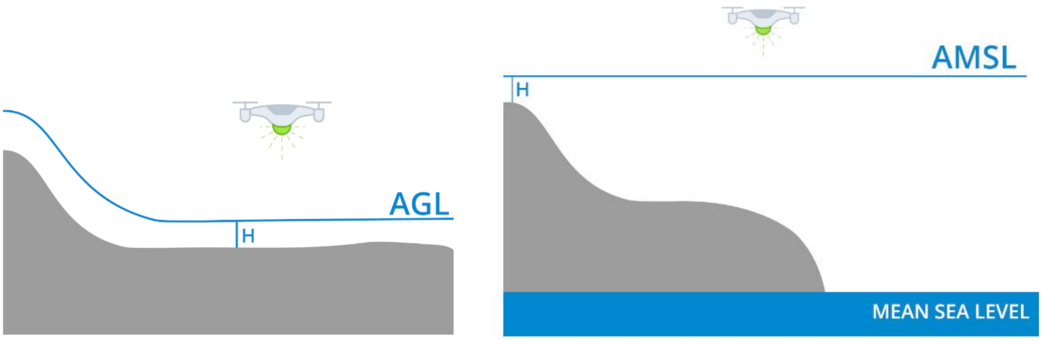


Figure 10: Height modes available in UGCS mission planning. AGL was used for this work.

3.5 Data Processing:

3.5.1 MicaSense RedEdge MX

UAV images were downloaded from the camera after each flight. The images of the calibration panel were separated from the remaining photos, to be used in the calibration procedure.

The positional data from the on-board inertial motion unit was downloaded, and then imported alongside the post processed base station data into the positional post-processing software PosPac UAV (see Appendix B: Software used in the assessment). The position of the raw UAV data is then updated using forwards and backwards Kalman filtering algorithms to obtain a refined UAV track, and an updated location for each image capture timestamp is then produced.

Each image timestamp is used to provide reference information for the photos imported into the image post processing software Agisoft Metashape. Each image has its position updated by matching the time of imagery from the image metadata, and the time in the position files. This updates the camera locations within the software, and positional accuracy was set to 10 cm and rotational accuracy to 1 degree, to allow flexibility when aligning the camera positions.

3.5.2 X4S directly georeferenced camera

The RGB images of the X4S are processed in much the same way as the MicaSense. Images are downloaded along with corresponding GNSS data and then Topodrone geotagging software is used (part of the topodrone processing suite – See Appendix B). The software assigns a geolocator tag to each image. The images can then be imported into Agisoft Metashape. In contrast to the multispectral imagery, there is no orientation data associated with this workflow, only positional data.

3.5.3 Agisoft Metashape processing (for Micasense and X4S RGB images)

For each flight, the imported photos are imported and aligned using feature detection algorithms to identify 'tie' points in multiple photographs, whereby objects can be detected, tracked, and then moved to align them accordingly (known as Structure from Motion, SfM). Once this has been done, a dense point cloud can be produced based on the locations of points within the image that match up with other points in overlapping imagery. This dense point cloud can then be used to make 3D models of a scene, or in this case produce an orthomosaic, which creates one image from the entire study region (Figure 11).

Inherently, the ability to produce good models lies in being able to know where the camera positions are, which is accomplished by the direct georeferencing, and the ability to detect points on the ground in the imagery. The latter in this scenario has proved challenging in certain regions, especially where the topography is varied and there are large areas of shadowing present. This makes it difficult to identify points within overlapping photos, and can subsequently cause poor alignment and scene reconstruction as is seen in places in Figure 14.

Once the reconstruction has taken place, the resultant orthomosaics can be exported and processed in traditional GIS and Remote Sensing software or imported into environments for manipulation with languages such as R, Python, and Matlab.

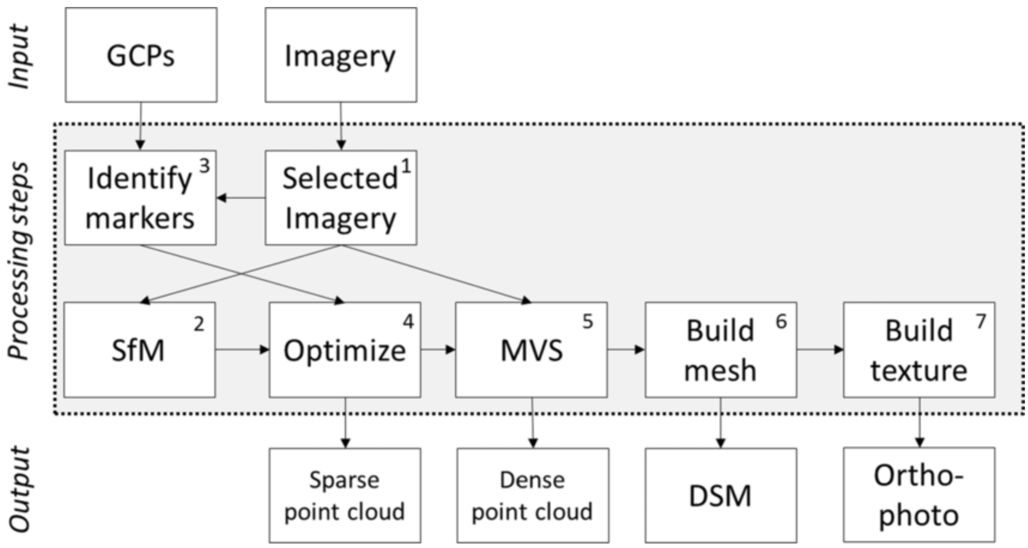


Figure 11: Agisoft Metashape processing workflow (Source: Anders et al., 2020).

3.5.4 TopoLiDAR Processing:

The LiDAR data from the topodrone is downloaded from the sensor after each flight as a zip file. Processing involves using the bespoke Topodrone Post Processing suite (see Appendix B) for the initial two stages. 1) a trajectory file is created by processing the on-board GNSS data from the TopoLidar along with the raw RINEX data from the GNSS base station. The base station position can also be input at this stage, calculated via an online precise point positioning service such as CNRS – see Appendix B). 2) The trajectory file (which includes the pitch, roll and heading data) is combined with the raw laser data to create a georeferenced point cloud.

A third step, Boresight calibration, is then completed in LiDAR360 software (see Appendix B). Boresight calibration fixes errors which result from variations in mounting angles of the LiDAR unit, meaning that the same area on the ground, but measured from opposite flight directions, can have small discrepancies between the points. Table 6 reveals the boresight calibration statistics for the flights undertaken. Note that RMSE are relatively high here due to the vegetation and complex topography captured.

Table 6: LiDAR360 boresight calibration statistics. Heading is typically the hardest aspect to calibrate, hence the larger variations in degree value.

Location	Date	Δ Roll (°)	Δ Pitch (°)	Δ Heading (°)	RMSE pre (m)	RMSE post (m)
Reighton	10.03.22	-1.3638	-0.02258	-1.01907	1.49	0.35
Reighton	11.03.22	-1.2013	0.06705	-1.14006	1.34	0.26
Reighton	11.03.22	-1.1828	0.00694	-0.82896	1.46	0.28
Mullion	16.03.22	-1.2053	0.05919	2.42399	1.03	0.22
Mullion	17.03.22	-1.1375	0.03705	2.37793	0.86	0.16
Mullion	17.03.22	-1.1807	-0.01611	2.3873	0.94	0.19

3.5.5 Machine learning classification

In order to classify the scenes, machine learning techniques were tested by combining a number of different layers of information. This included traditional image bands in the red, green, and blue, multispectral bands in the red-edge and infra-red regions of the electro-magnetic spectrum, and NDVI values from imagery datasets, and topographic information such as slope, canopy height, planarity (smoothness), and roughness (vertical variation) from the LiDAR datasets.

NDVI layers were created from the multi-spectral imagery, utilising both the red-edge and near-infrared channels to create two NDVI layers, maximising distinction between vegetation classes. Topographic datasets were created using the open source CloudCompare (https://www.danielgm.net/cc/) software to analyse the 3D point cloud created using the LiDAR data. Planarity was assessed over a 2 m footprint whereas roughness was computed over a smaller 0.5 m footprint. The reasoning for this was that to identify smooth surfaces with small breaks (such as a cliff), a larger footprint would be required, and to identify areas of high roughness and distinguish the edge of patches of vegetation, a smaller footprint would be required. Slope was calculated after vegetation had been removed using a cloth surface filter (ref) in order to only be using ground points for this aspect.

The classification approach was split into two approaches, one for Mullion and one for Reighton. First, a traditional pixel-based image classification approach was undertaken at Mullion. This uses training data to identify the spectral and structural characteristics of different 'user-defined' regions of the image (e.g. short grasses, exposed rock, water) and then classify the remaining pixels based on this information. Second, an object-orientated approach was undertaken at both Mullion and Reighton whereby instead of analysing images on a pixel-by-pixel basis, it combines pixels of similar spectral values together (such as a rock, or patch of grass) to create individual objects which can be classified. The level of detail of these objects (both spatially in their size and spectrally in their distinction) can be determined by the user.

For the pixel-based and object-orientated based approaches at Mullion, different classification techniques were tested. These included NN (Nearest-Neighbour), SVM (Support Vector Machines), and RF (Random Forests), totalling 6 different classification maps for Mullion. For Reighton, the impact of adding additional datasets for classification was investigated, by using just RGB imagery, RGB imagery and a LiDAR CHM, and finally RGB imagery, a LiDAR Canopy Height Model (CHM), and LiDAR based surface planarity and roughness. These were all tested with a SVM classifier for ease of comparison, allowing exploration into the depth of data collection required for beneficial mapping.

Training datasets were created based on the imagery and from survey notes in the field. This identified a total of 13 classes of data, listed in Table 7. These were determined based on the rough broad classes present in the National Vegetation Classification, with the aim of allowing a field user to update these regions with more detailed information or correct them accordingly. Some classes are only present at one site (e.g. Inland water) or are under the same broad classification name (e.g. Shrub Class 1 is different between Mullion and Reighton), but in reality, represent different assemblages.

Table 7. Classes used to inform the classifications undertaken at Mullion and Reighton Sands. Descriptions indicate both the type of class present as well as details on how they were identified. Example images of these class types can be seen in the Image column for visual distinction. Not all classes were present at both Mullion and Reighton.

CLASS	DESCRIPTION	PRESENT AT
SEA WATER	Areas explicitly containing sea water	Mullion
INLAND WATER	Areas of water not connected to the sea directly in any way	Reighton
CLIFF	This included area of steep bare rock which you would typically class as a cliff face, alongside the rocks at the interface with the sea.	Mullion
EXPOSED ROCK	This differed from cliffs due the orientation of slope and their location, focusing on those above the steeper cliff line.	Mullion
BARE GROUND	Areas of ground with no vegetation presence that was not from exposed rock. Examples of this would be muddy ground or footpaths that have removed vegetation but not exposed rock.	Both
SHORT GRASSES	Grasses which are short in nature, typically grazed or heavily trodden from foot traffic.	Both
LANDSLIDE	Areas (specifically at Reighton) where there was evidence of erosion typically underneath the base of the cliff.	Reighton
LONG GRASSES	Areas where there is lower grazing and/or foot traffic, allowing grasses to grow longer, without the presence of larger vegetation.	Both
NON-VEGETATED GROUND	Sections where vegetation was not present, typically found under the cliff edge. These were not exposed ground, more ground that had no vegetation presence instead.	Reighton
SHADOW	Areas of shadow severe enough that it would not be possible to discern which of the other categories an area fell within.	Both
SHRUB CLASS 1 (MULLION)	Distinguishable areas of vegetation which are taller and different in colour to the grasses at Mullion. These typically from in communities which likely comprise of X (e.g. gorse)	Both (Different Vegetation)
SHRUB CLASS 2 (MULLION)	As above, a distinguishable category of vegetation from which classification can be	Both (Different Vegetation)

	separated from both short and long grasses, as well as the other shrub class.	
TREES	Taller vegetation, clearly identifiable in the canopy height models. These are larger in height than shrub classes and are distinguishable from other vegetation types.	Reighton

4 Results:

4.1 Sensor Specific Outputs

Larger and more detailed graphics for individual outputs can be found in Appendix X, whereby there are also links to online viewers to see the output 2D and 3D datasets for some of the data.

4.1.1 RGB Imagery

The DJI X4S RGB imagery SfM output delivers a fully coloured point cloud with spatial referencing errors (as quantified from check point Ground Control Points; GCPs) of <0.1 m in the X, Y and Z directions, as seen in Figure 12. The main points of interest here are the level of detail provided by the imagery as well as some associated topography, including areas of accumulation below the cliff from recent slips as well as the variable colouring from different vegetation types. The structure of these point clouds can also be used to create continuous orthoimagery of both sites, as can be seen in Figure 13. These datasets have resolutions of approximately 2 cm, providing a continuous basemap upon which further data analysis can be performed, or for use in mapping exercises either I the field or manually within mapping software such as QGIS or ArcGIS.

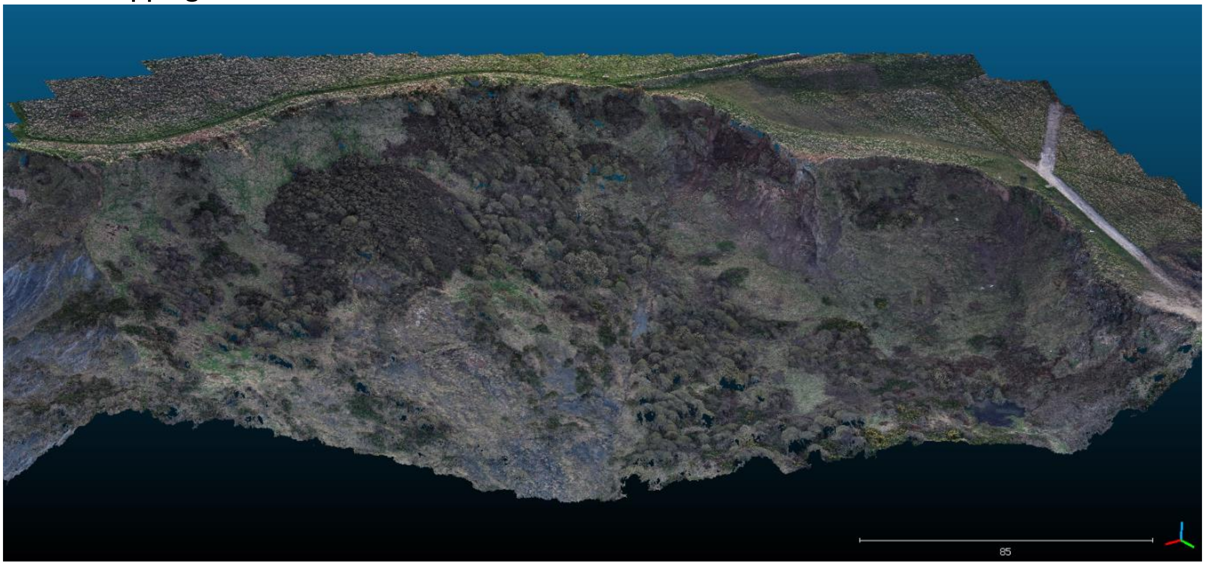


Figure 12: SfM output from Reighton, showing the ability of the software to build out accurate topography, but with a tendency to smooth features and lacking penetration through vegetation.

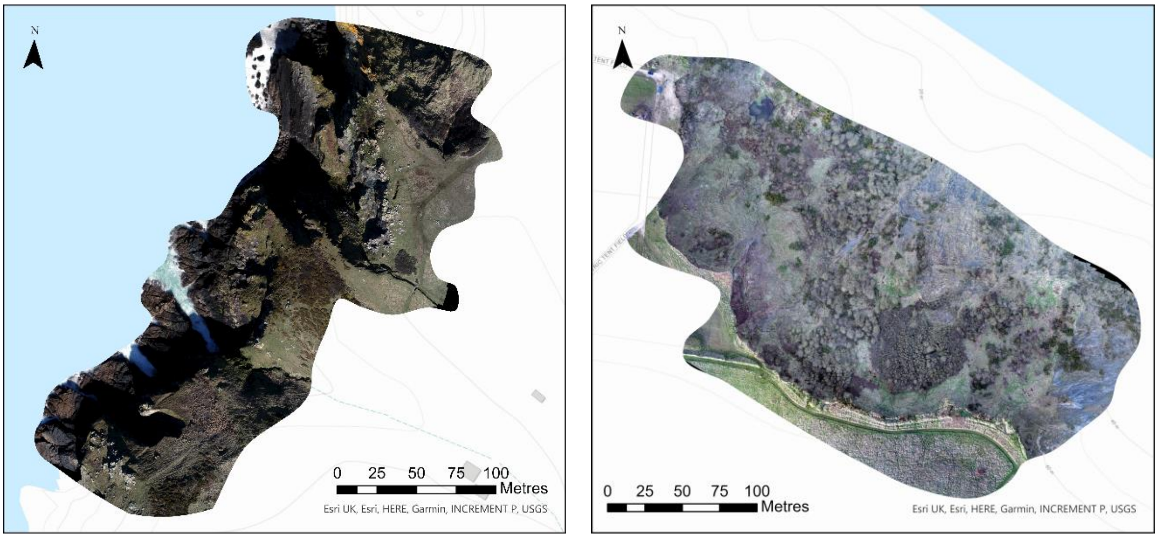


Figure 13. Orthomosaics outputs from Reighton (left) and Mullion (right), with a further panel highlighting the detail of the final datasets resolution.

4.1.2 Multispectral Imagery

In contrast to the above, the SfM outputs for multispectral imagery do not produce fully coloured point clouds at present. However, they do produce 5-band orthomosaics which can be used in the traditional spatial mapping software outlines prior.

The MicaSense produces a composite raster image which includes the red-edge and near infra-red bands, which are sensitive to aspects of vegetation type and health (e.g. chlorophyll). These can be seen in Figure X below, showing the reconstruction of the coastline at Mullion.

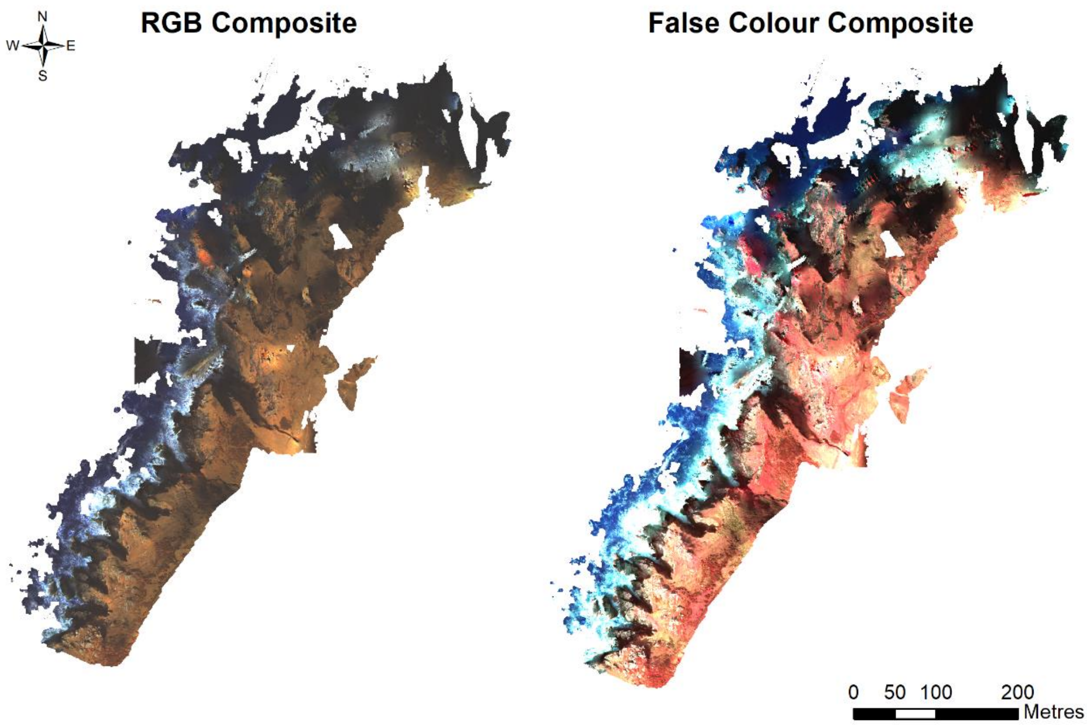


Figure 14: Orthomosaic of the Mullion Study Site (left) and False Colour Composite (FCC) comprising of the Infra-Red, Red, and Green wavelengths.

The coastline at Mullion has been reconstructed well on the whole, with large areas of cliff top visible as well as the cliff face sections moving down towards sea level. However, at the same time, towards the North of the site, and especially clear in the FCC image, there has been poor image alignment which has failed to distinguish clearly the transition from cliff top to sea, and resulted in parts of the cliff being missed or in some case duplicated in the imagery. This is most likely due to the sun's position during the spring surveys causing significant shadowing in this area, especially parts with North-facing slopes, as well as various image resolutions during acquisiton despite attempting to control for this during the mission planning phase. In contrast, the southern end of the study area is reconstructed to a higher standard, producing a much better final model, as seen in Figure 14.

4.1.3 LiDAR

The LiDAR surveys undertaken produce a full georeferenced point cloud which can be used to both interrogate the structure of vegetation above the surface, or have the vegetation removed to leave only the surface morphology. This is especially important at Reighton Sands where the structure of the vegetation is more variable and complex, meaning to both help identify different types of vegetation and determine the underlying morphology, LiDAR can be an effective tool. Examples of these outputs can be seen in Figures 15-18 below for both Reighton Sands.

4.2 Data Analysis

4.2.1 Introduction

Data analysis has sought to explore various element of the CSM Monitoring attributes requirements that include variables including habitat, geomorphology, vegetation structure, Vegetation composition and indicators of local distinctiveness (see Table 1). The analysis reported here includes the 3D vegetation extraction [4.2.2] (vegetation structure), habitat classification [4,2.3]. The geomorphology (cliff change analysis) is widely reported in other studies and the indicators of local distinctiveness are primarily specific habitat classes (other than the presence of notable species).

4.2.2 3D Vegetation Extraction

Much of the analysis below is built upon work undertaken within Tomsett and Leyland (2023), which seeks to characterise the complexity of vegetation structure. It predominantly focusses on Reighton Sands due to the variability in vegetation type and structure, but the same processes were used to extract bare earth and canopy height models at Mullion.

To segment points that are likely representing the ground surface, and those that are reflections from vegetation or other surface features, a CSF (Cloth Surface Reconstruction) is performed within the CloudCompare environment (Zhang *et al.*, 2016). In principle, this inverts the point cloud and drapes a cloth over the scene to extract the underlying terrain, with the user able to adjust the resolution and 'flexibility' of the cloth depending on the complexity of the surface. Such analysis will also benefit those looking beyond vegetation assemblages, for example geomorphologists mapping slope features and processes, making the data acquisition more economically justifiable.

Once undertaken, points that are deemed to be within a user define threshold limit of this cloth are counted as ground surface points, and those outside this threshold as non-ground points. In this case, non-ground points are likely to be from vegetation. The resultant classification of ground (brown) and non-ground (green) points can be seen in Figure 15.

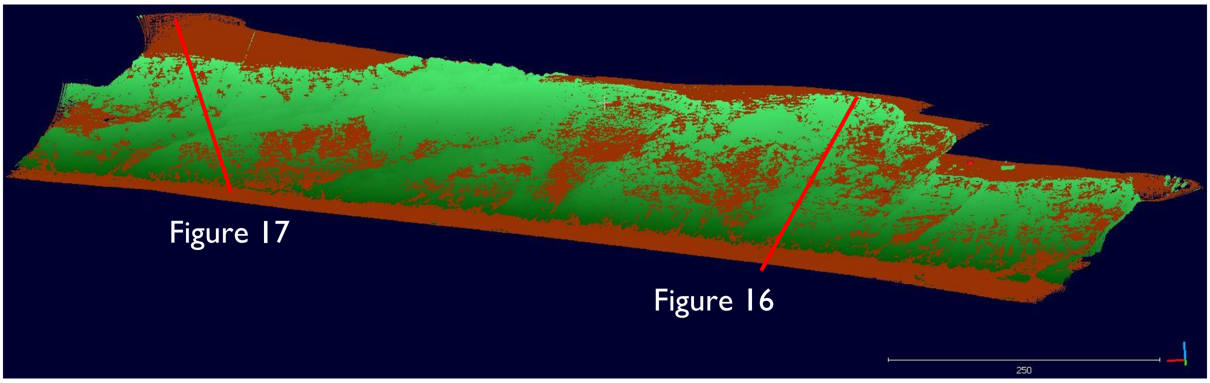


Figure 15: Output from a Cloth Surface Reconstruction to segment bare earth and vegetation. Points displayed in brown represent the surface, and those in green represent vegetation. Red lines mark the approximate locations of the transects shown in Figures 16 and 17.

From Figure 15 alone, it is hard to visually gain an understanding of classification performance, as large swathes of green are present obscuring the ground points below. To assess this in more detail, two transects are shown below, one down the cliff perpendicular to the shoreline (Figure 16), and a second across a vegetated gulley feature were extracted (Figure 17).

Figure 16 clearly shows the changing slope of the cliffs, and if all vegetation points were to be removed could be used to measure slope and pick out break points in the elevation and where risks of erosion/slumping may occur. It could also be used to relate the presence of vegetation to changes in erosion risk by comparing slopes of comparable steepness in vegetated and non-vegetated regions, as well as looking into how vegetation type and function may influence this also. However, at the cliff toe, it is clear some ground points have been classified as vegetation, where the cloth surface used to filter out these points has been too inflexible. The scalability of such approaches to examine the relationship between vegetation and slope is yet to be fully realised, but is an area of future research that may benefit a number of stakeholders.

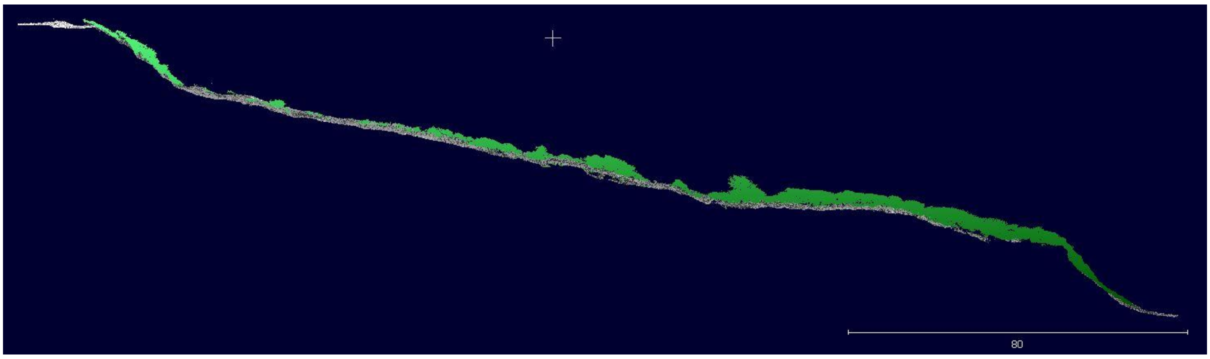


Figure 16: Cross section through a more sparsely vegetated section of the cliff.

Figure 17 shows a very different profile, with a clear outline of the vegetation structure within the gulley, picking out both the canopy layer, below plant structure, and the gulley floor. The clear advantage with this data is the ability to reconstruct individual vegetation models, helping with possible species identification, extraction of vegetation properties, and linking to slope stability or habitat models. The clear benefit is also shown in the second panel of this figure, whereby the different first and last return data is shown highlighted in yellow and blue, with the last returns picking out extra detail in the canopy that would have otherwise been missed. This sort of extraction would not be feasible with imagery alone, as not enough camera angles are available to fully reconstruct each piece of vegetation, and it is not possible to 'see' through a fully leaf-on canopy. The effect this has on CHM construction is outlined in section 4.2.2.2.

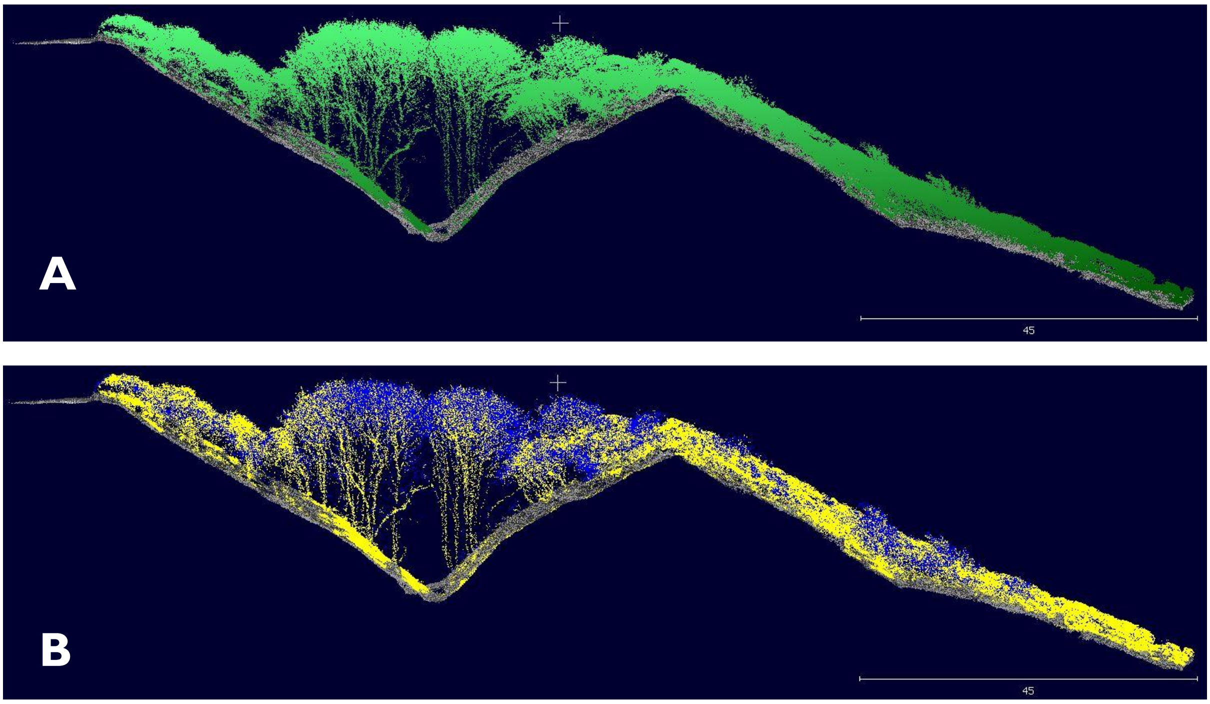


Figure 17: (A) Cross section showing vegetated vs ground points across a gulley (B) First and last returns highlighted in yellow (first) and blue (last), demonstrating the power of laser scanning in vegetated environments.

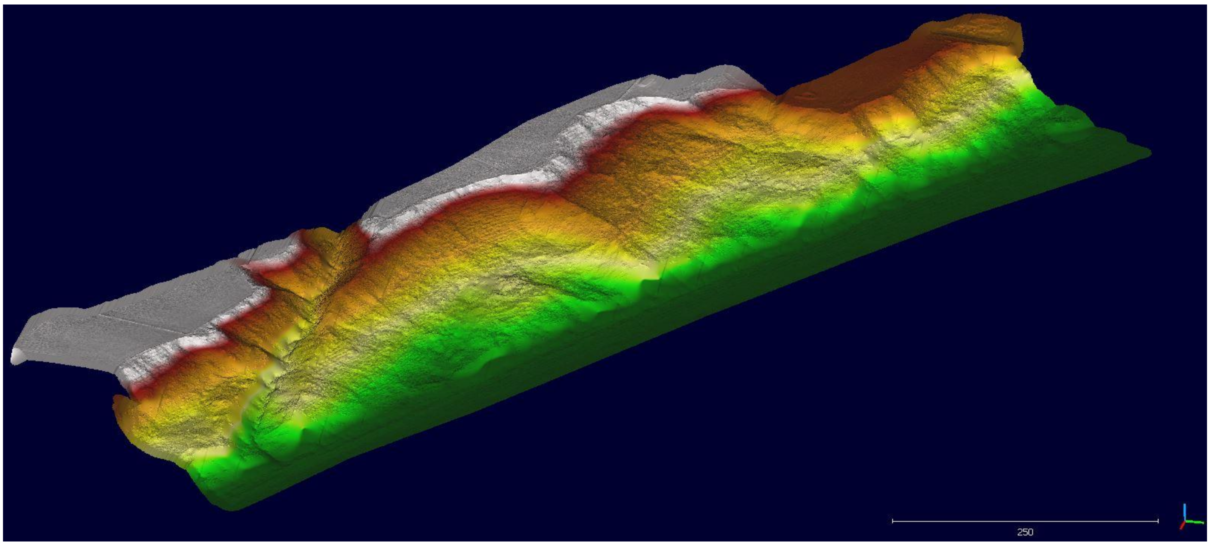


Figure 18: Terrain (DTM) for the Reighton study area, showing the form of the cliff slope and the beach at Speeton Sands, the valley bisecting the cliff line (Old Beck) and the two / three cliffed embayments of Black Cliff, Middle Cliff and

New Closes Cliff (as described in the first edition OS 1:25 inch mapping) from left to right in the image. The prominent ridge between the Black and Middle Cliff was termed the Black Cliff Nab.

Finally, the result of undertaking this classification is that those vegetation points can be removed to produce a detailed 3D surface of the study area, which can be used in a variety of applications, from mapping to modelling. An example of this surface for Reighton is shown in Figure 18, where the changes in slope gradient and angle vary widely throughout the study area, and would be missed through SfM alone. This suggests that not only does it have benefit for habitat mapping, but also geomorphological surveys as well.

4.2.3 Habitat Classification

As noted in 3.5.5, it is not possible with these datasets to classify the areas of interest at both sites fully down to NVC classification standards, and would also require a large campaign of data corroboration on the ground (see comments in Section 5). However, obtaining base level classifications of broad habitat types, and increasing specificity where possible, could help to expand coverage and also supplement in-field workflows. The following sections review the performance of the classifications undertaken at Mullion and then Reighton Sands, before synthesising the general patterns which can be seen in both.

4.2.3.1 Mullion Classification Analysis

The outputs from performing several different classification types can be seen in Figures 19 and 20, whereby the former shows the classifications over the entire reach, whereas the latter demonstrates the classifications over a smaller zoomed in subsection along one of the cliff edges. It is worth noting, that although some data was collected on the types of vegetation present, a full ground corroboration dataset was not collected and so the accuracy of the outputs cannot be determined beyond that of visual comparisons to the orthoimagery. This applies to both the Mullion and Reighton classifications.

Of note here is the differences obtained in output classifications both between pixel-based and object-oriented methods, as well as those between the various classification procedures employed. The clear difference between pixel and object-based approaches is the visual interpretation of the results. The object-based approach as expected provides a visually easier to interpret image with larger areas of homogenous classifications, creating defined zones of habitat. This is in contrast to the pixel-based approaches, whereby a more granular classification can lead to an excessive ‘salt and pepper’ effect which in turn leads to a number of classified pixels being encased by a different class. Whilst entirely plausible, this is more likely to occur due to an overlap in class definitions (i.e. similar spectral profiles) then real habitat composition. To eliminate such effects, a series of smoothing operations based on the spatial attributes of homogenous areas would be undertaken, which would involve making assumptions around likely minimum sizes of each class. Object-based approaches attempt to overcome this by grouping similar areas prior to the classification procedure, although as a result some of the more complex habitat mosaics may be missed.

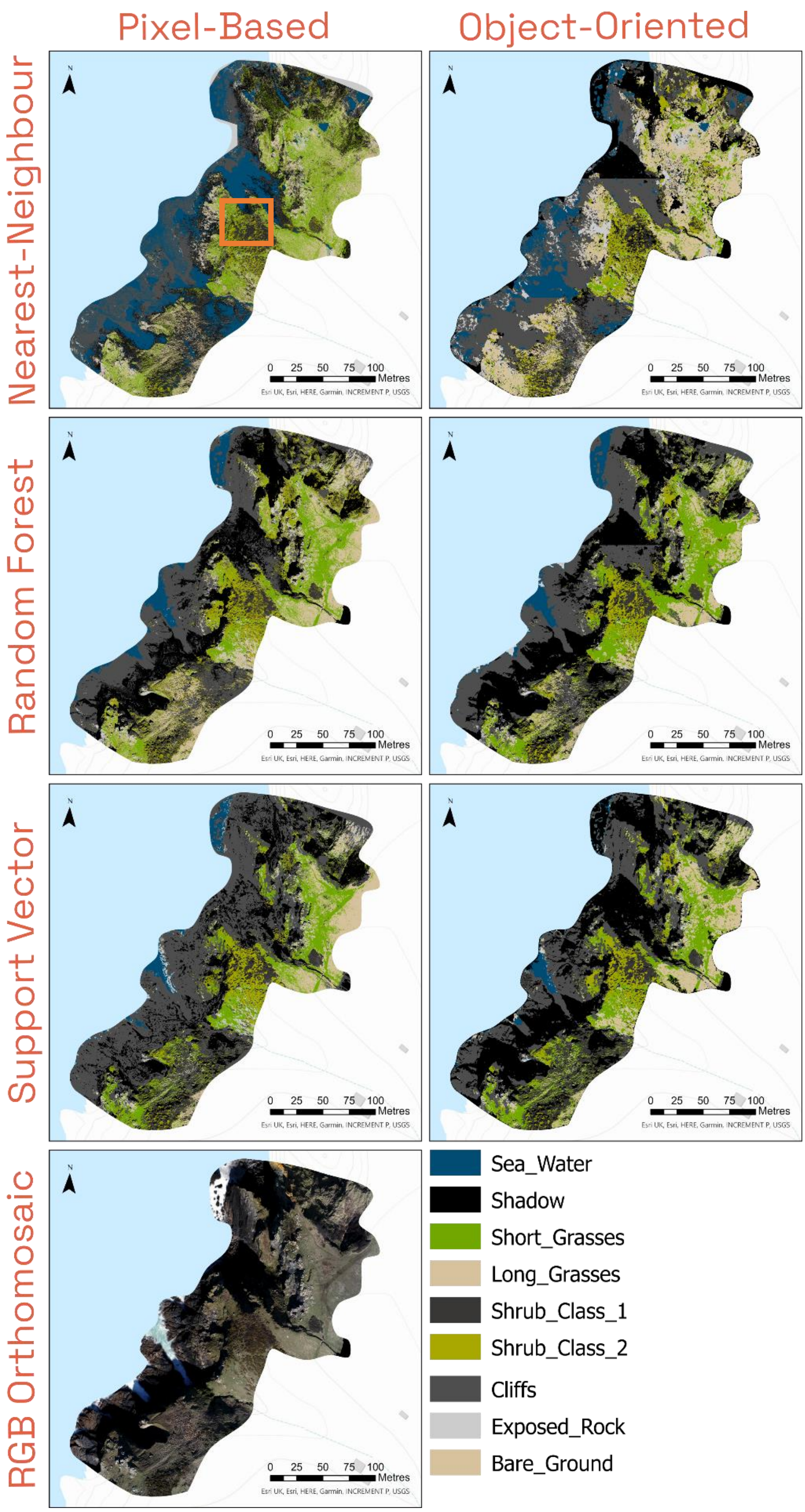


Figure 19. Output classifications for different land cover classes as outlined in Table 7 in section 3.5.5. The left column indicates classifications using a pixel-based approach, with the right object-oriented. Each row denotes the type of classification method undertaken. Finally, an RGB orthomosaic is provided for reference. The orange square denotes the area focussed on in Figure 20.

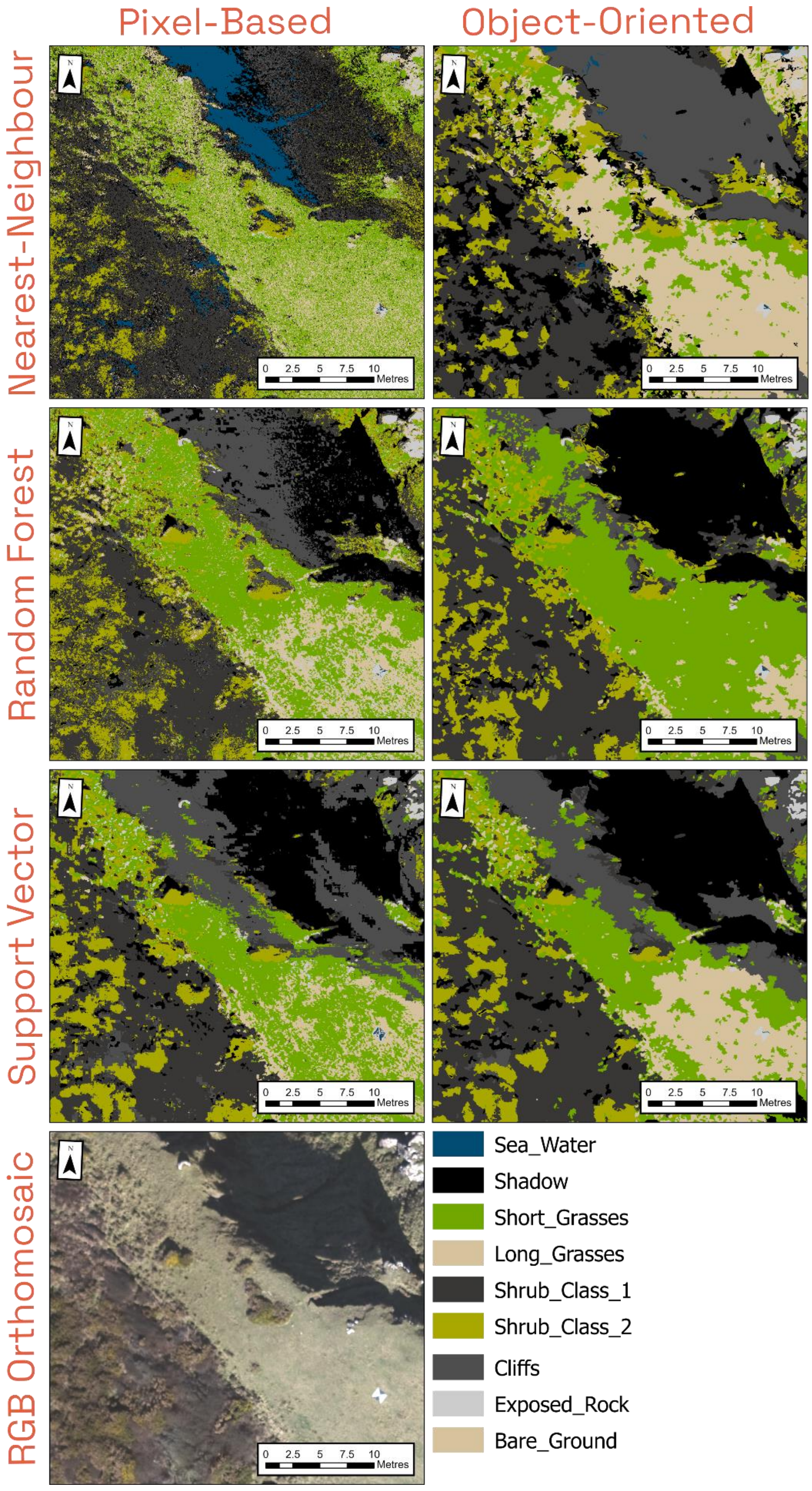


Figure 20. Focussed areas (as shown in orange square in Figure 19) from output classifications for different land cover classes as outlined in Table 7 in section 3.5.5. The left column indicates classifications using a pixel-based approach, with the right object-oriented. Each row denotes the type of classification method undertaken. Finally, an RGB orthomosaic of this focussed area is provided for reference.

Use of the NN methodology, which assigns classes based on the closest match in the training data, provides substantially different results between the pixel and object-based approaches. Moreover, the results of this method tend to differ greatly when compared to the RF and SVM outputs, with clear misclassifications of sea water and overclassification of long grasses. However, the more distinct spectral and structural features of the shrub classes appear to be picked out as well in the NN model as the RF and SVM for these zoomed in areas. This pattern holds across the entire study area, whereby long grasses dominant despite their being a variety of vegetation and non-vegetation classes in their place. Across the study area in Figure 19, it is clear that RF and SVM models produce similar, albeit different results, with the zoom panels in Figure 20 exemplifying the subtle differences. RF outputs appear to align better overall within the zoomed area, especially regarding the different types of grasses, and transition to the cliff/shadow region of the image. This fits with the wider scientific consensus that many machine learning algorithms are suitable, so long as there is sufficient training data to learn from.

4.2.3.2 Reighton Sands Classification Analysis

The main purpose of assessing classifications at Reighton, was to identify how adding LiDAR derived datasets would impact the outputs of the classification. Figure 21 displays three different classifications, using RGB alone, then RGB and canopy height, followed by RGB, canopy height, and point cloud planarity and roughness. There is a distinct improvement in classification performance with the inclusion of LiDAR derived datasets, specifically in the reduction of areas marked as tree classes in the RGB imagery alone. The survey here was undertaken during winter, with leaf-off conditions, contributing to this change in performance. Primarily, trees without leaves will appear similar to the ground vegetation below due to the lack of leaves to differentiate in colour, and also allowing the ground level to be visible inside the canopy footprint. Likewise, this allows the LiDAR to obtain a full structural profile to obtain true ground points, and as such create good canopy height models. The clear distinction in tree height then makes classifying them a far simpler task. Furthermore, going beyond the canopy layer to identify information about the surface properties such as roughness (surface variability) and planarity (surface smoothness) also appears to show some benefits. This is particularly evident around the edge of the study area where grasses dominate the imagery. However, in the RGB and for some of the RGB and CHM model areas, there is a tendency to indicate shrub and tree presence where there is none over particularly large scales. Yet this same inclusion also appears to overclassify the extent of inland water to a worse extent than the other two models, but overall performs the best, highlighting the benefits of both structural and spectral datasets for these methods.

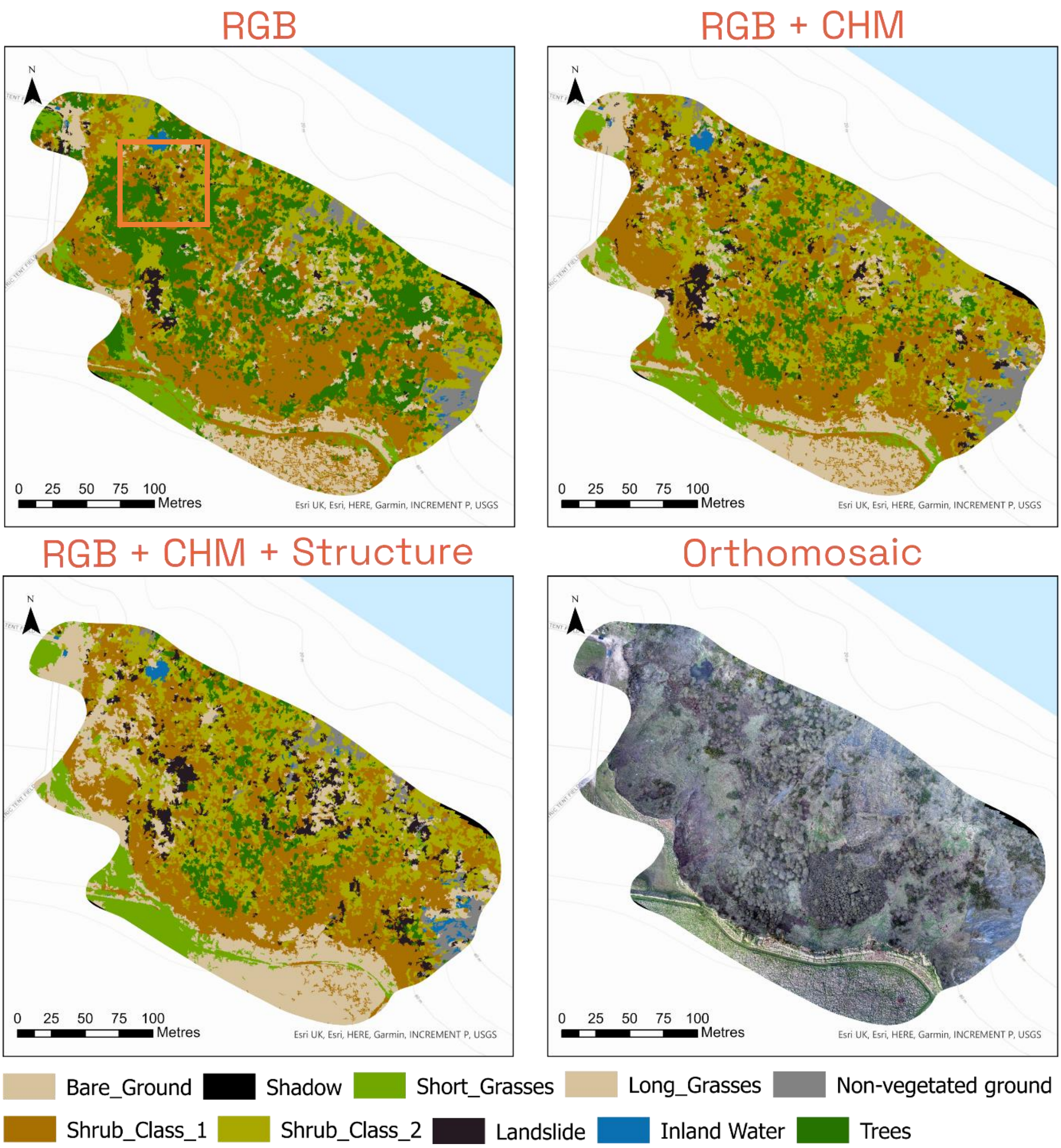


Figure 21. Output classifications from Reighton, showing the impact of including LiDAR derived datasets on model performance. Each heading refers to the image below, with the orange square displaying the extent of the imagery shown in Figure 22. An orthoimage is provided for reference.

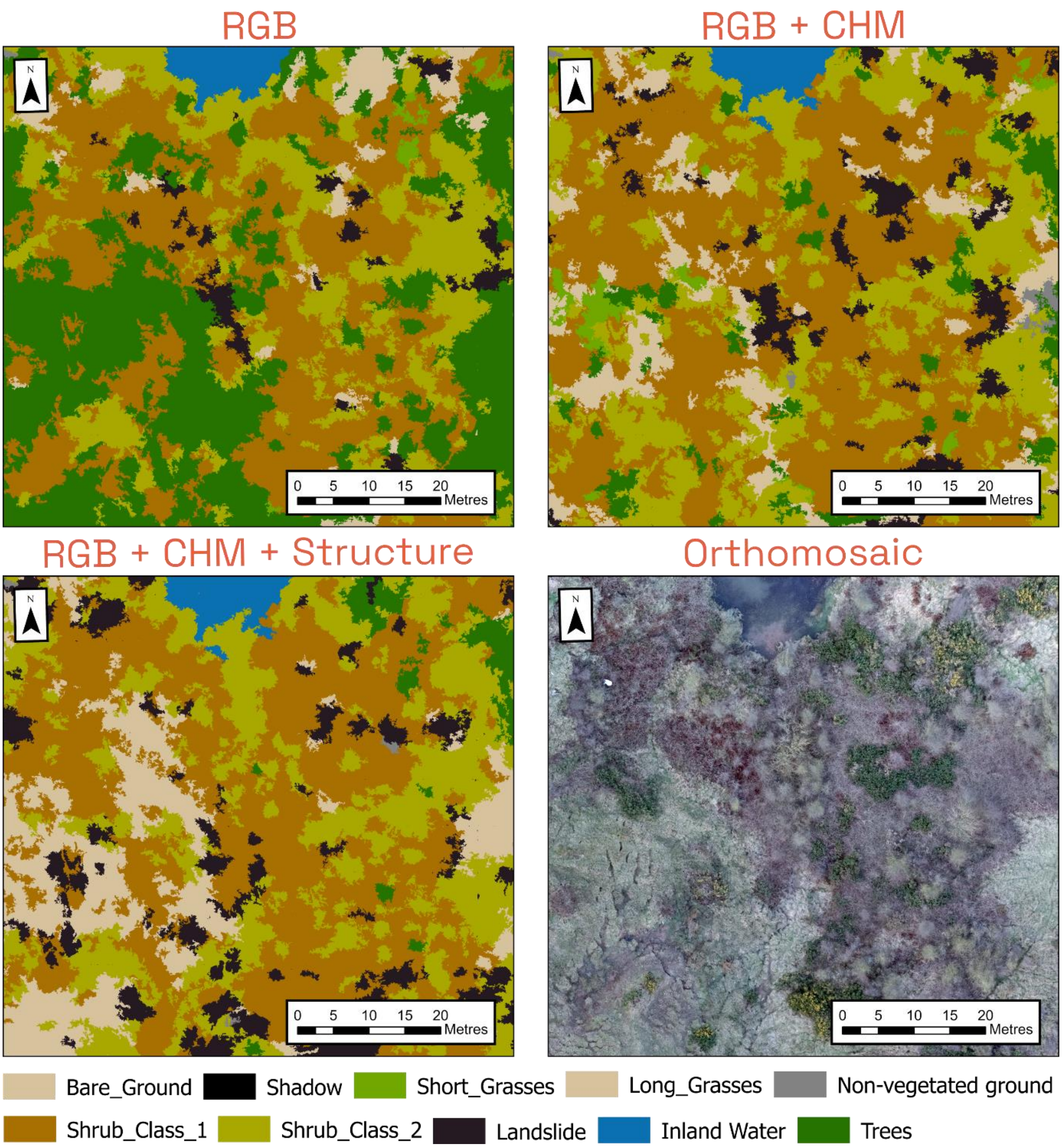


Figure 22. Area of interest highlighting the changes in output classifications when including LiDAR derived datasets on model performance. Each heading refers to the image below and an orthoimage is provided for reference.

The improved performance with LiDAR data is highlighted in Figure 22, with the extent of the inland water being better represented, and a clear reduction in the tree class extent over areas which are seen to be long grasses and shrubs in the orthoimagery. As discussed previously, the lack of ground truthing makes it harder to assess the correct classification of trees, but the alignment with areas of higher value in the CHM is good, and the general pattern of vegetation in the orthoimage is mimicked in the classification.

Of note is the ability to obtain 3D models from imagery alone. As a comparison exercise, a CHM model was produced using the same methods for the imagery point cloud as the LiDAR point cloud for Mullion, to understand what would be produced from a single sensor. The results of this can be seen in Figure 23.

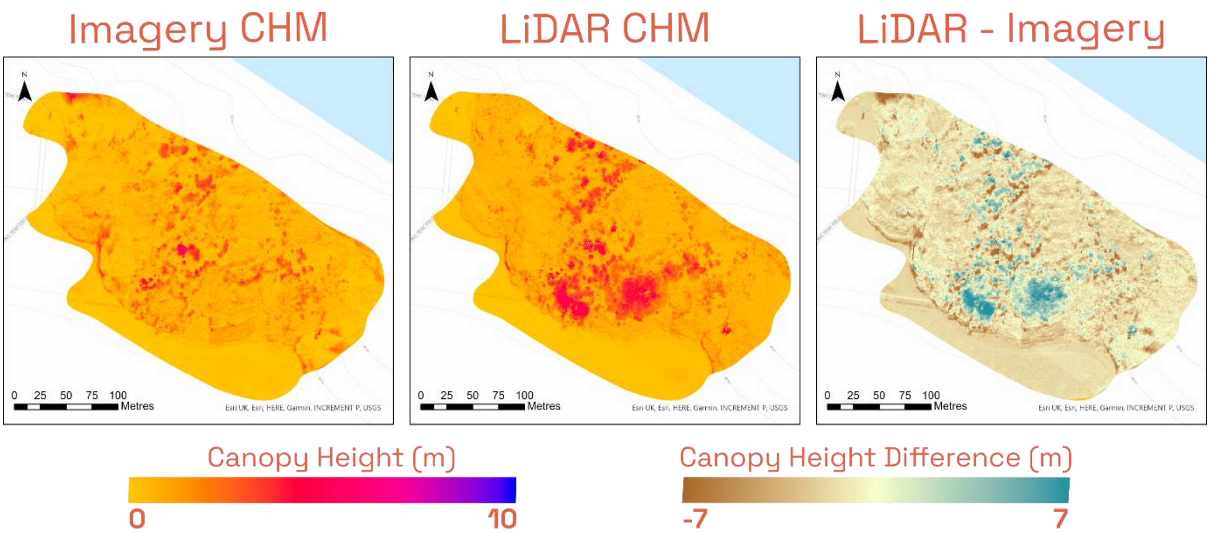


Figure 23. Comparisons between CHMs derived from UAV imagery and LiDAR, with the difference in these outputs shown in the right panel, whereby blues represent a larger CHM in the LiDAR, and brown in the imagery. There is a clear increase in canopy heights derived from LiDAR as would be expected, as well as larger imagery heights extracted around the cliff edge and some flatter areas.

As expected, the more consistent CHM is derived from LiDAR based on field imagery comparisons. The areas where vegetation is present show varying heights, with higher values associated with tree classes. The imagery outputs show a more sporadic pattern probably where large trees are present and picked out in the images, but not in the smaller shrub species where the imagery cannot obtain a true ground surface in comparison to the LiDAR. There are also more areas associated with a higher canopy in the imagery around the cliff edge and areas of flat ground across the study area, indicating the extraction of a true bare earth model may not have been as successful. Although this level of detail CHM may be suitable for improving classifications, it is unlikely to improve them to the extent of LiDAR derived models especially in areas of denser and smaller vegetation where obtaining a true ground surface is more of a challenge. This would be regarded as an even greater challenge for imagery in non-leaf-off conditions, where canopy penetration is highly limited.

4.2.3.3 General Observations

The main observations from this analysis fall into three distinct categories; 1) the type of classification procedure used, 2) the classifier that is used, and 3) the importance of structure in classification procedures.

The above outputs highlight the differences in both pixel and object-based approaches. Pixel based approaches can offer more granularity, highlighting the small variations in land cover down to the scale of the pixel itself. However, this is not always useful, especially when the land cover of interest is several orders of magnitude larger than the pixel. For example, a cliff will likely look grey, smooth, and sloped for a classifier across the majority of the pixels; a tree however will have lighter and darker shades of green, different canopy heights, and varying texture. This is often what causes misclassifications at these fine resolutions. Using object-based approaches which group these similar pixels together helps to overcome these issues, and also produces a more readable output. Moreover, these object-based outputs help to define regions of classifications better and could arguably be used by field surveyors to help make decisions on the extent of identified habitats, helping to overcome one of the primary limitations of observer-based habitat surveying in inaccessible locations.

The type of classifier used in clearly important, whereby correctly classifying habitats is key for the method to be used moving forward. Both the SVM and RF classifiers performed well when visually compared to the habitats in the orthoimagery, providing an improvement based on more traditional nearest-neighbour methods. There were noticeable differences in the classification outputs of the RF and SVM techniques, and there are other classification methods available to refine outputs. The refinement process can take time, and also lead to classifiers being overfitted to a specific site, and therefore less transferable even to sites in a similar location or with similar habitats. As such, having a useful classifier which can aid field observers, or to provide an assessment of change in habitat extents may be more beneficial and provide the best trade-off in terms of time and usability.

Finally, the classifiers used for comparing object and pixel-based approaches, as well as the type of classifier, all contained structural data. As outlined in Section 4.2.2.2, although it is possible to obtain structure from SfM, this tends to be of much lower quality and produces distinctly different patterns and values of canopy height when compared to LiDAR (Figure 23). When you include LiDAR derived datasets into the classification, the model tends to do a better job at separating spectrally similar but different classes, such as trees and shrubs, as well as the pattern between different types of grasses. Although not undertaken here, including the imagery derived CHM would be unlikely to cause such an increase in performance and as a result limit the classification potential. The extent to which this additional information is required may be dependent on the goal of that survey, e.g. zone delineation vs classification as well as the type of habitats present, e.g. highly vegetated vs exposed.

The other main benefit of obtaining LiDAR is the ability to relate vegetation to slope processes, as well as track geomorphic change and variables (such as cliff edges) through time over larger areas without the need for extensive surveying, helping to increase value for money for any specific survey. As a result, undertaken UAV surveys may not just reduce the time in the field for one particular purpose, but several.

4.3 Wider applications of surveying

The collection of UAV and remote-sensed datasets for assessing maritime cliff and slope environments present several benefits over traditional field survey, especially in hard-to-reach areas and for improving the quality of the baseline habitat extents. Field-based methods for delineating habitat on steeper slopes and hazardous areas are often uncertain – even where they are informed by use of aerial photographs to support boundary definition.

Thus, drone technology or drones combined with field survey offers improvements over field assessment alone, allowing more detailed characterisation of a suite of measures in parallel, thus capturing many of the CSM variables like morphology, change, and vegetation structure as well as allowing for processing of breaks in slope and vegetation classification. The collection of the UAV sensing also provide a dataset that allows for further use, employing future processing innovations (e.g. machine learning enhancements).

Alone, the UAV based data and processing may lack the potential to map to the complex categories of classification structure like NVC, but these categorisation levels are not strictly necessary for CSM level assessment. Alternative measures or surrogate measures of community change (e.g. scrub development, slippages, bare ground) are more readily captured and on a closer repeat cycle than using field data alone.

Primarily, in terms of monitoring, the use of UAVs allows for the collection of high-quality data at spatial resolutions not obtainable from satellite remote sensing. They also increase the temporal frequency available through current mapping procedures for improved change detection. This is especially pertinent when looking at geomorphological processes and monitoring; potentially including event (cliff erosion and collapse) monitoring.

The ability to detect slopes for modelling landslide probability, detecting breaks in slope and cliff tops though vegetated reaches, understanding the spatial extent and magnitude of morphological change, can all be obtained in parallel with monitoring vegetation. Likewise, with appropriate planning, collecting data for any of these mentioned applications specifically would also likely provide useful data for MCS mapping. Furthermore, the data collected may also offer insights (especially when collected across a number of sites) into how different classes of vegetation show different morphological responses, and what this may tell us about landscape processes through eco-geomorphological interactions.

Consequently, when viewing the cost-benefit of one technique over another, it is important to consider the wider benefits of them being undertaken. It is challenging for a land surveyor to undertake a habitat mapping exercise whilst delineating cliff lines, and vice versa. However, albeit with subsequent processing required by each group, a UAV survey can support both teams to improve both the spatial resolution and accuracy of their work. As such, the cost-benefit of undertaking or commissioning aerial surveys becomes increasingly justified.

5 Data storage and long-term access

A critical aspect of detailed data collection for habitat inventory and common standards monitoring is the ability to find, access, and use records of past cliff surveys. Appropriate metadata to support re-use becomes essential, including the details of acquisition, post-processing, and licencing conditions. These requirements are more important for digital data over field based records given the data volumes, changing formats, software compatibilities and storage media as well as the challenges of long-term access to the data.

Metadata should be compliant with national standards and include specific elements related to the nature of the survey platforms (JNCC 2019) and the Marine Environmental Data Information Network (MEDIN) standards[2] and related controlled vocabularies. This should include: (a) general information about the dataset such as name and origin, (b) details about data acquisition including sensor types, flight details, and date, (c) data processing such as software choices and parameters, (d) quality including 3D accuracy compared to GCPs and CPs, (e) data format and access, and (f) applications and limitations including known issues and any planned data updates will be undertaken.

NE uses the UK Gemini metadata[3] standard for spatial data and is mandatory for public sector bodies where the data is in scope for INSPIRE (which maritime cliff and slope would

[2] MEDIN data guidelines: http://www.oceannet.org/marine_data_standards/medin_data_guidelines.html
[3] GEMINI Metadata standards
https://guidance.data.gov.uk/publish_and_manage_data/harvest_or_add_data/harvest_data/gemini/#iso-19139

be). UK Gemini is based on elements within the international metadata standard ISO19139, but includes a geographic bounding box and requirements of INSPIRE records. UK Gemini is likely to need to be augmented to meet the needs of UAV data reuse and to cover raw data, processed data and generated products (habitat classifications / 3D vegetation structure, quality parameters etc). These should be recorded as a series metadata to ensure that all the relevant records for a survey campaign are discoverable together. The UK Gemini is a Discovery metadata standard and cover sufficient detail to fully describe the data, but is used for federated data discovery.

An example of the dataset metadata form used by ES@S can be found in Appendix D. This should be maintained alongside any data location to inform future users about when the data can be used for a specific purpose, and when it cannot.

Long-term access should enable all users to find and have access to the data through relevant data portals - including the MEDIN Data Centres. Although the records are 'coastal' rather than 'marine' the MEDIN standards and archives do include some coastal data. Wherever possible (related to the survey purpose) the data should be open access and accessible under and Open Government Licence. The publication should follow the principles of Findable, Accessible, Interoperable and Reusable (FAIR, Wilkinson, 2016). The NE Open Data GeoPortal is really only suitable for the derived products from analysis, and then typically only national coverages. Alternatives for managing discovery and long term access to the raw and processed cliff data and surveys includes the related coastal change monitoring data, habitat data etc are made available online as open data under the National Network of Regional Coastal Monitoring Programmes. The latter has the advantages of holding most of the other related coastal monitoring programmes records.

6 Process for survey and mapping

Use of UAV drones and aerial imagery for automated mapping of the range of variables that mark habitat classes and condition of soft and hard cliffs vegetation shows both advantages and limitations. The current approaches to mapping MCS habitats have largely been through field surveys, including use of remote observation where access is restricted and using vertical aerial images to help in mapping locations and boundaries.

The ground survey approaches on MCS sites have typically been to the level of NVC survey protocols and use of quadrats with vascular plants and bryophytes identified (or visual assessment where access is restricted). The resolution of habitat boundaries and level of discrimination to NVC sets a high bar for comparative remote-sensed surveys, which typically cannot discriminate to levels that reply on species data (Crick 2013).

The MCS field surveys have rarely sought to evaluate the condition of the habitat, rather they report the existence of the vegetation / bare ground coverage and species lists classified to NVC or often NVC sub-communities where there is a poor match to existing NVC classes or where there are mosaic habitats that are difficult to ascribe to a single NVC class. Thus, there is a gap in the availability of habitat condition data.

If NVC level discrimination is required, then ground-based surveys seem inevitable, but perhaps integrated with and facilitated by UAV-based surveys that provide better boundary discrimination on sloping ground, additional condition parameters and high resolution multispectral data in inaccessible areas. If characteristics of habitat condition are needed then UAVs surveys may again be more valuable, particularly at capturing structural information and helping to discriminate vegetation integrating structure derived from LiDAR data. Ground survey could also be modified to be more inclusive of condition criteria that are not currently included in most ground habitat surveys.

There remains the issue for ground surveys of the number of habitats that are not well represented by NVC classes. A programme to resolve these, based on the existing quadrat samples collected through the many additional MCS quadrat surveys that have now been undertaken since Rodwell's categorisation could help improve the situation.

Using drones is not a low-cost option, although it has added advantages over just ground based surveys. A field surveyor may be able to survey the same area and map the data within the same time and without a large post-processing commitment. However, the quality and potential of the UAV data collected within the time allows more accurate depiction of boundaries, greater potential for derivation of other attributes of sites and opportunities for analysis and provides a more robust baseline from which future monitoring and change assessment can be undertaken. Currently, a positionally accurate RGB surveying setup ranges from £6,000 – £20,000 from DJI depending on the endurance of the UAV and resolution of the sensor, as well as the cost investment in training and accreditation for operating in the specific category of airspace. UAV-based LiDAR requires the greater endurance of high-end UAVs and also extra investment in sensors and software packages.

The proposed procedure, if using remote sensed / UAV survey is set out below, but would still be likely to integrate secondary and primary (field survey) data sources for project planning and verifications / accuracy assessments.

1. Discussions with local groups (NE Area Teams / landowners/managers) and existing coastal monitoring programme teams working on cliffs for other purposes, as well as for conservation and habitat mapping. This may offer the opportunity to combine the interests of, for example the Regional Coastal Monitoring Programmes and the MCS survey requirements.

2. Address the site ownership and permissions to undertake UAV surveys.

3. Checking for flight restrictions, the category of flight to be undertaken, and NOTAMs (Notice to airmen) ahead of the planned flights and incorporating any further intel into a risk assessment and Mission Planning (section 3.4)

4. Acquire existing field habitat and relevant secondary sensing data for the site and habitat data, where possible in geospatial formats. Most English sites will have some survey and possibly habitat surveys from the regional coastal monitoring programmes that can inform the site selection / processing and automated classification routines (e.g. as per Table 2 sources).

5. Determine the sensor suite needed to collect relevant data and to generate outputs (e.g. sparse point clouds, dense point clouds, digital surface model, orthophotos) (section 5.2).

6. Mission Planning and Field data collection (3.4). Timing selection is a compromise between the best time for different aspects of the surveys. For terrain mapping using LiDAR a winter, deciduous time is preferred to ensure returns from ground surface. For vegetation a spring to early summer timing may be preferred, and from the perspective of surveying cliffs with nesting birds the post breeding season would be preferred. In this study surveys were conducted in winter (Dec – Feb) which may not be ideal from the habitat perspective. In some instances, a multi-date survey may be recommended.

7. Processing of the UAV derived data as illustrated in section 3.5 to derive the relevant parameters for site mapping, classification and condition assessment. This will vary for the data type collection but consists of (1) georeferencing the sensor used, (2) obtaining a model of the surface based on sensor locations, and (3) creating output datasets resulting from this surface model. Using a combination of methods allows for the inclusion of structural, spectral, and indices data into classification models, which ultimately improves classification performance. Use of segmented (object-oriented approaches) rather than pixel-based approaches is likely to offer greater applicability for assisting and complementing ground-based surveys and monitoring condition assessment and common standards monitoring.

8. Ground-truth data may still be needed, especially where the NVC classes are needed to meet reporting objectives. But there is strong potential to use UAV derived habitat boundaries, structural form data guide the evaluation of habitat parcels and the NVC classes, collect information and habitat boundary data in inaccessible locations and provide the basis for uncertainty / accuracy assessments.

9. Ensure that within the context of commissioning surveys that the resulting data are in geospatial data formats with appropriate discovery and re-use metadata and that the data are made accessible under the OGL. This involves all data being readable in open-source software or as archival storage formats, having appropriate CRS information, and to be stored in a secure long-term storage repository.

10. Ensure that the data (e.g. UAV, processed data and quadrat data) are effectively described by standardised metadata and are made available (open data) in a reusable format and are accessible in the longer term to enable future change mapping and integration of the data into PHI data products. Manage the data within a suitable repository. For example, the National Network of Regional Coastal Monitoring Programmes (NNRCMP) data store holds many of the other habitat and physical monitoring datasets for England and Wales and makes these available as GIS datasets as open data. This would allow a greater level of research use of the resulting surveys, (e.g. potential to re-run NVC classifications to identify new 'undescribed' habitats from the quadrat surveys from NVC surveys; re-evaluation of the habitat mosaics, update of Priority Habitat Inventories).

11. Allow for updates and amendments to the provisional classification to be undertaken by a field observer, or for them to be provided with the base data for helping define the extents of habitat in the field –withing the context of a final derived product from the UAV surveys.

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APPENDIX A – Exemplar CAA Risk Assessment

Risk Assessment	Reighton Gap Survey – Natural England	Location:	Reighton Sands Holiday Park, Ghyll Field, 60 The Willows, Reighton Gap, Filey YO14 9SH
Completed by:	Chris Tomsett		
Date Completed	03/02/2022	Job Reference:	Reighton Gap – Feb 2022

Hazard (Something with the potential to cause harm, how will it be realized and what is the potential injury?)	2. At Risk	3. Existing Control Measures	Risk 4. Severity	5. Probability	6. Risk	7. Further Control Measures	Risk 4. Severity	5. Probability	10. Risk
High winds or rain affecting the capability of the SUA	A	Weather forecast checked prior to deployment. The flight may be delayed or cancelled at any time if the weather risks the capability of the SUA. Weather to be monitored at all times during flight with a view to landing should weather deteriorate.	4	1	4				
Pilot Incapacitation	A	Follow IMSAFE mnemonic (Illness, medication, stress, alcohol, fatigue and eating). Crew to be appropriately dressed for weather conditions. Make all crew aware of existing relevant medical conditions. Brief observer/s on return to home procedures pre-flight in case there is pilot incapacitation and ensure controller has no additional inputs i.e. body lying on controller.	4	1	4				
Airspace Incursion and Collision	A	Check airspace in accordance with pre-flight survey and contact ATC if necessary. NOTAMS will be checked prior to flight for specific information relating to the deployment area. SUA will remain below 122m (400 ft) at all times unless permission is granted. Pilot or observer to monitor airspace for potential incursion pre and during flight. Descend or ascend as appropriate if height of crafts are similar. Notification of low flight booking cell due to near proximity to airspace used for high energy manoeuvres.	5	1	5				
Ground Incursion	P V	Check ground in accordance with pre-flight survey and perform site survey (take note of people, animals and their likely responses). If practicable notify public near flight area of your intention to fly e.g. door knocking, verbal briefing and letter dropping. If present, brief observer on monitoring and alerting pilot to potential incursions. Erect signs near TOL (take off landing) if incursion is likely. Wear high visibility clothing if there is a benefit of doing so. Mark TOL area clearly to avoid incursion i.e. with cones. Avoid overflying public and visitors, hover a safe distance from the incursion, ideally downwind of the incursion.	1	4	4				

		Identify a safe alternate landing location and proceed to land if safe to and is required. Make contact with site owners to notify them of intended flying times and locations so permanent residents can be informed of flights.							
Loss of control and/or data link / flyaway	A	Be able to fly in manual / ATTI mode should GPS signal be lost. Check site for presence of a HIRTA (High Intensity Radio Transmission Area). Check Kp index pre-flight. 4 and below is ideal. Configure antennae as per manufactures specifications pre-flight. Check for signal strength and interference in app pre and during flight. Monitor number of satellites tracked pre and during flight. Note battery level, flight speed and direction in the event of a flyaway. Use this information to estimate the maximum potential flight distance and who to contact. Have emergency contact information (e.g. ATC and police).	4	1	4				
Power Loss	A	Maintain battery log to enable assessment of long-term battery health. Check battery status of SUA and ground control equipment pre and during flight. Take account of additional battery drain of flying into wind (strength and direction). Land before flight battery becomes critically low. Ideally land before dropping to 25%. Ongoing assessment of alternate safe landing sites that are close to the current position of the SUA should battery level drop rapidly.	4	1	4				
Collision with Obstacles	A	Conduct pre-flight survey to identify potential hazards. Note any additional hazards during on site survey. Operate away from obstructions if possible. If possible, use spotters if close proximity to a structure is required. Note height of obstacles so that appropriate return to home height can be set. Ensure pre-programmed flight paths avoid any obstacles. If collision avoidance sensors are present on the SUA, configure them as appropriate.	1	2	2				
Bird Incursion	A	Check for signs of protected bird presence pre and during flight to avoid overflying ground nesting birds. Observer to maintain watch for any large groups of birds approaching survey site. Follow procedures outlined in the SoGES UAV Bird Impact document around flying patterns.	1	2	2				

Risk Assessment Sign off (By Pilot other than person completing)	Name: Chris Tomsett	Date: 03/02/2022

AT RISK (Column 2)	SEVERITY (Column 4 and 8)		PROBABILITY (Column 5 and 9)		RISK RATING (Column 6, 8 and 10)	
					Severity x Probability – 1 to 5	**LOW**
E – Employees	1	No Injury, Property damage	1	Extremely Unlikely	**May be acceptable, review to see if risk can be further reduced.**	
C – Clients	2	Minor Injury	2	Remotely Possible	**Severity x Probability – 6 to 12**	**MEDIUM**
V – Visitors	3	Reportable Injury	3	Will Possibly Occur	**Only proceed with specialist personnel / safety team**	
P – Public	4	Major Injury / Single Fatality	4	Will Probably Occur	**Severity x Probability – 12 to 25**	**HIGH**
A – All	5	Multiple Fatalities	5	Almost Certain	**Task should not proceed**	


Reighton Gap Survey
Possible study area of interest based on satellite imagery, TOL location identified, and a 30 m radius for TOL and the maximum VLOS extent from this location.
Legend
30 m TOL radius
500 m TOL VLOS
TOL Site 1
TOL Site 1
Google Earth
N
600 m

APPENDIX B – Software used in this project

Universal Ground Control Station (UGCS)

A fully featured commercial flight planning software which interfaces with DJI platforms. Available: https://www.ugcs.com/

Canadian Spatial Reference System Precise Point Positioning (CSRS-PPP)

This free online service allows the post processing of RINEX data to calculate an accurate base station position: https://webapp.csrs-scrs.nrcan-rncan.gc.ca/geod/tools-outils/ppp.php?locale=en

PosPac UAV

GNSS/INS direct georeferencing software from Applanix (used to merge GNSS/INS data for MicaSense): https://www.applanix.com/products/pospac-uav.htm

Agisoft Metashape

Used to create SfM models and orthomosaics from RGB and multispectral images. One of the best commercial SfM packages available: https://www.agisoft.com/features/professional-edition/

A suitable alternative would be Pix4D.

TOPODRONE post processing suite

Image geotagging and TopoLidar point cloud generation from blended trajectory, motion and raw laser data. This software is commercial: https://topodrone.com/product/software/193/1279/

LiDAR360 for Boresight calibration

This is commercial software for boresight calibration: https://greenvalleyintl.com/LiDAR360/

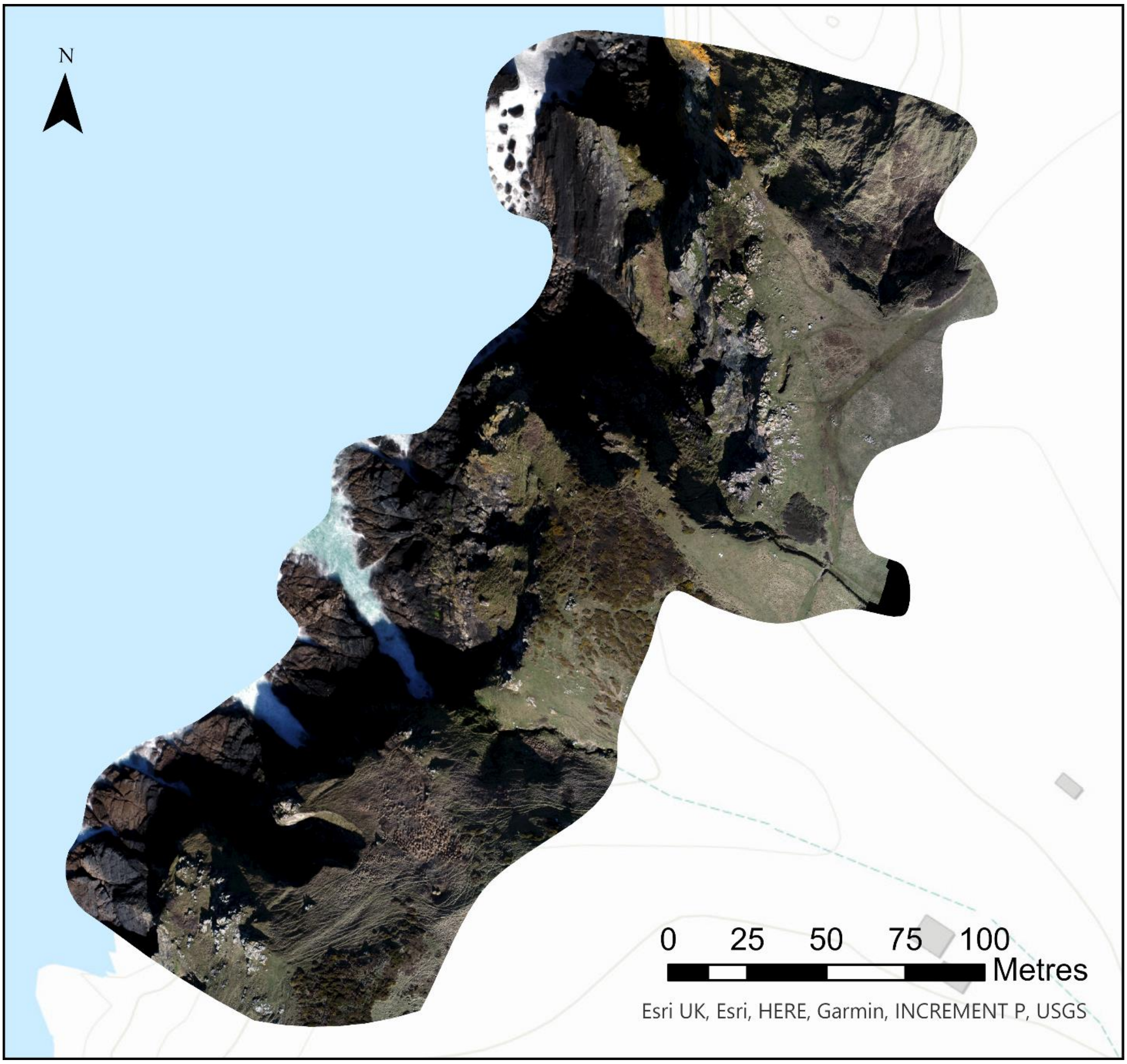
CloudCompare for point cloud viewing, cleaning and manipulation

The latest stable version of CloudCompare can be downloaded from:

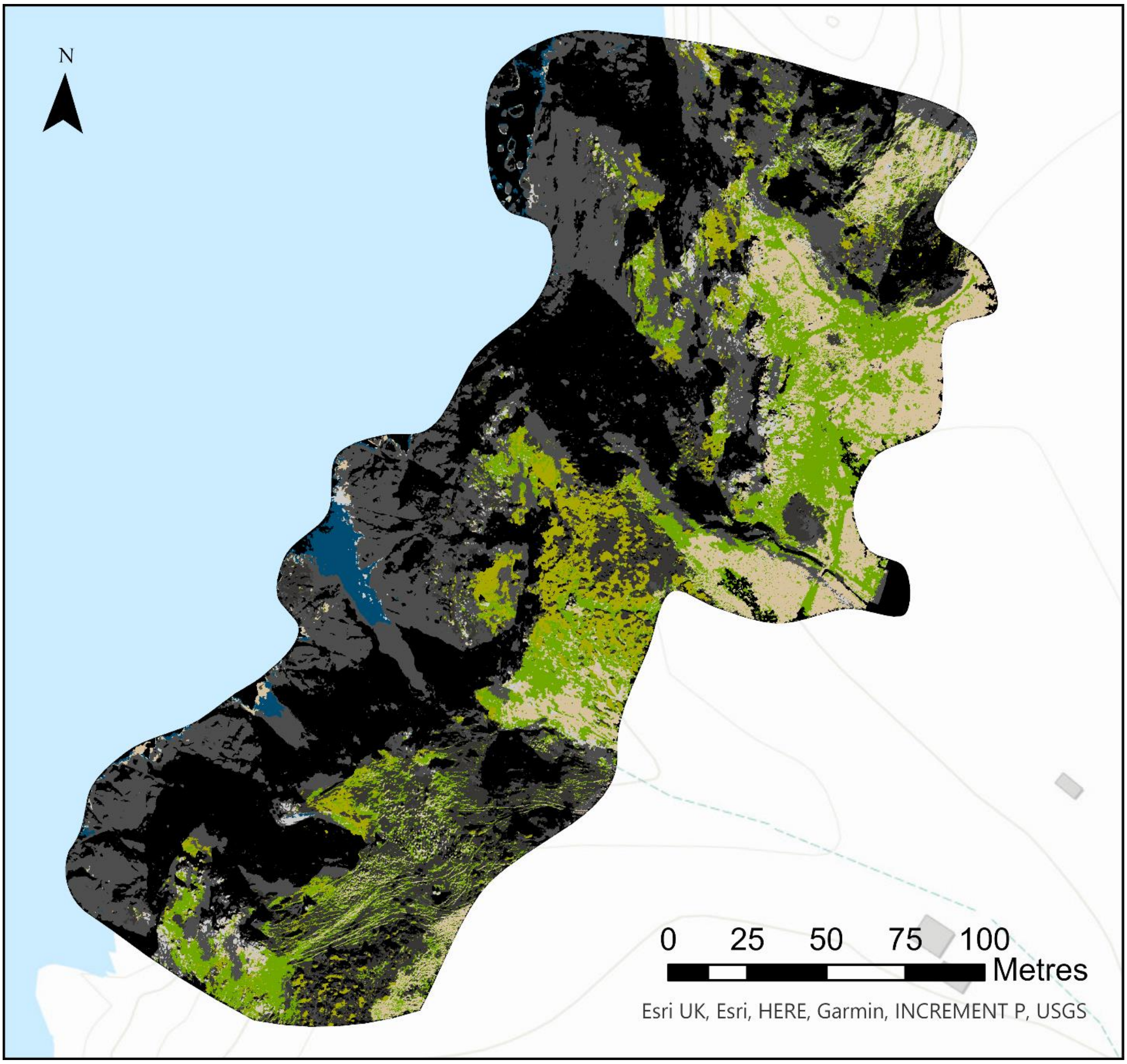
http://www.danielgm.net/cc/release/

Appendix C – Full scale data output images

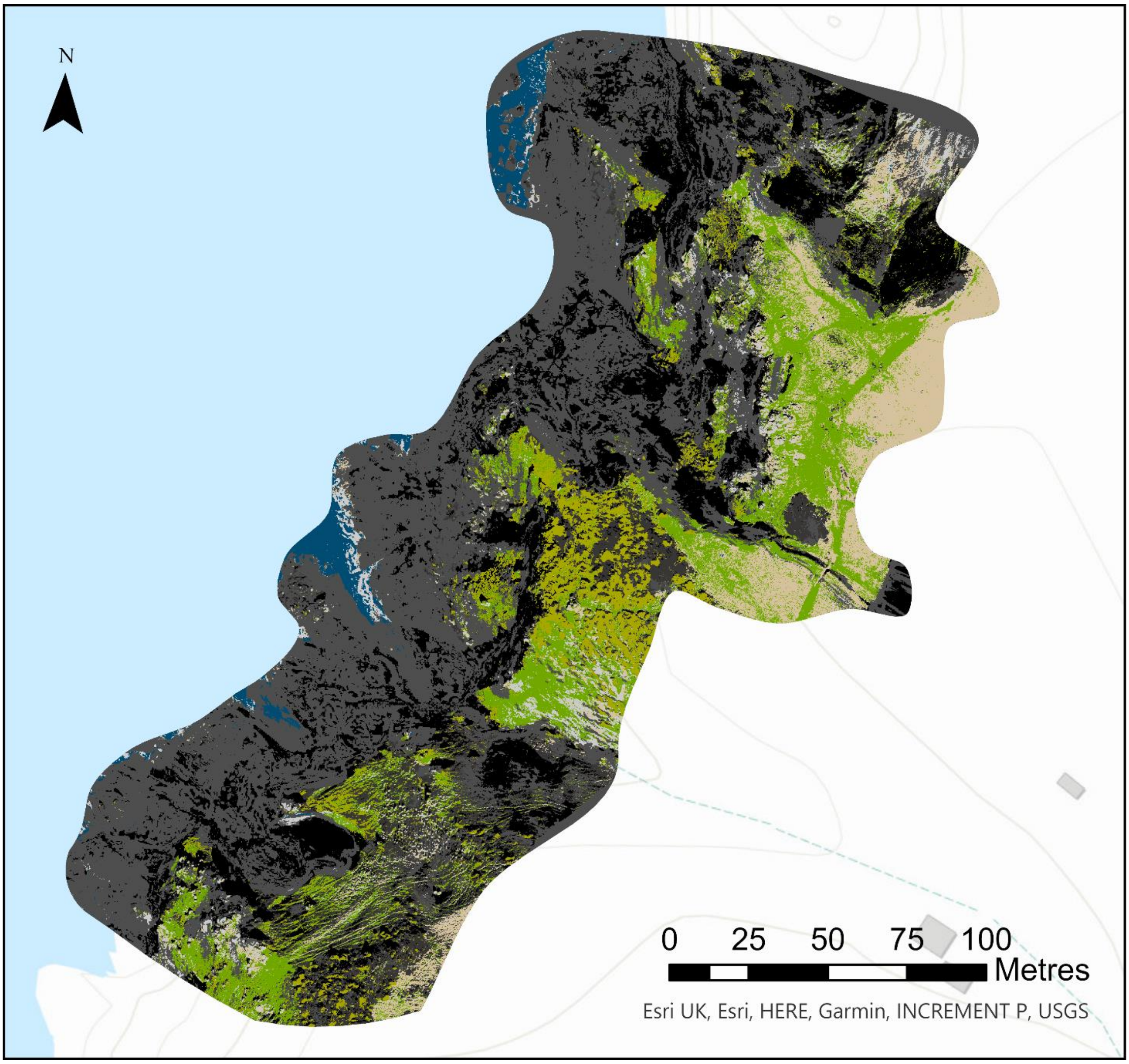
Mullion RGB Orthoimagery



Mullion SVM Object-Based Classification



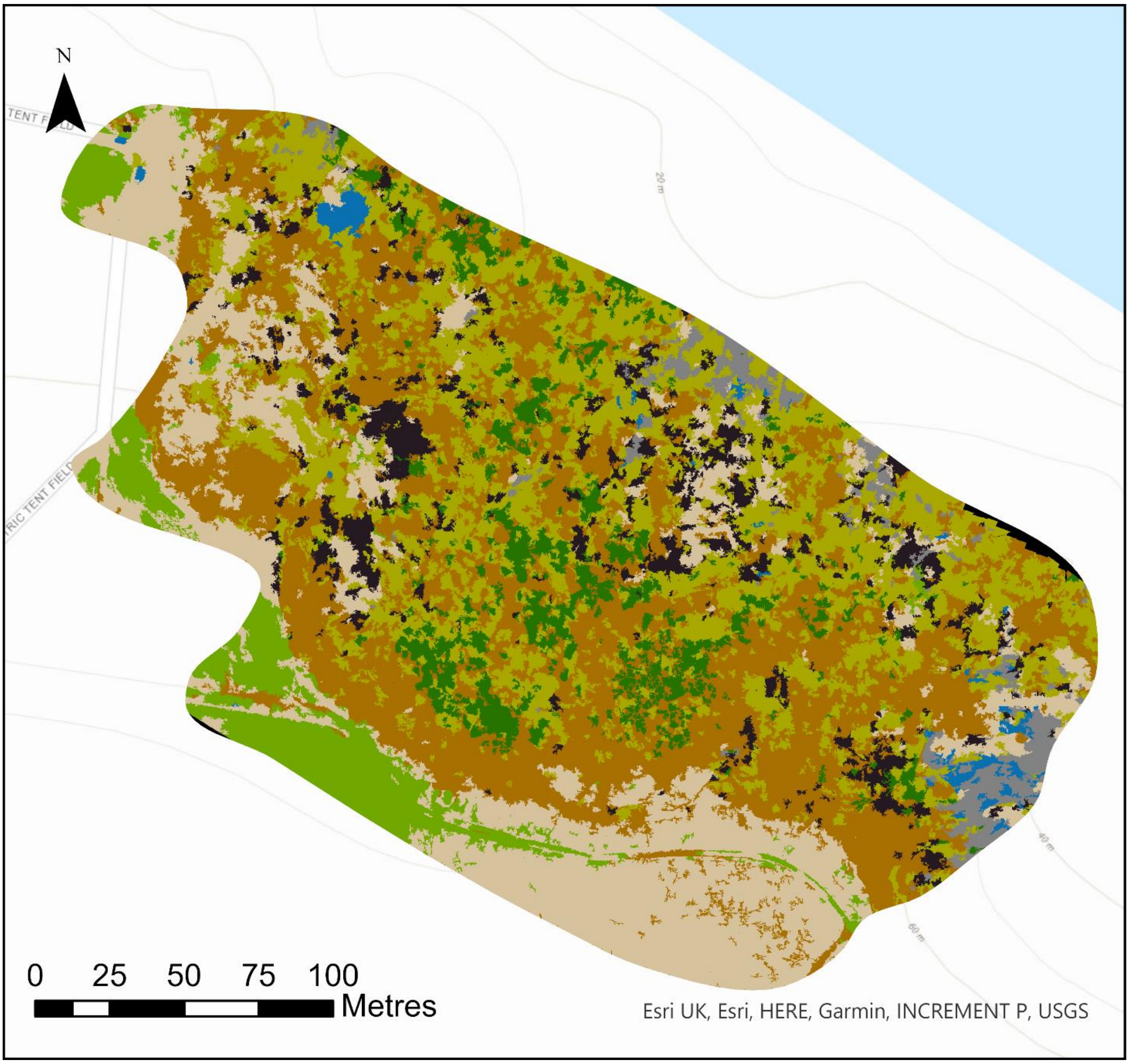
Mullion SVM Pixel-Based Classification



Reighton RGB Orthomosaic

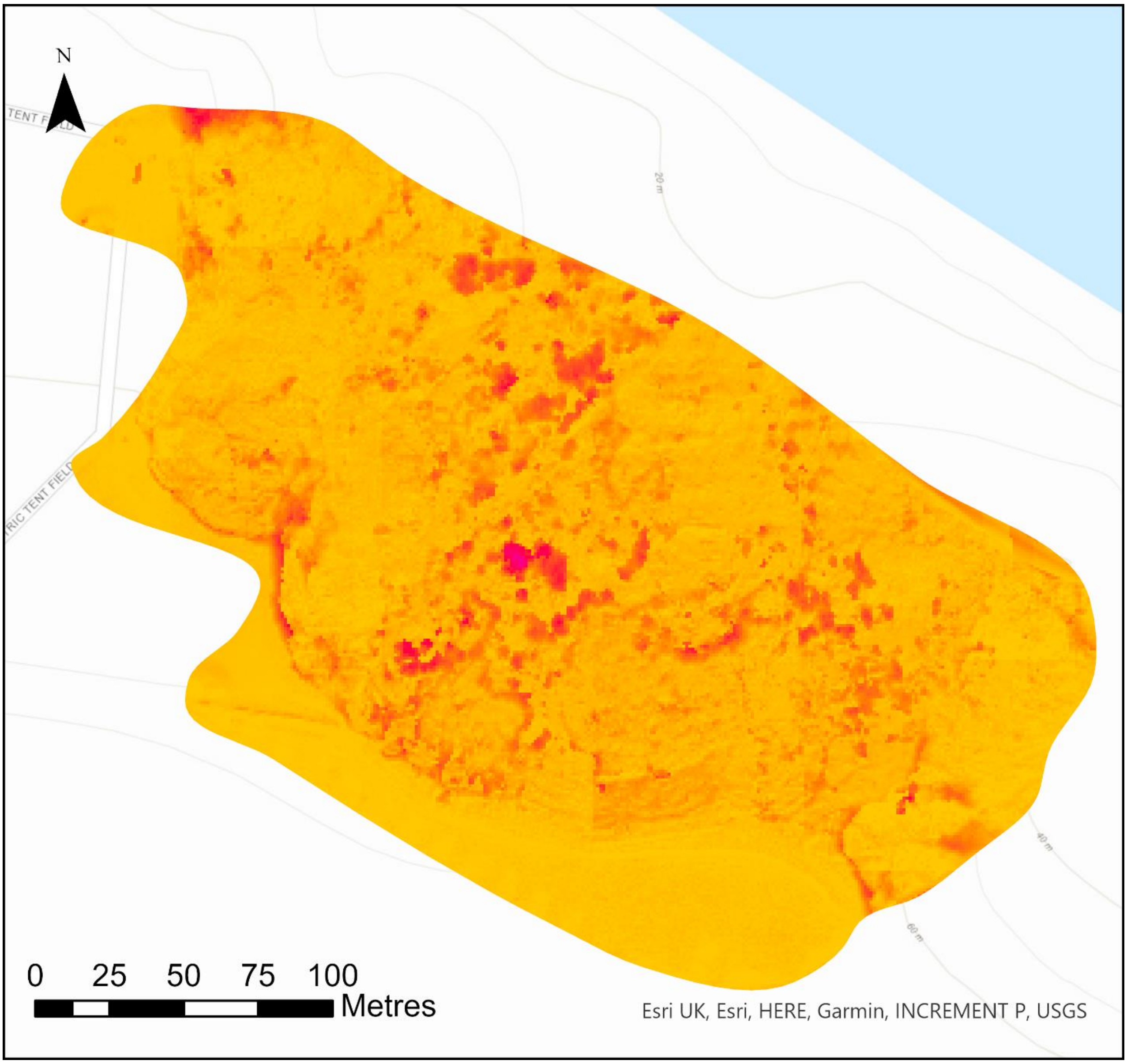
Reighton RGB Classification

Reighton RGB + CHM + Structure Classification



Reighton LiDAR CHM

Reighton RGB CHM

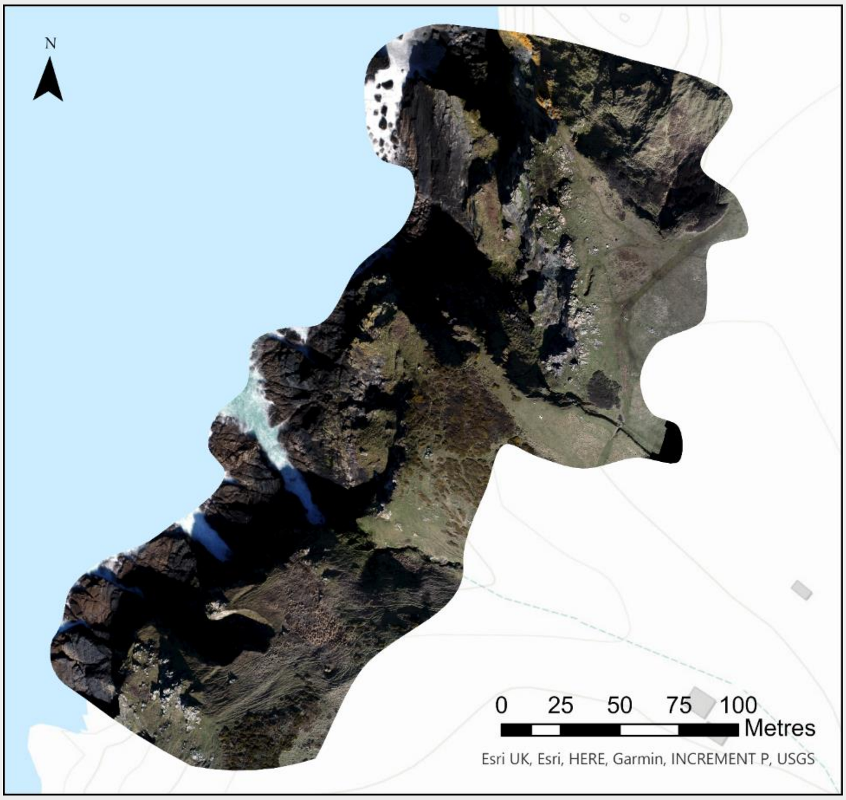


Appendix D – Example Metadata Documentation

Mullion RGB Orthomosaic

Overview	
Dataset Name	Mullion RGB Orthomosaic
Abstract	Orthomosaic imagery acquired from UAV-based imagery over Mullion Cover SSSI for Natural England as part of their MCS mapping investigation work.
Keywords	UAV, Orthoimage, RGB
Creator	Chris Tomsett
Date acquired	16-17/03/2022
Collected by	ES@S (Environmental Sensing @ University of Southampton) Website: https://esas.soton.ac.uk/ E-mail: esas@soton.ac.uk
Collected on behalf of	Natural England
Document author	Chris Tomsett
Document date	18/02/2025

Overview Image



Data Acquisition				
UAS model	DJI Inspire 2			
UAS sensor	DJI X4S			
UAS flight height (metres)	80 m			
Image overlap (imagery)	Unspecified			
Location (Approx)	Lat	50° 0'38.61"N	Lon	5°15'38.74"W
Area (ha)	10			
Data Processing				
Positioning quality	PPK			
CRS	Horizontal	BNG (27700)	Vertical	ODN (7405)
GCPs	Yes – 4			
CPs	Yes – 3			
Software	Agisoft Metashape			
Non-standard settings	N/A			
GCP accuracy	Mean	-	RMSE	-
CP accuracy	Mean	< 0.1 m	RMSE	-
Data Format, Accessibility, and Intended Use				
Data format	.jpg (georeferenced)			
Dataset size	29.6 MB			
Data license	Permission must be sought from natural England before using this dataset.			
Access	Access can be provided by Natural England			
Intended use	To assist in the identification of MCS habitats, identifying suitability of UAS-based data collection.			
Known issues	Shading in parts of image lead to reduced quality reconstruction and reductions in usability for these areas.			
Update frequency	No planned updates to this imagery are scheduled.			