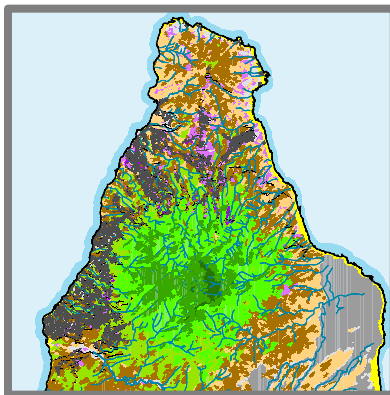
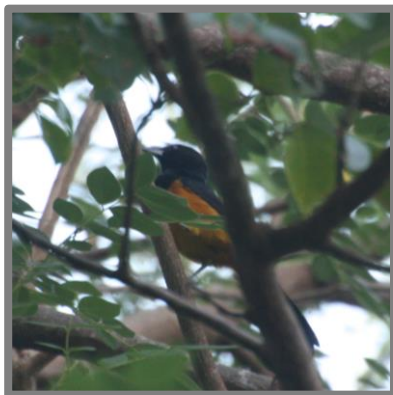
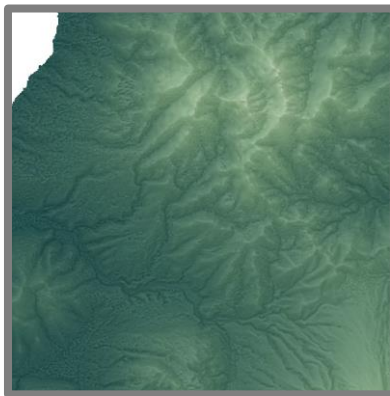
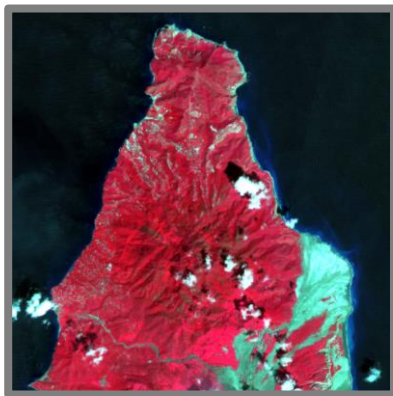


A National Ecosystem Assessment of the UK Overseas Territory Montserrat: Earth observation based mapping and interpretation

Final report

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1. Introduction

Montserrat is a highly biodiverse, volcanic and mountainous island within the UK Caribbean Overseas Territories. The islands' ecosystems provide multiple benefits such as the provision of fresh water, maintaining soil fertility and a variety of food resources, as well as being an important source of income through the exploitation of its unique biodiversity to promote tourism.

This project sits within the first phase of producing a baseline Natural Capital Account for Montserrat, and has three objectives:

- Use Earth Observation (EO) to enhance and update an existing Montserrat terrestrial map following the Living Maps for biodiversity and natural capital approach developed by Natural England.
- Use the updated habitat data to produce a suite of spatial metrics to inform a parallel project undertaking a baseline economic valuation of natural capital on Montserrat, carried out by Eftec Ltd.
- Provide recommendations for a monitoring and reporting system for Montserrat based on Sentinel-1 and Sentinel-2 data.

This report describes how the habitat map was produced, how it was used to produce spatial metrics on agricultural sub-categories, forest canopy density, forest clearing activity, coastal sediment plumes and soil erosion risk, and makes recommendations on future EO-based monitoring on the island.

2. Habitat Map Production

For this project Environment Systems Ltd was tasked to produce a terrestrial habitat map for Montserrat through use of the Living Maps classification script developed by Natural England (Natural England, 2017). No supporting documentation was available to support the implementation of the classification script, therefore the methodology and interpretation of results cannot be described in full, but are presented below in as much detail as possible given the information available at the time of writing.

2.1. Earth observation data

A range of image types was available to the project, ranging from high to medium resolution. The focus of the project was to develop a habitat classification based on Sentinel-1 and Sentinel-2 imagery. A dense image time-series was collected for both sensors covering the period January to December 2017; this time-series comprised 35 Sentinel-1 images and 14 Sentinel-2 images. In addition, three pre-processed Pléiades images were also available, as was a WorldDEM™ terrain model (12m resolution). The full list of input satellite images used by the project can be found in Appendix A, along with a description of the image processing steps undertaken.

For the Sentinel-1 image time-series a temporal statistics dataset was created comprising mean, maximum, minimum and standard deviation values for each pixel across the time-series. A temporal statistics dataset was also created for the Sentinel-2 imagery. In addition, a range of indices were calculated for each individual Sentinel-2 image (Table 1).

Table 1: List of Sentinel-2 indices used by the habitat classification

Index name	Abbreviation
BAI	Burn Area Index
GDVI	Generalised Difference Vegetation Index
MCARI	Modified Chlorophyll Absorption in Reflectance Index
MNDWI	Modified Normalised Difference Water Index
MSAVI	Modified soil adjusted vegetation index
MTICI	MERIS Terrestrial Chlorophyll Index (Sentinel-2 used)
NBR	Normalised Burn Ratio
NDRE1	Normalised Difference Red Edge
NDRE2	Normalised Difference Red Edge 2 (using 705 nm and 740 nm)
NDRE3	Normalised Difference Red Edge 3 (using 705 nm and 783 nm)
NDVI	Normalised Difference Vegetation Index
NRI	Nitrogen Reflectance Index
OSAVI	Optimised soil adjusted vegetation index
PSRI	Plant Senescence reflectance index
TCARI	Transformed chlorophyll absorption and reflectance index

2.2. Field survey

During December 2017 and January 2018 field work was undertaken by an experienced ecologist from Montserrat National Trust. In total 215 points were collected. Habitat class names and descriptions followed the definitions detailed in Young (2008), excluding certain habitats that were absent from the island (Mangrove), and those which ground survey found to be highly modified/transitional. Transitional habitats were not targeted as they could be classified as more than one broad habitat class; this was found to be the case for Riparian habitat, which was highly variable and transitional on the ground, and not definable as a distinct habitat type. The habitat descriptions are summarised in Table 2.

Additional information regarding vegetation canopy composition, the presence of notable or invasive species, and ecosystem service provision was also collected. A further 601 data points were digitised by manual image interpretation by the field ecologist (for vegetation classes) and experienced image interpreters (for urban/marine water/ash classes), giving a total number of 816 points (Figure 1). The total number of points collected per habitat is detailed in Table 3.

Table 2: Habitat descriptions used during field survey, taken from Young (2008)

Habitat	Description
Dry Scrub	A combination of the sub-classes 'Dry scrub' and 'Dry Scrub (Cacti Dominated)'. Shrubby vegetation 0.5-2.5m tall in lower elevations with low rainfall Typical taxa: <i>Comocladia dodonaea</i> , <i>Agavaceae</i> , <i>Croton spp.</i> , <i>Galactia spp.</i> , <i>Acacia spp.</i> , <i>Malpighia linearis</i> , <i>Stigmaphyllon spp.</i> , <i>Tetramicra canaliculata</i> , <i>Melochia spp.</i> , <i>Jacquinia armillaris</i> , <i>Corchorus aestuans</i> , <i>Cactaceae</i> , <i>Oncidium urophyllum</i> .
Dry Thicket	Large shrub/small tree dominated vegetation 2.5-5m tall in lower elevations with low rainfall Typical taxa: <i>Cordia spp.</i> , <i>Bouyeria succulenta</i> , <i>Oplonia microphylla</i> , <i>Cassine xylocarpa</i> , <i>Piscidia carthagenensis</i> , <i>Pithecellobium unguis-cati</i> , <i>Pisonia spp.</i> , <i>Coccoloba spp.</i> , <i>Verbenaceae</i> .
Mesic Forest	Medium/Large tree dominated vegetation >5m tall in mid elevations with medium rainfall. Typical taxa: <i>Begonia obliqua</i> , <i>Araceae</i> , <i>Lauraceae</i> , <i>Inga laurina</i> , <i>Eugenia spp.</i> , <i>Piper spp.</i>
Wet Forest	A combination of the sub-classes 'Wet Forest', 'Wet Forest (lower)' and 'Wet Forest (upper)': Medium/Large tree dominated vegetation >5m tall in high elevations with high rainfall. Typical taxa: <i>Elaeocarpaceae</i> , <i>Phyllanthus spp.</i> , <i>Podocarpus coriaceus</i> , <i>Asplundia spp.</i> , <i>Orchidaceae</i> , <i>Marcgravia umbellate</i> , <i>Arecaceae</i> , <i>Sloanea spp.</i>
Elfin Woodland	Shrubby vegetation 0.5-2.5m tall in high elevations with high rainfall and greater abundance of the following taxa: <i>Wercklea tulipiflora</i> .
Anthropogenic	Landscape modified and maintained through human activity.
Cultivated Area	Land currently under cultivation. Typical taxa: <i>Cocos nucifera</i> , <i>Mangifera indica</i> , <i>Carica papaya</i> , <i>Manihot esculenta</i> , <i>Psidium spp.</i> , <i>Poaceae</i> .
Ash/Mud	Land covered with volcanic ash or mud. Typical taxa: <i>Poaceae</i> , <i>Cyperaceae</i> .

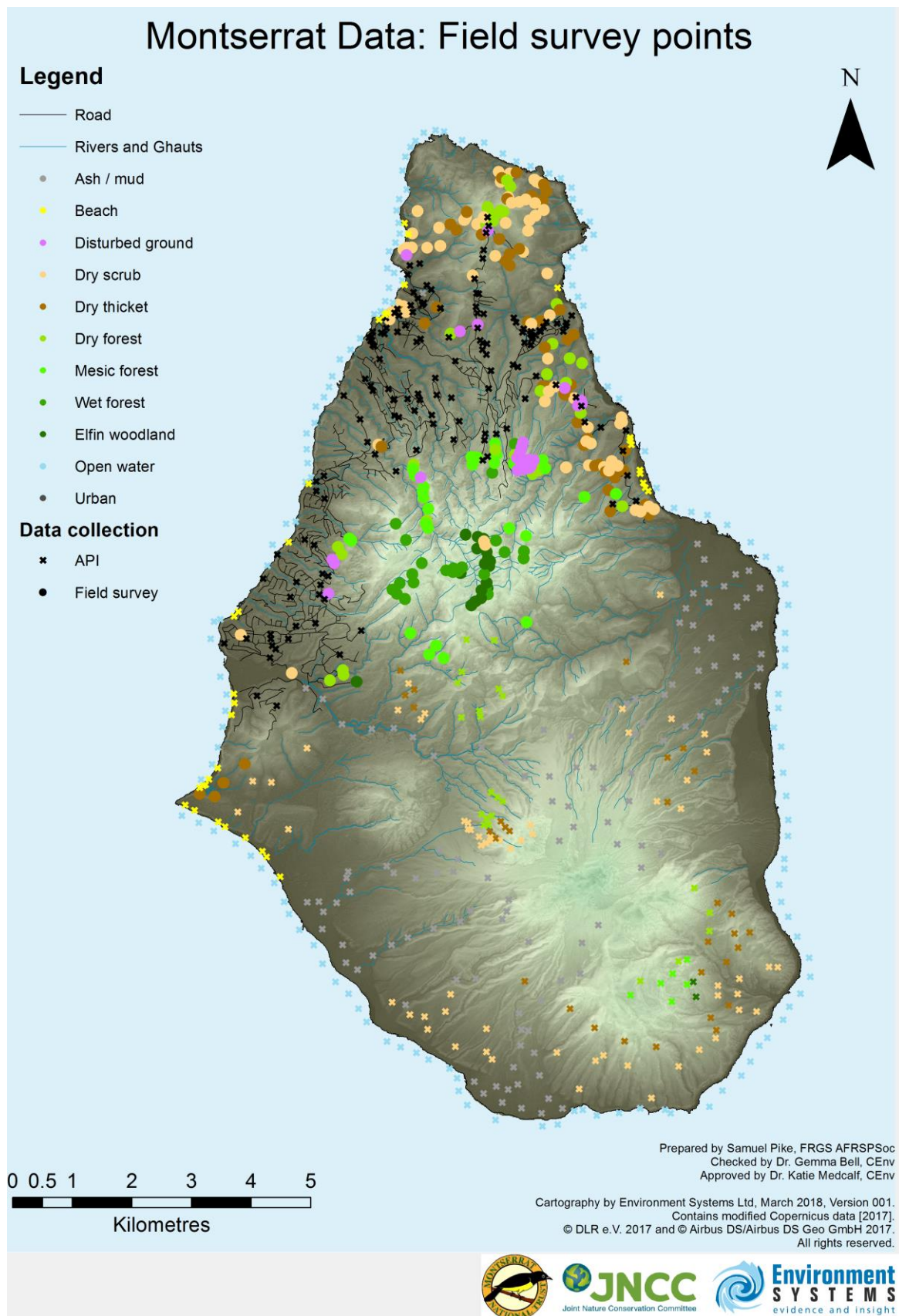


Figure 1: Training points for the classification collected through field survey work and visual interpretation.

Whilst efforts were made to capture representative samples of all habitats across the entire island of Montserrat, it was geographically not possible to access all areas of the island due to steep terrain and general inaccessibility of the south of the island. All training data points in the south of the island were captured by image interpretation, not field survey. As a result of these restrictions some habitat classes are under represented in the training dataset; notably Elfin woodland (21 data points) and Wet forest (24 data points), therefore there may be more uncertainty in the classification accuracy of these classes.

A further stage of field validation was carried out in early March 2018. This was specifically targeting habitat polygons displaying unusual characteristics (see Section 5.3).

Table 3: Field survey/habitat classification training points

Habitat	No. of points by field survey	No. of points by image interpretation	Total number of points
Ash/mud	0	120	120
Beach	0	36	36
Disturbed ground/Agriculture	0	29	29
Dry forest	31	22	53
Dry scrub	67	59	126
Dry thicket	50	31	81
Elfin woodland	19	2	21
Mesic forest	24	11	35
Open water (marine)	0	145	145
Urban	0	146	146
Wet forest	24	0	24

2.3. Additional datasets

Slope, aspect and curvature datasets were derived from the WorldDEM™ image. In addition, island-wide 2m resolution raster proximity datasets were created, showing proximity to known agricultural areas, buildings, roads, rivers, trails and the coastline. The proximity datasets were based on vector data supplied by the Government of Montserrat.

3. Terrestrial Classification Method

3.1. Image segmentation

A detailed image segmentation was carried out in eCognition 9.0 to define the boundaries between different vegetation and land cover types on Montserrat. Due to the coarser resolution of the Sentinel-2 imagery and very high prevalence of cloud cover, the segmentation was based on Pléiades imagery. A single cloud-free image for the island was not available, so a composite of three Pleiades images was used for the segmentation resulting in only a small area of cloud cover above the peak of the volcano (Figure 2). An example of the resulting segmentation is shown in Figure 3.

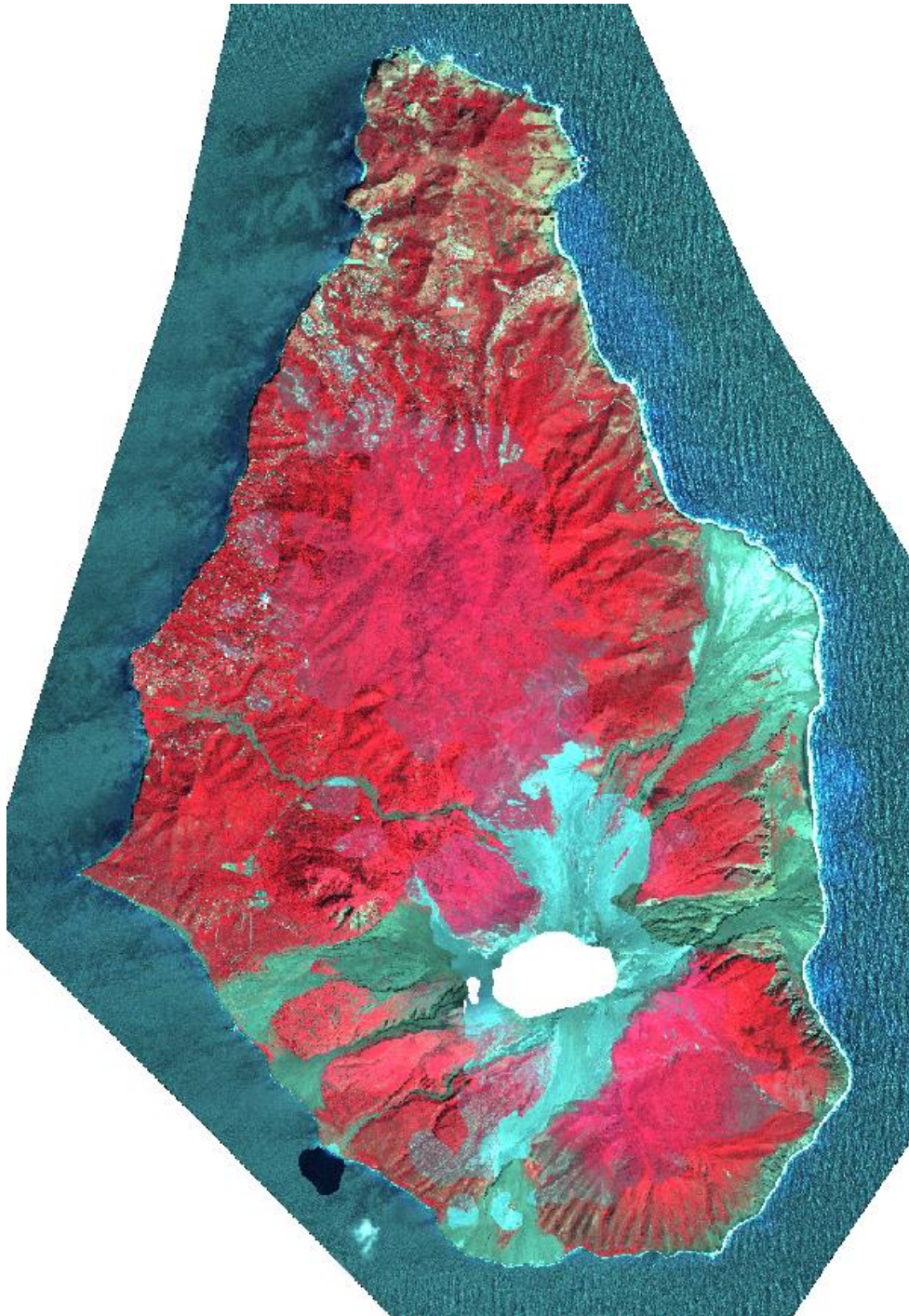


Figure 2: Composite of three Pléiades images used for segmentation

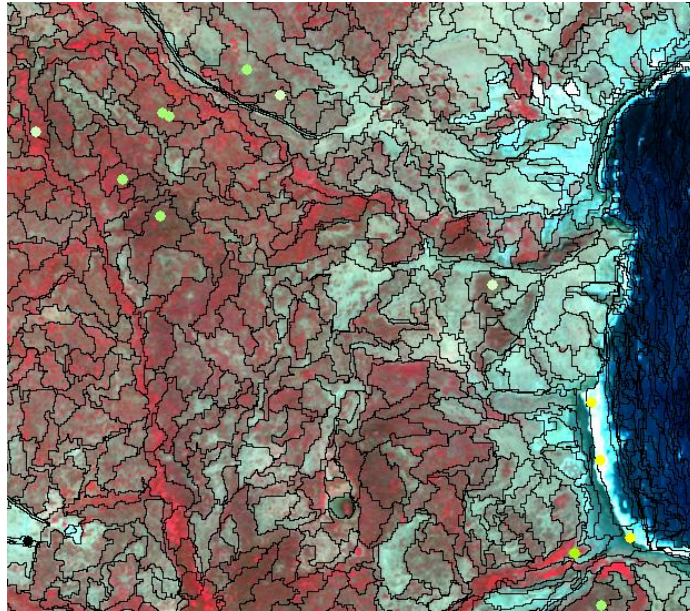


Figure 3: Example of image segmentation used by the Living Map habitat classification

3.2. Living Map process

The Living Map habitat classification process is a Random Forest-based classifier implemented in R, developed by Natural England (Kilcoyne *et al.*, 2017). It takes the locations of the training data (from field survey and image interpretation) and analyses the attributes of the entire image stack on the basis of zonal statistics, using the image segmentation to define zone boundaries. On this basis the characteristics of each habitat/land cover class present in the training data are defined. The process then assigns a habitat/land cover class to every image segment based on the similarity of the image stack zonal statistics to the class characteristics.

As inputs, the Living Map script reads in all rasters (images, image segmentation, indices and proximity layers) and the vector point dataset containing training data. The process removes data gaps (such as those resulting from cloud cover) by imputing values into the zones with missing values; it analyzes the values across the image stack where there are no data gaps, and models what the values should be within the gaps themselves.

The code requires the user to specify a maximum number of training points per class, with the default set at 30. However, this was seen as an unnecessary constraint to the classification, and the value was increased to allow all training points to be used. Training points obtained from field survey were given a higher weighting than points obtained by image interpretation. Following classification, the script creates a confusion matrix to generate an accuracy assessment for each class, but no documentation was available to explain how the point data set was apportioned between training and validation.

The resulting classification was manually supplemented through the fusion of existing vector datasets for buildings and roads, in order to better-define these features. The output class 'Disturbed ground' was also split into 'Cultivated area' and 'Disturbed ground/cultivated area' through fusion of known agricultural areas.

During the course of the analysis a number of features within the existing code were identified which will make the code more suitable to running in the tropical

environment found in the Caribbean. The recommended updates which improve operating efficiency and accessibility, are summarised in Appendix A along with recommendations for future development of the script.

4. Terrestrial Classification Result

4.1. Habitat map of Montserrat

The complete terrestrial habitat classification is shown in Figure 5. There are five fields in the habitat dataset: "A_pred" describes the random forest primary prediction with "A_prob" illustrating the corresponding probability. "B_pred" describes the random forest secondary prediction with "B_prob" illustrating the secondary probability. "Class" describes the habitat after thematic layers have been introduced.

The attribute table of the habitat map contains four fields, intended to serve as a record of future map version updates. Following field and/or image interpretation the column 'CLASS' should be updated along with the columns 'DATE_UPDAT', 'VERSION', 'UPDATE_BY' and 'METHOD' (e.g., aerial photographic interpretation (API) or field survey (FS)). See Figure 4 below. The field name 'ORIG_CLASS' contains the original habitat classification from the Living Map analysis, and should not be overwritten.

ORIG_CLASS	CLASS	DATE_UPDAT	VERSION	UPDATE_BY	METHOD
Bare ground	Bare ground		0		
Bare ground	Dry scrub	28/03/2018	1	SP	API
Bare ground	Dry scrub	28/03/2018	1	SP	API
Bare ground	Dry scrub	28/03/2018	1	SP	FS
Bare ground	Dry scrub	28/03/2018	1	SP	FS
Bare ground	Dry scrub	28/03/2018	1	SP	FS
Bare ground	Dry scrub	28/03/2018	1	SP	FS
Bare ground	Dry scrub	28/03/2018	1	SP	API
Bare ground	Dry scrub	28/03/2018	1	SP	FS
Bare ground	Bare ground		0		
Bare ground	Bare ground		0		
Bare ground	Bare ground		0		

Figure 4: Example of manually updated habitat data

The habitat descriptions are shown in Table 2, Section 2.2. If further habitat classes are needed following field investigation then they can be added in the CLASS field, and the habitat description table should also be updated.

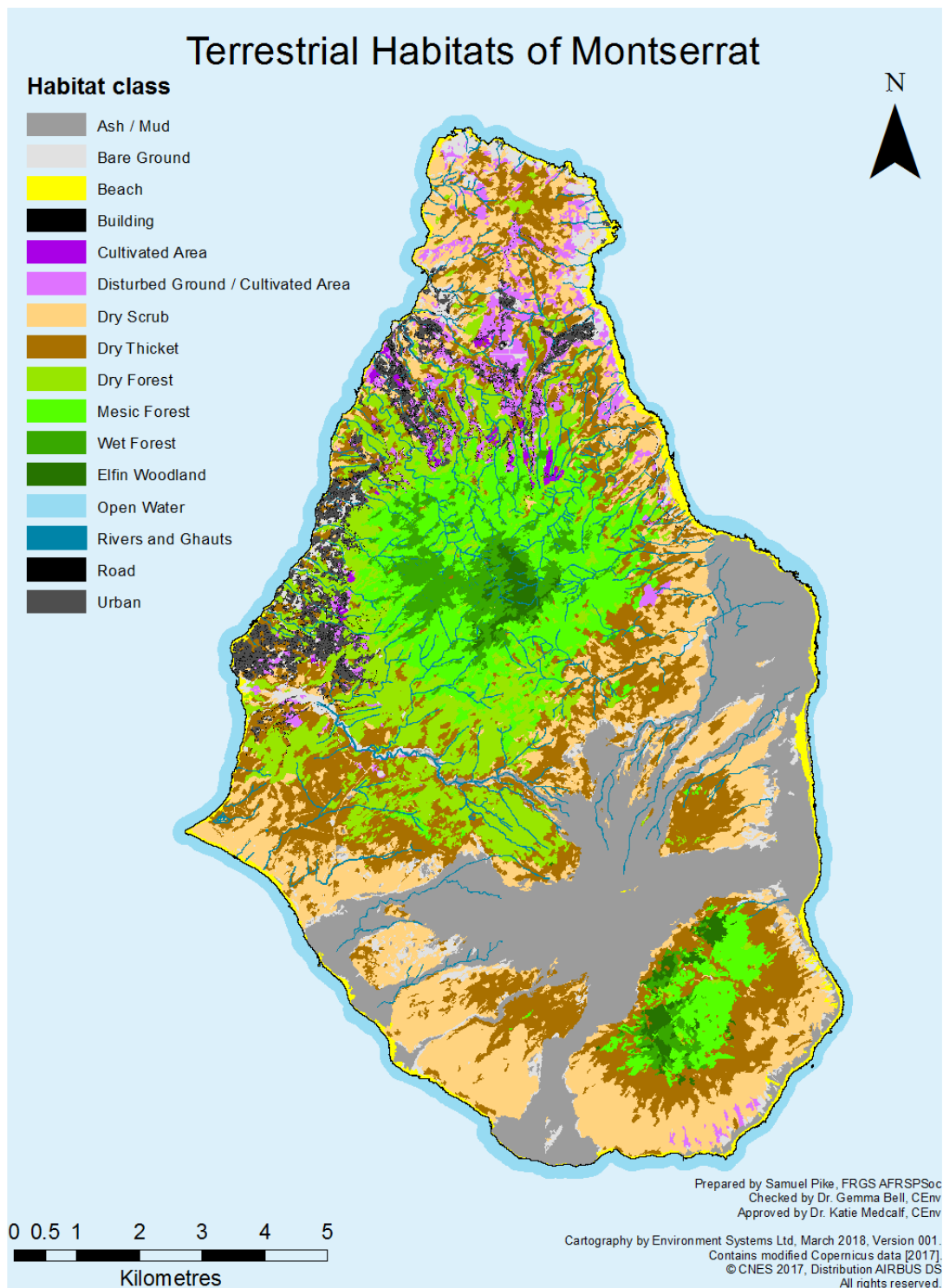


Figure 5: Habitat classification of Montserrat based on the field "Class"; Living Map method

4.2. Classification accuracy

The Living Maps script automatically generates an accuracy assessment, the results of which are shown in Figure 6 and Figure 7. At the time of writing it was unclear how many data points had been used for training the habitat classification, and how many had been used for the accuracy assessment.

The overall map accuracy is calculated as 73.44%. Disturbed ground and Dry scrub had the highest classification accuracies out of the vegetated classes, at 83.3% each (Table 4). Dry forest had the lowest accuracy, at 16.7%, even though a relatively high number of training points were available for this habitat type. Upon closer inspection of the additional field survey information recorded against these data points it can be seen that the vegetation in most of these locations displayed some evidence of disturbance and/or transitional characteristics. It is likely that this led to the low classification accuracy, as the training samples did not allow the classification script to define the characteristics of 'pure' dry forest areas.

Figure 7 provides information on the ways in which classes have been misclassified. From this graph it can be seen in the Ash/mud class, two thirds of the samples (66.7%) were classified successfully, but that the remaining samples were misclassified as Urban. In the Beach class 83.3% of samples were classified successfully, with the remaining samples being misclassified as Open water. The information displayed in the graph is summarised in Table 3. With the exception of the Dry scrub/Urban confusion, the class confusions can be explained by gradations between one habitat type and another (e.g., in the case of Dry forest, Dry thicket Dry scrub) or similar reflectance characteristics of bare earth features (e.g., Ash/Urban).

Table 4: Summary of classification accuracies and confusion between classes

Class	Classification accuracy	Misclassified As
Ash/mud	66.7%	Urban
Beach	83.3%	Open water
Disturbed ground	83.3%	Dry forest
Dry forest	16.7%	Dry thicket, Mesic forest
Dry scrub	83.3%	Urban
Dry thicket	66.7%	Dry scrub
Elfin woodland	80.0%	Disturbed ground
Mesic forest	66.7%	Dry forest
Open water	100%	n/a
Urban	83.3%	Disturbed ground
Wet forest	80.0%	Elfin woodland

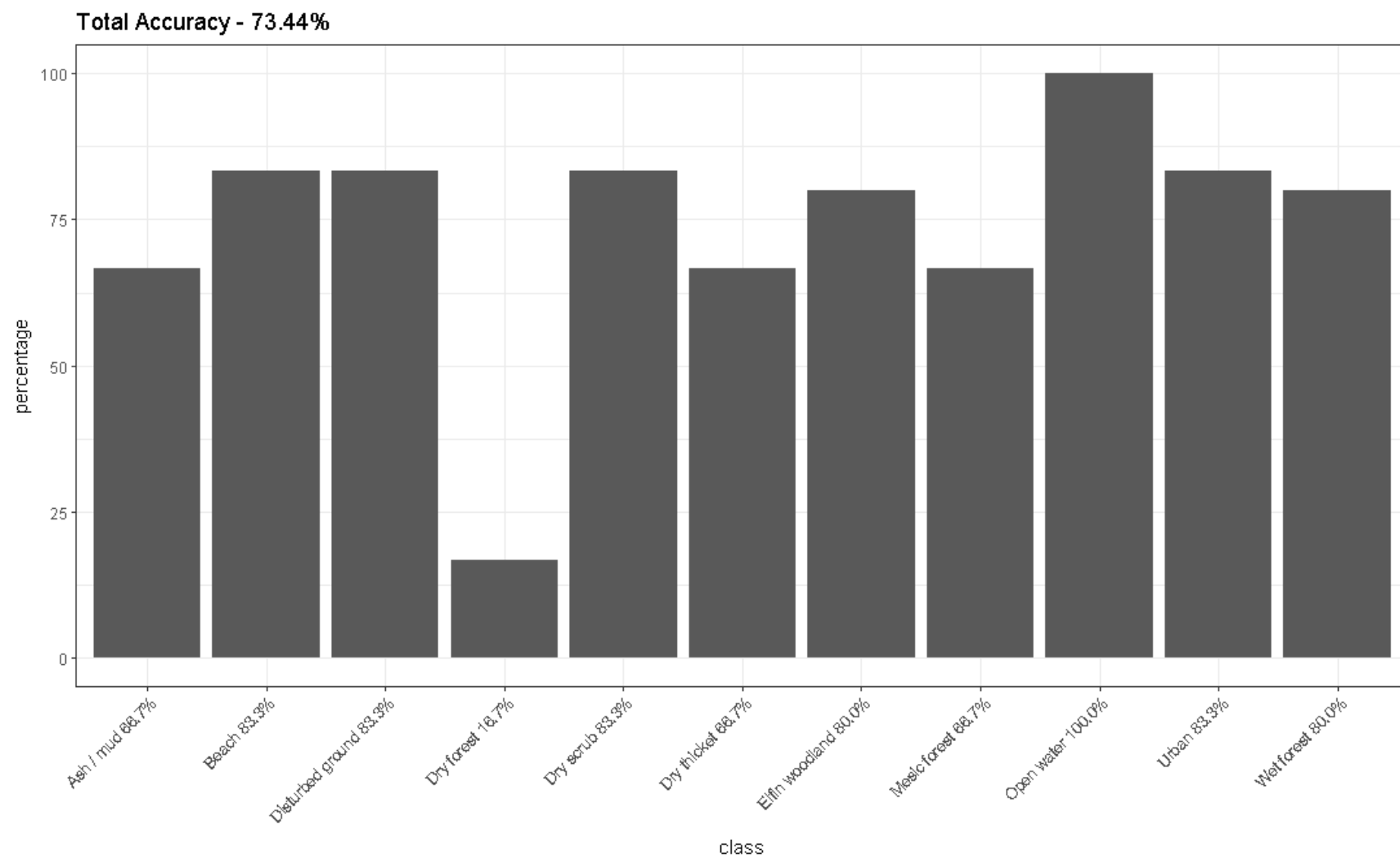


Figure 6: Breakdown of accuracy by class

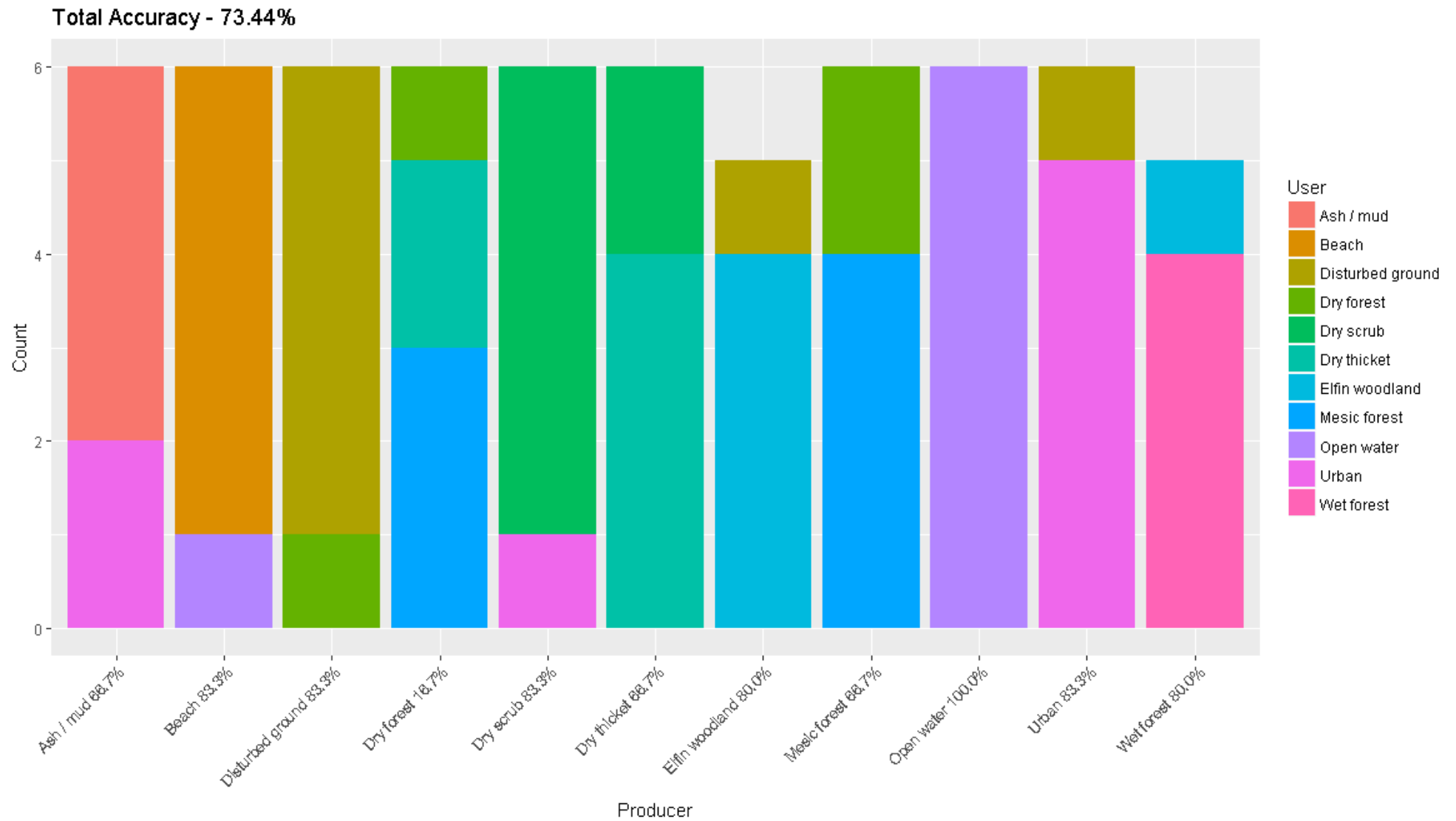


Figure 7: Breakdown of classification errors by class

4.3. Production of a habitat map for economic valuation

The habitat map was found to contain too much detail with respect to some classes for the purpose of economic valuation of natural capital. As a result an amended version of the habitat classification was produced, with certain classes merged together (Table 5). In addition, existing marine benthic habitat data from the Blue Halo project (Blue Halo, 2017) were incorporated to produce a seamless habitat map for the entire territory of Montserrat. This version of the habitat was produced as a standalone output for the purposes of the economic valuation, and was not used for calculation of spatial metrics. Figure 8 shows a hybrid version of the habitat map, presenting the detailed terrestrial habitat classes alongside the Blue Halo marine habitat classes.

Table 5: List of habitat classes merged together for economic valuation

Original habitat class	Merged 'SuperClass'
Elfin woodland	Wet woodland
Wet forest	Wet woodland
Mesic forest	Wet woodland
Dry forest	Dry scrub
Dry thicket	Dry scrub
Dry scrub	Dry scrub
Cultivated area	Cultivated area
Disturbed ground / cultivated area	Cultivated area
Urban	Developed land
Buildings	Developed land
Roads	Developed land

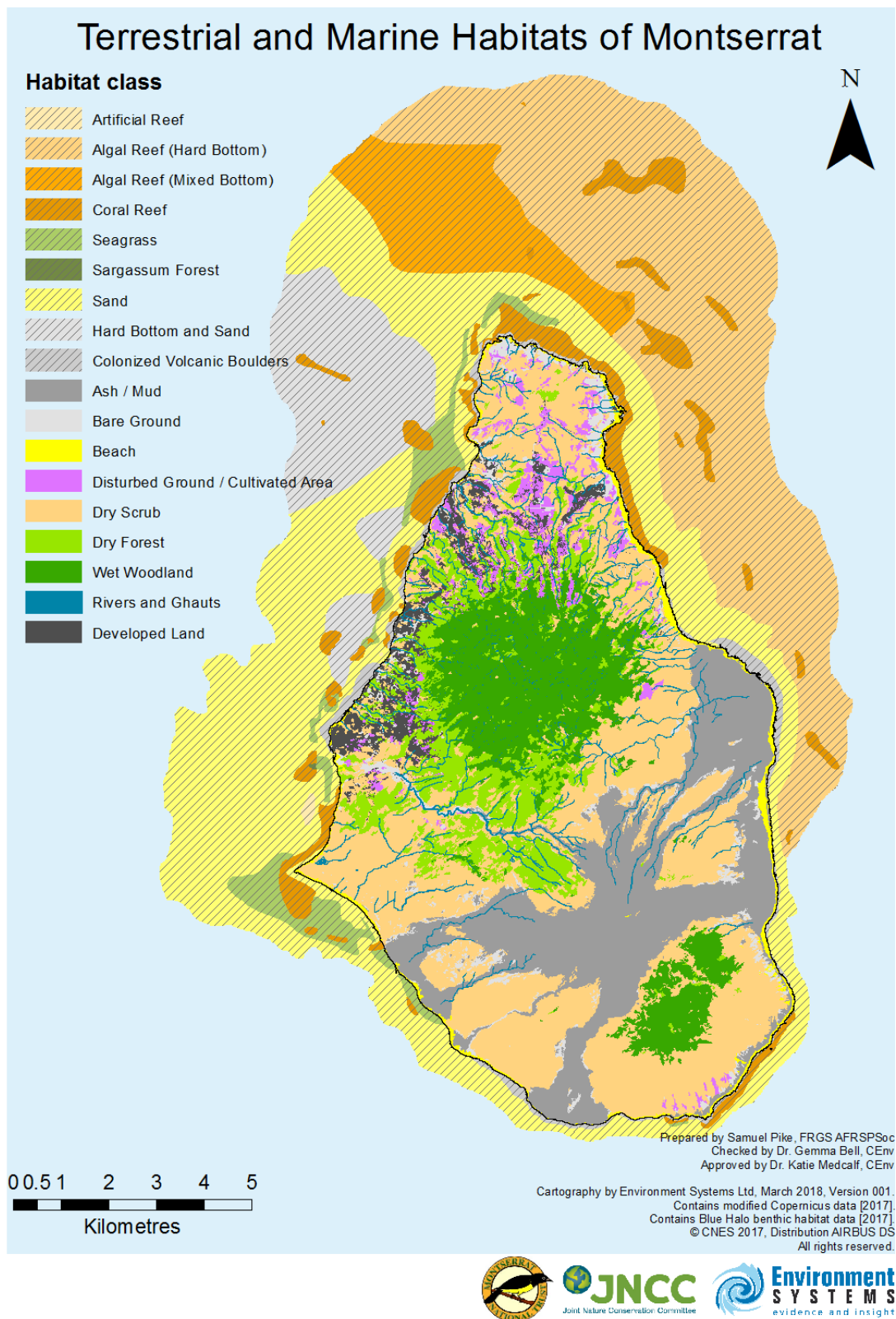


Figure 8: Combined terrestrial (detailed classes) and marine habitat map of Montserrat.

5. Spatial Metrics

Sentinel-2 and Pléiades imagery were analysed to produce spatial metrics to inform a baseline natural capital valuation. The spatial metrics were chosen based on an assessment of island priorities in terms of ecosystem service provision.

Island priorities were first scoped with a range of stakeholders during a Territory to Territory Partnership workshop, held between 13th-17th November, 2017, through discussion of how each of the habitats of Montserrat provide key ecosystem services. These initial findings were then further explored by Eftec Ltd to identify a short-list of island priorities. These priorities were then assessed alongside the capabilities of EO analysis to identify key spatial metrics to be generated for the project. The chosen metrics were habitat extent, extent of different agricultural activities, forest canopy density, forest clearing activity, and coastal sediment plume mapping. In addition an erosion risk layer calculated using Sensitive Catchment Integrated Modelling and Analysis Platform (SCIMAP), showing how risk areas on the land may be relating to the sea has been run for the island. This is described in Section 5.6

The original, unmerged habitat classification was used for this analysis. This is because the habitat extents from the original habitat could easily be summed to produce the extents for 'SuperClass' habitat classes, and all of the other spatial metrics were required to be generated for the more detailed habitat classes.

5.1. Habitat extent

Table 6 provides a summary of habitat extent for the habitats of Montserrat both, using the detailed terrestrial habitat classes and Blue Halo benthic habitat classes. It shows total habitat extent across the island, and the area of habitat contained within the forest park protected area. Figure 9 shows the percentages of each habitat contained within the forest park boundary. It can be seen that more than 50% of the total island resource of Wet forest and Mesic forest are located within the park (78% and 56% respectively), and just under half of the islands' Elfin woodland (49%). The majority of the Dry forest, Dry scrub and Dry thicket on the island lie outside the protected area (90%, 99% and 97%, respectively), as does 79% of the area of Rivers and ghauts.

Previously to this map it was thought that all the Elfin forest lay within the Centre Hills Protected Area. It has not been possible to reach the south of the island to check if Elfin forest has developed in this area since the volcano erupted. It is possible that Elfin forest is present or it may be that there is a specific very dense fern dominated habitat developing in this area which shares spectral characteristics with the Elfin forest. The exact classification of this area in the south of the island will require a field visit.

Table 6: Summary of marine and terrestrial habitat extents

Habitat Type	Habitat	Total Extent (Ha)	Extent within Forest Park (Ha)
Marine	Algal Reef (Hard Bottom)	4149.00	0
Marine	Algal Reef (Mixed Bottom)	1043.00	0
Marine	Artificial Reef	14.00	0
Marine	Colonised Volcanic Boulders	266.00	0
Marine	Coral Reef	872.00	0
Marine	Hard Bottom and Sand	1339.00	0
Marine	Sand	4589.00	0
Marine	Seagrass	446.00	0
Terrestrial	Ash / mud	2148.57	0
Terrestrial	Bare ground	436.05	0.13
Terrestrial	Beach	248.80	0
Terrestrial	Buildings	48.32	0.01
Terrestrial	Cultivated area	30.59	0.09
Terrestrial	Disturbed ground / Cultivated area	302.33	1.40
Terrestrial	Dry forest	1220.50	117.66
Terrestrial	Dry scrub	1995.32	18.13
Terrestrial	Dry thicket	1973.80	60.54
Terrestrial	Elfin woodland	122.07	59.22
Terrestrial	Mesic forest	1077.26	597.95
Terrestrial	Open water	849.32	0
Terrestrial	Rivers and ghauts	101.39	20.94
Terrestrial	Roads	45.82	0.19
Terrestrial	Urban	295.40	0.36
Terrestrial	Wet forest	333.80	259.78

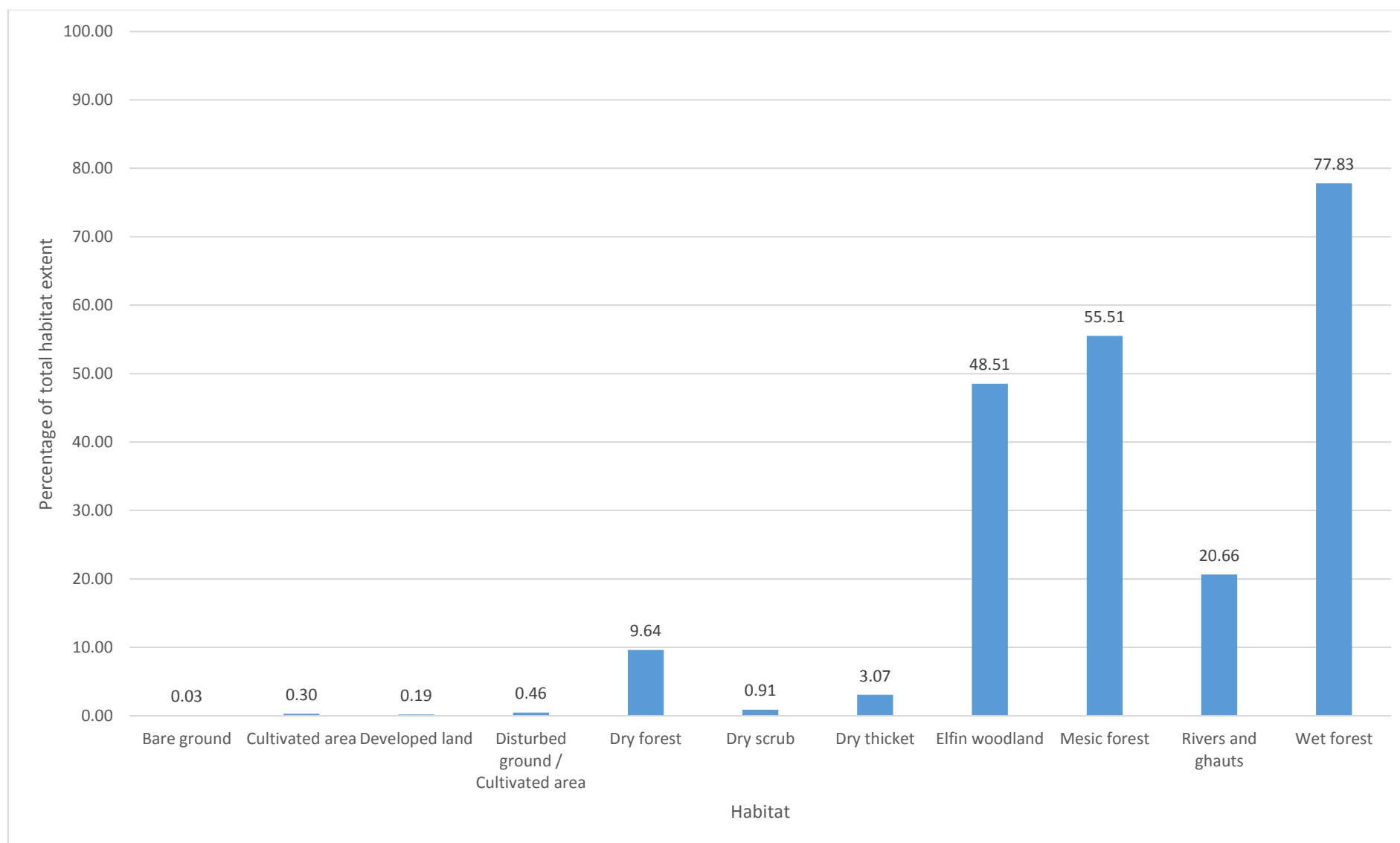


Figure 9: Percentage of habitat area falling within the forest park boundary.

5.2. Agricultural sub-categories

Analysis of the type of agricultural activities is a useful metric for understanding the relative importance of different agricultural sectors. It can be used to describe the level of food provision provided by the land, and how this impacts on other ecosystem services; for example agricultural areas can have both positive and negative impacts on the surrounding areas depending on the way in which they are managed, and habitat clearance to make way for new agricultural areas will result in a change in the balance of ecosystem services provided at the location in question.

The habitat classes 'Cultivated areas' and 'Disturbed ground / Cultivated area' were used for this analysis to identify areas of probable crop cultivation ('Agriculture'), areas of probable pastureland, and areas of trees (crop and non-crop).

All areas classified as 'Cultivated areas' or 'Disturbed ground / Cultivated area' were re-analysed in eCognition in order to create a classification of the three agricultural sub-categories using a rule-based approach. Figure 10 presents the resulting classification of agricultural sub-categories throughout Montserrat.

Cultivated trees and shrubs ('Trees') were classified by their high productivity values in the annual mean NDVI Sentinel-2 composite. Areas of probable crop cultivation were identified using the PSRI index, which is sensitive to the onset of canopy senescence and plant fruit ripening; analysis of the homogeneity of this index over time provided the basis for distinguishing between cultivated and non-cultivated areas, with the more homogenous areas being classified as 'Pastureland' due to there being less evidence of planting-ripening-harvesting cycles. Classification training was undertaken using visual image analysis; no ground data were available, and so the accuracy of this classification cannot be assessed at present.

The results of the analysis of the 'Disturbed ground / Cultivated area' contain greater uncertainty as the class is a mixture of disturbed ground, formal and informal agriculture, whereas the habitat class 'Cultivated area' has been mapped to greater level of confidence through inclusion of existing Government of Montserrat GI data (Section 4.2).

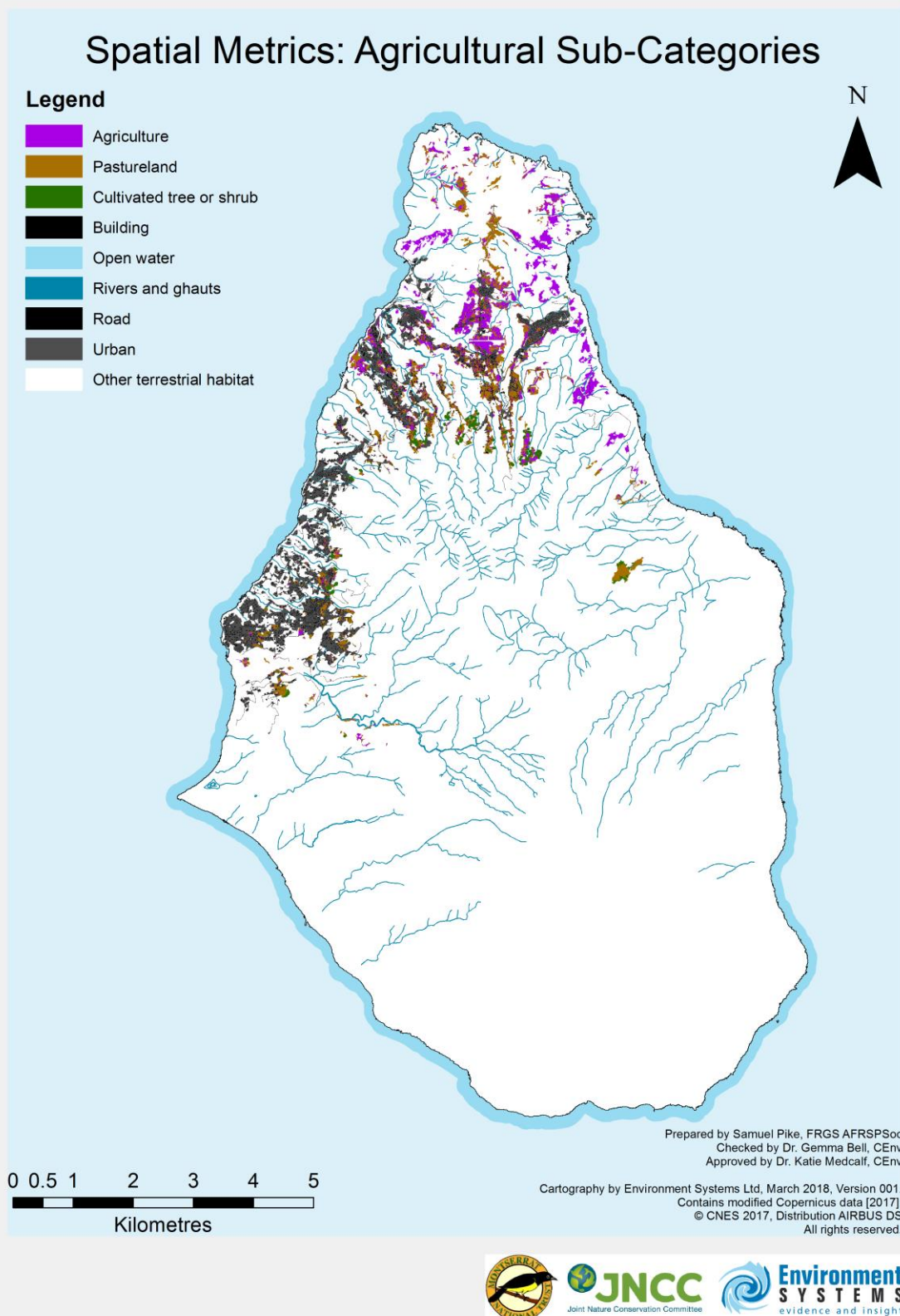


Figure 10: Classification of agricultural sub-categories from the 'Cultivated areas' and 'Disturbed ground / Cultivated area' habitat classes.

5.3. Forest canopy density

Forest canopy density assessments can be used to infer information about habitat condition, and the associated level of ecosystem service provision. For example, dense forest canopies may provide a greater level of soil protection from erosion and higher water quality from reduced sediment load.

Canopy density can be used to infer biodiversity value or general habitat condition for many habitats, and changes in the canopy characteristics can provide information on the likely direction of change over time e.g., increasing canopy density over time on disturbed ground that is becoming colonised by shrubs and trees, or decreasing canopy cover as a forest is thinned by logging.

Analysis of forest canopy density followed the method of Banerjee *et al.* (2014) using the mosaic of Pléiades images from 2014, 2016 and 2017 to attain a near cloud-free dataset. Forest canopy density values were derived by calculation of Advanced Vegetation Index (AVI), Bare Soil Index (BSI) and Canopy Shadow Index (SI) of Pléiades imagery, which were then combined in a weighted model ($3NRI + 2AVI + BSI$) to represent canopy density.

Ideally the resulting canopy density model would then be calibrated against ground-based measurements. No such bespoke field data were available, although subjective qualitative estimates of the degree of canopy closure had been logged during the field campaign for producing the habitat classification. This field dataset was reviewed for its potential use as training data for the canopy density model but found to be unsuitable as there were insufficient points to be statistically robust. Calibration of this layer using field data, would require a targeted ground survey effort.

Repeat analysis of canopy density using the same formula weighting will produce a similar range in image values and should allow broad comparisons over time, particularly by using zonal statistics. This will give a useful monitoring tool for the island even though the canopy density output is uncalibrated by ground collection. The full canopy density classification is shown in Figure 11.

The image segmentation created during production of the habitat classification was used to derive zonal statistics for each forest habitat class, calculating mean, maximum and minimum canopy density values for each habitat type. Outlier polygons displaying unusual canopy characteristics were then identified by selecting all habitat polygons with mean canopy density outside two standard deviations of the class mean; these polygons were identified to highlight potential areas of unusual habitat, which may be in transition to another habitat class, or display other differences in habitat condition which become manifest in the canopy characteristics. The outlier polygons for each habitat class are shown in Figure 12.

Further field validation revealed the main causes for this difference in canopy characteristics:

- In the south of the island around the volcano the unusual characteristics of the forest types are caused by successional development of one habitat type to another following re-colonisation of land affected by ash downfall.
- Around Centre Hills to the north, high up on the mountains, the areas with unusual canopy were found to be abandoned agricultural ventures such as banana plantations reverting back to forest.

- In the north of the island, the unusual characteristics were most likely caused by re-development, or new agricultural ventures.

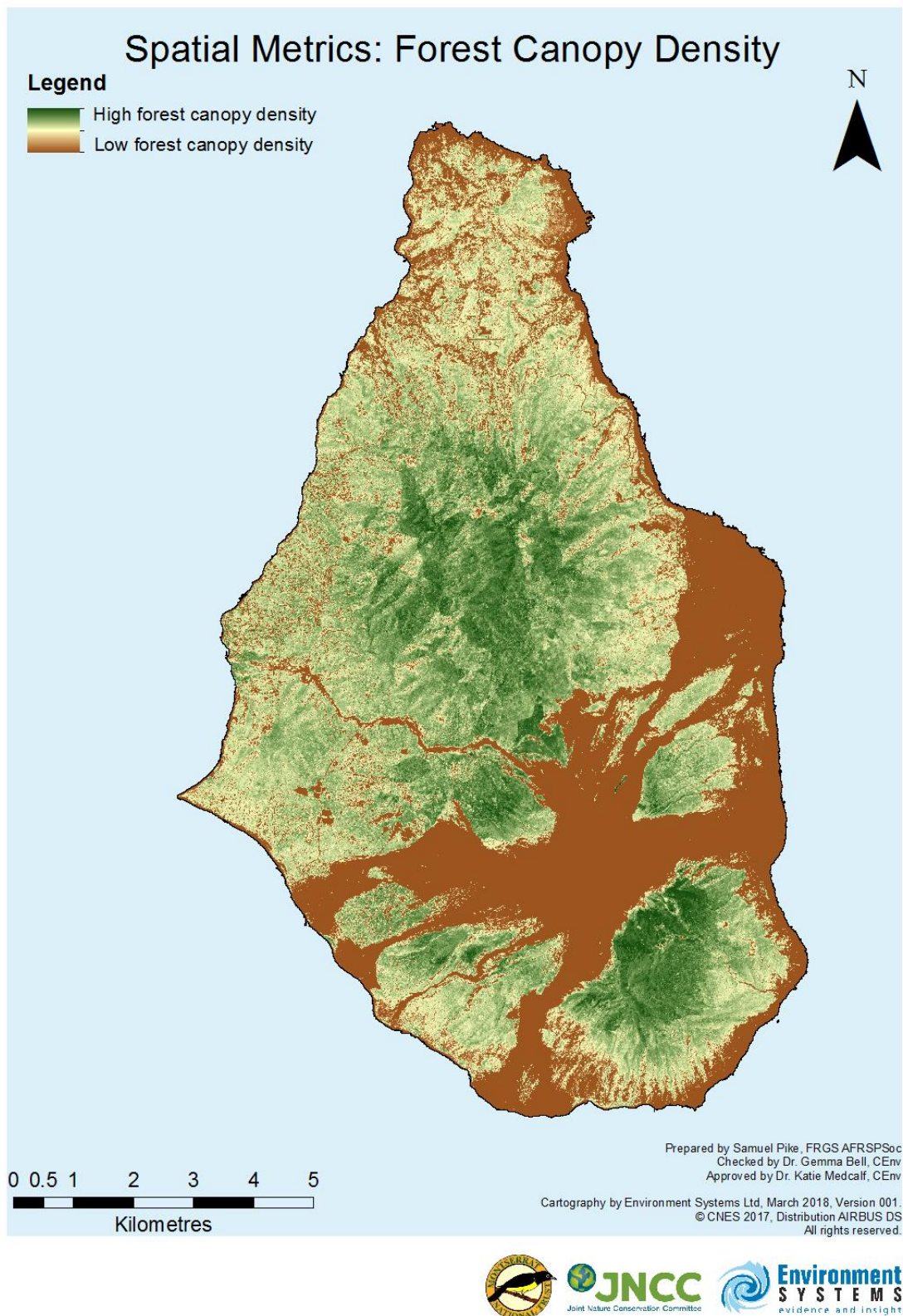


Figure 11: Forest canopy density across Montserrat (derived from 2014, 2016 and 2017 Pléiades image mosaic).

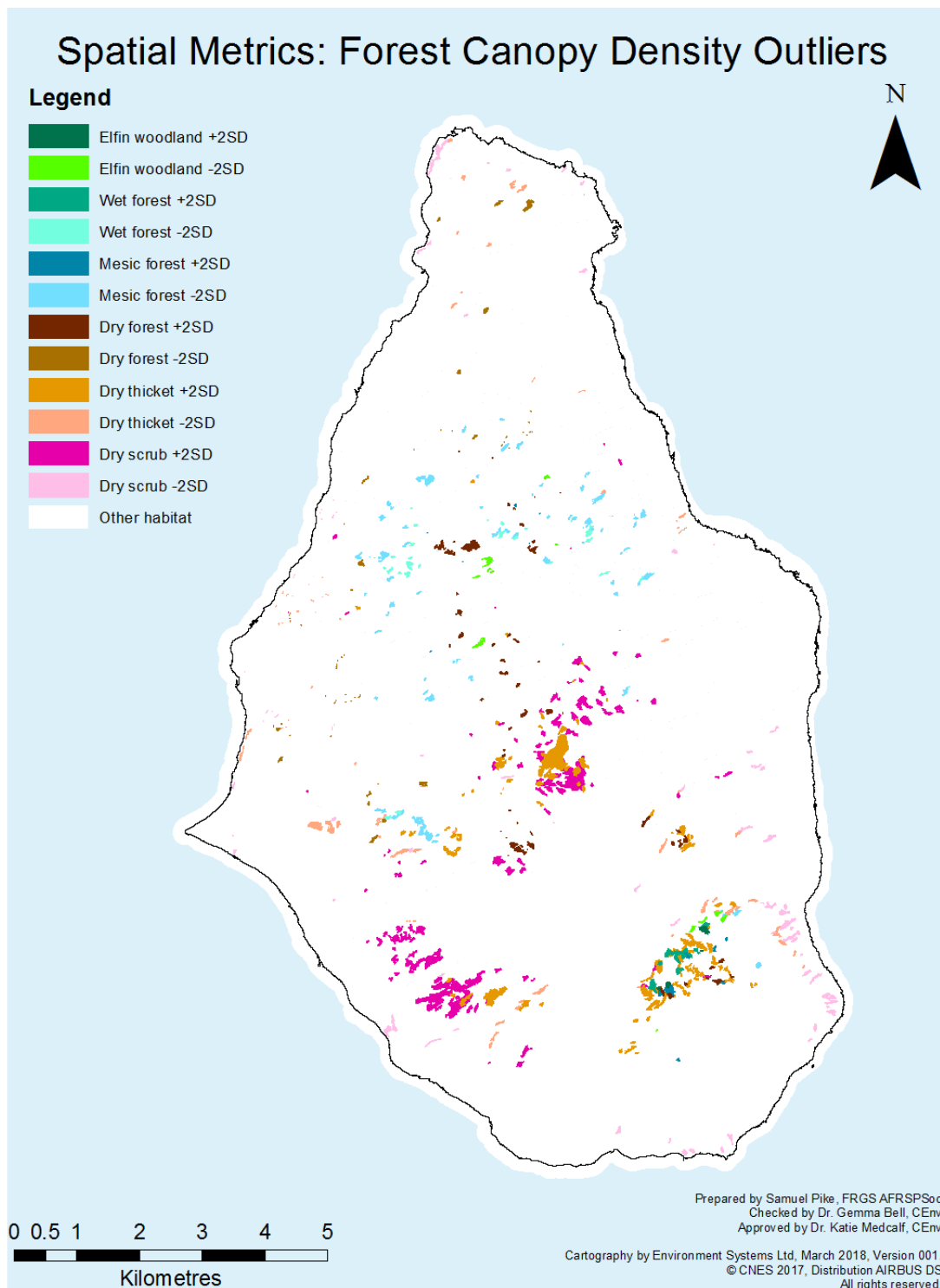


Figure 12: Habitat polygons displaying higher or lower canopy densities than average(+2SD: greater than two standard deviations from the mean; -2SD: less than two standard deviations from the mean).

5.4. Forest clearings

An analysis of forest clearing activity provides an overview of urban and agricultural, agricultural expansion and forest management activities.

For this metric, it was important to select data that would both visually and spectrally identify within-forest variations of canopy cover. Pléiades imagery was chosen for the initial analysis due to high frequency and extent of cloud-cover in the Sentinel-2 imagery. However, in spite of careful image selection to minimize the impact of cloud cover, there was still a high level of cloud cover across forested regions in central Montserrat, meaning that these areas could not be analysed (Figure 13).

Of the seven indices created using Pléiades (Table 1), the Nitrogen Reflectance Index (NRI) was selected as the basis of the analysis. This was based on the dynamic range of values between forest and non-forest cover and the visual assessment of its relatively low sensitivity of saturation over dense areas of productive vegetation.

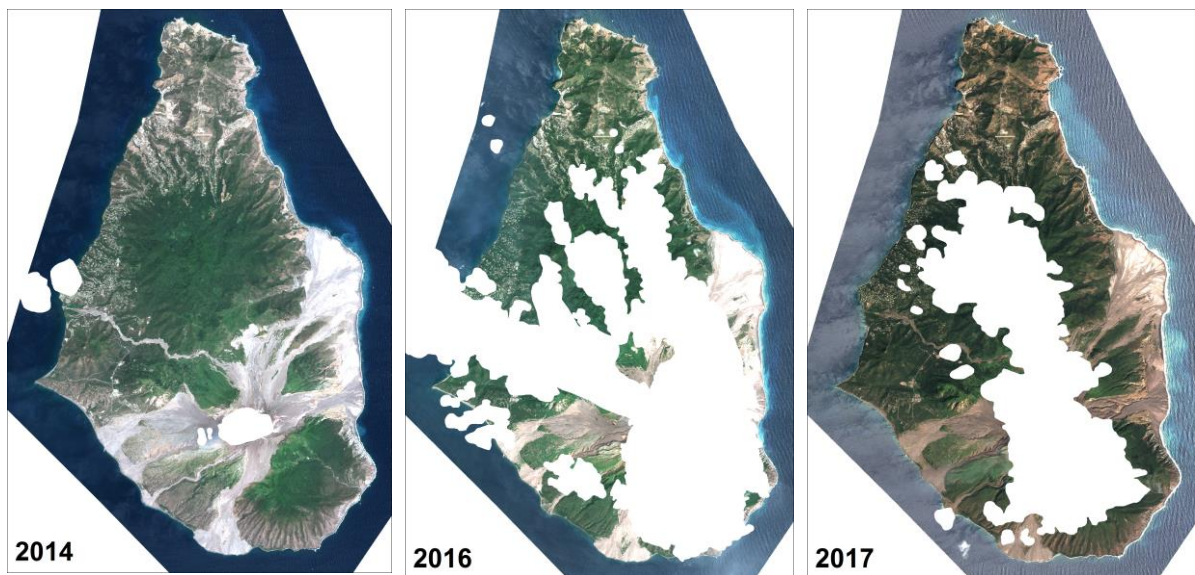


Figure 13: Comparison of Pléiades images showing extent of cloud cover (masked areas).

Two NRI difference products were created by comparing the NRI values between 2014/2016 and 2014/2017. A difference product between 2016/2017 would have been preferable, but, would not have provided much spatial information due to cloud cover extents.

Mean zonal statistics were extracted from both NRI difference dataset using the VHR segmentation created for the baseline habitat classification. Only habitat polygons previously classified as a forest type were taken forward for further analysis (Dry forest, Dry scrub, Dry thicket, Elfin woodland, Mesic forest, Wet forest). Forest clearings were identified within these habitat areas based on visual determination of a NRI zonal statistic threshold. Separate thresholds were used for the 2014/2016 and 2014/2017 difference products. The final forest clearing output was created by using the 2014/2017 classification in all cloud-free areas, and filling in the cloudy areas with the forest clearing classification from 2014/2016. Figure 14 shows a close-up example of small areas of forest being cleared over time, and how this has been detected by the NRI-based forest clearing classification. The complete classification for the whole of Montserrat is shown in Figure 15.

The resulting classification identifies forest clearings in the lower-elevation areas of the island, with no clearings being found in the Centre Hills. However, the limitations of the input imagery must be recognised when interpreting this output, as the central region was totally covered by cloud in both the 2016 and 2017 Pléiades images, therefore it was not possible to identify change in these areas.

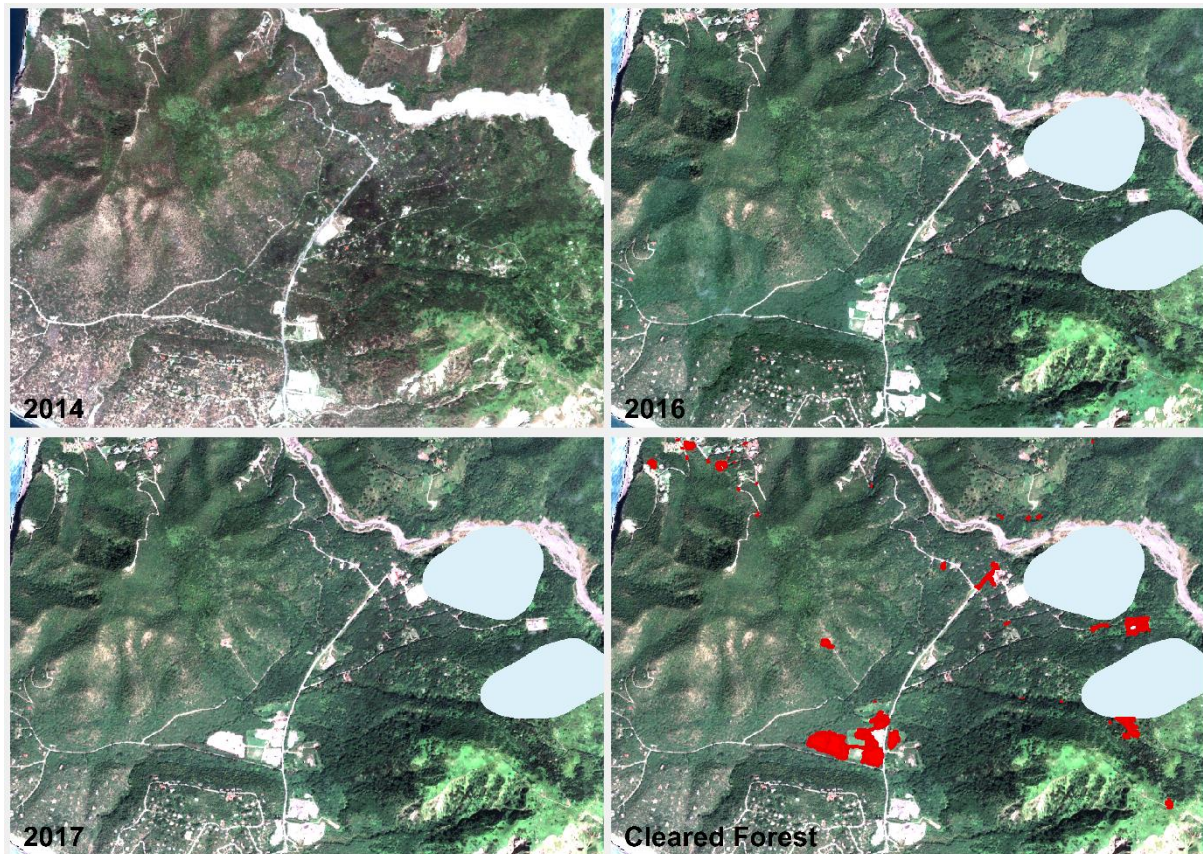


Figure 14: Example of forest clearing classification alongside the Pléiades image time-series.

Due to data restrictions and cloud cover, this technique focused on the very high resolution (VHR) image data (Pléiades), which provided a direct near-annual comparison. Cloud cover permitting, the same technique could be applied to Sentinel-2 imagery for both within-year and between-year analyses.

Informal field validation of this data set in March 2018 revealed the following features:

- In the south of the island unusually sparse vegetation could be due to goats grazing out the understory species, making more open habitat types.
- In the west of the island sand mining activities are responsible for the clearance.
- In the north of the island, clearings are generally the result of new housing or agricultural areas which are being developed to help maintain and enhance Montserrat's economic future.

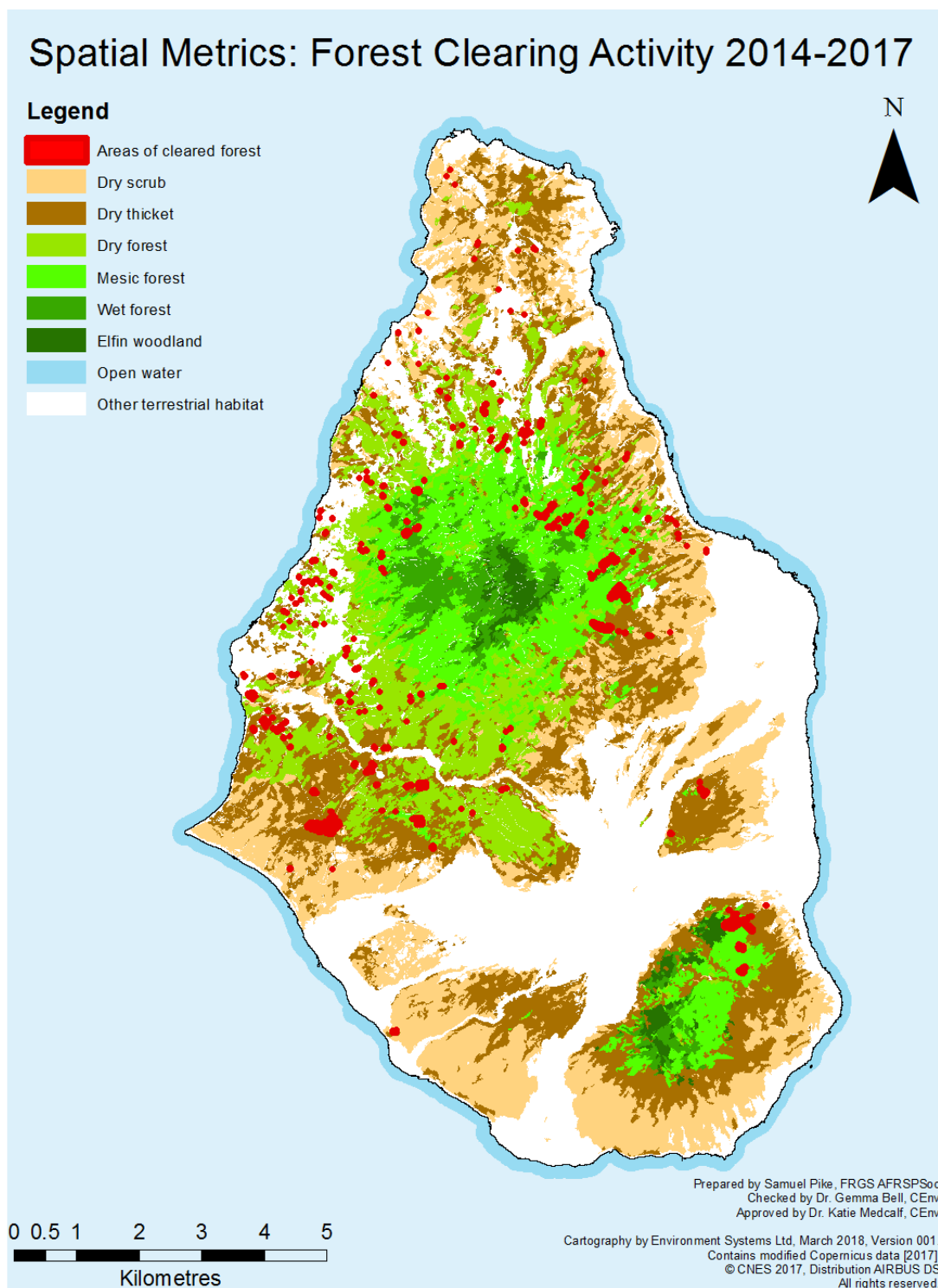


Figure 15: Forest clearings identified by analysis of 2014, 2016 and 2017 Pléiades imagery.

5.5. Suspended sediment analysis

Sediment loads in the coastal marine zone show high temporal variability with respect to particle concentration and plume extent, and sediment plumes can be created or exacerbated by anthropogenic activities such as dredging or land clearance around drainage channels. Increased sediment load can have significant negative effects on water quality, affecting coral reef health by reducing their photosynthetic capability, through smothering, and reduced coral recruitment (Richmond, 1993), with the most sensitive species exhibiting mortality following high sedimentation events lasting less than 24 hours (Erftemeijer *et al.*, 2012). An analysis was undertaken to define the extent of sediment plumes in the coastal waters surrounding Montserrat on different dates, to examine the feasibility for longer-term monitoring.

Using the 2017 catalogue of Sentinel-2 imagery, each dataset was visually studied for cloud cover, sea conditions and suspected plume extents. Three images were selected for analysis of suspended sediment; April 2nd, August 25th and October 9th, 2017.

As light behaves differently in the marine environment, both on the water surface and within the water column, it is necessary to reduce the visual and spectral impact this has on the imagery. An example of this is sun glint, where a specular reflection of light from the sun is directed towards the sensor, reading as high digital values which can make it impossible to retrieve any meaningful information. To compensate for these affects, correction techniques following the method of Hedley *et al.*, (2005) were applied to the selected data, in order to reduce the impact of sun glint on the image values. An example of this is shown in Figure 16.

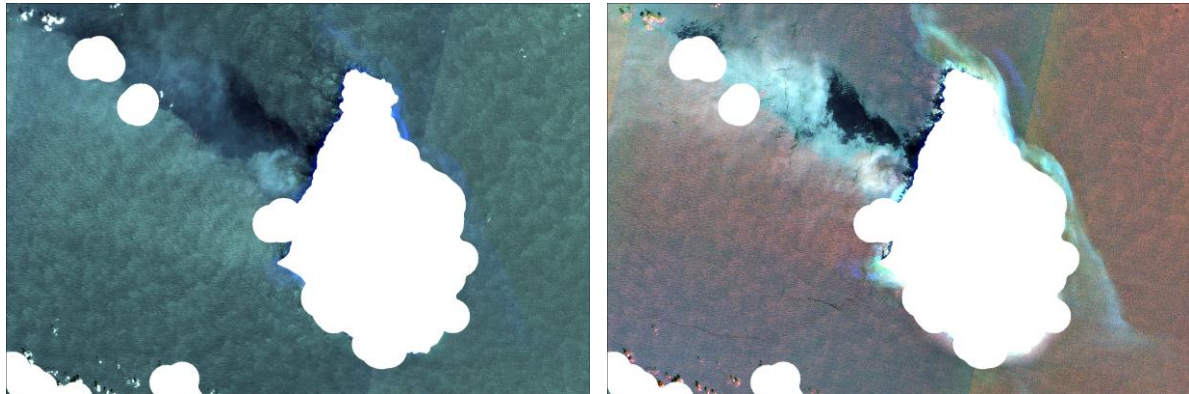


Figure 16: An example Sentinel-2 image of sunglint before (left) and after (right) applying the method of Hedley *et al.* (2005.)

In order to model Total Suspended Solids (TSS) from an aquatic environment, the reflectance values of the data must be converted to remote sensing reflectance (R_{rs}) products (Pahlevan *et al.*, 2017). This ideally requires measurements taken in the field which was not feasible, so the method as proposed by Watanabe *et al.* (2015) was used as an alternative, by which the image values were divided by π (π).

Suspended sediment algorithms were applied based on the findings of Ouillon *et al.* (2008) using R_{rs} at 443nm and 670nm. Ideally the suspended sediment outputs would be regressed against field values, but in the absence of field data the outputs were viewed as relative concentrations. Threshold values were assessed to extract TSS from oceanic water, and converted into a binary mask. Figure 17 shows the TSS classification for the three individual dates. These images show how suspended

sediment loads vary in intensity and distribution over time. These images were then summed to produce a single relative suspended sediment output (Figure 18), which shows the areas with the highest suspended sediment load over time.

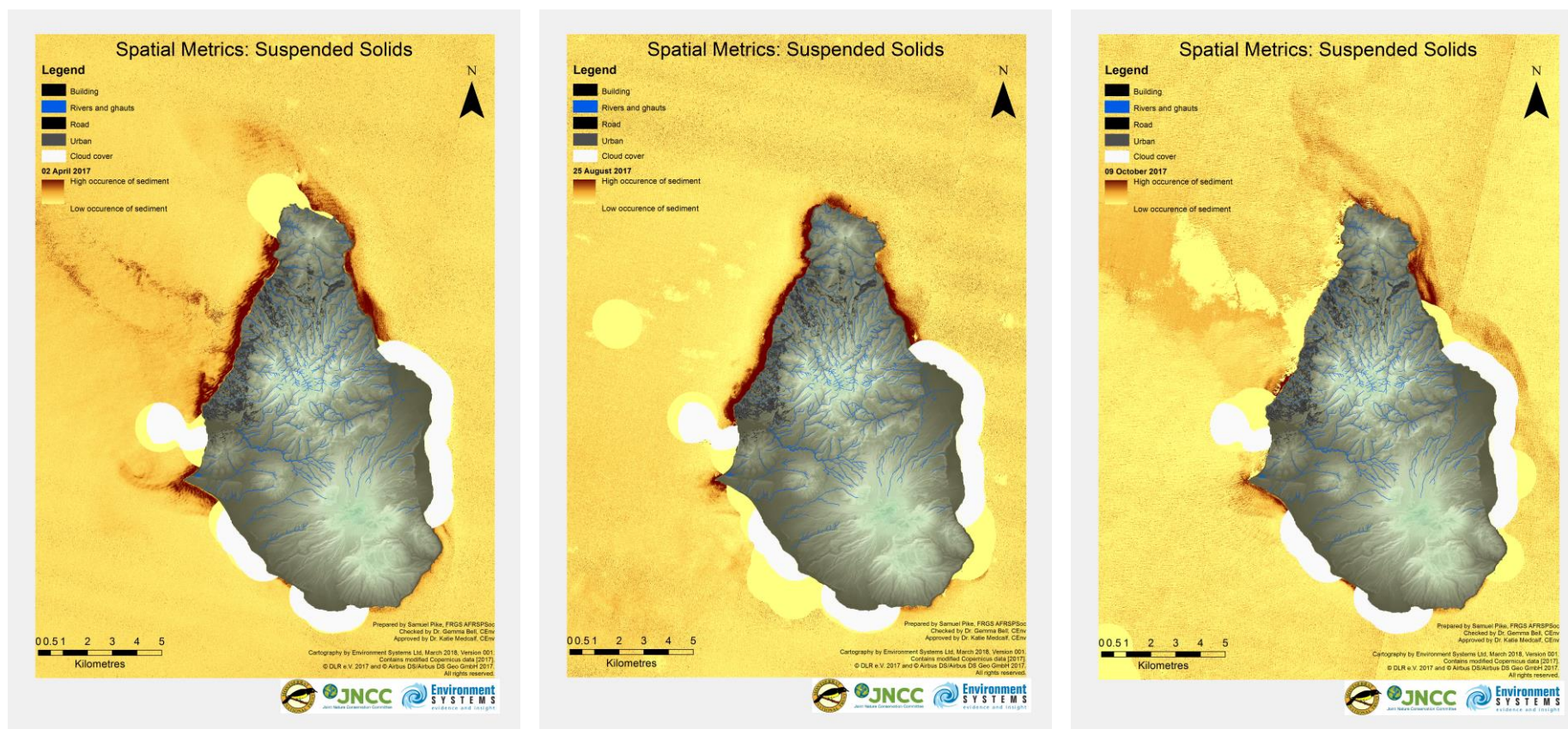


Figure 17: The three individual suspended sediment outputs used to create the composite, from 02 April (left) 25 August (centre) and 09 October (right) 2017. White areas denote 'no data' zones due to cloud cover.

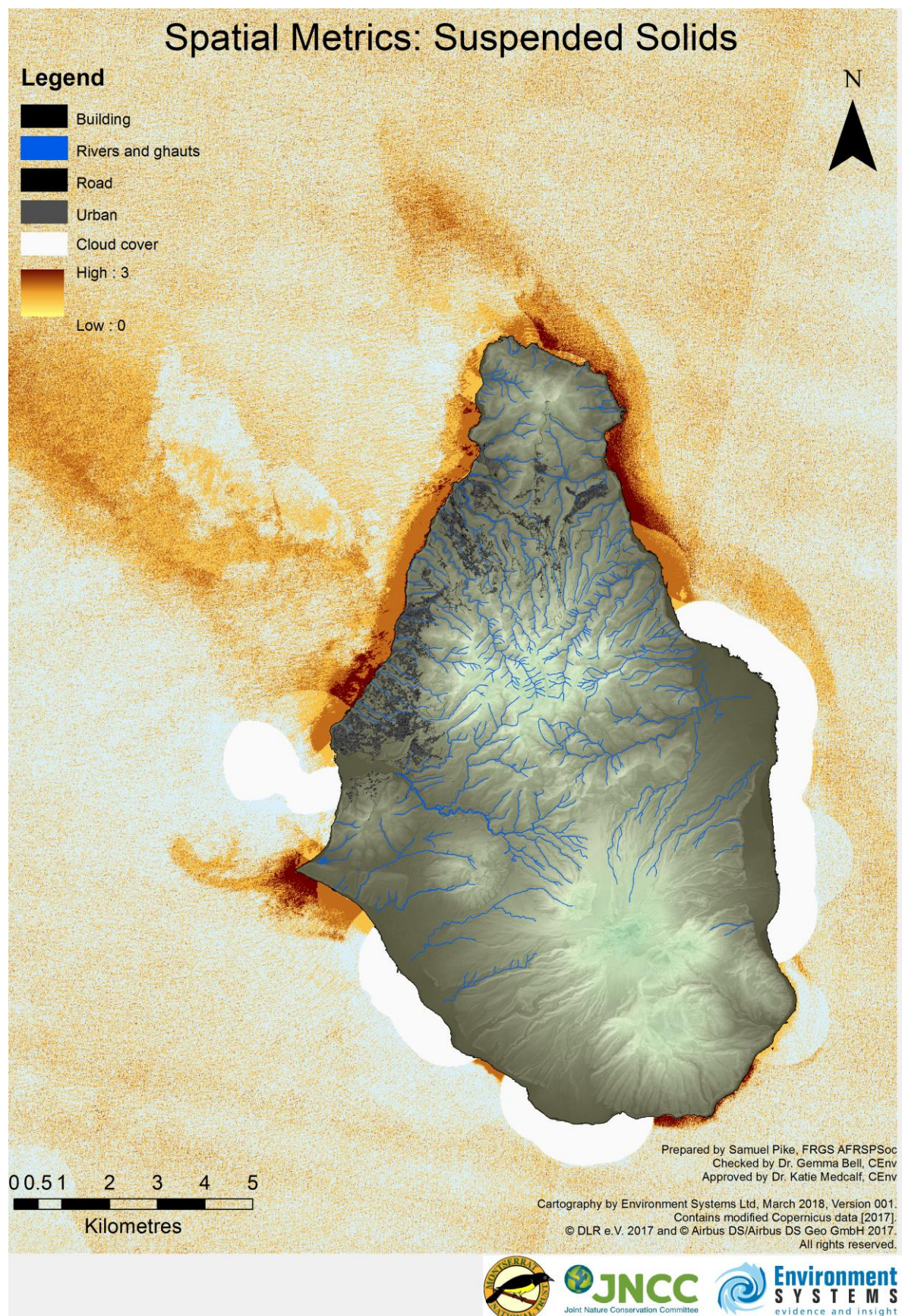


Figure 18: Summed relative suspended sediment analysis over three dates: 02 April, 25 August and 09 October 2017.

5.6. Erosion risk analysis

Erosion describes the process of terrestrial soil and sediment being removed from the land by erosive forces such as wind and rain, particularly rain causing overland flow. Globally, erosion is a hazard because the loss of soil, an important natural resource that only renews over very long time scales, can negatively affect the capacity of the land to support agriculture. However, on tropical islands the effect goes farther, with water with heavy sediment loads entering the coastal zone (see Section 5.5), where the excess sediment can smother corals, thereby contributing to coral loss and, consequently, reduced protection of the land from storm surges and wave action.

The main erosion prevention mechanism is vegetation. The more the ground is covered by a both temporally and spatially continuous cover of vegetation, the less likely erosion is to occur, as the soil is kept in place by the layer of vegetation on top of the soil, as well as by the roots underground. Additionally, the enhanced surface roughness provided by vegetation slows down the speed, and thereby erosive power, of overland flow, and interception of falling rain in the canopy reduces the initial impact of rain on the soil.

Consequently, targeted planting at terrestrial locations at high erosion risk is a measure that can drastically reduce sedimentation within the rivers and ghauts, and ultimately the coastal zone.

To identify locations at high erosion risk this project used SCIMAP, a fine sediment risk evaluation module created by Durham University (2016) for the open source GIS package SAGA. This module calculates erosion risk and several related factors based on information on elevation (DTM), rainfall (annual average in mm), and erodibility.

For this project, the WorldDEM™ was used as an elevation model and erodibility was assigned based on land cover Table 7. The class 'Dry forest' was assigned the same erodibility score as 'Mesic forest' due to the low classification accuracy of the 'Dry forest' class, and understanding that the most common cause of confusion for this class was with 'Mesic forest'. To inform upon the spatial pattern of precipitation, a JPG displaying average annual rainfall was digitised, taken from Hemmings *et al.* (2015). The full list of data inputs used by the model is shown in Table 8.

Table 7: Erodibility scores assigned to each habitat class

Habitat type	Erodibility score
Urban	0.7
Bare ground	0.9
Disturbed ground / Cultivated area	0.7
Beach	0.5
Dry thicket	0.05
Dry scrub	0.3
Dry forest	0.03
Cultivated area	0.7
Mesic forest	0.03
Ash / mud	1
Wet forest	0.05
Open water	0
Elfin woodland	0.06
Buildings	0
Roads	0
Rivers and ghauts	0

An additional output produced, using the SCIMAP computer program, is hydrological connectivity, which expresses how well connected an area of land is to the wider hydrological environment. This score is one component for the final erosion risk score, as only areas at high risk of eroding that are also well connected pose a risk for sediment input into rivers and ghauts.




The hydrological connectivity output can be taken as a useful standalone dataset, as it identifies many smaller hydrological flow paths which feed into the rivers and ghauts, or which flow directly into the sea. These smaller channels are shown in Figure 19 as an overlay to the erosion risk map. They could be a useful addition to existing spatial data for water courses, and assist in targeting sedimentation reduction measures such as planting vegetation, to help prevent sediment influx into drainage channels. The resulting erosion risk map for Montserrat is shown in Figure 19.

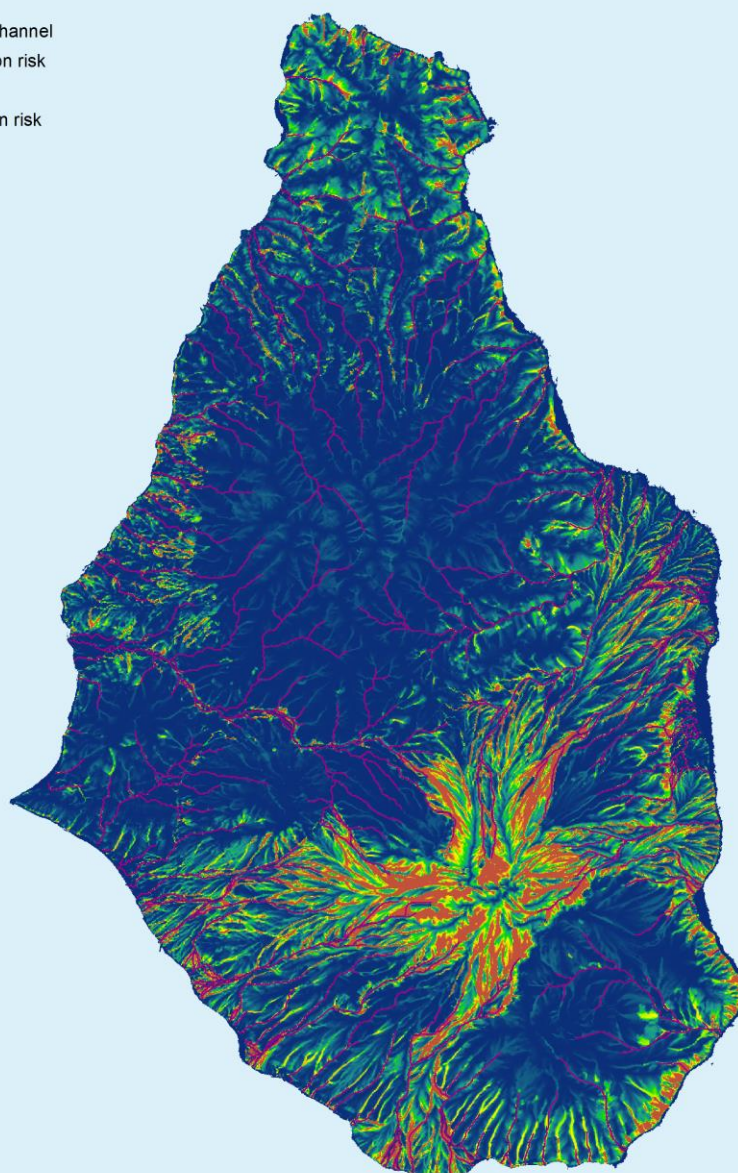
Table 8. Summary of data usage and data gaps for erosion risk modelling

Type of data	Data used	Data gaps
Elevation	WorldDEM TM	Resolution of 12m, small scale features could be better identified at higher resolution
Erodibility	Land cover map	Erodibility is also affected by soil type, so incorporating soil into the erodibility score could enhance modelling results. The habitat data used is modelled itself, so that any modelling inaccuracies will affect the erosion risk model
Precipitation	Digitisation of JPG image on annual average rainfall (Hemmings et al., 2015)	Montserrat is topographically diverse, and rainfall is not distributed evenly across the island. Particularly, areas with higher rainfall will be at higher erosion risk. Higher resolution rainfall data could improve the model.

Spatial Metrics: Erosion Risk and Drainage Channels

Legend

-  Drainage channel
-  High erosion risk
-  Low erosion risk



0 0.5 1 2 3 4 5
Kilometres

Prepared by Elsa-Kristin Naumann
Checked by Dr. Gemma Bell, CEnv
Approved by Dr. Katie Medcalf, CEnv

Cartography by Environment Systems Ltd, March 2018, Version 001.
Contains modified Copernicus data [2017].
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Figure 19: Erosion risk identified by analysis of habitat, elevation, and rainfall data

6. EO-based Monitoring

EO-data provides a means of collecting data over a large geographic area on a regular basis, in a repeatable fashion, meaning that EO-based analyses can play an important role in long-term monitoring of the environment in Montserrat.

Due to continual changes in land use and ecological condition the habitat map should be reviewed periodically in order to ascertain its currency, and to establish whether an update is needed. Generally, a full update should be considered every three to five years. A complete update could be carried out using similar methods applied by the current project (machine learning algorithms such as random forest, or rule-based classification).

6.1. Considerations for undertaking EO-based habitat map updates

At the present time, implementation of the Living Maps script in the tropical environment assumes a good level of technical understanding of Earth observation image processing; this is also true for other classification methods, but potential users should be aware of the developmental status of the current version of the script, requiring a certain level of troubleshooting and sense-checking data inputs and outputs.

The script is designed to be used for projects with a limited number of input images, such as those in the temperate environment with a single leaf-on and leaf-off image. In its current form, applying the script to a project with a high number of input images is extremely time-intensive. Time efficiencies can be made, but this requires knowledge and experience of programming in R.

In the tropical environment multiple images may need to be used due to the high frequency and extent of cloud cover. Further script development would help streamline the process for projects using many images. A user guide/supporting documentation would also significantly enhance the potential for wider uptake of the method. The method has the advantage once set up of being fast to process, and repeatable when new field data are collected.

It should be noted that the success of the random forest algorithm is dependent on the quality of the input training data, which can come in the form of either field data or remote image interpretation (e.g., from aerial photographs).

Any field campaign / training data collection for remote sensing purposes must be carefully planned to ensure that the data are fit for purpose. For example, the random forest method will only identify habitat classes that are present within the training dataset; therefore training data must be collected for all of the habitat/land cover classes to be classified. Some habitat types will not be discernable from the air, such as habitats found in very small patch sizes (e.g., small ponds), and those obscured by canopy cover.

Training points must also be spread across the entire geographical area to be classified, incorporating samples from the full range of topographic scenarios in which a habitat can be found; if the training dataset only captures samples of a habitat in lowland, coastal areas, then the random forest may not allow the habitat to be classified in the mountains. The same is true for different aspect and slope

considerations; if a habitat has only been sampled on west-facing slopes (due to accessibility perhaps), then this is likely to bias the classification of this habitat towards western-facing slopes, and constraining it in other areas.

Additionally when working with object-based classifications it is important that training points are captured for the vegetation type that is representative for the object. The image segmentation process carried out for this project aimed to create image objects which grouped similar vegetation/land cover types as far as possible, by analyzing the subtle differences in pixel colour across the different sensor bands. Inevitably, in some cases the objects contain a mixture of vegetation/land cover types, or the vegetation cover within different parts of a single object may change at different rates over time (e.g., one part of an object may become more scrubby while the rest of the object is grazed short); if such a polygon is encountered during field survey, the sample points should be located within areas of representative habitat, identifying habitat sub-classes if necessary.

As an alternative to carrying out repeated EO-based analyses of the whole island, updates could be carried out on a rolling basis using a polygon-by-polygon approach based on new field surveys or other trusted sources of information. Using this method, the precise location of field work points is much more flexible, as polygons can be split if they are found to contain more than one habitat/land cover type.

6.2. Targeted field survey

In order to maximise resource use efficiency field surveys should be targeted to capture information on priority areas. These may be particular habitats of interest, such as the Dry forest class, which currently has a low level of classification accuracy, and could at present be considered for complete reclassification as Mesic forest or Dry scrub. Other ways of prioritizing field survey could focus on particular geographical locations, habitats that are currently less well represented by field survey (e.g., Elfin woodland, Wet woodland), or habitat polygons that display unusual characteristics as determined by zonal statistics.

The method used to identify habitat canopy density outliers in this project is an example of a way in which potentially unusual habitats can be identified and prioritised for field survey. Outlier habitat areas may display certain attributes of condition that are in themselves worthy of monitoring (e.g., increasing or decreasing abundance of particular species), or the statistical outlier values could also indicate instances where the habitat polygon has been mis-classified. In both instances field survey is required to confirm the initial interpretation, but the use of zonal statistics provide a powerful tool to identify potential anomalies and make best use of limited resources.

6.3. Indicators of condition

The canopy density index is one habitat attribute that can be used to interpret condition by analyzing the zonal statistics. For most effective use of this algorithm field data should be collected to calibrate the algorithm. If this is not possible the absolute values of the algorithm can be used to compare between classes for the same image date, and as a rough comparison between dates.

Alternatively, simple indices such as NDVI (or OSAVI in particularly densely vegetated areas) require no calibration and can provide much information on habitat condition

and the direction of change when monitored over time. Increases in productivity of natural habitat can indicate increased shrub/tree cover, while decreases could indicate land clearance, urban expansion or environmental impacts such as lag effects of drought and flooding. NDVI values range from -1 to 1, with lower values representing the least productive areas (bare ground and anthropogenic structures) and higher values representing very productive vegetation such as trees, shrubs and fertilised crops.

A NDVI image can be produced from an analysis-ready optical EO image such as Sentinel-2 using the Raster calculator function in QGIS to isolate the red and NIR bands, and combine them following the NDVI formula $(\text{NIR}-\text{Red}/\text{NIR}+\text{Red})$. Once again, zonal statistics can be produced to identify average productivity values for different habitat types, and the outliers.

The basic requirements for undertaking zonal statistics analysis are a zone dataset (e.g., detailed image segmentation, existing habitat map), an analysis-ready EO image, and access to a zonal statistics algorithm such as currently available as a core raster analysis tool within QGIS (version 2.18.2).

6.4. Manually updating the habitat map

When new information is available the relevant polygons on the existing habitat map can be edited to produce an updated version. An update procedure should be established prior to editing the habitat map, in order to maintain data quality and traceability. This procedure should contain provisions for storage location, a standardised file naming convention, version control, updating metadata, and maintaining topology.

Should editors wish to change the boundaries of the existing polygons through merging, splitting and manual digitizing, they should be aware of the potential for creating topology errors such as hair-line gaps and overlaps between polygons, and be able to take steps to prevent/remediate these issues. Measures could include ensuring that node-snapping is enabled whilst editing, running topology checks on the edited dataset (e.g., "v.clean", a GRASS tool available within QGIS). When comparing the habitat map against other datasets as the basis for carrying out updates, all datasets should be based on the same co-ordinate system, and transformed to a common co-ordinate system if necessary.

Cloud cover provides challenges for some types of EO monitoring, and so greater use of Sentinel-1 could be explored, although image interpretation of this type of radar imagery can be less intuitive, and is less effective at identifying small-scale features.

7. Conclusions

The map and supporting spatial metrics created for Montserrat were well received as significant new data sets. EO was found to be particularly suitable for Montserrat due to the rugged inaccessible terrain, in part due to the active volcano, and the time efficiency of the techniques. In addition EO-based monitoring is becoming increasingly accessible due to the availability of high-temporal resolution imagery, and an expanding range of both licensed and open-source analysis tools.

The random forest classification method was used, with implementation via the Living Map script. Although initial set-up of the script was time-intensive, subsequent iterations of the habitat map were rapid, allowing new versions of the map to be quickly produced once additional training data became available.

The use of zonal statistics for investigation of was used in this project provided some useful insights. Analysis of habitats with unusual characteristics provided additional data relating to agricultural activities (including abandonment and expansion), urban expansion, sand mining, and biodiversity resilience. This type of statistical analysis of habitat/land cover types provides a rapid method for identifying areas of potential change, and an indication of the type of change.

8. Impact

The habitat map, marine sediment map, erosion and spatial metrics maps were presented at a workshop on island during March 2018. The maps and data were seen as being significant for a number of projects and policies on the island including:

- Understanding the biodiversity of the island.
- Considering the ecological condition of habitats in the different parts of the island, to understand how well they are functioning and where positive action might be needed.
- For planning to know what type of habitat is present on areas scheduled for development and to understand if there needs to be special condition put in place to protect habitats or prevent erosion.
- Marine planners were interested in the main erosion channel into the sea to understand where positive action might be placed to help prevent or minimize this.
- The maps including erosion risk could also be used as to help public and land managers understand the role and importance of the environment and the islands native vegetation.
- The maps also feeding into the Natural Capital accounts developed for the island as a further part of this project.
- The maps could be an important component in evaluating the regulating ecosystem services on the island in order to understand the opportunities to enhance them and possible risks.

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Appendix A.

Complete list of satellite images used to produce the terrestrial habitat classification.

Pléiades

11/04/2014	23/09/2016	04/03/2017
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Sentinel-1

09/01/2017	14/01/2017	02/02/2017	07/02/2017	19/02/2017
26/02/2017	03/03/2017	10/03/2017	15/03/2017	22/03/2017
27/03/2017	03/04/2017	15/04/2017	27/04/2017	09/05/2017
21/05/2017	02/06/2017	14/06/2017	26/06/2017	08/07/2017
20/07/2017	01/08/2017	13/08/2017	25/08/2017	06/09/2017
18/09/2017	23/09/2017	30/09/2017	12/10/2017	24/10/2017
05/11/2017	17/11/2017	29/11/2017	11/12/2017	23/12/2017

Sentinel-2

12/01/2017	01/02/2017	13/03/2017	23/03/2017	02/04/2017
22/04/2017	06/07/2017	11/07/2017	26/07/2017	15/08/2017
04/09/2017	18/11/2017	18/12/2017	28/12/2017	

Pléiades imagery was processed and supplied by JNCC

Sentinel-1 imagery was processed to ARDL1 using ESA SNAP v6.0, GDAL v2.2 and RSGISLib 3.3 libraries. Processing included slice assembly to 10m resolution, border and thermal noise removal, radiometric calibration, terrain correction, terrain flattening, speckle filter, clipping to region, projection to UTM 20 North. The band ratio for each image was calculated (VH/VV).

Sentinel-2 imagery was processed using Sen2Cor 2.4, RSGISLib 3.3 and GDAL 2.2. This included atmospheric correction on a per-tile basis, based on ESA's Sentinel-2 tiling grid, clipping to region and cloud-masking. 20m bands were resampled to 10m resolution.

Appendix B.

The random forest method provides a useful means for classifying vegetation type with good training data. Using R-code as implemented with 'Living Maps' is an accessible way of accessing the technique, however some issues were encountered with the existing version of the script and these are detailed in the table below. By addressing these points the accessibility and effectiveness of the 'Living Map' method will be enhanced.

Issue	Details
Requirement to manually input a list of input imagery	<p>The script is not currently designed to efficiently handle large stacks of input imagery, such as is becoming increasingly available under the Sentinel program. It is time-intensive to include a large image stack in the current version of the code.</p> <p>For each image the user has to manually create a variable, in addition a variable for each band (e.g., Sentinel-2 has 10 bands after processing), and a variable for each index. When dealing with an image stack of several images this process is time intensive. Additional program development and automation would be extremely helpful to deal with this.</p>
Checks for cross-correlation	<p>With increasing availability of high temporal resolution imagery comes the increased risk of introducing correlation biased variables into the analysis; this issue should be highlighted to users in any accompanying documentation.</p> <p>Correlation needs to be checked for and managed. If this is not undertaken Random forest is not appropriate analysis technique (Millard and Richardson, 2015). The script documentation and notation needs to be explicit about if and how cross correlation is considered.</p>
Code stipulates maximum number of training points per class =30	<p>The code currently specifies a maximum number of training points per class; the default being 30 points per class. This stipulation decreases the statistical robustness of the method substantially; as a rule of thumb it is generally accepted that for areas less than one million acres in size and fewer than 12 classes, remote sensing studies should aim to collect at least 50 samples for each map class (Conglaton, 1988).</p> <p>Although the maximum sample size is a user-modifiable parameter, the inclusion of an upper threshold encourages the user to unnecessarily constrain their dataset, disproportionately affecting users with less knowledge of statistical methods.</p>
Use of training points by code	<p>No supporting documentation was available to support the application of the Living Map code, and there is limited use of comments within the code itself. It was not clear whether the specified maximum number of points would all be used for training by the subsequent random forest analysis, or whether the random forest further splits this number to use a portion for training and a portion for validation. For example in the case of sample max = 30, not all 30 points would be used for training the classification.</p>
Requirement for pre-	<p>Assumes a high level of technical expertise in earth observation image processing, and availability of image processing software. Prerequisite</p>

processing and scaling imagery	image processing/scaling requirements (including creation of the image object layer) should be made explicit in the supporting documentation.
Graphical representation of accuracy	The graphical outputs showing the causes of confusion between different habitat classes are difficult to interpret; the order in which the correct vs incorrect classes are presented is inconsistent, and it is difficult to distinguish between different classes in the current colour scheme. Some columns do not add up to 100%.

Recommendations for modification of the script for improved efficiency and ease of use:

- File paths in the code are currently hardcoded. These could be taken as parameters or all defined in one group at the start of the code for ease of reference and traceability.
- Paths contain platform specific notations and separators. These could be constructed dynamically using the correct path separator for the operating system to keep it cross platform.
- Some values which could be considered as configuration parameters are defined as they are used. For ease of reference and traceability all potential configuration parameters (e.g., nmax) could be collected at the top of the file to allow easier configuration and use.
- A random selection of training points is currently selected using a static seed value. This means that each time the classification is run, the same training points will be selected. This feature may not be apparent to the user and should be explicitly explained in the code comments and documentation.
- The line specifying a maximum number of training points per class should be removed to allow the code to function statistically as the user requires based on their knowledge of their environment and its variance.

Full documentation should be supplied with the code, and commenting should be expanded within the code itself to ensure the ease of use.