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Energy & Natural Resources



**Geological Survey of Ireland Research Programme
- Short Call 2015, Final Report -**

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Organisation name	Trinity College, the University of Dublin.		
Organisation type:	☒ HEI	☐ Public Sector (other)	☒ Private Sector
Department/section	Geography		

Project Title	Innovative approaches to coastal landslide identification and mapping
Contract No.	2015-sc-076



Integrated Mapping for the
Sustainable Development
of Ireland's Marine Resources



2. Project information:

Title of project	
Did you make any formal amendment to the project workplan / budget?	☐ yes ☒ no If yes, please specify:

Project Report (max 1500 words, excluding figures and headings):

The research aim of this project is to determine if automated detection techniques can be effectively deployed to i) map and ii) detect Irish coastal landslides.

Landslide inventories are required for the assessment of susceptibility and for understanding risk. However inventories are, by their nature, a time and resource-intensive activity. Recently

methodologies for the automatic detection of landforms have made significant advances that may enable a more accurate and efficient approach to be taken. Coastal landslides have not received sufficient treatment in Ireland due to the inaccessibility of most coastal environments. This is a concern as future climate change predictions for Ireland suggest that there may be an increase in the frequency of coastal landslides as both rainfall intensities and coastal storms are set to increase. We have explored the use of machine learning algorithms (i.e. artificial neural networks) and drone technology to enable more accurate mapping and therefore inventory building capability of coastal landslides. This approach will result in a more time-effective framework to produce coastal landslide inventories.

This project contributes to the Quaternary mapping program and specifically the geohazards research theme of the Geological Survey and their work with the Irish Landslides Working Group (ILWG). The proposed research is a fundamental step towards a more complete understanding of the response of Ireland's coastline to future climate change.

Specific objectives:

1. To test the use of UAV technologies for landslide mapping
2. Develop a procedure for the automated detection of landslides in a GIS environment using an artificial neural network approach and apply to Irish coasts.

Approximately one third of Ireland's coastline has been classified as coastal cliffs (Barrett-Mold and Burningham, 2010). Failures that occur along coastal cliffs constitute a hazard for the cliff top infrastructure and adjacent pocket beaches that are used recreationally. However, cliff coastlines in Ireland have received very little attention. Given Ireland's extensive coastline, reports of coastal landslides (occurring as mudslides, rock falls/topples/slides and debris flows are under-represented in the scientific literature, with some notable exceptions (e.g. McKenna et al., 1992). This is likely due to the difficulty associated with accessing many coastal sites and the often unobserved occurrence of coastal landslides in areas with lower population densities. As a result, large gaps in our knowledge still exist with regards to coastal slope instability.

We undertook an initial survey of coastlines that had LiDAR data available. For the hard rock sites we concentrated in Co. Clare. For the east coast we investigated potential sites between Dublin and Wexford. We undertook the survey in ArcMap using ESRI World Imagery, Google Earth, and OSI DigitalGlobe image sources. From these data we selected 2 contrasting sites to survey. The first site (A) is a hard rock cliff and the second site (B) is a Quaternary sediment cliff.

Study sites:

Site A: Ballard Bay is located on the Loop Head Peninsula 5 km south of Doonbeg, Co. Clare (Fig. 1). It encompasses a 1 km stretch of hard rock cliffed coastline comprised of an upward coarsening sequence of deltaic mudstone, siltstone and sandstone facies, capped by up to 5m of Quaternary sediments. The cliff is 65m at its highest point and is fronted a gently sloping platform (max width 160m) which terminates in a cliff at its seaward edge. The rock cliff is subject to frequent rockfalls which transports debris to the rock platform. Despite the platform width, rockfall debris is frequently cleared from the surface.

Site B: The Killiney, Shankill section is situated north of Bray (Fig. 1). It consists of a >6 Km long portion of soft coastline composed of a narrow gravelly beach and a continuous soft sediment cliff. The site is flanked by the hard coast areas of Bray Head to the south and Dalkey Head to the north. Measured maximum cliff heights are 18 m. Further south, a cliff section that extends from Bray Head to Greystones village was examined (Fig. 1). A cliff line length of 1.67 km was studied at the Greystones section, while a 5.05 km long section was studied north of Bray Head (Fig. 1). Measured maximum cliff heights are 21 m. It is clear from the cliff morphology that the eastern coastline site is subject significant and ongoing erosion.

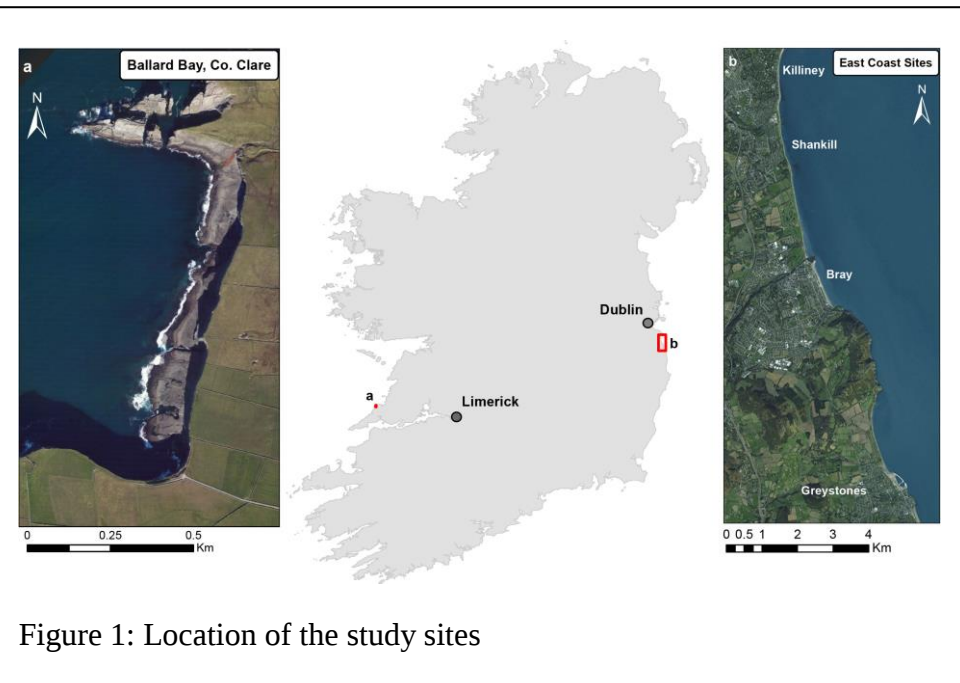


Figure 1: Location of the study sites

Mapping landslides:

Aim: To map landslides using available regional-scale data sets.

Methods: We used the LiDAR and available ESRI World Imagery, Google Earth, and OSI DigitalGlobe data. We selected not to use the Office of Public Works (OPW) Helicopter View data, as it is from 2003 and too old given the dynamic nature of the coastlines.

Results: For site A, we found that the data sets (LiDAR and image) were not useful because the cliff morphology combined with the time of image acquisition resulted in significant shadowing of cliffs and mass wasting could not be accurately mapped. There was also image distortion at some of the steeper cliff sections. Therefore a regional inventory is not available for site A.

For site B, we produced an inventory from the image data (Fig. 2). However we found that the LiDAR data was not at suitable resolution (2 m) to detect many of the failures.

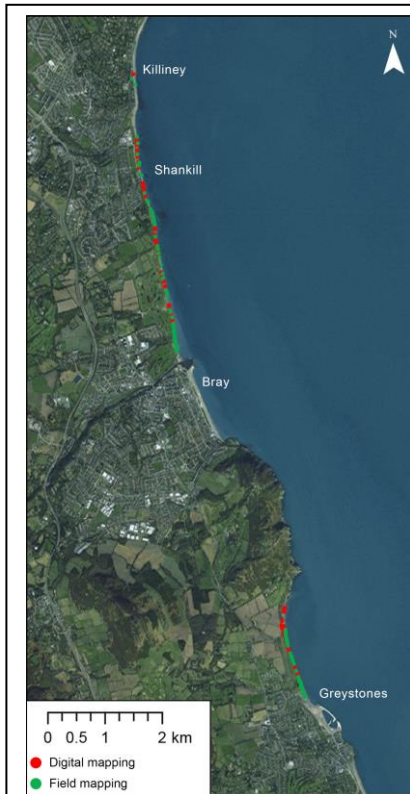


Figure 2: Comparison of inventory from regional data sets (digital) and from drone and field mapping (Field)

Outcome: Given the high frequency of small scale failures at both sites, regional-scale data sets are not of sufficient resolution or clarity to be used to produce a reliable inventory.

Aim: To deploy drone technology to enable mapping of coastal landslides and construction of high resolution DTMs.

Method: The study sites were visited in the field. A Phantom 3 Professional UAV was used, equipped with an f/2.8 lens with a 94° field of view and a fixed focal length of 20 mm. The camera was set to image the site using a fixed ISO > 200; shutter speed was dependent of lighting conditions and varied from 1/30 s to 1/200s. Our requirement for low ground sampling distance (GSD) led to us flying the drone at >10 m from target, flying at velocities of ~0.5 m/sec and automatically taking images every 5 seconds. Images have embedded GPS and ground control points were recorded for georectifying and scaling of drone-derived DTMs.

Results:

Mapping: Orthophoto mosaics of the cliff sections were built using Agisoft and used to map landslides. Landslides were mapped as polygons and discrete points with an associated confidence value ranging from 1 (high) to 3

(low) (Fig. 3). These data were validated in the field where a) confidence values were adjusted, b) mass movements were classified (Table 1 and 2, Figures 4 and 5). The drone inventory differs significantly from that constructed using the regional data set because i) the data is at higher resolution and ii) the dynamic coastline has changed in the time since image acquisition.

Our data suggest that rock cliffs composed of sedimentary rocks have a fairly uniform style of high frequency failure (i.e. rock falls). The Quaternary sediments show a range of failure types from falls to topples to flows. Importantly the image and field data show that these features are significantly modified by surface flows (rills, gullying). This modification has a distinctive topographic signature. The implication of this for our ANN modelling is 1. The parameters used in the ANN model (slope, aspect, area etc) reflect 'modified'/composite feature that included processes of mass movement and fluvial activity at site B. The failures on the west coast site display

a more ‘pristine’ morphometry as rocks can have a longer recovery time and are less ‘sensitive’ to subsequent rainfall events.

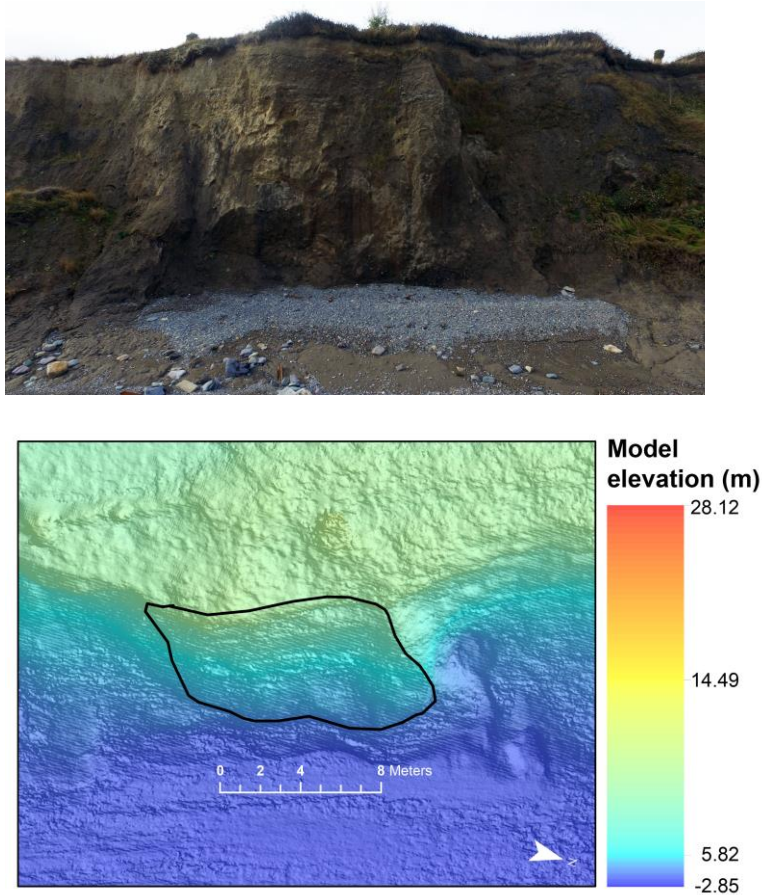


Figure 3: Figure illustrates the method of mapping locations of slope failure zone seen in top panel onto high resolution topographic data. Top panel is a drone image taken of the cliff face.

Mass movement type	Number of features
Rockfall	23

Table 1: Inventory of mass movement type at site A.

Mass movement type	Number of features
Debris fall	15
Earth flow	62
Rotational slide	8
Slump	14
Topple	3

Table 2 Inventory of mass movement type at site B.



Figure 4: Examples of typical landslides found at site B. a) debris flows; b) Debris falls; c) slumps (small) arrow to left is location of mud flows; d) slump (large)

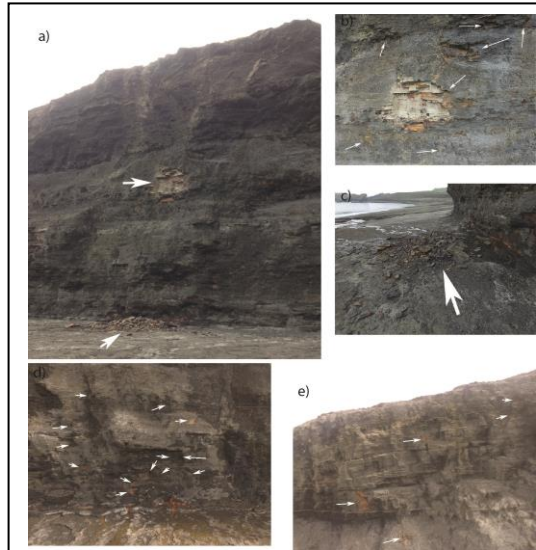


Figure 5: Examples of rockfalls at site A. a) fresh rockfall showing b) source and c) deposit; d) swarm of small-scale rockfalls on lower cliff face; e) rockfalls located approximately 50 m above platform which were only revealed in drone images.

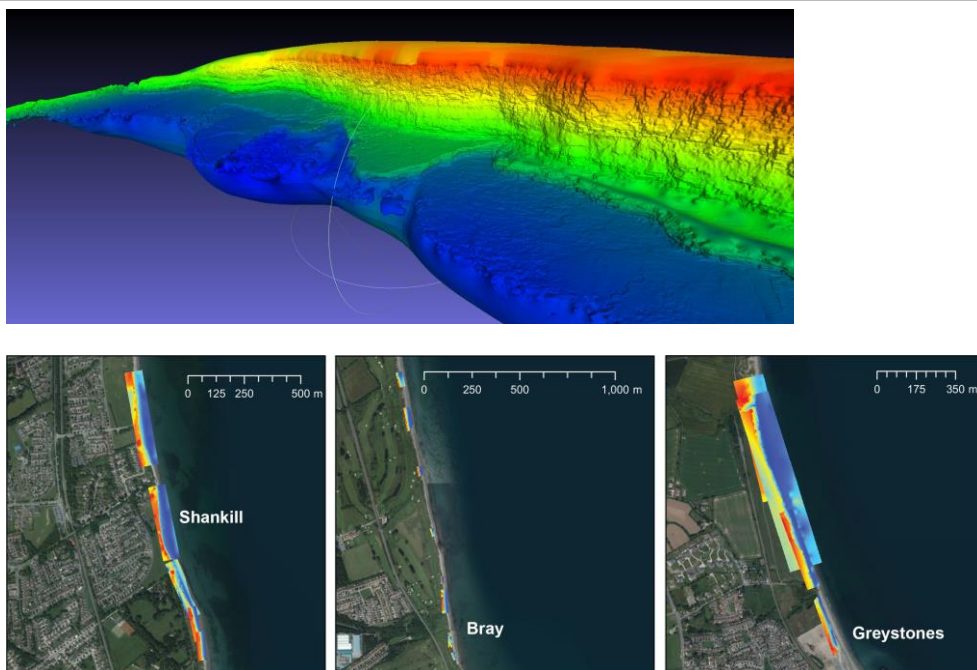


Figure 6: location of DTMs at site A (top) and site B (bottom)

DEM: We have generated a new DTM data set for two coastline sites using UAV technology (Fig. 6). The total length of DTM for site A is 1 km and for site B is 3.05 km. DTM resolutions range from 3.79 cm/px to 0.6 cm/px. These data are used to generate precise slope, aspect, elevation and surface area data for use in the ANN. These data will facilitate the acquisition of precise roughness and curvature data as well as sediment volume estimates. In addition they provide baseline data from which future changes in response to extreme events can be quantified.

Outcome: The drone inventory at site B differs significantly from that constructed using the regional data set. This is because i) it is larger as the data is at higher resolution and ii) the dynamic coastline has changed in the time since image acquisition.

Outcome: We find that drone technology is a useful and important tool for imaging high cliff sections in high resolution. For site A, which has a maximum height of 65 m, it is an essential tool to survey the higher sections of the cliff which cannot be accurately surveyed from the ground or safely surveyed from the cliff top. For site B, although lower, the image data revealed several terraced-type movements that were not apparent from eyelevel.

Outcome: Production of new high resolution DTMs and image data for significant lengths of sites on the east and west coast of Ireland. These data are base line data which can be used for further analysis (e.g., estimates of sediment delivery budgets to local coastline section by mass movement; repeat survey following coastal storms or rainfall events to determine geomorphic response to extreme events).

Outcome: New inventory of mass movements at two sites on the West and East coast of Ireland.

Beyond the state of the art: The combined use of images from a UAV platform and SfM for DTM building in a study of coastal mass movements is the first in Ireland and one of the first for high energy, high wind Atlantic coastlines.

Using Machine learning techniques to predict landslide

We used the data collected by the drone to apply four different machine learning techniques in order to attempt to predict landslide locations. The simulation processes were fed data acquired from the landslide inventory and included elevation, slope, aspect and the distance from local drainage.

All the input data are continuous variables. The dependent variable (landslide) is a categorical variable with two values (0: no landslide, 1: landslide). The continuous input data are in the 1cm X 1cm pixel size and this results in approximately a hundred data points of landslide categorical variable for site B (see figure 7).

Machine learning techniques are data driven models, so the more data for both the dependent and independent variables that exist, the more accurate models are simulated. We found that the observed landslide data (the dependent variable) relative to the very large number of points for the independent datasets, resulted in an unbalanced dataset for use in the simulation. This is an artefact of both the small size of the failure features relative to the area surveyed and the relatively low inventory numbers. Unfortunately increasing the size of the inventory would not resolve the issue. The result is very poor models that cannot be used for prediction.

Results:

Binary Logistic Regression

As shown from the fitted model (figure 7) the R² is approximately 20% which means the model fails to predict the landslide, and that can be seen from the map (figure 8), as well.

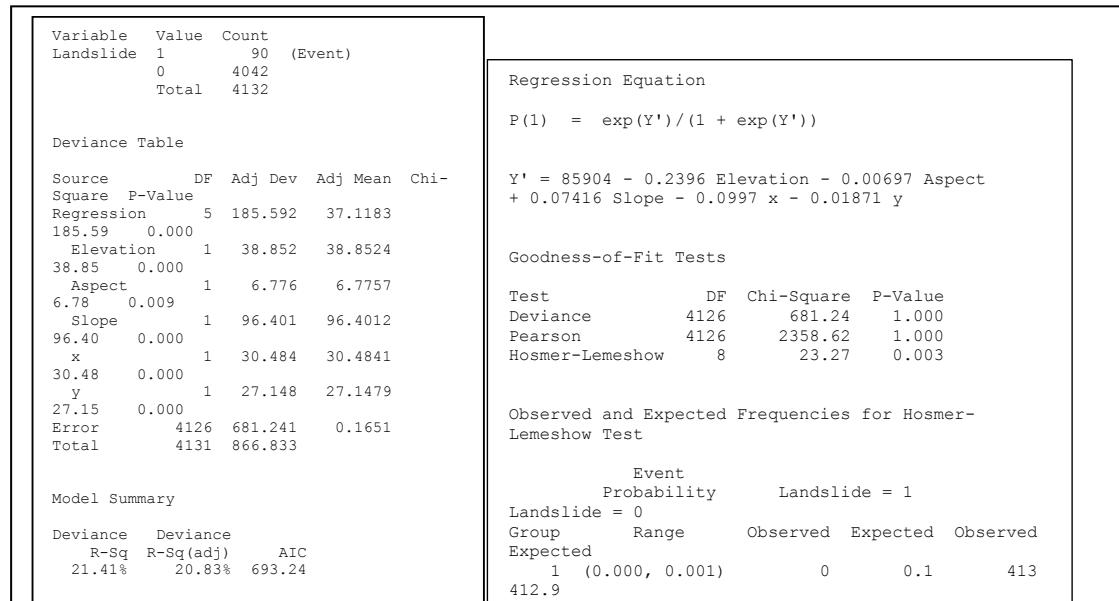


Figure 7: Binary logistic regression model fitted for a landslide data set.

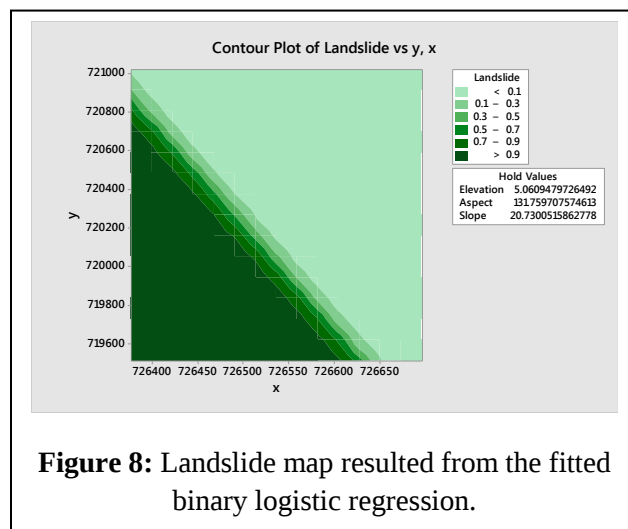


Figure 8: Landslide map resulted from the fitted binary logistic regression.

Decision tree

As can be seen from the decision tree fitted model the model failed to simulate any occurrence for a landslide, around 98% of the resulted records from the model were 0 (no landslide). See figure 9-11 for the input, data matrix.

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Performance Vector:
accuracy: 97.82%
Confusion Matrix:
True:  0    1
0:  4032  90
1:    0    0
precision: unknown (positive class: 1)
Confusion Matrix:
True:  0    1
0:  4032  90
1:    0    0
recall: 0.00% (positive class: 1)
Confusion Matrix:
True:  0    1
0:  4032  90
1:    0    0
AUC (optimistic): 1.000 (positive class: 1)
AUC: 0.500 (positive class: 1)
AUC (pessimistic): 0.000 (positive class: 1)

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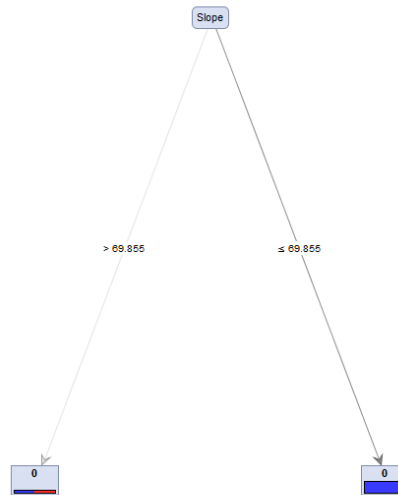


Figure 9: Decision tree fitted model.

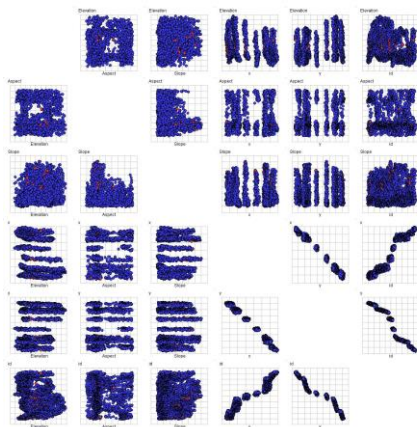


Figure 11: Matrix plot for the data (the blue points are (0) no landslide, the red points are (1) landslide).

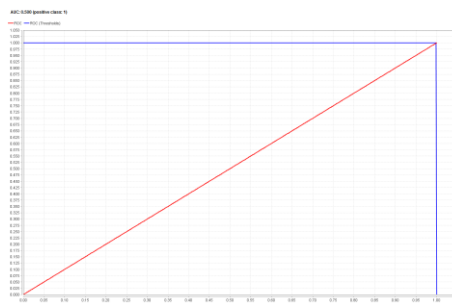


Figure 10: The AUC graph, AUC is the Area Under the Curve of the Receiver Operating Characteristics (ROC) graph which is a technique for visualizing, organizing and selecting classifiers based on their performance.

Artificial Neural Network (ANN)

The same datasets have been standardized and feed to the ANN. The ANN model is designed to have two hidden layers with 5 nodes in each one, (see figure 12). The sigmoid method has been assigned to each node. The model trained for 100000 cycles. The ANN model did not work for modeling the landslide because of the previously mentioned reasons.

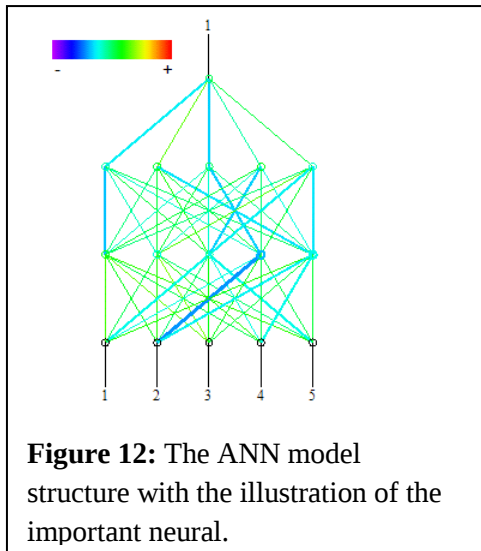
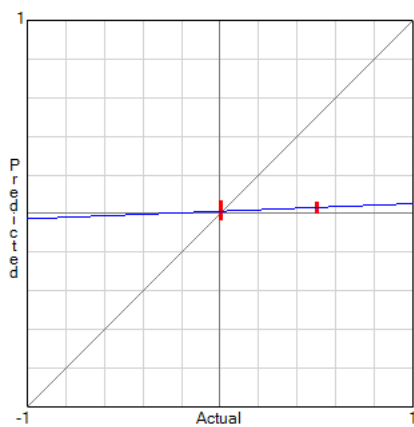


Figure 12: The ANN model structure with the illustration of the important neural.



Training	0.03958612	0.03929644	0.01245357
Validation	0.02836776	0.04454319	0.01176902

Figure 13: The ANN model validation process, which shows that the model does not work.

Improved Neural Network

The same datasets have been feed to the INN. The INN model designed to have one hidden layer with 6 nodes, see figure 13. The modified Sigmoid method has been assigned to each node. The model trained for 1000000 cycles. The INN model shows some sign of improvements compared to the ANN, as it can deal with the categorical output, but, in summary, it did not work for modelling the landslide because of the previously mentioned reasons. Figure 14 shows the validation INN AUC chart and figure 15 shows the SOM map for the trained INN.

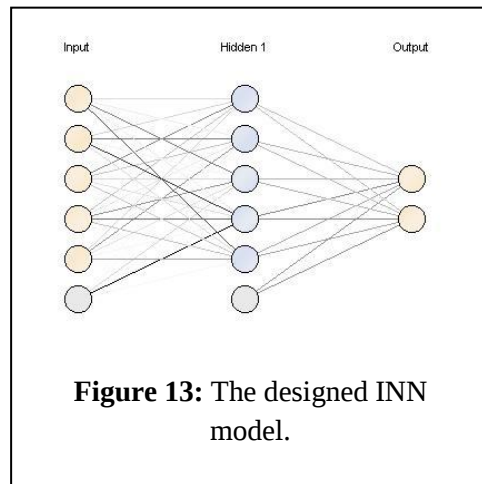


Figure 14: The INN AUC graph. AUC is the Area Under the Curve of the Receiver Operating Characteristics (ROC) graph which is a technique for visualizing, organizing and selecting classifiers based on their performance.

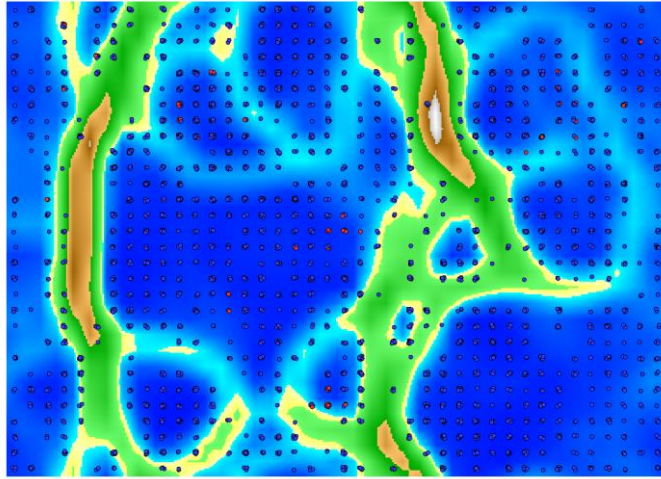


Figure 15: A self-organizing map (SOM) for the trained INN model, which is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples. Self-organizing maps differ from other artificial neural networks as they apply competitive learning as opposed to error correction learning and in the sense that they use a neighborhood function to preserve the topological properties of the input space (the red points are the landslide predicted points mapped on the SOM, the blue points are the no slide predicted points).

Outcome: We find that the automated approaches tested for site B were unsuccessful and do not recommend them for use on Irish coastline landslide. The data for the east coast resulted in our not applying the approaches to the west coast sites.

(ii) Implementation (including reference to timelines, milestones, management)

Our hired researcher (Rory Flood) took a teaching position in the UK after 5 months. We were able to rapidly hire a replacement (Ciaran Nash) however this led to some unanticipated delays in progress.

We had to hire additional staff for the construction of the inventory. This increased the salary component of the budget.

(iii) Outputs (please use bullet points)

- We have completed an assessment of the application of ANN to coastal landslides in Ireland.
- Produced high resolution DTMs for two coastal erosion sites.
- Produced inventory of coastal landslides at two locations in Ireland.
- We plan to have a paper submitted (2017) 'The application of UAV technology for the mapping and detection of landslides at coastal sites in Ireland' to a Q1 Journal.

Impact/value of the project (Max 500 words):

This project provides a significant advancement in mapping methodologies for relatively coastal cliffs. We provide a proof of concept for an innovative framework for mapping of landslides in difficult and non-accessible coastal environments using UAVs.

Machine learning algorithms will be designed, tested and validated as part of the proposed work. The framework is designed in a comprehensible and operative way in order to be accessible and usable by practitioners for strategic purposes. The data from this project will be published in high-impact journal in the field of GIS and remote sensing, environmental research and management. This high profile dissemination, along with planned presentations at EGU, will reflect Ireland's cutting edge research capacity.

Some clear applications of this framework which will result in positive impacts are in the area of cultural heritage and geotourism. Both of Ireland's UNESCO World Heritage sites (The Giants Causeway and Skellig Micheal) are associated with coasts and more specifically with steep rocky terrain where rockfalls and other landslide types occur.

An additional impact will be the increased time efficiency for detecting coastal landslides due to the use of UAVs. This will allow the assessment of long stretches of coastline in relatively short times. As such, it will be an ideal way to monitor areas such as the highly popular Wild Atlantic Way, which is also a key contributor to the tourism sector. Identifying areas of slope instability along this highly popular tourist route is economically important. There is a responsibility to provide a safe environment for visitors to our shorelines and also to preserve our coastal heritage sites.

We have shown that the data are unsuitable for the four automatic detection approaches taken. There are however other approaches that may be more suitable and future work can employ our data set to test its rigour.

In light of recent climate change predictions for increases in the intensity of extreme rainfall events and an increase in coastal storm surges (e.g., Wang et al., 2008), there is an urgent need to map the current extent of coastal landslides so that areas of higher risk can be identified through landslide susceptibility and risk analysis. Our work demonstrates an approach that is significant step towards increasing the efficiencies and potentially the accuracies of current inventory systems. At present the weak knowledge of coastal landslide distribution represents a significant gap in our understanding of the potential response of Ireland's coast to the impacts of future climate change, specifically sea level rise and increased storminess.

References

Barrett-Mold, C., Burningham, H., 2010. Contrasting ecology of prograding coastal dunes on the northwest coast of Ireland. *Journal of Coastal Conservation*, 14, 81-90.

Appendix 1 – Publications & Presentations:

Bourke, M.C., Pilla, F., Nash, C., Cullen, N., Flood, R., (2016). Automated detection of coastal landslides using drone platforms. *Integrated Mapping for the Sustainable Development of Ireland's Marine Resource*. Galway.

Appendix 2 – Any additional information not included above: