Habitat Data layer for Natural Capital assessments

Deliverable 2.3a for the

Project D5-2 Climate Change Impacts on Natural Capital

January 2023

Summary

This report is a product of the Scottish Government Strategic Research Programme project JHI-D5-2 ‘Climate Change Impacts on Natural Capital’. The purpose of this report is to assess the potential of habitat – land cover data layers for integration in the Risk and Opportunities Assessment Framework (ROAF) to enable the spatial representation of Natural Capital (NC) types and subsequent assessment of the impacts of climate change on NC assets.

The aim of this report is to provide insight on the quality of two of the main available, national data layers of land cover: the UKCEH Land Cover Maps (LCM) and Scotland’s Habitat and Land cover maps (SLAM-MAP). The objective is to understand how their integration in the ROAF could influence the accuracy of generated spatial assessments of climate change impact on NC assets. For this reason, we present mapping accuracy results from a comparison and a ground-truthing exercise to assess the performance of the two data layers for mapping specific land cover classes.

Key Messages:

- LCM and SLAM-MAP data layers are both considered as appropriate datasets for integration to ROAF because they provide national mapping at fine spatial resolution and can be used for detecting change in land cover extents.
- Both data layers provide similar mapping for arable and horticulture areas, and to some extent also for woodland mapping, but we identified considerable disagreement in distinguishing extensive, mainly, upland habitats (e.g., bogs and peatlands, wet heather, and wet grasslands).
- Ground-truthing of the two data layers used available, surveyed vegetation information from mainly coastal habitats, hence it cannot be considered representative at national scale.
- Due to the inconclusive results from this study, our suggestion is to use LCM for the initial development of the ROAF because it is a more mature product, and our team has extensive experience in using it in relevant applications.
- It needs to be confirmed whether LCM classes can correspond directly to NC typology developed in D1.4b.

Advances in Technical Capabilities

This report has been developed through technical advances made in the JHI-D5-2 Project related to building spatial samples datasets, harmonisation of land classification systems and calculation of land classification accuracy metrics.

Contents

Citation:

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Introduction

The purpose of this report is to assess the potential of specific data layers for integration in the Risk and Opportunities Assessment Framework (ROAF) to enable the spatial representation of Natural Capital (NC) types. Please note that the NC typology is being developed in a follow-on Deliverable (D1.4b). This report is a Deliverable for the Strategic Research Programme project 'Climate Change Impacts on Natural Capital' (JHI-D5-2). The aim of this work is to provide insight on the quality of available data layers and potential implications for ROAFF spatial assessments related to uncertainties in the classification of certain land cover classes. In particular, the objective of this work was to provide an assessment of two land cover data layers deemed as appropriate for ROAF integration, related to their performance for mapping specific land cover classes. This was achieved by comparing the two data layers using a dataset of "virtual" samples that was representative of land cover classes nationally, and through a ground-truthing exercise using surveyed vegetation.

Advancing analytical capability

Input data layers of land cover classes and NC types are integral to the ROAF implementation and functioning, and their inherent properties (e.g., classification certainty, spatial resolution) can influence the accuracy of the resulting spatial assessments of climate change impacts on NC assets. In this context, work presented here has advanced our technical analytical capability by:

- Building spatial sample datasets and automated and reproducible script routines for data layer comparison.
- Devising the harmonisation of different land cover classification systems.
- Providing accuracy metrics for the mapping (classification) of individual land cover classes.

The benefits of this technical development are that results can inform the development of the NC typology, and also inform approaches developed in this (and other SRP-funded projects) for improving land cover data layers.

Technical Developments

Habitat data layers

Introduction

The project 'Climate Change Impacts on Natural Capital' (JHI-D5-2) aims to develop a Risk and Opportunities Assessment Framework (ROAF) that has the ability to conduct spatial assessments of climate change impacts on selected Natural Capital (NC) assets, at various scales (e.g., catchment to regional to national). ROAF development is based on devising an appropriate NC typology (this is to be presented in D1.4b), and data layers of habitats or land cover classes that are required to provide accurate mapping of respective NC types and assets. At the same time, the ROAF should be flexible enough to accommodate integration of different or multiple habitat data layers, depending on availability and required level of spatial detail.

A previous review of existing spatial datasets to support land evaluations in Scotland (Gagkas, 2021) identified multiple datasets, developed and maintained by a wide range of scientific and public bodies, that can be used to assess the extent and condition of different land covers (habitats, agriculture, and forestry).

Examples include: NatureScot's data on Protected areas; the Habitat Map of Scotland (HabMoS); the National Vegetation Classification (NVC) and Phase 1 survey data; the recent Scotland Habitat and Land cover maps (SLAM-MAP) produced in partnership with Space Intelligence; UK CEH's Land Cover Maps (LCM); Land Cover Scotland 1988 (LCS88, Macaulay Institute/The James Hutton Institute); various datasets from the Forestry Commission or Forest Research (e.g., the National Forest Inventory, the Caledonian Pinewood Inventory and various tree suitability for planting maps); the Integrated Administration and Control System (IACS) land parcels and crop information managed by Scottish Government's (SG) Rural Payments and Inspections Division (RPID); and datasets and maps from the Countryside Survey and EU LUCAS and CORINE programmes.

However, this review has also identified issues that are related to data replication and duplication and spatial and temporal fragmentation:

- Different classification systems are used for mapping the same land cover or habitat class, which means that different datasets are not always compatible or directly comparable, and hence they are difficult to harmonise or jointly interpret.
- Datasets can be produced using different methods (e.g., ground surveying vs. remote sensing) at different spatial scales or resolutions and in different dataset formats (e.g., vector/polygons vs raster/grid cell); this can produce spatial inconsistencies when different spatial layers need to be combined or produce different assessments for a specific land cover class depending on the map used.
- Datasets may provide detailed mapping within designated areas or at regional or catchment scale or provide coarser mapping at national scale, while others map only specific land cover or habitat classes. Regarding their temporal resolution, most datasets provide mapping at just one time period, meaning that these cannot be used to detect temporal change in land cover extents.

Overall, these are well-known issues and need to be considered when integrating habitat and land cover data in the ROAF as they can impact the accuracy of respective spatial assessments. In this context, we selected two data layers to assess how appropriate they are for the initial development and trialling and testing of the ROAF, CEH's Land Cover Map (LCM)[1] and Space Intelligence's SLAM-MAP[2] (Table 1). These data layers were selected because both:

- Provide national coverage at high spatial resolution (10m-20m pixel).
- Use well-established land cover classification systems, the UK Biodiversity Action Plan (UK BAP) and the European Nature Information System (EUNIS) that have been widely used in relevant NC applications, such as in the Natural Capital Asset Index (NCAI) assessment (McKenna et al., 2019).
- Have been produced using remotely-sensed data and similar earth observation (EO) analysis techniques.
- Provide mapping for more than one year that enables detecting and assessing land cover changes.
- Are freely-available either entirely (SLAM-MAP) or for academic use (CEH LCM, which is updated on an annual basis).

[1] https://www.ceh.ac.uk/data/ukceh-land-cover-maps
[2] https://www.space-intelligence.com/scotland-landcover

Table 1 Summary of CEH LCM and SLAM-MAP specifications.

Data layers	Format	Source	Resolution	Year	Access
Land Cover Maps (LCM)	Geotiff	UK Centre of Ecology and Hydrology	25m pixel rasterised land parcel	1990 2000 2007	Environmental Information Data Centre (https://eidc.ac.uk)
			25m classified pixel	2015	
			20m classified pixel	2017 2018 2019	
			10m classified pixel	2020 2021	
Scotland Habitat and Land cover map (SLAM-MAP)	Geotiff	Space Intelligence	20m classified pixel	2019 2020	SG Spatial Data Portal (https://spatialdata.gov.scot)

Land Cover Maps (LCMs)

The UKCEH Land Cover Maps (LCMs) map land cover by describing the physical material on the surface of the UK providing an uninterrupted national dataset of land cover classes from grassland, woodland, and fresh water to urban and suburban built-up areas. UKCEH has a long history of using satellite imagery to map land cover from the first national Land Cover Map of Great Britain in 1990 to the current production of annual Land Cover Maps and land cover change data. Land cover in the newer products (post 2015) is given as 21 UKCEH Land Cover Classes based upon UK BAP Broad Habitats[3] (Figure 1 and Table 2). Recent UKCEH LCMs (post 2015) have been created using new automatic techniques that combine Bootstrap Training with a Random Forest (RF) classifier to classify Sentinel-2 Seasonal Composite Images generated using the Google Earth Engine, representing median reflectance per season (Morton et al., 2020).

Classified Pixels datasets (20m and 10m, Table 1) are provided as 2-band, 8-bit integer rasters. The RF classifier assigns each pixel a probability of membership for each of the 21 UKCEH Land Cover Classes. The nominate land cover, Band 1, is the class with the highest membership probability, while Band 2 is this probability, but rescaled and rounded giving an integer value over the range of 0 to 100 (Morton et al., 2020). This gives an indication of per-pixel classification confidence (uncertainty); high values equate to high confidence and low uncertainty. Unlike pixels of the 25m Rasterised Land Parcels datasets, the Classified Pixels have not been generalised by combination with the UKCEH Land Parcel Spatial Framework. This preserves intricate features of the landscape such as narrow linear features and small patches of habitat that fall below the 0.5 hectare minimum mappable unit (MMU).

[3] UK BAP Priority Habitats | JNCC - Adviser to Government on Nature Conservation

SLAM-MAP

The Scotland Habitat and Land cover maps (SLAM-MAP) were produced by Space Intelligence in partnership with NatureScot to provide insight into how Scotland's Natural Capital is changing over time. A workflow was developed that can generate repeatable nationwide habitat maps of 22 habitat/land cover classes at EUNIS Level 2 (Figure 1 and Table 2) at 20m pixel resolution. SLAM-MAP products were produced by using collected data samples across Scotland for these 22 types of land cover and analysis of satellite imagery using a cloud-based Artificial Intelligence (AI) platform. Currently, two SLAM-MAP data layers have been produced for the years 2019 and 2020, along with an additional change map showing how the landscape has changed over this 12-month period[4].

Map evaluation

Objective

The objective of the evaluation of the LCM and SLAM-MAP products was a) to compare mapping of different habitat/land cover classes at randomly generated locations at national scale to assess how similar or dissimilar the two maps are and b) to assess the performance of the two maps for mapping specific land cover classes using surveyed data (ground-truthing). To conduct the map evaluation, we developed R Markdown files in R Studio to ensure the reproducibility of the analysis (available upon request).

Here we present the results of the map evaluation for the year 2019, for which both maps are available in the same spatial resolution of 20m pixel (Figure 1). We have also done the same analysis for the 2020 data layers by aggregating the LCM data layer from 10m to 20m pixel, but these results are not presented here because they were very similar to the 2019 comparison.

Map comparison

Random samples

We generated ~355,000 virtual random samples using the software QGIS 3.22.3, equating to roughly a density of at least 4 points/km^2, to create a samples dataset that is representative of all land cover classes at the national scale. We then extracted the LCM and SLAM-MAP codes at the locations of the generated random samples and used them to build a confusion matrix of LCM vs SLAM-MAP mapped land cover classes and calculate mapping accuracies using the *caret* package in R (Kuhn, 2022). Performance of both data layers for specifically mapping woodland areas was also assessed by counting the number of samples classified as woodland by LCM or SLAM-MAP within the woodland areas defined from the National Forestry Inventory (NFI) Woodland Scotland (available from Forestry Commission's Open Data portal[5]).

[4] https://www.space-intelligence.com/scotland-landcover
[5] https://data-forestry.opendata.arcgis.com

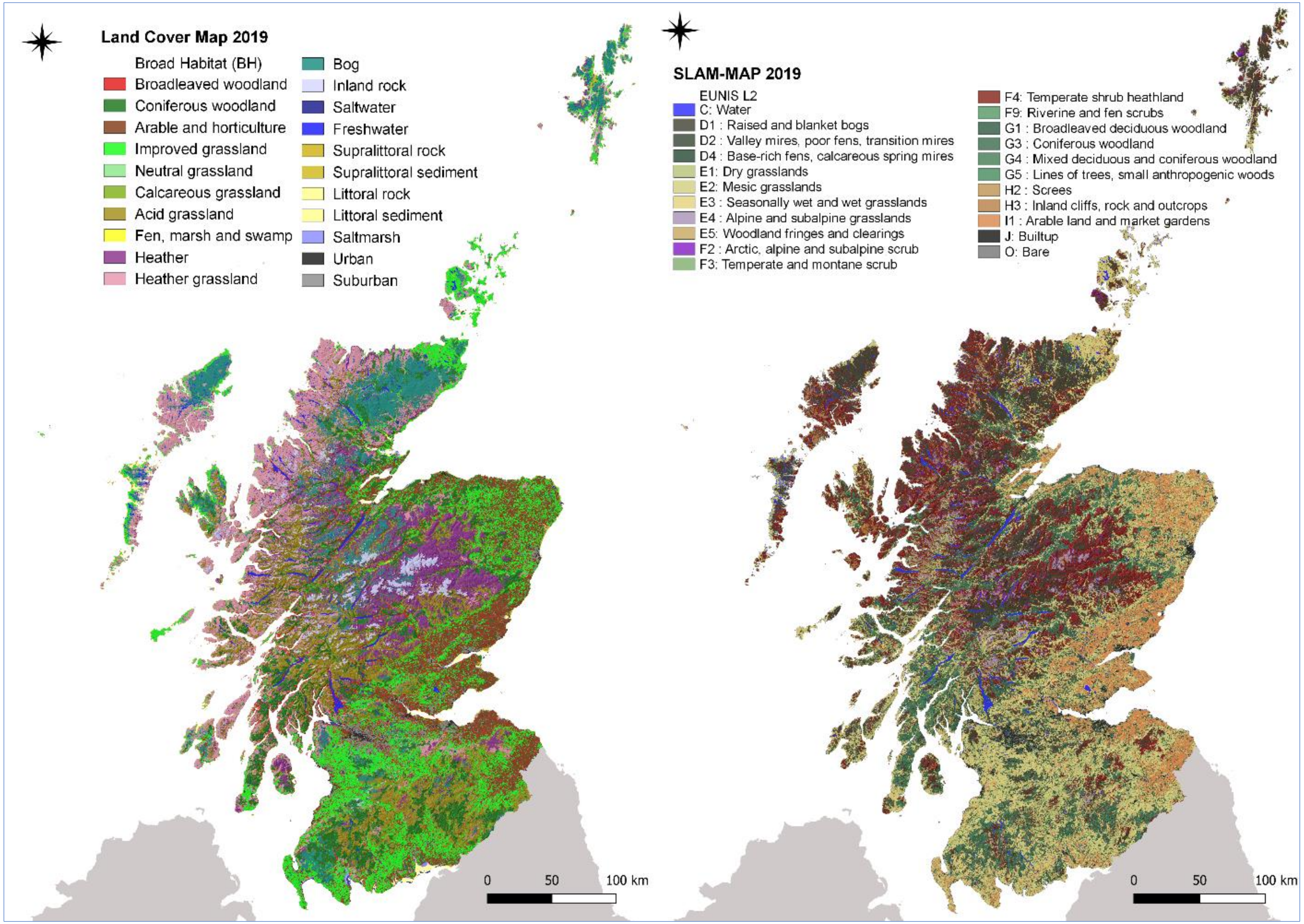

Figure 1. Land Cover Map (LCM) 2019 and Scotland Habitat and Land cover map (SLAM-MAP) 2019. Colour scheme of land cover and habitat classes is provided by the respective data layers.

Land cover harmonization

In order to be able to construct confusion matrices for comparing land cover classifications of generated samples, LCM Broad Habitats (BHs) and SLAM-MAP EUNIS Level 2 categories were harmonized to higher (aggregated) BHs as shown in Table 2. Note that LCM BHs of “Supralittoral sediments” and “Littoral sediments” correspond to EUNIS A (Marine habitats) and B (Coastal habitats) habitat types, respectively. However, because SLAM-MAP doesn’t map the EUNIS A and B habitat types, samples falling inside areas of marine and coastal sediments based on LCM were omitted from the analysis.

Table 2. Harmonisation of LCM Broad Habitats (BH) and SLAM-MAP EUNIS Level 2 (L2) classes into aggregated (“Higher”) BHs. LCM BHs of “Supralittoral sediments” and “Littoral sediments” are not shown.

LCM BH	SLAM-MAP EUNIS L2	Higher BH
• Arable and Horticulture	I1 Arable land and market gardens O Bare field	Arable
• Bog • Fen, Marsh, and Swamp	D1 Raised and blanket bogs D2 Valley mires, poor fens and transition mires D4 Base-rich fens and calcareous spring mires	Bogs & peatlands
• Acid Grassland • Calcareous Grassland • Neutral Grassland	E1 Dry grasslands E3 Seasonally wet and wet grasslands E4 Alpine and subalpine grasslands E5 Woodland fringes and clearings and tall forb stands	Grasslands
• Improved Grassland	E2 Mesic grassland	Grasslands improved
• Inland rock • Supralittoral rock • Littoral rock	H2 Screes H3 Cliffs and rock pavements	Rock
• Heather • Heather grassland	F2 Arctic, alpine and subalpine scrub F3 Temperate and Mediterranean-montane scrub F4 Temperate shrub heathland F9 Riverine and fen scrubs	Shrubland
• Urban • Suburban	J Built-up	Urban
• Freshwater • Saltmarsh • Saltwater	C Surface standing and running waters	Water
• Broadleaved Woodland • Coniferous Woodland	G1 Broadleaved deciduous woodland G3 Coniferous woodland G4 Mixed deciduous and coniferous woodland G5 Lines of trees, early-stage woodland and coppice	Woodland

Based on this harmonisation process, we calculated the proportions of samples belonging to different Higher BHs based on the LCM and SLAM-MAP data layers (Figure 1). Main observed differences were that that SLAM-MAP classified twice as many samples as Bogs & peatlands compared to LCM, while LCM mapped around 7% and 2% more samples as Shrubland and Woodlands, respectively. These differences are assessed in more detail in the following sections.

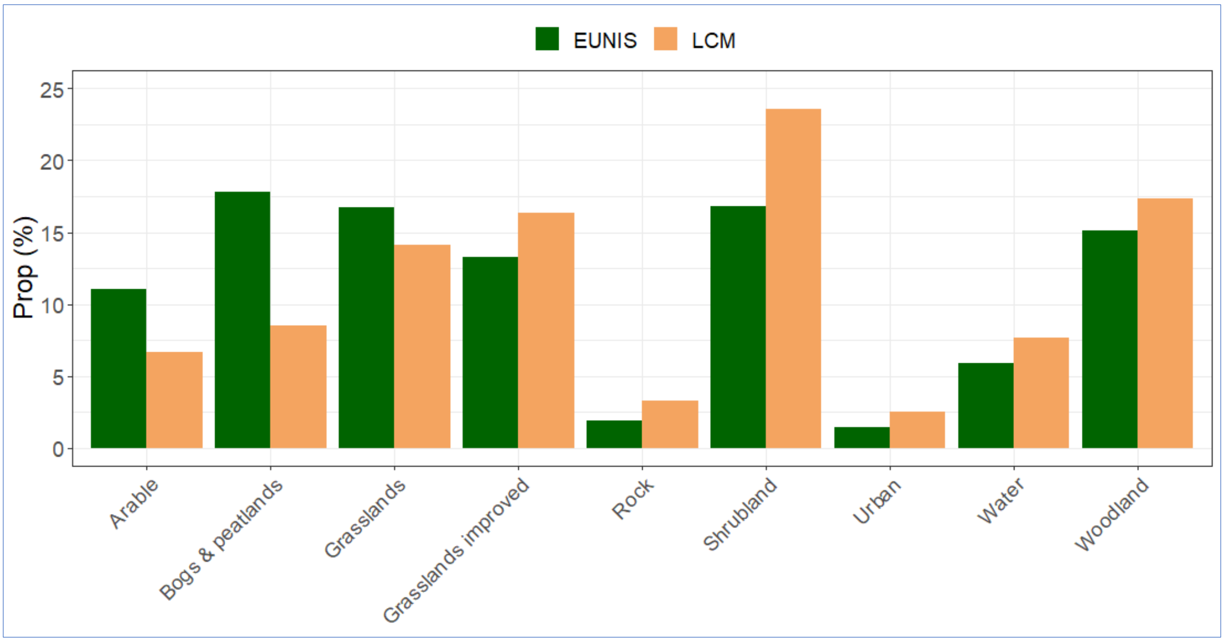

Figure 2. Proportions (in %) of samples classified per harmonised BHs based on the LCM and SLAM-MAP data layers.

Results

For the purpose of building the confusion matrix, we assumed that LCM, since it is the more-established and longer-running product, gave the "observed" mapping and that SLAM-MAP provided the "predicted" mapping of generated samples (Table 3).

Table 3. Confusion matrix showing counts of samples classified as different Higher Broad Habitats (BHs) based on the LCM and SLAM-MAP layers. Shaded cells give counts of Higher BH classification agreement between the two maps.

	SLAM-MAP Higher BHs								
LCM Higher BHs	Arable	Bogs & peatlands	Grasslands	Grasslands improved	Rock	Shrubland	Urban	Water	Woodland
Arable	20,064	482	404	4,997	1,569	1,770	2,584	3,849	3,493
Bogs & peatlands	77	21,426	9,472	1,203	1,731	25,384	67	1,549	2,448
Grasslands	701	4,022	28,845	9,681	2,715	10,201	170	576	2,631
Grasslands improved	2,220	115	2,168	38,670	180	735	876	312	1,783
Rock	0	124	129	6	2,167	2,237	4	2,088	56
Shrubland	73	3,321	8,299	912	2,589	39,992	149	490	3,835
Urban	234	33	37	289	64	125	3,813	185	372
Water	33	461	31	102	487	659	81	17,870	1,174
Woodland	416	165	700	2144	205	2694	1295	258	45,838

Agreement between the two maps, based on producer's accuracy (i.e., number of samples with the same Higher BH based on both LCM and SLAM-MAP divided by the total count samples with the respective Higher BH based on LCM), was good for Arable (84%), Woodlands (74%), and Bogs &

peatlands (71%), moderate for Improved grasslands (67%) and Water (66%), low for Grasslands (58%), Shrubland (48%), Urban (42%) and very low for Rock (19%). Overall accuracy (number of samples with the same Higher BH for both maps divided by total samples count) was 62%. To better understand differences between the mapping provided by the two data layers, we explored classification mismatches of LCM BHs by the SLAM-MAP at EUNIS L2 level for the most extensive land cover classes (Figure 3).

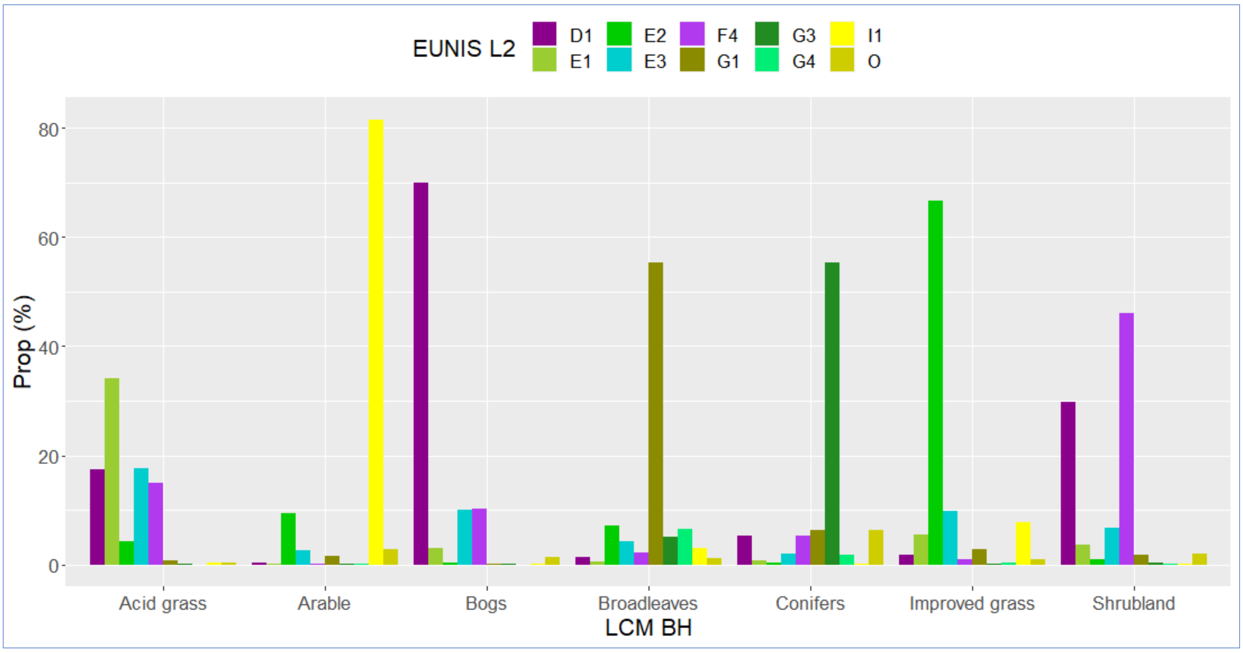

Figure 3. Proportions of SLAM-MAP EUNIS Level 2 classifications of samples mapped by LCM as one of the main BHs: Acid grassland, Arable, Bogs, Broadleaves, Conifers, Improved grassland and Shrubland. Description of EUNIS L2 codes given in Table 2.

Regarding mismatches for samples mapped by LCM as BH=Arable (*n*=23,818), SLAM-MAP classified 9% as E2 Mesic grasslands (BH=Improved grasslands) and ~3% as E3 Wet grasslands (BH=Grasslands). Most of these samples (~82%) were classified as I1 Arable land and market gardens, which matched LCM's classification (Figure 3).

Main classification mismatches by SLAM-MAP for samples mapped by LCM as BH=Bogs & peatlands (*n*=30,149) were for samples classified as E3 Wet grassland (10%, BH=Grassland) and F4 Shrub heathland (10%, BH=Shrublands), while around 3% and ~2% were mapped by SLAM-MAP as E1 Dry grasslands and O Bare fields, respectively. SLAM-MAP's classification matched LCM's for around 70% of these samples that were classified as D1 Raised and blanket bogs, and a further 1% that was classified as D2 Valley mires, poor fens, and transition mires.

All but 94 of the 50,085 samples mapped by LCM as BH=Grassland belonged to BH=Acid grassland. SLAM-MAP classified around 18% of the samples mapped as Acid grassland as D1 Raised & blanket bogs (BH=Bogs & peatlands), while 4% were classified by SLAM-MAP as E2 Mesic grasslands (BH=Improved grassland). Main classification mismatches by SLAM-MAP of samples classified by LCM as BH=Improved grassland (n=*58,004*) were for E3 Wet grasslands (~10%, BH=Grasslands), I1 Arable land (8%, BH=Arable) and E1 Dry grasslands (~6%, BH=Grasslands).

Regarding samples mapped by LCM as BH=Shrublands (*n*=83,797), main classification mismatches by SLAM-MAP were for D1 Raised & blanket bogs (~30%, BH=Bogs & peatlands), E3 Wet grasslands (~7%, BH=Grasslands) and E1 Dry grasslands (~3.5%, BH=Grasslands).

There was agreement between the LCM and SLAM-MAP classifications for 55% of the 22,951 samples mapped by the LCM as BH=Broadleaved woodland. Around 6% and 5% of these samples were classified by SLAM-MAP as G4 Mixed deciduous and coniferous woodland and G3 Coniferous woodland, respectively, with a further 7% of the samples being classified as E2 Mesic grassland (BH=Grasslands). Regarding samples mapped by LCM as BH=Coniferous woodland (*n*=38,679), around 55% of these were classified by SLAM-MAP as G3 Coniferous woodland and a further 13% as G5 Lines of trees, early-stage woodland, and coppice. Around 5% of these points were classified by SLAM-MAP as either D1 Raised and blanket bogs (BH=Bogs & peatlands) or F4 Temperate shrub heathland (BH=Shrublands), while, surprisingly, a further 6% was classified as O Bare field. Moreover, around 90% of the samples falling within NFI woodland polygons were mapped as either broadleaved or conifer woodland by LCM, while 78% of these points fell in the EUNIS G (Woodland) level categories. Around 3% of these samples were mapped as Heather grassland by LCM, while around 4% were mapped as either D1 Raised and blanket bogs or F4 Temperate shrub heathland by SLAM-MAP.

Visual inspection using Google satellite imagery in QGIS showed differences in mapping close to woodland edges, especially around conifer plantation blocks, where samples falling in these areas were mapped by LCM mostly as forest while SLAM-MAP tended to identify these areas as non-forest vegetation and not map these samples as forest. Also, it was observed that SLAM-MAP tended to pick-up the understorey vegetation in less dense, mainly deciduous, woodlands, resulting in classifying samples falling within these areas as some type of grassland or heather, while these were usually classified as a type of woodland by LCM. Similarly, SLAM-MAP tended to classify locations in waterlogged areas of standing waters within broader peatland areas as standing waters, whereas LCM tended to map the same locations as bogs and peatlands.

Discussion – map comparison

The results of the comparison of the LCM and SLAM-MAP data layers show that they both provide similar mapping for arable and horticulture areas, and to some extent also for woodland mapping. However, there was considerable disagreement between the two mapping products in distinguishing between seminatural habitats such as bogs and peatlands, heather moorlands (mainly on the west of Scotland so probably wet heather) and wet grasslands. This is probably caused by mixed spectral signals caused by vegetation and soil wetness levels, and probably depends on how differently the LCM and SLAM-MAP process these spectra, also considering seasonality effects in the satellite imagery time-series used to produce the maps. Considerable differences also exist in the mapping of water features and bare fields, which is surprising since they tend to have distinct spectral signatures. The same also applies to urban areas to some extent. For example, visual inspection showed that SLAM-MAP classified samples falling within small clusters of trees in, e.g., urban parks, as woodland while these samples were mapped as urban or peri-urban by LCM.

Overall, this exercise provides some indication that SLAM-MAP provides greater granularity compared to LCM, which tends to favour the mapping of entities instead of individual features (e.g., woodland vs. tree). However, it is uncertain whether SLAM-MAP can provide more detailed mapping than LCM for certain land covers or whether this granularity is an artifact of the methodology used to produce the map, such as overfitting of the classification models.

Ground-truthing exercise

Methods

The dataset used for ground-truthing the LCM and SLAM-MAP data layers was compiled by Robin Pakeman and comprised of vegetation information from 2,532 surveyed, mostly coastal, locations (Figure 4, Pakeman et al., 2015). Vegetation information was given in National Vegetation Classification (NVC) codes (see Column: "First" in Table 4). The allocation of vegetation samples to NVC has been done using the programme TABLEFIT rather than by the observer, and so it is considered to be independent. Almost half of the sampled locations had vegetation belonging to fixed dunes (*n*=1,034) and other coastal habitats, followed by heath and acid grassland, with fewer than 40 locations sampled found in woodlands or bogs/swamps.

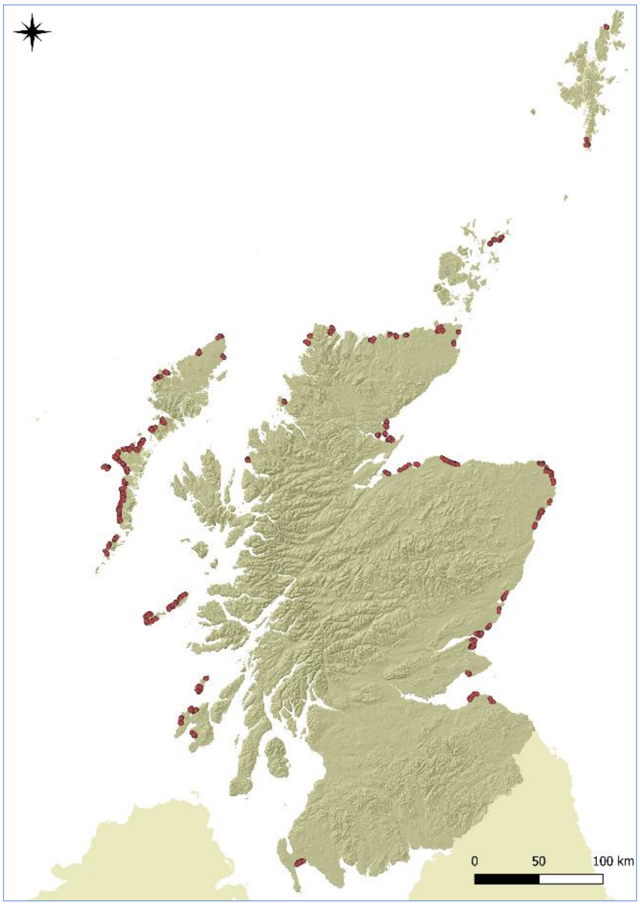

Figure 4. Locations of surveyed vegetation used for ground-truthing the LCM and SLAM-MAP data layers.

A correspondence table[6] was used to translate NVC codes from column "First" to the respective BAP BH and EUNIS L2 codes. This process resulted in 1,729 NVC samples belonging to the EUNIS A (Marine habitats) and B (Coastal habitats) (plus D5: Sedge and reedbeds), which were not specifically mapped by SLAM-MAP (Table 1). In order to keep these locations in the analysis, the NVC codes of these locations were translated to SLAM-MAP EUNIS L2 codes using expert opinion (Robin Pakeman), with most of them re-allocated to the EUNIS E categories of: Grassland and lands dominated by forbs, mosses, or lichens. On the other hand, LCM provides mapping of Marine and

[6] Available from here: https://hub.jncc.gov.uk/assets/9e70531b-5467-4136-88f6-3b3dd905b56d

Coastal habitats (Supralittoral and Littoral BHs, respectively). Table 4 gives an example of the correspondence between NVC codes and the EUNIS and LCM systems for a subset of the 218 unique NVC codes found in the dataset.

Ground-truthing was done by extracting the BH and EUNIS L2 codes at the locations of the vegetation samples from the LCM and SLAM-MAP layers, respectively, and then calculating match accuracy between observed (based on sample NVC correspondence) vs predicted (classified) BH and EUNIS L2 by LCM and SLAM-MAP land cover at both BH and Higher BH levels.

Table 4. Example of correspondence between NVC and LCM BH and EUNIS L2 classification systems for selected NVC codes from the vegetation samples dataset.

Group	First (NVC)	LCM BH	LCM Higher BH	EUNIS L2	EUNIS Higher BH
Acid grassland	U20	Acid grassland	Grasslands	E5 Woodland fringes and clearings and tall forb stands	Grasslands and lands dominated by forbs, mosses or lichens
Acid grassland	U2a	Acid grassland	Grasslands	E1 Dry grasslands	Grasslands and lands dominated by forbs, mosses or lichens
Acid grassland	U6a	Acid grassland	Grasslands	E3 Seasonally wet and wet grasslands	Grasslands and lands dominated by forbs, mosses or lichens
Short grassland - calcareous	CG10	Calcareous grassland	Grasslands	E1 Dry grasslands	Grasslands and lands dominated by forbs, mosses or lichens
Short grassland - calcareous	CG13	Calcareous grassland	Grasslands	F2 Arctic, alpine and subalpine scrub	Heathland, scrub and tundra
Heath	H10	Heather-Heather grassland	Heathland	F4 Temperate shrub heathland	Heathland, scrub and tundra
Carex Sphagnum mires	M10	Fen, marsh and swamp	Bogs and fens	D4 Base-rich fens and calcareous spring mires	Mires, bogs and fens
Wet heath	M15	Heather_Heather grassland	Heathland	F4 Temperate shrub heathland	Heathland, scrub and tundra
Tall grass mire	M22b	Fen, marsh and swamp	Bogs and fens	E3 Seasonally wet and wet grasslands	Grasslands and lands dominated by forbs, mosses or lichens
Unimproved grassland	MG1a	Neutral grassland	Grasslands	E2 Mesic grassland	Grasslands and lands dominated by forbs, mosses or lichens
Unimproved grassland	MG1c	Neutral grassland	Grasslands	E3 Seasonally wet and wet grasslands	Grasslands and lands dominated by forbs, mosses or lichens
Improved grassland	MG6	Improved grassland	Grasslands	E2 Mesic grassland	Grasslands and lands dominated by forbs, mosses or lichens
Fixed dune	SD11	Supralittoral sediment	Coastal habitats	B1 Coastal dunes and sandy shores	Coastal habitats
Fixed dune	SD11a	Supralittoral sediment	Coastal habitats	B1 Coastal dunes and sandy shores	Coastal habitats
Fixed dune	SD11b	Supralittoral sediment	Coastal habitats	B1 Coastal dunes and sandy shores	Coastal habitats

LCM

At BH level, LCM correctly mapped 30 of the 40 Improved grassland samples (75% accuracy) and 849 of the 1,518 Supralittoral sediment points (56% accuracy). However, match accuracy was low for all other BHs (2-21% accuracies) and overall accuracy was 40%. At Higher BH level, there was moderate agreement between LCM and samples belonging to the Coastal habitat group, with 886 of 1,650 points mapped correctly by LCM (56% accuracy), while LCM also mapped correctly 235 of 408 Grassland samples (58% accuracy). Accuracy at BH higher group level was low for Bogs and fens, Shrubland and Woodlands (7%, 23% and 38%, respectively). Overall accuracy improved slightly to 47% when BHs were aggregated to Higher groups.

SLAM-MAP

At EUNIS L2, SLAM-MAP mapped correctly 67% of the 1,605 samples belonging to E2 Mesic grasslands and 8 of the 12 G3 Coniferous woodland samples. However, 650 and 323 E3: Wet grassland samples were mapped by SLAM-MAP as E2 Mesic grasslands and E1 Dry grasslands, respectively, while most of the F4 Temperate shrub heathland points were mapped by SLAM as either D1 Raised and blanket bogs or E3 Wet grasslands. Overall match accuracy was low at 20%. At Higher BH level, SLAM gave good match accuracy for Grasslands (80%) and moderate accuracy for Woodlands (53%). Around 10% of the Grassland samples were mapped by SLAM as O Bare land. Only 51 of the 258 Heathland samples were mapped correctly by SLAM-MAP, with 104 samples mapped as Grasslands and 39 samples mapped as Mires and bogs, while of the 37 samples belonging to Mire and bogs, only 7 were mapped correctly by SLAM-MAP, with 16 samples mapped as Grasslands and 6 samples as Shrubland. Overall, using the Higher BHs improved overall accuracy to 72%, driven by the SLAM-MAP's good performance in mapping the Grassland category, which comprised 85% of the sample dataset.

Discussion – Ground truthing

This exercise used an extensive dataset of surveyed vegetation in Scotland to ground-truth mapping provided by the LCM and SLAM-MAP products, both generated from analysis of satellite imagery at fine spatial resolutions (20m pixel). The samples dataset comprised mostly of locations in coastal habitats, such as fixed dunes, slacks and mobile dunes, with few points located in other habitats such as peatlands and heathlands. Hence, this exercise cannot be considered as representative of all Scottish habitat conditions.

Based on the analysis results and considering the stated caveats, LCM performed twice as well as SLAM when mapping land cover at habitat level. However, SLAM-MAP's accuracy improved greatly when the aggregated EUNIS groups were used, while there was a much smaller improvement for LCM when the higher BH groups were used. This difference in relative improvements was driven by the better prediction by SLAM-MAP of various grassland vegetation types. However, it is possible that expert judgement used to allocate the samples to sensible alternative EUNIS L2 types, due to SLAM-MAP not including the Marine and Coastal EUNIS classes, may have benefited SLAM-MAP’s performance in mapping those samples assigned to grassland types. On the other hand, no expert judgement was used to correspond these, mostly coastal habitat samples to LCM BHs since LCM maps them explicitly, mainly as Supralittoral sediment.

Therefore, the results seem to indicate that LCM is probably the preferred option when looking at land cover at a habitat level, while SLAM-MAP could work better when looking at broader habitat groups. However, these results for both SLAM and LCM maps are mostly relevant to various grassland communities. Therefore, in order to provide a better accuracy assessment of both maps, more surveyed vegetation information is needed to improve the sampling coverage of other extensive habitats, such as peatlands and heathlands.

Conclusions

The results of the comparison and the ground-truthing of the LCM and SLAM-MAP data layers confirm that both datasets are appropriate for the initial development of the D5-2 Risk and Opportunities Assessment Framework (ROAF) because they provide good levels of accuracy for mapping most land cover classes nationally and at a fine spatial resolution. Both maps seem to provide accurate classification of cultivated land (arable and improved grassland classes) and of dry, seminatural grasslands. However, observed disagreement in classifying areas of peatlands, wet heather, and wet grasslands, which are extensive upland habitats in Scotland, is problematic because this indicates that spatial assessments for these land cover classes would probably be quite different depending on which data layer is used. This is issue is well-recognised because these seminatural habitats expected to occur on peaty soils show a cluster of interclass confusion due to similar spectral signatures (Morton et al., 2020). Unfortunately, only a small number of the ground survey vegetation samples was from either peatlands or heathlands or grasslands, hence we cannot establish with confidence which of the two data layers performs better for these specific habitats. To overcome this issue, we have submitted a request to CEH for access to the Countryside Survey dataset, which includes a greater and more spatially-distributed number of samples collected from different land cover classes; ground-truthing LCM and SLAM-MAP with more samples could provide a better insight on their performance for mapping specific land cover classes.

Due to the inconclusive results from this study, our suggestion is to start the initial development of the ROAF using the LCM data layer; this is a more mature product than SLAM-MAP, and our team has extensive experience in using it for relevant applications. LCM also has the advantage of providing an estimate of classification uncertainty for each pixel, which can be useful during the integration of the data layer and in the interpretation of spatial assessments conducted using it. However, this suggestion of LCM for initial ROAF development is subject to confirmation that the LCM's BH classification system can correspond well with the NC typology developed in Deliverable D1.4b. It is possible that an alternative approach might need to be adopted that combines elements of both LCM and SLAM-MAP data layers if this results in more accurate mapping of specific land covers or if this is more compatible with the NC typology.

Next Steps

- Assess correspondence of LCM and SLAM-MAP classification systems with the proposed NC typology.
- If access is granted, conduct an additional ground-truthing exercise for both data layers using vegetation information from the Countryside Survey.
- Integrate LCM (and or SLAM-MAP) land cover data layers with spatial climate change projection data (Threats and Opportunities). See Deliverable D2.1a (Rivington and Jabloun, 2022)
- Develop Vulnerability and Exposure criteria for Natural Capital indicators and Ecosystem Service types
- Liaise with the RESAS C3 Land Use Transformation and D3 CentrePeat projects to explore the feasibility of future ROAF integration of new, improved land use datasets produced.
- Liaise with the RESAS C5 Large Scale Modelling project to facilitate use of improved data integration, modelling capabilities, and output visualisation.

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