Developing a model of habitat use by White-tailed eagles in Iceland

Alan Fielding

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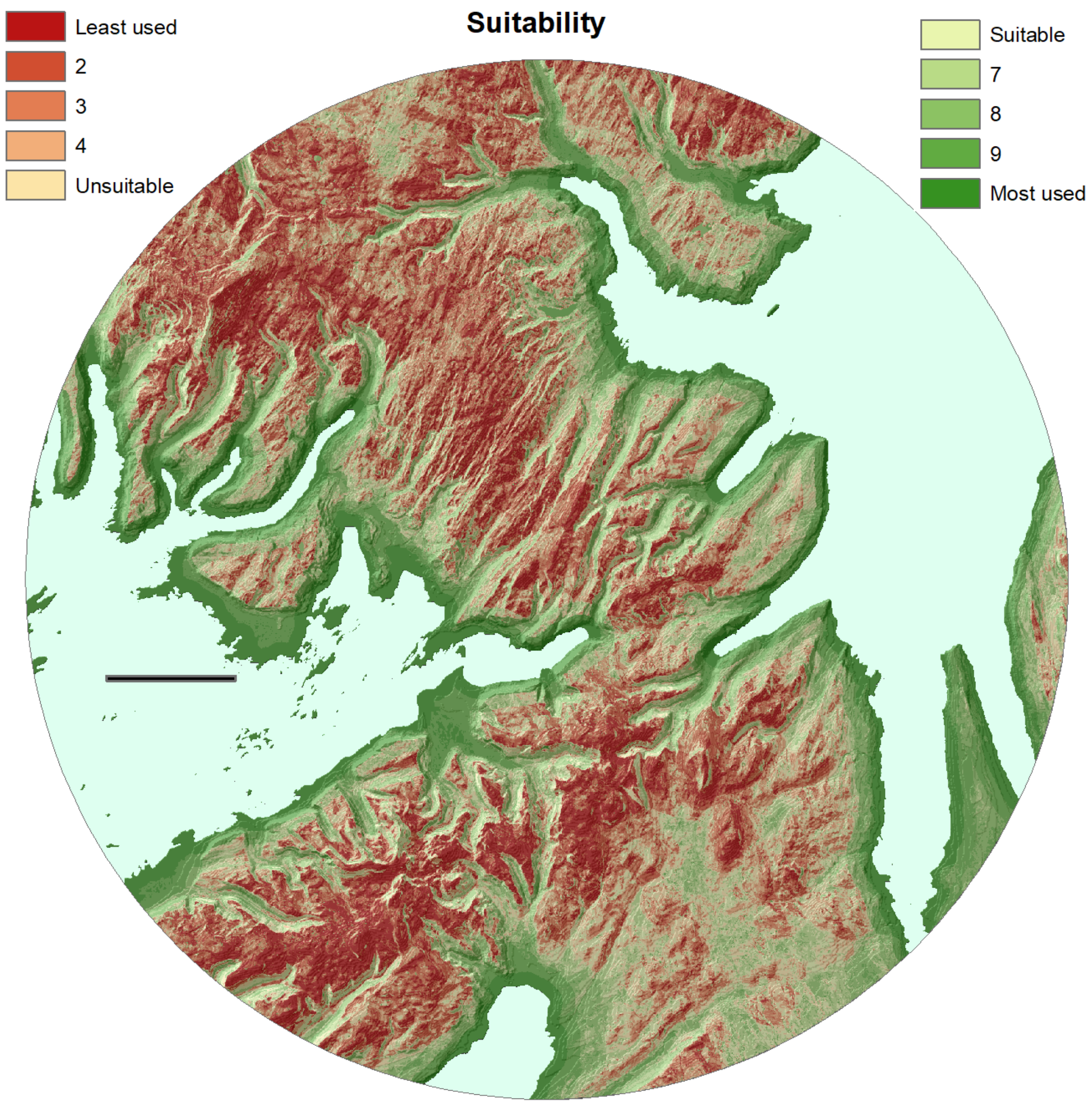
The habitat suitability model (White-tailed eagle Topographic (WET) Model)



Model background

A species distribution model (SDM) was developed to identify regions in NW Iceland that may be attractive to white-tailed eagles. A successful model could be used to identify locations that are unlikely to be used by white-tailed eagles and form the basis for an environment impact assessment of a proposed development.

The Species Distribution Model (SDM)

SDMs belong to a class of models called classifiers. Deciding which of the many classifier algorithms to use is not a simple choice. There is no 'best' classifier and classifier performance varies with the classification problem (Fielding, 2006). Fielding (2006) suggested that an ideal SDM would be accurate (correctly predicts where a species can be found or is absent) and has utility (results can be translated into actions).

SDMs are developed using a training data set (a subset of satellite tracking data in this SDM). The role of the training data is not to produce a SDM capable of producing exact representations of the training data, but rather to build a general model of the relationship between locations used by white-tailed eagles and the predictors. The ability to generalise is influenced by the SDM's complexity because, in general, SDMs with too few, *or* too many, predictors may perform poorly with new data. This means a SDM's complexity must be optimised. This is a difficult trade-off which needs to take account of the SDM's **bias and variance**.

It is a trivial task to produce a model which correctly predicts the locations of all tag records by assuming everywhere is suitable. Clearly such a model has no utility so the task is to produce a model which makes correct predictions for most (~90%) tag records but not at the expense of overpredicting the extent of suitable habitat. There is unlikely to be a SDM which is 100% accurate with training data without over-predicting areas likely to be used.

Bias measures the SDM's accuracy, i.e. closeness of predictions to reality. Low bias = high accuracy which is a very desirable property. *Variance* measures precision or repeatability. If variance is high, accuracy will change markedly between different training sets, for example two SDMs developed using the same predictors, but with data from different tags, could make very different spatial predictions. It is difficult to have confidence in a SDM with high variance because current accuracy may not be repeated with different data. Consequently, a SDM with low variance is desirable. Unfortunately, simultaneous low bias and low variance is impossible because of a trade-off such that one increases as the other declines. Low bias depends on an ability to adapt to differences in training sets, which is only possible with many predictors. Unfortunately, a classifier with many predictors is likely to have high variance. This trade-off is reflected in the different relationships between training and testing error rates and increasing classifier complexity. As complexity increases, training data errors decline to a minimum. Although errors in test data show an initial, parallel, decline with increasing SDM complexity the errors begin to increase as the SDM passes its optimum complexity. This trend has to be incorporated into a SDM's design to avoid developing models that are sub-optimal with new data. In general terms, a simpler model, that does not aim for 100% accuracy for the training data, is likely to result in a better bias-variance trade-off.

The approach

Two very different SDMs were investigated: Point Process Modelling (PPM, Renner *et al.* 2015) and Selection Index (SI) modelling. Both have been used successfully in modelling raptor distributions. The PPM was dropped at an early stage. Although a PPM model was used by AF and others to successfully model hen harrier distributions on the Isle of Mull (Geary *et al.,* 2018) subsequent attempts to use the same method in other parts of Scotland were unsuccessful (unpublished analyses undertaken for the Joint Forests and Raptors Working Group). Recent changes to the software needed to develop a PPM made it unreliable and time consuming.

Selection Index modelling

The second approach uses a simple SI model based on the method used to model golden eagle habitat from topography (Fielding *et al.,* 2020). Since its development the Golden Eagle Topographic (GET) model has been tested with new, independent data, including from range holding birds, and the model has performed very well (See Appendix A in Fielding *et al.* 2023). NatureScot now advise that "from now on, in cases where modelling is necessary for the assessment of the impacts of forestry or wind farm proposals on golden eagles, GET model assessment is recommended to support Environmental Impact Assessment Reports"[1].

Whilst a reliance on ridges, as seen in the GET model, is less likely it is improbable that a large bird, such as the white-tailed eagle, would move around independently of topography. Consequently, a topographic model was developed – the White-tailed Eagle Topographic (WET) model.

The WET model uses a simple SI resource selection function approach (Manly *et al.* 2002). In the context of these models, it is more appropriate to refer to preference indices (PI) rather than SI (Beyer *et al.* 2010). Abundance, rather than accessibility, was used as a measure of availability (Hall *et al.* 1997). A PI does not explain the underlying habitat selection process but it highlights differences between suitable and unsuitable habitat.

A PI is the proportion of all tag records divided by the proportion of all available habitat in the landscape associated with a particular habitat predictor value. For example, 6.7% of the landscape has an altitude between 1 and 20 m but 54.3% of tag records were on a pixel with this altitude. The PI for an altitude between 1 and 20 m is, therefore, 8.07 (0.5431/0.0673). A PI of one indicates use that is directly proportional to availability whilst divergence from 1 indicates under (PI <1) or over-use (PI >1). A PI of 8.07 is strong evidence of over-use, a strong 'preference' for land at this low altitude.

A problem with a PI is its dependence on how available habitat is defined, different definitions affect the divisor (Beyer *et al.* 2010, Paton and Matthiopoulos, 2016). The definition of 'available habitat' used here approximates to Johnson's (1980) third scale of availability of habitat use and was based on the 40 km wide bounding buffer surrounding the location of the proposed wind farm. Available habitat for white-tailed eagles was all land within this buffer. Some records were over the sea but for the purposes of this model they were not used.

PIs were standardised (SPI) by dividing each PI by the sum of that predictor's PIs. Standardisation ensures that PIs sum to one. An SPI, rather than a PI, simplifies interpretation: for example, an SPI of 0.3 indicates that a habitat feature is three times more likely to be used than one with an SPI of 0.1. In a final step, to simplify subsequent GIS operations, SPIs were multiplied by 1,000 and retained as integer values. SPI calculated for seven predictors, stored as raster images with 50 m pixels.

Model Data and Predictors

All GIS Operations were undertaken using QGIS Desktop 3.38 software and various spatial libraries, particularly terrra (1.7-83), in the R statistical program (R version 4.4.2).

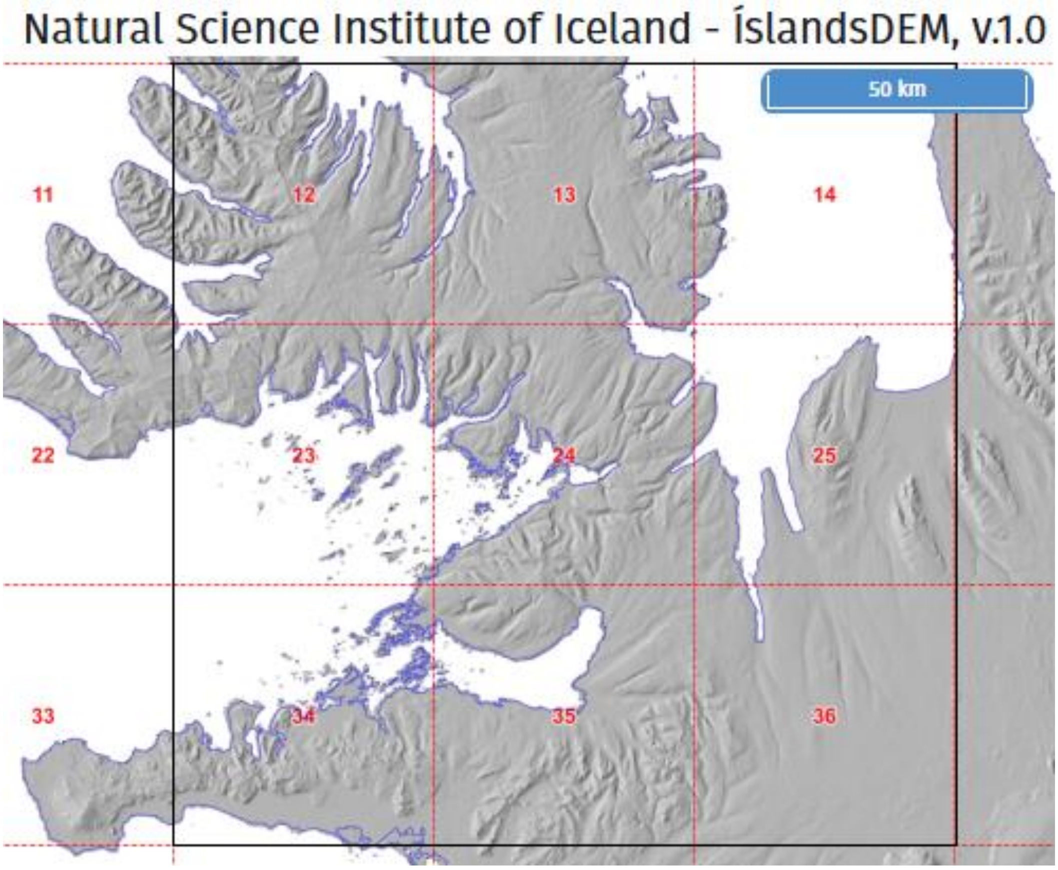
[1] https://www.nature.scot/doc/naturescot-statement-modelling-support-assessment-forestry-and-wind-farm-impacts-golden-eagles

Satellite tag data were provided in a 40 km buffer centred on a proposed wind farm. Consequently, all predictors were clipped to the same 40 km buffer.

The WET model is mainly a topographic model based on Digital Elevation Model (DEM) data. DEM data were available at various spatial resolutions. A 50 m pixel model was considered appropriate for these data for computational and spatial accuracy reasons. The other dataset was a 2012 Corine Landcover map which was converted from a vector to a raster image with 50 m pixels.

50 m DEM data were downloaded as nine 50 km tiles from the Náttúrufræðistofnun website. The tile numbers were: 12; 13; 14; 23; 24; 25; 34; 35; 36 (Fig. 1). The data projection was ISN2016 (epsg: 8088). The nine tiles were mosaiced into a single tile which formed the basis for all modelling and six raster data sets were derived from the raw DEM data.

Figure 1. The nine 50m DEM tiles used in the modelling (https://atlas.lmi.is/mapview/?application=DEM) These data are free for public use under the International CC BY 4.0 licence.



Corine data were downloaded (https://www.lmi.is/is/landupplysingar/gagnagrunnar/nidurhal) for the whole of Iceland. The vector data were cropped to the 40 km tag buffer and converted to a raster image with a 50 m pixel resolution.

The Predictors

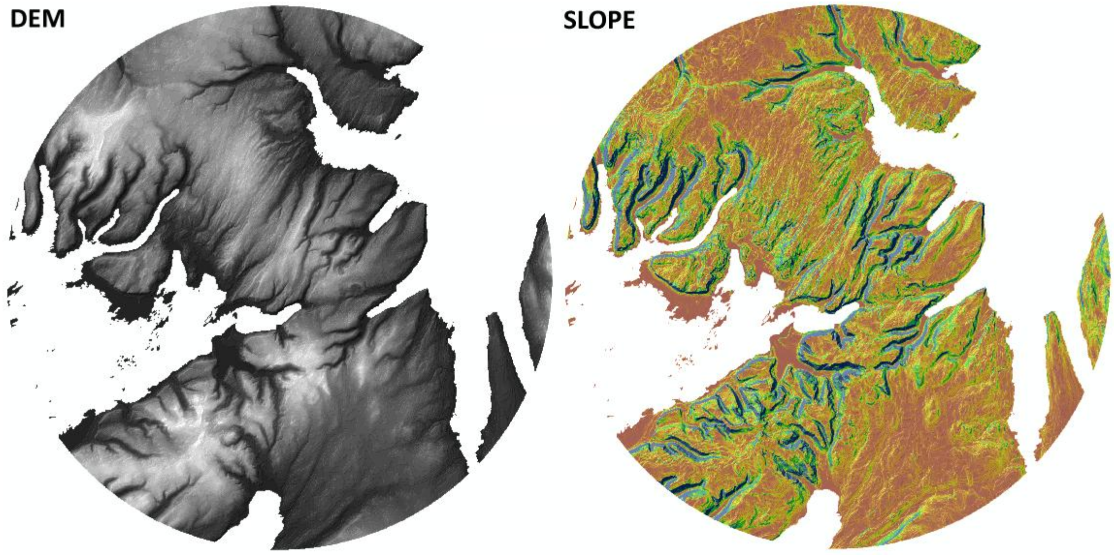
DEM20m

Altitude was placed in 20 m height bands (1-20 m, 21-40 m, etc). Binning the data into 46 20 m classes simplifies the preference analyses, compared with the original 920 1 m values (Fig. 2). Altitude above 500 m was placed in a single 500+ m class.

Slope

Slope was estimated using the QGIS terrain analysis function and binned into 5° classes (0 - 4°, 5 - 9°, etc) (Fig. 2).

Figure 2. left: DEM and right: Slope in the 40 km radius wind farm buffer.



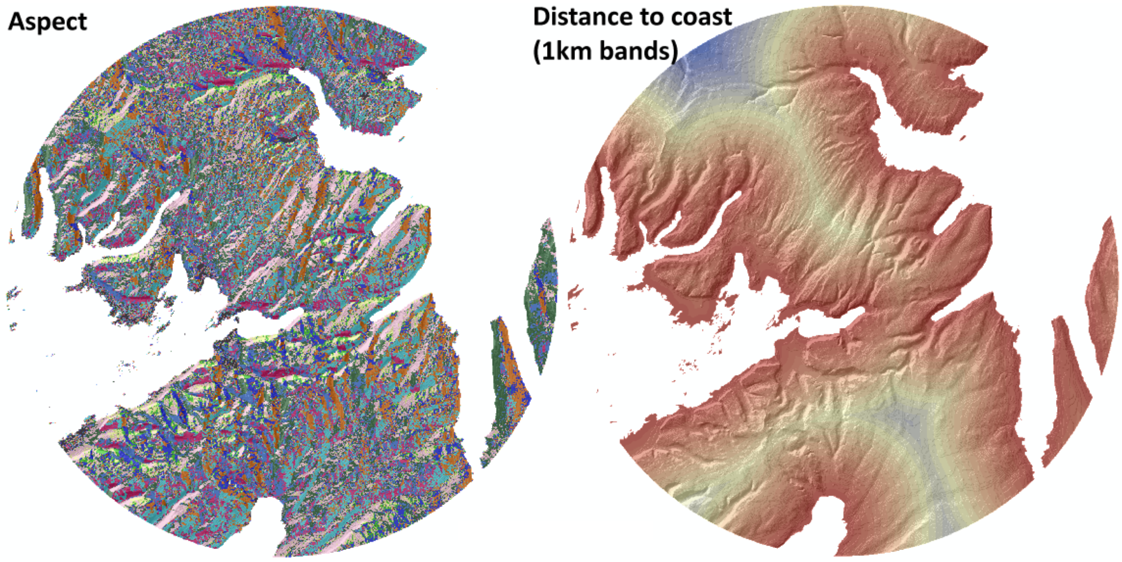
Aspect

Aspect was estimated in 10 directional zones using QGIS terrain functions: 1 flat; 2 N; 3 NE; 4 E; 5 SE; 6 S; 7 SW; 8 W; 9 NW; and 10 N (Fig. 3).

Distance to the coast

A binary image (land/sea) was created from the DEM and distance to the sea was estimated using the QGIS Raster Proximity function. Distances were binned into 1km bands (Fig. 3).

Figure 3. left: Aspect and right: Distance to the coast.

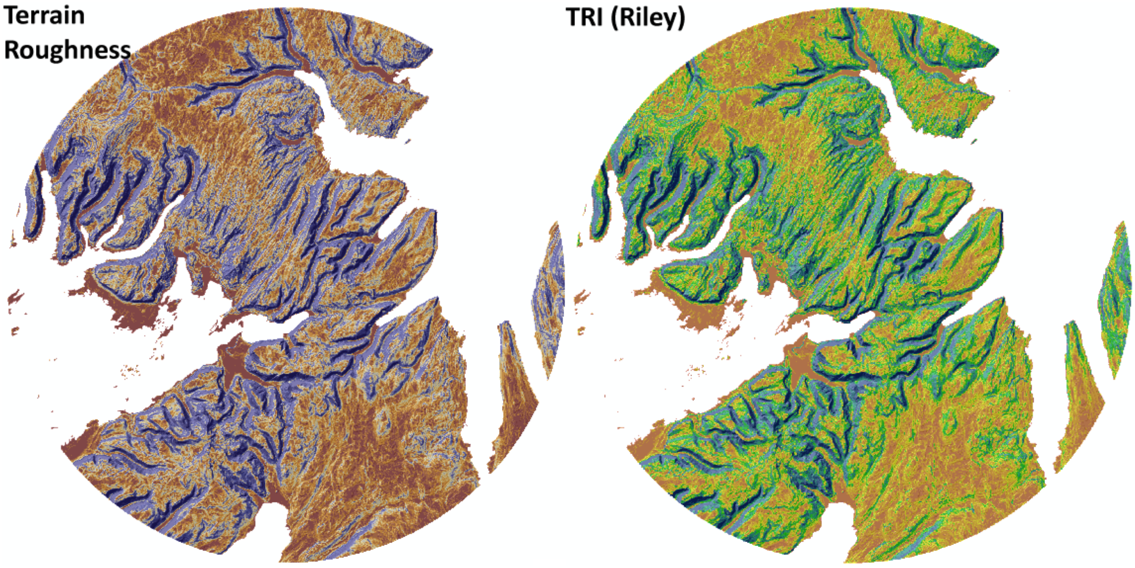


Riley's Terrain Roughness Index (Riley)

Surface roughness (terrain evenness) was estimated using the terrain function in the R terra package (Fig. 4). Three measures were considered: Roughness, Topographic Preference Index and Riley's Terrain Roughness Index (TRI, Riley *et al.,* 1999). Only the TRI, was retained. TRI measures topographic variation as the elevation difference between a central grid cell and its surrounding cells.

The scale is from low values (even ground) to higher values (rugged). Suggested categories are: 0-80, level; 81-116, nearly level; 117-161, slightly rugged surface; 162-239, intermediately rugged surface; 240-497, moderately rugged; 498-958, highly rugged surface and > 959, extremely rugged surface. The range of values in these data were 0 to 187 and for the purposes of these analyses the TRI values were placed in 10 quantiles (same number of pixels per quantile). The 0 values are around the coast where the algorithm did not calculate a value. These are retained as white-tailed eagles are often associated with the coast. This means that the 10-point quantile scale became an 11-point scale.

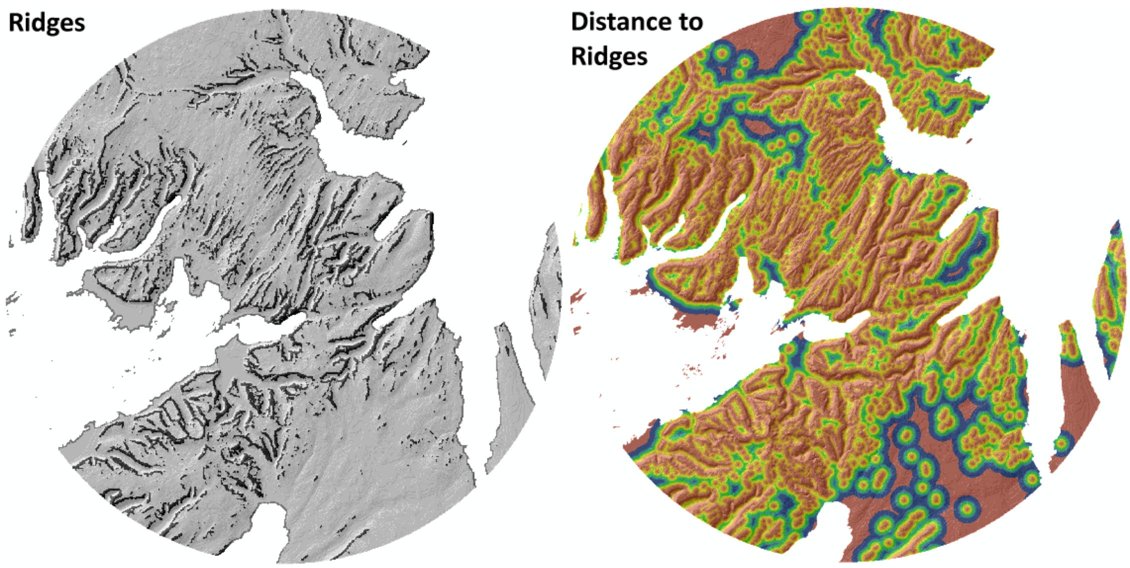
Figure 4 left: Terrain roughness (not used) and right: Riley's Terrain Roughness Index



Ridges and distance to a ridge

Ridges were identified using R code developed for the GET model (available in the Supplementary table S1 in Fielding *et al.,* 2020). In summary, a threshold (height in m) is set for the detection of ridges. This threshold is used in a comparison of the altitude of a putative ridge pixel against a mean calculated from filters running in four cardinal directions (N-S, E-W, NE-SW and NW-SE). The selected threshold is 54 m (26 m either side of the target pixel + 2 m). This threshold produces a ridge map which matches the terrain as judged from contour maps. Distance to a ridge is a continuous value so these were binned into 50 m distance classes, as in the GET model (Fig. 5).

Figure 5. left: Ridges and right: Distance to a ridge

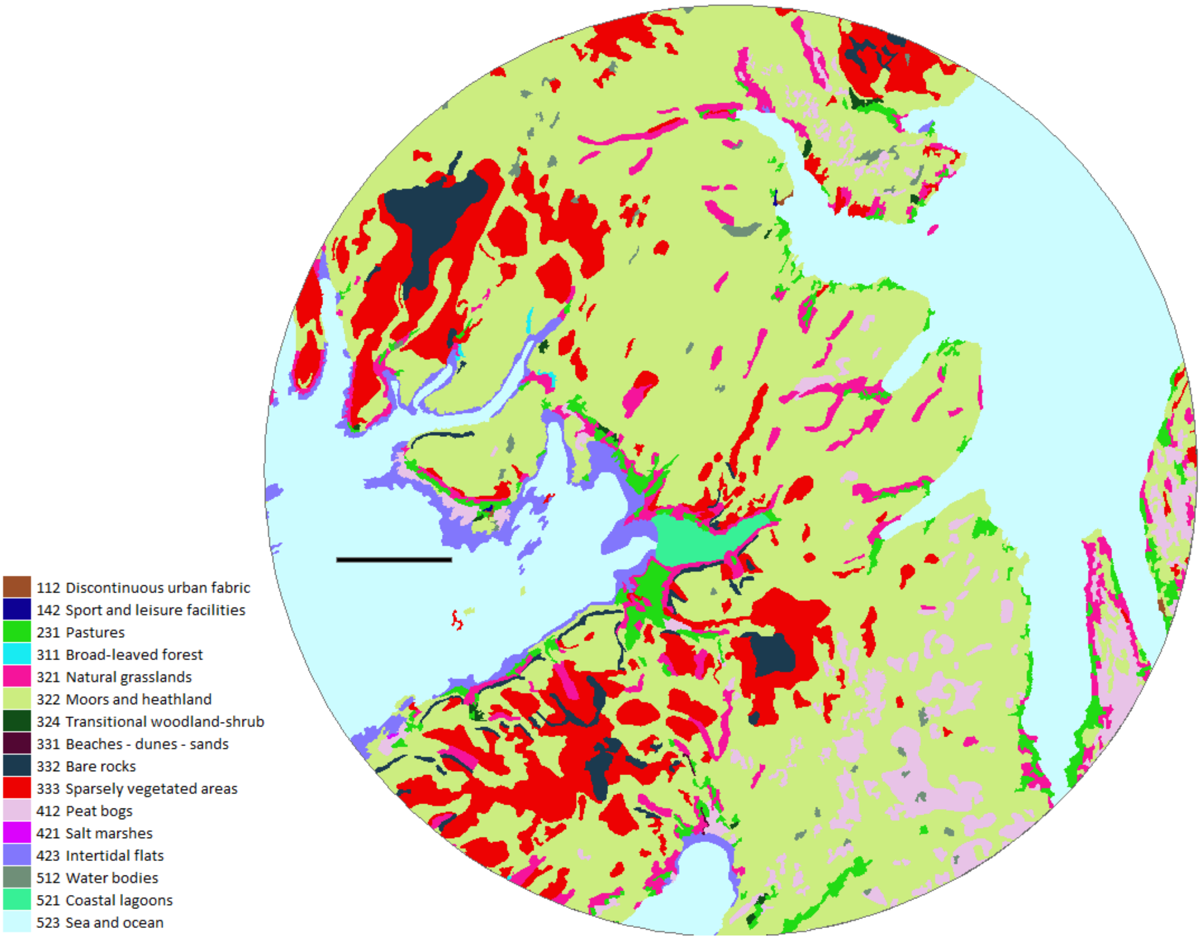


Corine Land Cover (CLC)

Corine Land Cover (CLC) provides consistent information on land cover and land cover changes across Europe, based on photointerpretation of satellite images by national teams of participating countries. There are 44 landcover classes in the hierarchical three level Corine nomenclature with a minimum mapping unit (MMU) of 25 ha.

Only 15 landcover classes are present in the 40 km tag buffer (codename - cover type): 112-Discontinuous urban fabric; 142-Sport and leisure facilities; 231-Pastures; 311-Broad-leaved forest; 321-Natural grasslands; 322-Moors and heathland; 324 Transitional woodland-shrub; 331-Beaches - dunes - sands; 332-Bare rocks; 333-Sparsely vegetated areas; 412-Peat bogs; 421-Salt marshes; 423-Intertidal flats; 512-Water bodies; 521-Coastal lagoons. The sea (code 523) is also present but as this is a primarily a topographic model it was not included (Fig. 6).

Figure 6. Corine land cover classes



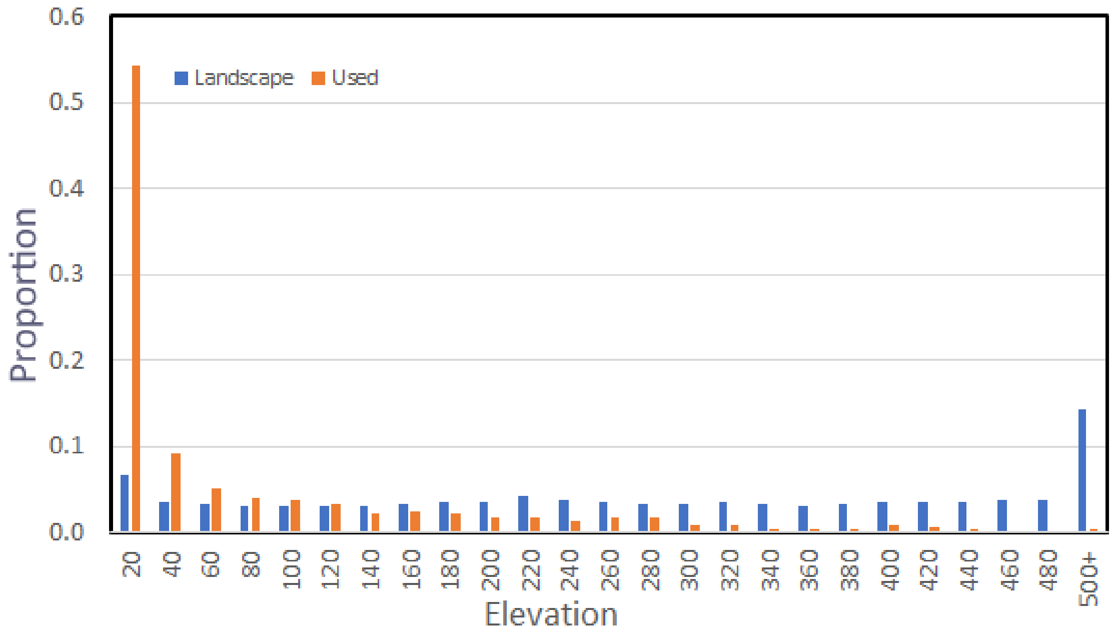
Preference Indices and Predictor Use

Data used to calculate the PIs are in Appendix 1.

Altitude

There was a very marked preference for land below 100 m (Fig. 7).

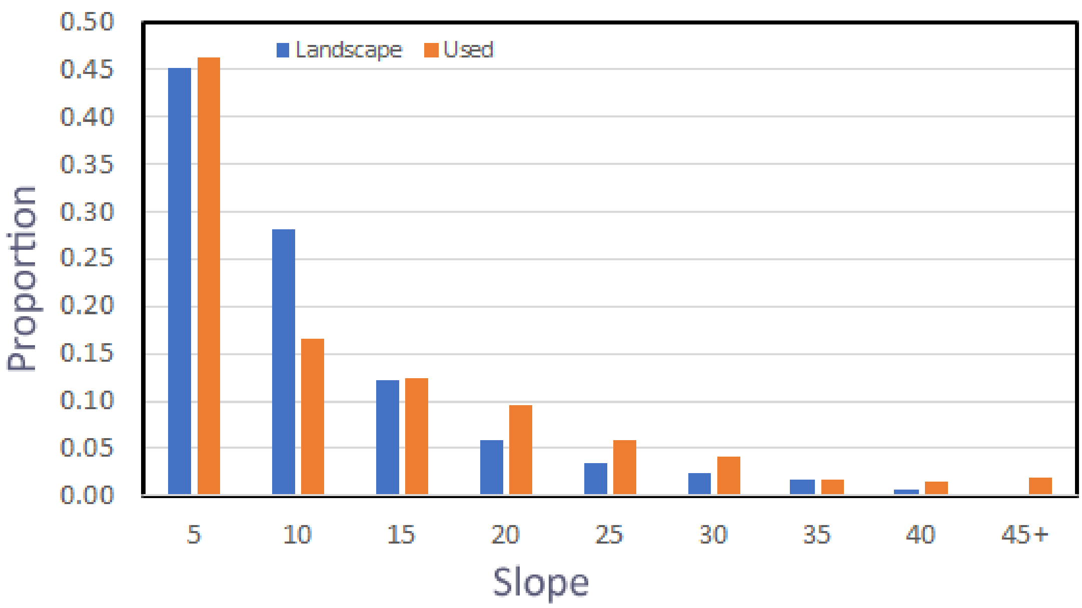
Figure 7. Proportions of habitat in 20 m altitude bands in the landscape and the proportion of satellite tracked white-tailed eagle records.



Slope

There were no large differences between what is available in the landscape and what was used (Fig. 8). There was some evidence of slight underuse of slopes between 5 and 10° and a moderate preference for slopes between 16 and 30°.

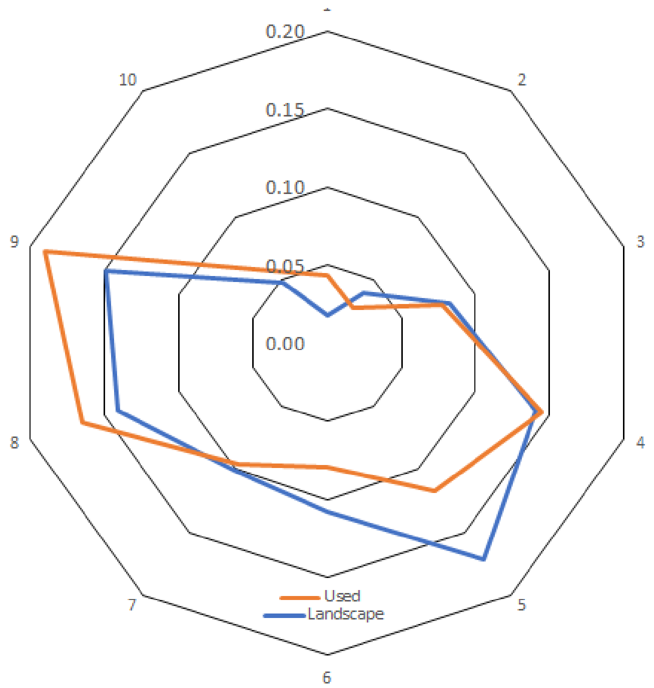
Figure 8. Proportions of habitat in 5°slope bands in the landscape and the proportion of satellite tracked white-tailed eagle records.



Aspect

As with slope, there were no large differences between what was available in the landscape and what was used (Fig. 9). Most PI values are close to 1. Only land with no aspect (flat) has a PI that deviates significantly from 1, its value is 2.4 but only 1.8% of the landscape is flat.

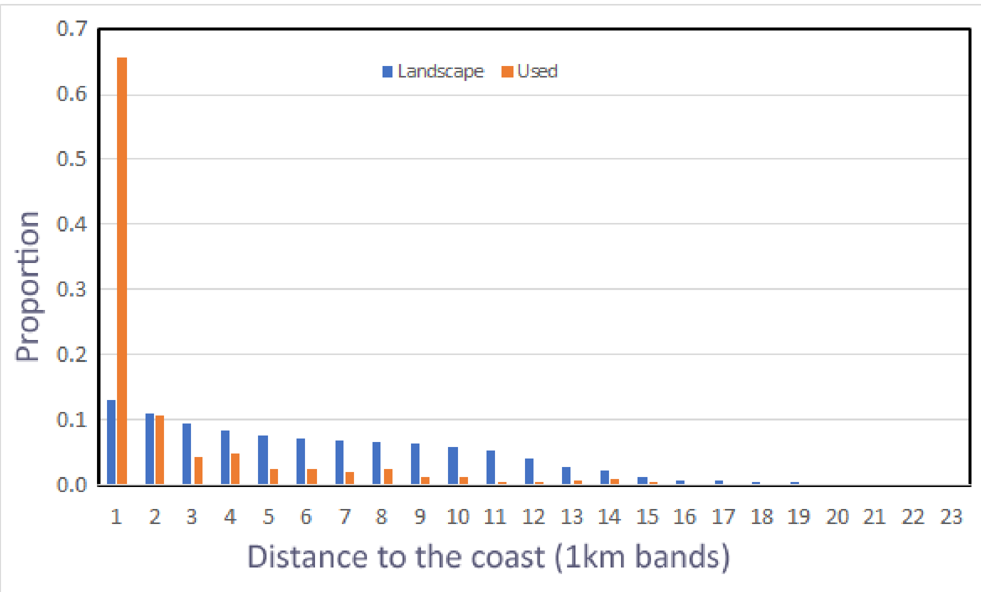
Figure 9. Proportions of habitat with different aspects in the landscape and the proportion of satellite tracked white-tailed eagle records.



Distance to the coast

Unsurprisingly the proportion land decreases with increasing distance to the coast but the overwhelming majority of white-tailed eagle tag records are within 1 km of the coast. After 2 km there are fewer records than expected from the area (Fig. 10).

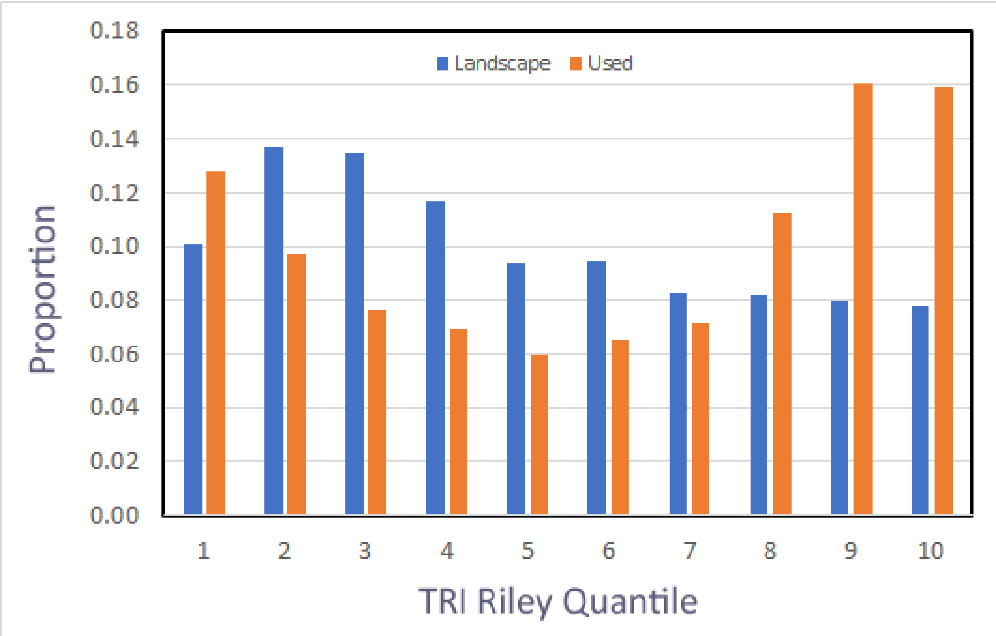
Figure 10. Proportions of habitat in 1 km wide bands from the coast in the landscape and the proportion of satellite tracked white-tailed eagle records.



Riley's Terrain Roughness Index

Riley's Terrain Roughness Index was binned into 10 quantiles. There are some large differences between what was used and what was available with a marked preference for quantiles 8 to 10 and underuse of quantiles 2 to 7 (Fig. 11).

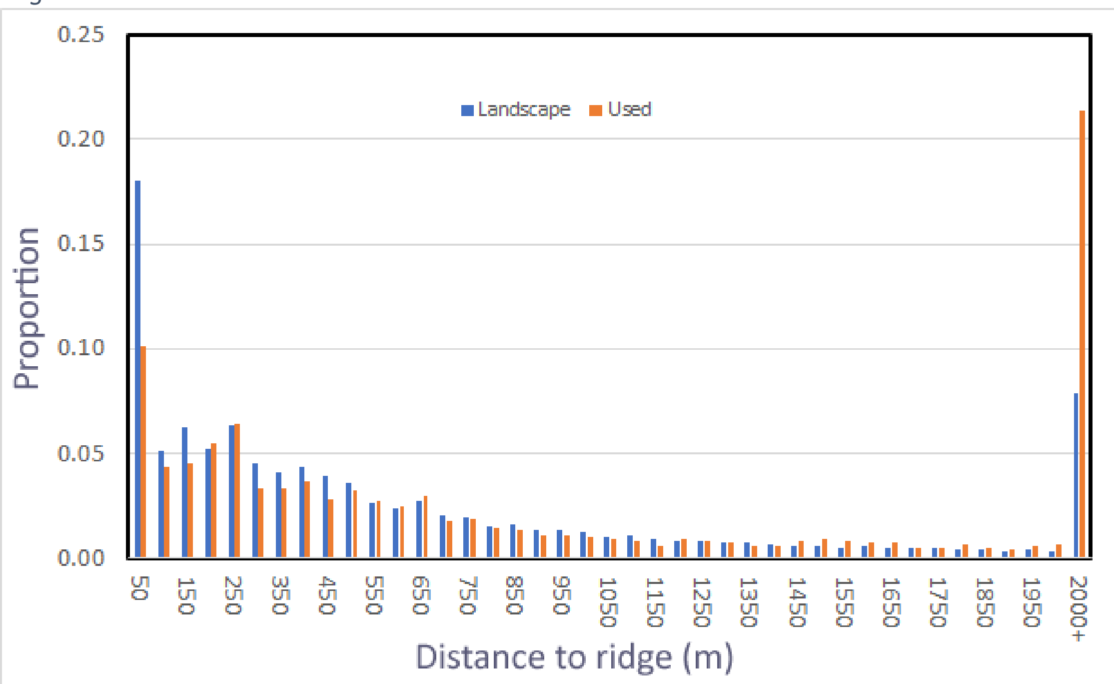
Figure 11. Proportions of the TRI Riley quantiles and the proportion of satellite tracked white-tailed eagle records.



Distance to a ridge

White-tailed eagles tended to avoid ridges and the greatest difference in proportions was at distances >2,000 m where there is strong evidence of over-use (Fig. 12).

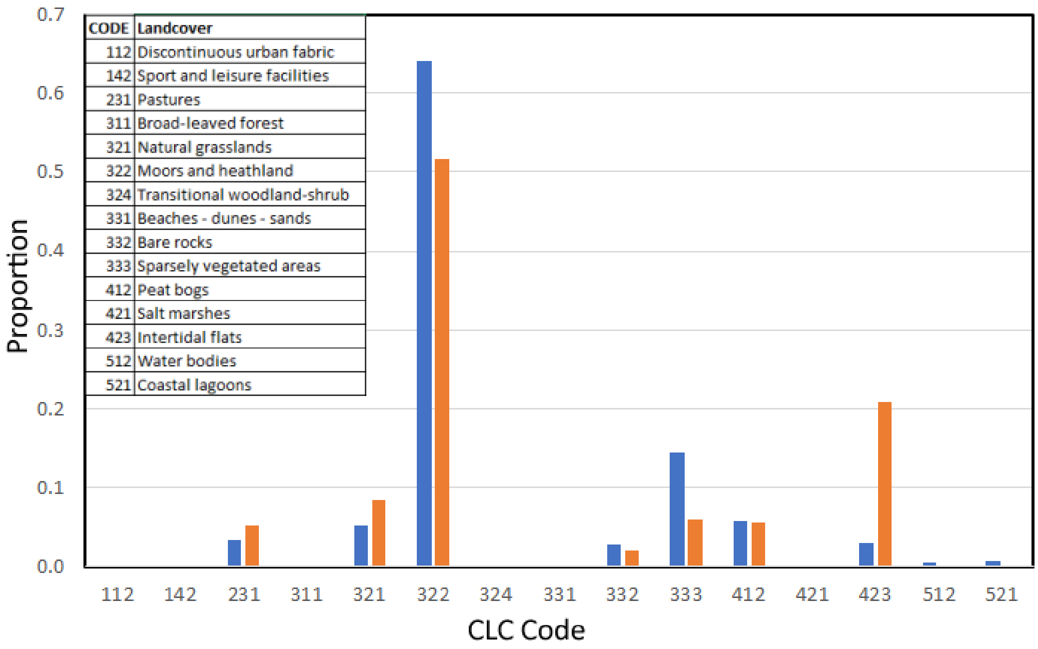
Figure 12. Proportions of distances to ridges (m) and the proportion of satellite tracked white-tailed eagle records.



Corine Land Cover (CLC)

The Corine landcover, in this region, is made up of seven main classes, dominated by Moors and Heathland which comprises 64% of the cover (Fig. 13). Bare rocks is the next largest landcover. The remaining five are Pastures; Natural Grasslands; Sparsely Vegetated Areas; Peat Bogs and Intertidal flats. White-tailed eagles only showed a preference for Pastures; Natural Grasslands and, most significantly, Intertidal flats.

Figure 13. Proportions of the Corine Landcover classes and the proportion of satellite tracked white-tailed eagle records.



Satellite tracking data

Satellite tracking data, within a 40 km radius buffer, were provided in gdb format with both point and line data. There were 979,841 records from 37 tags. The point data were extracted to shapefiles, one per tag, and re-projected into the ISN2016 projection. Table 1 summarises the tag data.

Table 1. Tag identification, number of records, first and last record dates, number of unique days with records.

tag_ident	records	1st record	last record	Days
7110	61,482	17/01/2020 12:00	01/05/2024 13:25	1,566
7111	97,985	28/01/2020 12:00	01/09/2024 16:00	1,678
7306	37,936	14/04/2020 12:10	25/04/2024 17:20	1,472
7307	87,402	24/04/2020 17:30	03/06/2024 14:15	1,501
7308	131,072	16/12/2020 00:00	14/08/2024 13:55	1,337
7309	24,340	07/02/2020 18:00	02/05/2024 19:45	1,546
7310	4,600	01/04/2020 10:00	27/07/2021 23:55	482
7311	72,446	24/10/2019 00:00	02/08/2024 21:05	1,744
201943	10,803	12/02/2021 06:52	01/09/2024 23:45	1,297
201944	27,579	11/09/2021 17:07	25/08/2024 15:28	1,079
201945	50,575	28/02/2021 14:37	29/07/2024 18:47	1,247
201946	13,214	24/03/2021 14:10	08/05/2024 13:13	1,141
213375	56,915	13/03/2022 16:55	01/09/2024 23:51	903
213376	54,139	24/10/2021 01:51	07/08/2024 10:49	1,018
213377	62,926	09/11/2021 00:11	01/09/2024 16:42	1,027
213378	14,611	25/04/2022 14:06	03/08/2023 00:35	465
213379	20,601	16/04/2022 08:09	01/09/2024 23:36	869
213380	15,624	06/02/2023 13:53	22/10/2023 19:34	258
213381	5,587	21/01/2022 13:08	26/08/2024 15:51	948
213382	4,647	02/11/2021 02:15	01/09/2024 10:49	1,034
213383	33,274	18/02/2022 22:22	15/04/2023 13:41	421
223971	15,786	18/04/2023 13:37	01/09/2024 23:48	502
223972	14,546	02/03/2023 15:32	17/08/2024 11:13	534
223974	550	29/12/2023 14:52	03/06/2024 05:55	157
223975	29,613	12/04/2023 15:29	01/09/2024 23:47	508
223976	2,566	27/04/2023 18:40	30/06/2024 15:01	430
223977	1,351	30/11/2022 12:43	23/07/2024 12:45	601
223979	6,246	04/04/2023 13:45	28/05/2024 18:47	420
223980	1,185	02/12/2022 12:40	07/08/2024 04:11	614
223981	900	27/03/2023 09:35	19/04/2024 15:03	389
234377	2,818	01/05/2024 14:41	01/09/2024 23:43	123
234379	3,163	20/02/2024 11:04	01/09/2024 10:09	194
234380	7,711	09/10/2023 16:36	01/09/2024 23:39	328
234381	419	02/02/2024 16:12	12/08/2024 14:08	192
234383	2,693	13/12/2023 15:05	01/09/2024 23:37	263
234385	2,496	01/01/2024 04:05	20/04/2024 18:04	110
234387	40	26/12/2023 13:35	22/04/2024 04:36	118

The tag data were split into model training and testing data to give an approximate 66/33% training/testing ratio. The tags used for training were: 7110; 7306; 7308; 7309; 7311; 201945; 213375; 213377; 213379; 213380; 213383; 223971; 223975; 223976; 223979; 234377; 234380; 234383; 234385 (19 tags). This is a split of 637,120 training records and 342,721 testing records.

However, the time interval between some records was very small, potentially creating spatial autocorrelation problems. In order to reduce this potential problem, the training and test data were sampled so that records were separated by at least 30 minutes. The technique for doing this is explained in Fielding *et al*., (2024). Additionally, as this is a topographic model, all records over the sea were excluded. This process also helped to reduce the magnitude of differences in the number of records between tags. There were 33,086 training records (Table 2) and 20,544 test records.

Table 2 Number of training records per tag

	Records				Records		
Tag	**Training**	**All**	**%**	**Tag**	**Training**	**All**	**%**
7110	4516	61,482	7.3	213383	424	33,274	1.3
7306	287	37,936	0.8	223971	108	15,786	0.7
7308	1427	131,072	1.1	223975	544	29,613	1.8
7309	301	24,340	1.2	223976	57	2,566	2.2
7311	287	72,446	0.4	223979	285	6,246	4.6
201945	9376	50,575	18.5	234377	19	2,818	0.7
213375	7450	56,915	13.1	234380	1560	7,711	20.2
213377	3076	62,926	4.9	234383	28	2,693	1.0
213379	2166	20,601	10.5	234385	1029	2,496	41.2
213380	146	15,624	0.9	All	33,086	637,120	5.2

The Model

Seven SPI raster images were summed (aspect, slope, dem, coast distance, ridge distance, TRI and CLC). There were 1,680 unique sums ranging from 156 to 2,225. The distribution was multimodal with the majority having low sums below 560 (Fig. 14). The final model was produced by binning the raw SPI sums (Fig. 14) into 10 quantile classes (~145,000 pixels per quantile). Fig. 15 shows the distribution of the quantiles and all tag records.

Figure 14. Frequency distribution of the raw sums of seven SPI raster images.

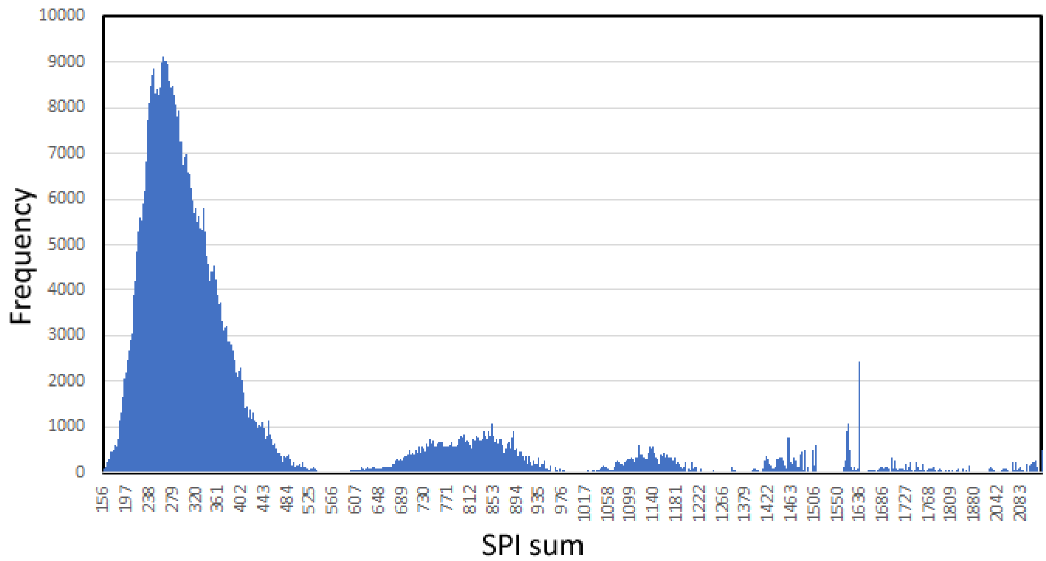
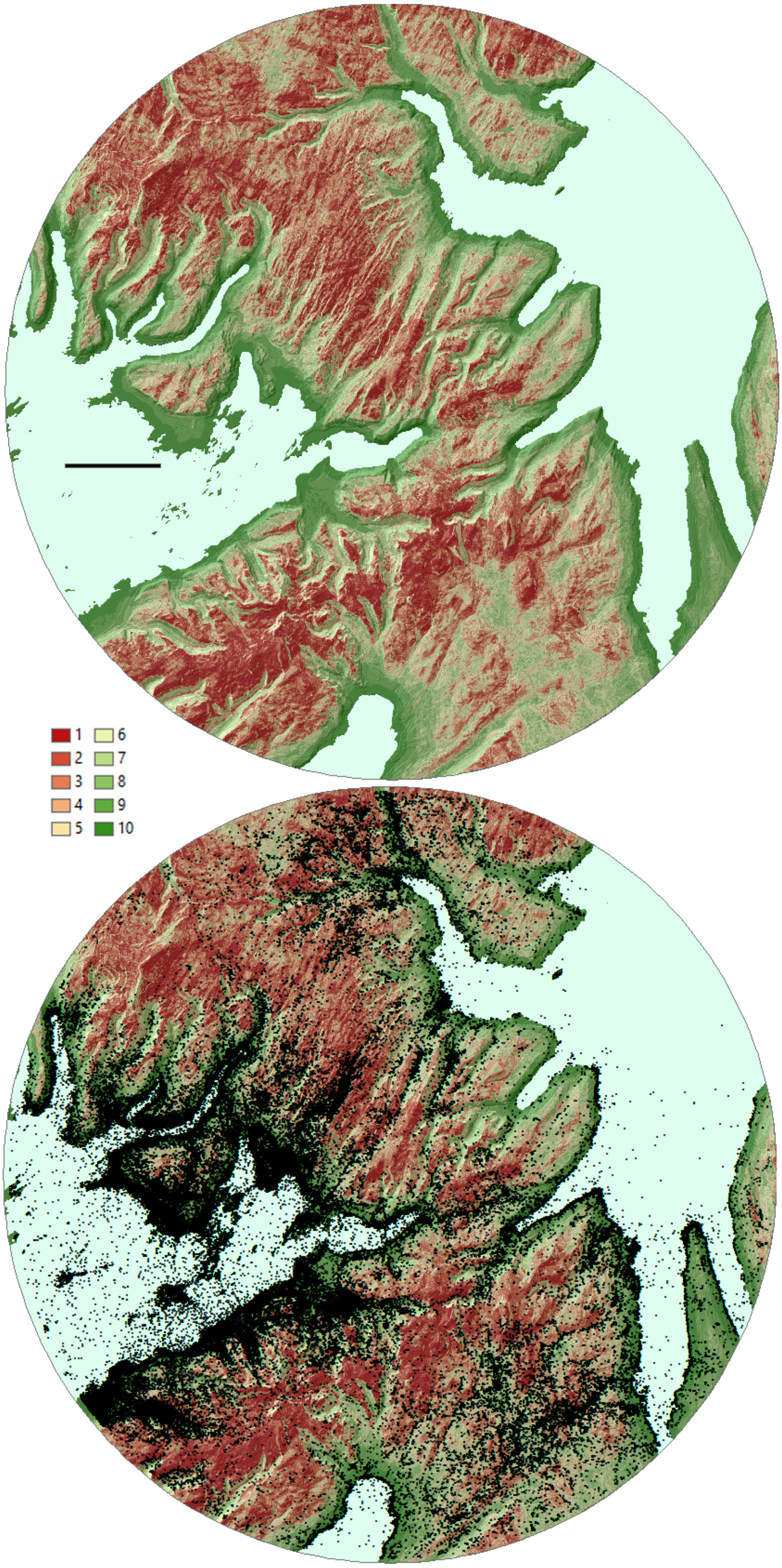


Figure 15. Distribution of the 10 SPI quantiles (above) plus with all satellite tracking records. The black bar is 10km.



Tag records are not spread evenly through the 10 SPI sum quantile classes. Unsurprisingly, they are seen less frequently in the lower values as these are derived from smaller SPI sums indicating under-use of a habitat feature. The proportion of landscape in each SPI quantile is approximately 0.1, as expected for a 10-class quantile scale. The proportions of tag records are much less than the landscape proportion until a value of 9 (Fig. 16 and Table 3).

There are only small differences between the train and test data indicating that the model has some general utility for predicting where white-tailed eagles are likely to fly in this part of Iceland.

Figure 16. Proportions of the landscape and tag records in each SPI Quantile class.

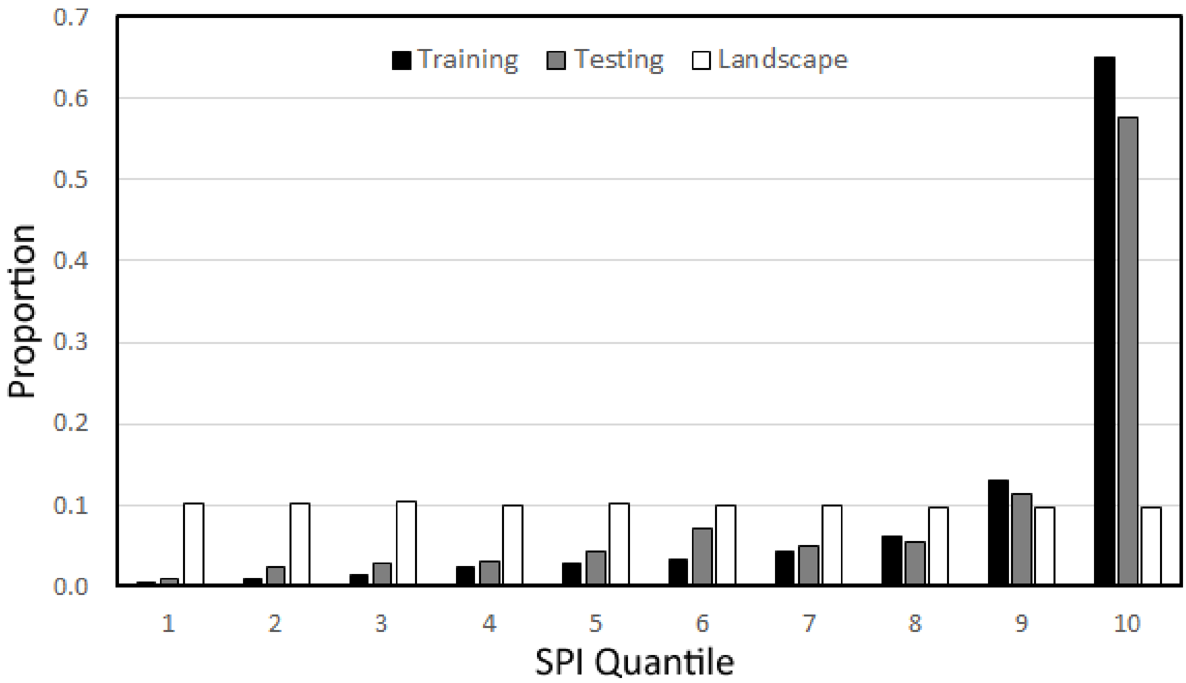


Table 3. Model results: number of records (n); proportion of records (p); and cumulative proportion of tag records (cumulative) for the training, testing and all tag records in each SPI Quantile class.

	Training records			Testing records			All records		
SPI Q10	**n**	**p**	**cumulative**	**n**	**p**	**cumulative**	**n**	**p**	**cumulative**
1	142	0.004	0.004	211	0.010	0.010	7,900	0.009	0.009
2	311	0.009	0.014	485	0.024	0.034	13,849	0.016	0.024
3	445	0.013	0.027	560	0.027	0.061	19,850	0.022	0.047
4	780	0.024	0.051	615	0.030	0.091	23,004	0.026	0.073
5	976	0.029	0.080	870	0.042	0.133	31,541	0.036	0.108
6	1,112	0.034	0.114	1,470	0.072	0.205	41,794	0.047	0.155
7	1,417	0.043	0.157	1,030	0.050	0.255	53,292	0.060	0.215
8	2,072	0.063	0.219	1,127	0.055	0.310	69,459	0.078	0.294
9	4,299	0.130	0.349	2,331	0.113	0.423	140,991	0.159	0.452
10	21,532	0.651	1.000	11,844	0.577	1.000	486,504	0.548	1.000

The GET model (Fielding *et al.,* 2020) also has a 10-point quantile scale and a threshold of 6 is used to separate good from poor golden eagle habitat. Habitat with a GET score in the 1 - 5 is considered to be poor golden eagle habitat while habitat with a score of 6 – 10 is considered to be good golden eagle habitat. If the same threshold is applied for the WET model the proportions of tag records in the 6+ class are: 0.92 for the training records, 0.87 for the testing records and 0.89 for all records (Table 3).

If a larger threshold of 9+ is used the proportions are 0.78, 0.69 and 0.71; suggesting that the model is performing better with the training data. However, even with the smaller 0.69 of test records this is still predicting that 69% of tag records will be seen in only 20% of the landscape and is, therefore, useful for identifying areas that could be problematic for white-tailed eagles if a wind farm was constructed there.

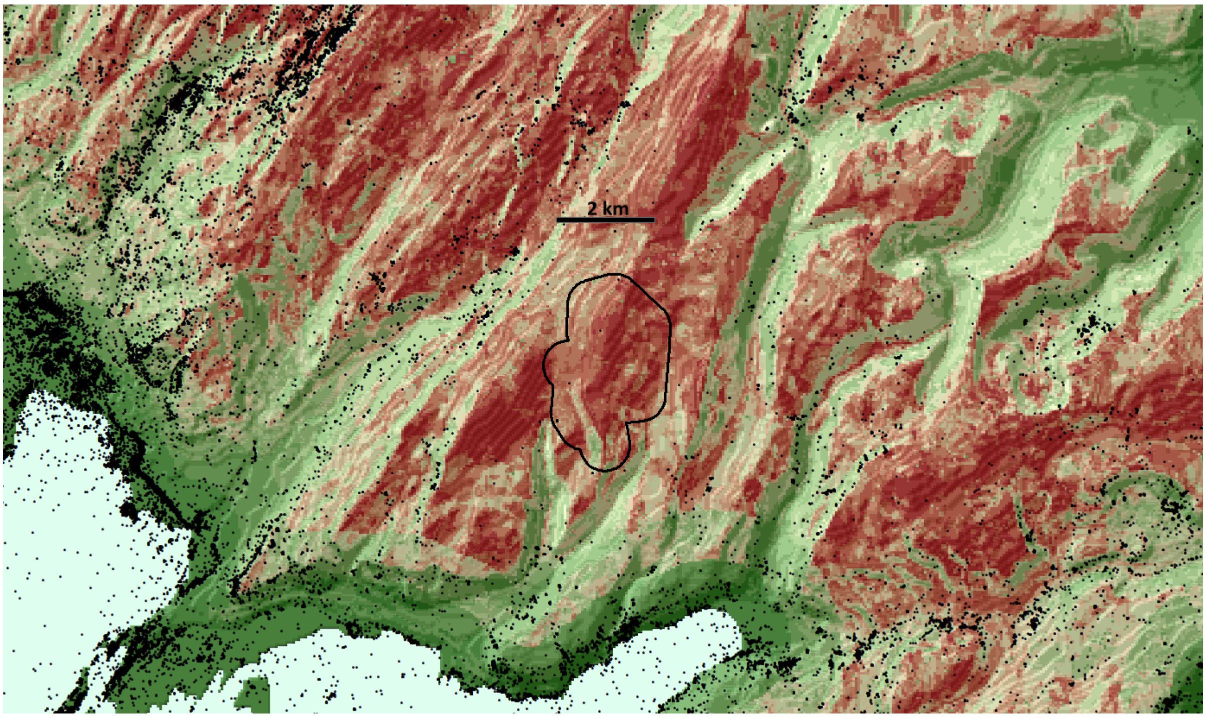
It is recommended that the same 6+ threshold is used for the WET model as the GET model as this will correctly predict 90% of tag locations whilst being restricted to 50% of the landscape.

An assessment of the proposed development

Normally, when using the GET model to assess the potential impact of a wind farm there would be two parts to the assessment. The first part, related to habitat loss, is less relevant to white-tailed eagles as they do not appear to show the same level of turbine avoidance seen in golden eagles. The second part is more relevant and involves a qualitative assessment of the position of a proposed development in the GET landscape.

Fig. 17 shows a 500 m buffer around the proposed layout. Green shading is indicative of good white-tailed eagle habitat whereas the darkening red scale highlights increasingly unused habitat. The proposed development is in a block of unsuitable habitat and is, therefore, unlikely to see very much activity from white-tailed eagles and it would be unlikely to create a significant collision or habitat loss problem.

Figure 17. 500 m turbine buffer in relation to the WET landscape.



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Appendix 1

The landscape column is the proportion of the land area in that class. The Used proportion is the proportion of tag training records in that class. PI is the preference index calculated as the used proportion / landscape proportion. The SPI is the standardised PI (PI/sums of the PIs)

Altitude

Altitude	Landscape	Used	PI	SPI
20	0.067	0.543	8.065	374
40	0.035	0.092	2.635	122
60	0.034	0.052	1.521	71
80	0.031	0.041	1.307	61
100	0.031	0.039	1.257	58
120	0.031	0.033	1.055	49
140	0.032	0.022	0.690	32
160	0.034	0.023	0.683	32
180	0.036	0.022	0.621	29
200	0.036	0.018	0.496	23
220	0.041	0.017	0.408	19
240	0.038	0.012	0.316	15
260	0.035	0.017	0.482	22
280	0.033	0.018	0.536	25
300	0.033	0.008	0.244	11
320	0.034	0.007	0.215	10
340	0.032	0.004	0.131	6
360	0.031	0.005	0.154	7
380	0.032	0.003	0.089	4
400	0.035	0.009	0.250	12
420	0.035	0.006	0.175	8
440	0.035	0.004	0.121	6
460	0.037	0.002	0.053	2
480	0.037	0.002	0.045	2
500+	0.143	0.003	0.019	1

Slope

Slope	Landscape	Used	PI	PPI
5	0.451	0.461	1.022	58
10	0.281	0.165	0.586	33
15	0.122	0.124	1.017	58
20	0.060	0.096	1.620	92
25	0.035	0.060	1.682	96
30	0.024	0.041	1.694	96
35	0.016	0.018	1.117	63
40	0.007	0.016	2.182	124
45+	0.003	0.019	6.682	380

Aspect

Aspect	Landscape	Used	PI	PPI
flat	0.018	0.043	2.411	217
N	0.039	0.028	0.723	65
NE	0.083	0.078	0.941	85
E	0.141	0.144	1.024	92
SE	0.171	0.117	0.681	61
S	0.109	0.08	0.736	66
SW	0.101	0.096	0.953	86
W	0.141	0.165	1.172	105
NW	0.149	0.19	1.279	115
N	0.048	0.058	1.196	108

Distance to the coast

Coast	distance1km band	Landscape	Used	PI	PPI
	1	0.130	0.658	5.059	496
	2	0.109	0.108	0.988	97
	3	0.094	0.042	0.448	44
	4	0.085	0.047	0.562	55
	5	0.077	0.026	0.337	33
	6	0.070	0.024	0.337	33
	7	0.067	0.018	0.273	27
	8	0.065	0.023	0.359	35
	9	0.063	0.011	0.169	17
	10	0.059	0.012	0.205	20
	11	0.053	0.005	0.096	9
	12	0.039	0.005	0.128	13
	13	0.028	0.006	0.196	19
	14	0.022	0.010	0.457	45
	15	0.012	0.004	0.339	33
	16	0.007	0.000	0.031	3
	17	0.006	0.000	0.021	2
	18	0.005	0.000	0.026	3
	19	0.004	0.000	0.130	13
	20	0.003	0.000	0.044	4
	21	0.002	0.000	0.000	0
	22	0.001	0.000	0.000	0
	23	0.000	0.000	0.000	0

Riley's Terrain Roughness Index Quantile

RileyTRI 10	Landscape	Used	SI	SSI
1	0.101	0.128	1.269	118
2	0.137	0.097	0.712	66
3	0.135	0.077	0.568	53
4	0.117	0.070	0.597	56
5	0.094	0.060	0.636	59
6	0.094	0.065	0.690	64
7	0.083	0.072	0.868	81
8	0.082	0.113	1.369	127
9	0.080	0.160	2.012	187
10	0.078	0.159	2.037	189

Distance to a ridge

Distance to a ridge	Landscape	Used	SI	SSI
50	0.180	0.101	0.560	12
100	0.051	0.043	0.848	19
150	0.062	0.045	0.724	16
200	0.052	0.055	1.047	23
250	0.063	0.064	1.017	23
300	0.045	0.033	0.732	16
350	0.041	0.033	0.812	18
400	0.043	0.036	0.835	19
450	0.039	0.028	0.713	16
500	0.035	0.033	0.924	21
550	0.027	0.027	1.005	22
600	0.024	0.024	1.019	23
650	0.027	0.030	1.104	25
700	0.021	0.018	0.853	19
750	0.020	0.019	0.941	21
800	0.015	0.015	0.958	21
850	0.016	0.013	0.831	19
900	0.013	0.011	0.818	18
950	0.013	0.011	0.863	19
1000	0.012	0.010	0.816	18
1050	0.010	0.009	0.937	21
1100	0.011	0.009	0.793	18
1150	0.009	0.006	0.676	15
1200	0.008	0.009	1.142	25
1250	0.009	0.008	0.978	22
1300	0.007	0.007	1.024	23
1350	0.007	0.005	0.760	17
1400	0.006	0.006	0.979	22
1450	0.006	0.008	1.344	30
1500	0.006	0.009	1.626	36

Distance to a ridge	Landscape	Used	SI	SSI
1550	0.005	0.008	1.611	36
1600	0.005	0.008	1.478	33
1650	0.005	0.008	1.669	37
1700	0.005	0.004	0.951	21
1750	0.005	0.005	1.127	25
1800	0.004	0.007	1.815	40
1850	0.004	0.005	1.235	28
1900	0.003	0.004	1.264	28
1950	0.004	0.005	1.398	31
2000	0.003	0.006	1.900	42
2000+	0.079	0.213	2.703	60

Corine Landcover (excluding sea)

CODE	Landcover	Landscape	Used	SI	SSI
112	Discontinuous urban fabric	0.0004	0.0000	0.000	0
142	Sport and leisure facilities	0.0002	0.0000	0.000	0
231	Pastures	0.0333	0.0520	1.562	81
311	Broad-leaved forest	0.0006	0.0004	0.746	38
321	Natural grasslands	0.0529	0.0844	1.596	82
322	Moors and heathland	0.6413	0.5165	0.805	42
324	Transitional woodland-shrub	0.0021	0.0010	0.476	25
331	Beaches - dunes - sands	0.0002	0.0000	0.158	8
332	Bare rocks	0.0270	0.0209	0.775	40
333	Sparsely vegetated areas	0.1435	0.0589	0.411	21
412	Peat bogs	0.0570	0.0565	0.992	51
421	Salt marshes	0.0001	0.0004	4.587	236
423	Intertidal flats	0.0293	0.2078	7.096	366
512	Water bodies	0.0051	0.0005	0.096	5
521	Coastal lagoons	0.0072	0.0007	0.096	5