REMOTE MAPPING OF SOIL EROSION RISK IN ICELAND

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ABSTRACT:

The use of remote-sensing based methods for soil erosion assessment has been increasing in recent years thanks to the availability of free access satellite data, and it has repeatedly proven to be successful. Its application to the Arctic presents a number of challenges, due to its peculiar soils with short growing periods, winter storms, wind, and frequent cloud and snow cover. However, the benefits of applying these techniques would be especially valuable in arctic areas, where ground local information can be hard to obtain due to hardly accessible roads and lands. Here we propose a solution which uses a Support Vector machine classification model and ground truth samples to calibrate the processed remote images over a specific area, in order to then automate the analysis for larger, less accessible areas. This solution is being developed for soil erosion studies of Iceland specifically, using Sentinel 2 satellite data combined with local assessment data from Iceland's Soil Conservation Services department.

1. INTRODUCTION

Soil erosion is a major global land degradation threat. Improving knowledge of the probable future rates of soil erosion, accelerated by human activity and climate change, is one of the most decisive factors when it comes to making decisions about conservation policies and for earth-system modelers seeking to reduce uncertainty on global predictions (FAO, 2015). Accurate information about it is, however, usually known only at the local scale and based on limited field campaigns (Verheijen et al., 2009).

Such is the case of Iceland, where most of the available information about its soil degradation comes solely from such campaigns, carried out by Landgræðslan, the national Soil Conservation Service[1]. The degradation of Iceland's ecosystem can be described as desertification. Due to the lack of vegetation, its wastelands have striking similarities to barren areas in arid countries. Soil erosion prediction plays a key role in mitigating the process (Arnalds et al., 2001).

Historically, pioneers include Björn Johannesson (Johannesson, 1961), who early on introduced a soil map and a book on the soils of Iceland. An attempt was made decades later to adopt the present-day FAO classification for Icelandic soils (Gudmundsson, 1994). The main work on soil science in Iceland has been undertaken by the Agricultural Research Institute of Iceland (Rala), which in 2005 became a part of the Agricultural University of Iceland (AUI). Much information about the physical and chemical properties of soils in Iceland can be drawn from the joint European COST-622 Action (Bartoli et al., 2003, Arnalds and Stahr, 2004). Research contributions in relation to the impact of man and degradation are numerous and include both Icelandic and foreign research efforts.

Nowadays the Icelandic government aims at bringing soil erosion under control and achieving sustainable land use as soon as possible. Desertification is mainly caused by the interaction of grazing effects, both past and present, with sensitive soils and vegetation. The soil conservation authorities, mainly the soil conservation service, were given stronger capacities to manage and monitor grazing practices in protected areas threatened by erosion and to restore denuded land (UNEP, 2002).

The methods used to assess the evolution of soil erosion involve measurements in the field and use of aerial photographs from different time intervals. There are two techniques used with aerial photographs. One way is scanning and image analysis, the other is digitizing. The use of aerial photographs involves a certain margin of error. These are expensive tasks, especially in certain areas of the country which are very hard to access, making on-site measurement a challenge. Consequently, at the moment not all areas of interest can be explored.

In addition to the impact that climate change can have on the ecosystem of Arctic regions like Iceland, one can also wonder about the impact that soil erosion in these areas can have on the global climate. Soil in northern latitudes stores up to half of the Earth's soil carbon; about twice the amount of carbon stored in the atmosphere. The importance of this carbon sink is immeasurable. Permanently frozen ground keeps this organic carbon locked in the soil and, together with extensive peatlands, ensures that northern circumpolar soils are a significant carbon sink (Jones et al., 2009). Current estimates from the Northern Circumpolar Soil Carbon Database indicate that the northern permafrost region contains approximately 1672 Pg of organic carbon, of which approximately 1466 Pg, or 88%, occurs in perennially frozen soils and deposits (Tarnocai et al., 2009).

To improve on the above limitations, one extremely useful tool has been made available through the advancement in satellite

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[1] `https://land.is/`

remote sensing technology (Phiri et al., 2020). Its application to assess soil erosion, even when based on freely accessible satellite data, has given many successful results in recent years (Žížala et al., 2019, Huffman et al., 2000). Previous studies employ certain multi-resolution approaches to soil erosion risk mapping, but focus on using rainfall and vegetation cover as indicators, which need to be generalized for the application of similar methods to Iceland.

Here we propose a solution which uses ground truth samples to calibrate the processed remote images over a specific area, to then automate the analysis for larger, less accessible areas. This solution is being developed for soil erosion studies of Iceland specifically, using Sentinel 2 satellite data combined with local assessment data from Landgræðslan. Their historical data is more extensive than usual, since they are the oldest soil erosion department in the world.

This is made possible by using a set of geo-environmental parameters to train a Machine Learning (ML) algorithm able to produce appropriate weights that can represent areas susceptible to erosion. ML models have become important components of operation research on designing mathematical and computational tools for supporting the intellectual evaluation of criteria and alternatives by decision makers (Arabameri et al., 2018).

Available data includes parameters of bare ground cover, which can be calculated from satellite images alone, after using information from observationally correct areas without vegetation for calibration; Icelandic soil profiles, to be analyzed to find how the profile relates to soil erosion intensity; as well as the parameters of agriculture use and arable land data including plant species in cultivated lands.

Classification is one of the domains of ML that help to assign a class label to an input. Among the available ML algorithms, Random Forest (RF) and Support Vector Machine (SVM) have drawn attention to image classification in several remote sensing applications. The choice of the most appropriate image classification algorithm is one of the hot topics in many research fields that deploy images of diverse resolutions taken by different platforms, while including many limitations and priorities. Medium and high spatial resolution images are the most used imageries for SVM and RF, respectively. In the case of low spatial resolution images, the RF method offers consistently better results than SVM, although the number of papers using SVM for low spatial resolution image classification exceeded the RF method. (Sheykhmousa et al., 2020).

2. STUDY AREA

Iceland, a region with a size of 103 000 km^2, presents unique erosion factors, such as glaciers (covering 11% of its area and melting), volcanic and seismic activity, carbon rich volcanic soils, freeze-thaw cycles, intense sheep grazing and extreme winds. Access to historical data about its soils is provided by Landgræðslan, detailing their original thickness and properties.

The data we need includes, the parameters of bare ground cover, which can be calculated from satellite images alone, after using information from observationally correct areas without vegetation for calibration; Icelandic soil profiles, which need to be analyzed to find how the profile relates to soil erosion intensity; as well as the parameters of agriculture use and arable land data including plant species in cultivated lands.

Due to the arctic atmospheric conditions, cloud coverage is an exceptionally significant problem. Most images are covered by clouds or by snow being carried over by wind into cloudless areas.

Elements to be taken into account during classification of erosion:

- Advancing Sand Fronts (Encroaching Sand): The advancing sand front into a vegetated area because of wind blowing the sand over the plants
- Soil Escarpments (Rofabards): Small patch of vegetation on top of an eroded cliff, abrupt changes between vegetation and soil, visual spectrum differences
- Erosion Spots: Small patches of barren soils in otherwise vegetated areas
- Solifluction: A hillslope process, slow downhill movement of the soil leading to wave-like steps and eventually erosion spots
- Water channels: A hillslope process, occurring on vegetated hill slopes and eventually become rofabards
- Landslides: A hillslope process, common in Iceland due to non-cohesive andosols and overwatering
- Mudslides: A hillslope process, common due to saturation of soil during snow melt

3. METHODOLOGY

For this project, we chose to train a Support Vector Machine classifier to predict the level of soil erosion using Sentinel 2 image data, height data and slope data as inputs.

3.1 Data preprocessing

Sentinel 2 data

The satellite data we used to train our classifier was imported from WEkEO, and comes in the form of georeferenced and atmospherically corrected Sentinel 2 images of Iceland between 23 June 2015 and present day. It contains scene classification layers for each image, which can be projected into the original image to see which pixels represent snow, clouds or non-data pixels. An automated process is then used to build a combined image devoid of these non-desirable effects. For the results presented here, this was done using images taken over a Summer period of 30 days. The data is available every 5-10 days depending on satellite pass (Main-Knorn et al., 2017).

For Sentinel 2 data Level-1C and Level-2A, images come in granules, also called tiles, of 10980×10980 pixels ($\approx$ 600 MB) and cover an area of approximately $100 \times 100 km^2$ UTM/WGS84 projection. Each UTM zone has a vertical width of 6° of longitude and horizontal width of 8° of latitude. Specifically for Iceland this means data comes in EPSG:32626-32628 (WGS84 projected), so radiometric calibration was required.

This data also provides a multi-spectral instrument with 12 bands of varying wavelengths[2], and with a resolution from 10

[2] `https://www.indexdatabase.de/db/is.php?sensor_id=96`

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to 60 m. We focused on bands with resolution between 10 and 20 m. Data from different spectral bands were combined to create indices which represent or highlight certain features, such as vegetation, soil crusting, bare soil, and red edge indices.

The development of new masks for the arctic constitutes a central part of this project. These include litter, lupines, lichen, permafrost, and bodies of water that are not as big as ones that can already be masked. For litter, the task is to create a mask that is sensitive to the specific gases that come off it. For cloud masking, the most common method is Fmasking (Frantz et al., 2018). For arable land masking, there exist machine learning methods developed to distinguish crop type and agricultural systems (Vogels et al., 2018).

To improve the accuracy of our eventual model, we addressed the low separability of erosion classes, which usually limits the applicability of classification methods, especially in spectrally complex areas. We chose an unsupervised classification approach using ISODATA and minimum distance methods. Principal Component Analysis (PCA) is used for the integration of Sentinel-2 data with other remotely sensed data in a pan-sharpening approach (Wang et al., 2016). A first linear approach was used to determine the weight of each index and then used standard deviation to classify into categories (Gadal et al., 2021) in a Stepwise Multiple Linear Regression (SMLR) (Nzuza et al., 2021).

The tools for geometric and topographic correction include SNAP (Sentinel application platform), Sen2Core, FLAASH (Fast line-of-sight atmospheric analysis of hypercubes), DOS (Dark Object Subtraction) and ATCOR software. This software handles the part of the geometric and topographic correction, which focuses on reducing effects due to shadows and surface irregularities (Pahlevan et al., 2017). The collective correction reduces effects due to shadows and surface irregularities and corrects the single-date Sentinel-2 Level-1C Top Of Atmosphere (TOA) products from atmospheric effects in order to deliver a Level-2A Bottom-Of-Atmosphere (BOA) reflectance product.

Arctic Digital Elevation Models

Height data and slope data was based on Arctic Digital Elevation Models (DEMs). Elevation data from the Arctic (north of 60°N, including Iceland) started to be openly available since 2015 through the ArcticDEM project[3], led by the Polar Geospatial Center, University of Minnesota. The Digital Elevation Models are derived from satellite sub-meter stereo imagery, particularly from WorldView 1-3 and GeoEye-1. This information can be used to detect to what extent plant growth is reduced at greater heights because of longer snow cover, shorter growing period and stronger winds on one side. By using the variation of DEM and building a slope map, we can see that soil erodes more on steep slopes which leads to a higher likelihood of erosion the steeper they are.

This data consists of a large amount of DEMs repeatedly acquired (multitemporal), typically from 2012-present, and the oldest data reaching back to 2008. The DEMs are derived from satellite sub-meter stereo imagery, particularly from WorldView 1-3 and GeoEye-1. The processing of the DEMs was done using SETSM, an open-source digital photogrammetric software, in the Bluewaters supercomputer (University of Illinois). Each DEM has $2 \times 2\,m$ resolution and a footprint of $\sim 18 \times 100\,km$. In a collaborative effort between the National Land Survey of Iceland, the Icelandic Meteorological Office and the Polar Geospatial Center, methods were developed to handle and process a large amount of data available for Iceland.

The methods developed consisted of:

1. Spatial adjustment of all the available DEMs, for homogeneity and consistency in the location of each individual DEM.

2. Robust mosaicking into one single DEM of Iceland, by taking advantage of the multi-temporal coverage of DEMs. Each pixel of the mosaic corresponds to a median elevation value from the possible elevations available from the ArcticDEM.

Drone-based lidar data from Svarmi at 5 locations was used to validate spatial accuracy. Results indicate that *IslandsDEMv1* has a positional accuracy better than $2\,m$ (XY) and better than $0.5\,m$ (Z).

The output from image preprocessing consists of $N = 553$ labelled samples (of 747 total) in the form of an XY = 11×11 pixel raster ($110 \times 110\,m = 1.2$ hectares) with a depth (D) of approx. 10 (color bands, NIR and SWIR, DEM) so an array of $N \times 11 \times 11 \times D$ and an output of the processing is expected as $1 \times 11 \times 11 \times 1$ in the first iteration. An idea to increase data compactness would be to do a synthetic image of D and reduce it to 1 by normalizing and summing the parameters altogether.

The tiles are in the EPSG:3057 (ISN93) coordinate system (projected system of Iceland) but can easily be converted into a more convenient frame.

The prepared set consisted of 747 tiles of DEM height in meters, 747 tiles of DEM slope in degrees, and 8978 tiles of sentinel 2A data for bands 2, 3, 4, 8 in $10\,m$ resolution and bands 5, 6, 7, 8a, 11, 12 in $20\,m$ resolution (around 900 tiles per band, more than 747 because of multiple images being necessary to cover Iceland).

A code is created to check if a tile has no value or is not the right size. Each preprocessed tile has been checked for an 11×11 size and to ensure that maximum and minimum pixel values do not correspond to useless tiles. It also allows for a quick gdal reprojection (warp) to fit into the desired output coordinate system of the tile.

Training and validation data set

For the training phase, we employed a data set composed of cropped georeferenced and atmospherically corrected Sentinel 2A images (specifically, we used normalised satellite image arrays in bands 2, 3, 4, 8 and 8a), DEM-derived height and slope data, and a calculated quantity known as the Normalized Difference Vegetation Index (NDVI), which is defined by the following equation:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}},$$

where NIR and R represent the Near-Infrared (Band 8) and Red (Band 4) wavelengths respectively. The NDVI quantifies the amount of vegetation present in a specific location, as vegetation strongly reflects near-infrared wavelengths and absorbs red

[3] `https://www.pgc.umn.edu/data/arcticdem`

light. It is also known to be correlated with the level of land degradation.

A normalisation approach was used to scale down the elements in the image arrays by 10,000 and apply a ceiling of 1, in order to reduce the impact of any over-saturated pixels in the images. The height of the soil would be expected to correlate with temperature and humidity, with higher altitude soils more likely to be poorer in quality than lower altitude soils, while the slope is associated with the likelihood of landslides and therefore chance of soil erosion.

The dataset is also labelled by six degrees of erosion severity from 0 to 5, with 0 indicating no erosion and 5 indicating extreme erosion. These erosion values were provided by Landgræðslan, based on manual measurements they performed to assess soil quality.

We removed the duplicate observations from the full data set to avoid introducing bias into the model, leaving us with 487 unique objects. However, given the noisy data we had, this was not enough to produce a robust, accurate model. We divided the images up into single pixels and treated the pixels as tiny images for the classifier to learn to classify. Each pixel represents a $10\,m$ length square. This resulted in a training set of 47141 samples.

The validation sets we used to assess the SVM classifier performance were randomly sampled from this training set, with an 80:20 split for training and validation.

3.2 SVM classifier

We trained a SVM classifier to predict the soil erosion severity of specific regions of Iceland based on Sentinel 2 satellite images of the regions in multiple wavebands, height, slope and the calculated NDVI. The classifier was built in Python 3, using the SVM algorithm available within the SCIKIT-LEARN Version 1.1.1 library (Pedregosa et al., 2011). The Support Vector Machine classification algorithm is a supervised machine learning algorithm that works by identifying the hyperplanes (or decision boundaries) that best separate the categories in the data. The best-fitting hyperplanes are the ones that maximise the distances between the hyperplane and the nearest data points within each category it separates. For a training set with n features, the hyperplanes found by the SVM algorithm will be n-dimensional. The motivation for starting with the SVM algorithm for our classification problem is both its higher speed and better performance on problems with smaller training sets than neural networks.

The SVM was trained using a radial basis function kernel. We trialed a large range of values for the parameters C and γ, which control the margin of error for the decision boundaries and the similarity radius for data points in the same category, respectively. For C, we tested values between 0.101 and 99.999, and for γ, we tested values between 0.001 and 9.999. The values that produced the highest accuracy without being either too small or too large (to avoid overfitting while also maximising performance) were $C = 5.00$ and $\gamma = 0.50$.

4. RESULTS

The overall accuracy achieved with the SVM model with $C = 5.00$ and $\gamma = 0.50$ was 0.91. To assess the model for overfitting, we performed k-fold cross-validation with 5 folds, and found very little variation in overall model performance across all our cross-validation runs. The average accuracy achieved across the runs was 0.907 with a standard deviation of 0.001.

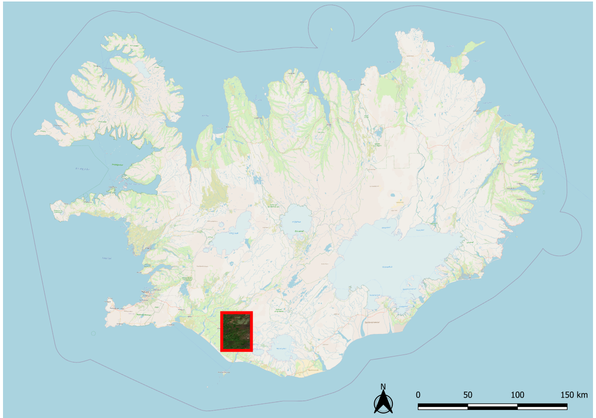

Figure 1. Georeferenced location of selected patch.

The F1 scores for each soil erosion class ranged from 0.88 to 0.93, recall ranged from 0.86 to 0.95 and precision ranged from 0.89 to 0.92, indicating a very accurate model.

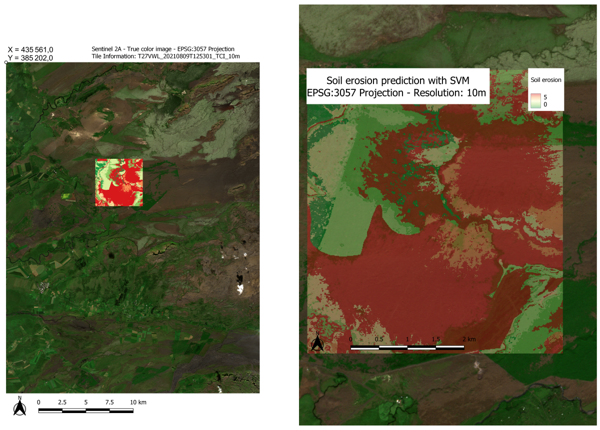

Figure 2. Soil erosion prediction with SVM EPSG:3057 projection over true color map.

For illustrative purposes, we have selected a small window in the map (see Figures 1-2) for which we can visualise these results.

The erosion level is color coded, represented from 0 (green) to 5 (red). When comparing our results to the underlying true color map from the sample data, we see an overall correct high to low erosion classification but with a certain tendency to average the risk downward. Slopes seem to enhance the risk as can be seen in areas with a rapidly changing slope.

We found that a pixel-based approach, dividing the images up into single pixels, allowed for a better variability within the images compared to the 11×11 or 3×3 pixel training approaches. While the 11×11 approach is more accurate, it averages out over a bigger area, missing out specific details with high erosion.

Features such as rivers are recognized as higher erosion, as can be seen in the selected patch. Figure 2 shows an overlapping composite, while Figure 3 shows the true color map next to the soil erosion prediction results. This riverbed is shown as high

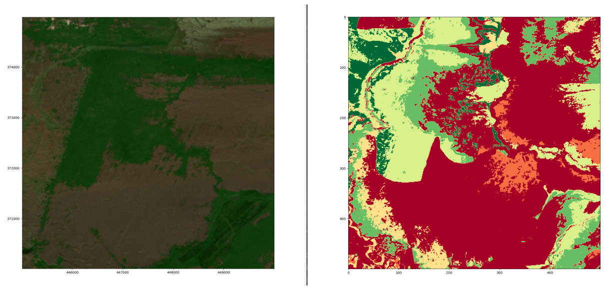

Figure 3. True color map of the selected area and soil erosion prediction result from SVM.

erosion while the field nearby with vegetation is shown as not eroding. The tops of the hills are also predicted as high erosion, probably due to wind exposure.

These results should be understood as preliminary, since at this stage accuracy is being improved frequently by tuning the parameters in the classification model in order to minimise the amount of mislabeling in the images.

5. DISCUSSION

There is multiple evidence for dramatic ecosystem degradation after the arrival of man in Iceland about 870 AD. The woodlands and shrublands were nearly destroyed with massive soil erosion and degradation of the surviving vegetated systems. An attempt is made to introduce the various research efforts and methods from many scientific disciplines on the anthropogenic impacts on Icelandic ecosystems (Karlsson, 2000).

There is a large difference in the resilience and stability of different areas, with thinner (less aeolian deposition) and finer-textured soils far from aeolian sources and volcanoes being more resistant to the degradation processes than thick coarse soils (Gudmundsson, 1997). These areas also have a large extent of relatively resilient wetlands and are presently with more vegetation cover than the active volcanic zone. Thick coarse-textured soils with coarse tephra layers near active aeolian sources and volcanoes have been subjected to massive erosion, leaving barren deserts behind in many areas (Arnalds, 2013). Land use reduced the stability and resilience of these systems to disturbances such as the cold spells of the Middle Ages and intermittent volcanic eruptions. Elevation is also an important factor that reduces the resilience of ecosystems to land use.

Soil erosion has been mapped for all of Iceland, showing both the continuous severity of the problem, but also vast differences between the different regions, soil types and ecosystems in terms of erosion problems. Land literacy is important in recognizing land degradation problems. Revegetation and ecosystem restoration activities are an important part of environmental conservation efforts in Iceland, with many examples of successful projects. Iceland boasts one of the oldest Soil Conservation Agencies in the world (established 1907). Much of the destroyed systems can be restored back to full potential with time, but protection from grazing and facilitation by nitrogen inputs through direct applications and biological activity (including biological soil crusts) are important (Mattsson, 2016).

Sentinel-2 data is widely used by the scientific community, government agencies and private sectors for a great variety of applications, most of them carried out in Europe (Phiri et al., 2020). It covers land surfaces from 56º S to 84º N (Iceland is located between 64º and 66º N). It can be more accurate when analyzing large areas, since the Sentinel-2 mission has a wide swath of 290 km field view and is sun-synchronous. Its 12 bands have spatial resolutions ranging from 10 to 60 m, of which we are most interested in the 10 m resolution ones since we need this accuracy to explore agricultural lands and urban areas. The temporal resolution is 5 days, which is a very short period between the acquisition of images. An interesting property of these images is that they have a low radiometric calibration uncertainty, which is very important to produce reliable results through our methodology. They also use a red-edge band, which is reliable in retrieving biophysical parameters.

On the downside, Sentinel-2 data has been observed to mismatch with Landsat OLI-8 data, it lacks thermal bonds and has differences in spatial resolution among its bands. NASA developed the Harmonized Landsat and Sentinel-2 datasets to reduce the geolocation error and the 38m sensor-to-sensor misalignment between the Sentinel-2 and Landsat-8 that Sentinel-2 data has.

Two factors that affect the accuracy of the delineation of eroded soils using spectral images are the intensity of the soil erosion processes and changes in the spectral characteristics of disturbed soils, so these are limitations to keep track of. Other common limitations include the lack of cloud masks, lack of information on where soil types change, and lack of historical data. Fortunately, this is not be the case for our project, thanks to the mentioned availability of historical data for Iceland.

Mention forestry projects in Iceland which need soil (Mattsson, 2016). Vegetation is important, with the objective of creating a regular cover that preserves the soil, stabilizes the land and makes it resilient, thus avoiding the liberation of CO_2 into the atmosphere.

Our project will provide more advanced and objective information than any ground fieldwork could. There has been no progress in accuracy or methodology in this field since the 1990's, when ESVs started to be used for aerial imaging. Satellite remote sensing will allow to see change year to year of any region in Iceland, with virtually no impediments of accessibility.

6. CONCLUSIONS

The present study tested the potential of building a classification algorithm to assess the erosion stages of Icelandic soils. The training process has been performed in a study area comprising $100 \times 100\,km^2$, which will be followed by an application to the entire country. The impact of erosion was obtained through an SVM classification model employing satellite Sentinel-2 images combined with the visual interpretation of ground truth data provided by the Icelandic Soil Conservation Services department.

This methodology has been proven to provide good results, achieving an overall land cover classification accuracy of 94% (Gadal et al., 2021), a performance that can be attributed to the spectral complexity of Sentinel-2 data, particularly the red-edge bands which give room for separability of erosion classes. Low separability is a common limitation to the applicability of classification methods. We address this by using ISODATA and minimum distance methods. Two factors that could affect the accuracy of the delineation of eroded soils using spectral images are the intensity of the soil erosion processes and changes in the spectral characteristics of disturbed soils.

The research described in this work aims at producing a reliable, widely applicable and cost-effective method to classify Icelandic soils into different categories of erosion risk, a proof of concept which, once engineered, could be straightforwardly expanded and applied to other Arctic areas, such as Greenland and Canada.

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