Geomorphic and Hydrological Mapping of Sheskinmore Lough and Wetland, Co. Donegal, Ireland

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Abstract

Wetlands are one of the most protected ecosystems in Europe (Glinmann, 1994). Sheskinmore Lough and wetland in County Donegal, Ireland is a sedimentary lake formed around c. 1000 years ago and it is a protected site (Shaw & Carter, 1994). Wetlands are complex hydrological systems where water flow is restricted, obstructed and retained. In recent years the water levels have been dropping due to natural siltation and ad hoc drainage, this has had a negative impact on the water levels and subsequently on the flora and fauna of the site. A sluice has been installed to maintain the water levels in the Lough. Topography is one of the main influences on water bodies and water flow (Pervalo, 2004). Therefore to accurately model the hydrology of the site a digital elevation model (DEM) is essential. This paper presents a high resolution raster grid DEM generated from a differential GPS (DGPS) survey. Six interpolation models are analysed, they include Inverse distant weighting, kriging, minimum curvature splines (both regularised and with tension), natural neighbour and the Australian National University DEM interpolation model (ANUDEM). Different DEM smoothing techniques are also analysed in an attempt to create a more realistic surface, these include subsampling the dataset, smoothing the dataset and smoothing the output DEM. Superficial sediment is modelled, soils are sampled using a stainless steel hand auger. The DEM and soil data presented in this paper will be used to accurately model the hydrological processes of the site using a MIKE SHE model in future studies. Water volume in the Lough is modelled under different scenarios to assess the performance of the sluice using the DEM generated.

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1. **Introduction**

Wetlands are an essential part of the environment, acting as sources, sinks and transformers for chemical, biological and genetic materials. They also provide invaluable protection for wildlife and plants. Wetlands act as a ‘cleanser’ for the environment; they receive and cleanse both anthropogenic and natural waste from their catchment area, protect shorelines and recharge water aquifers. A vital part of the environment (Mitsch & Gosselink, 2000). The idea of wetland management has drastically changed over time, until the middle of the 20th century it meant draining to increase agricultural production. Nowadays management means setting strict objectives to maintain and protect wetlands (Glinman, 1994; Mitch & Gosselink, 2000). In the light of climate change, much of human interaction has been a response, attempting to maintain wetlands (Knight & Burningham, 2007). Sheskinmore Nature Reserve is a large area of sand dune, lake and marsh that is situated in North West Donegal, Ireland. The area is designated as a Special Area Conservation (SAC), a Special Protection Area (SPA) and a Wildfowl Sanctuary. It is home to a diverse range of coastal habitats associated with dune-impounded lake and wetland systems. The eco-hydrological regime of the lake and wetland is complicated due to the sedimentary drape of calcareous dune sand over metamorphosed granitic bedrock. The Lough formed around c. 1000 years ago when dune remobilisation separated two branches of the Loughros More Estuary, resulting in the impounding of small rivers and the development of a shallow lake. Since then, salinity in the lake has decreased and it is now classed as freshwater (Shaw and Carter, 1994). The National Parks and Wildlife Service (NPWS) have suggested that water levels in the lake have declined in recent years, citing natural siltation and ad hoc drainage works as causes. This has led to negative impacts on roosting birds but more importantly the *Najas Flexilis* population. *Najas Fleixilis* is an endangered aquatic plant in Europe and is strictly protected. As a result a sluice has been installed to maintain water levels in the Lough. Understanding the flow of water in the area and the influence of the sluice is essential in the future preservation of the site. Climate change will have a range of effects on Sheskinmore Lough; one of them will be impacts to the water resources available. The Intergovernmental Panel on Climate Change (IPCC) projects that runoff will increase in Northern Europe by approximately 5 to 15% by the 2020s and 9 to 22% by the 2070s (IPCC AR4, 2007).
Topography is the main control on water and water flow in the environment; this in turn influences ecology, morphology and sedimentology (Pervalo, 2004). In environmental studies it is essential to accurately model topography. Topography is commonly represented by 3D computational models known as digital elevation models (DEM). DEMs have addressed the issue of how to characterise the earth’s surface from finite measurements (Kidner, 2003). There are three main DEM data structures in GIS, a grid raster DEM, a triangulated irregular network (TIN) and a contour model. The U.S. Geological Survey define a grid based DEM as the digital cartographic representation of the elevation of the land at regularly spaced intervals in x and y directions, using z-values referenced to a common vertical datum (Guo et al., 2010). Essentially they are in the form of a raster, with the pixel size (or cell size) defining the spatial resolution. DEMs are also known as digital terrain models (DTM). In this study DEM will only be used as the model is derived from elevation measurements. A digital surface model (DSM) is a model that includes vegetation and manmade objects, while DEMs only represent the earth’s underlying terrain (Aguilar et al., 2005). DEMs are generated from interpolating elevation points to create a surface that represents the extent of the site (Binh & Thuy, 2008). Interpolation plays an important role in grid raster DEM generation. The quality of the DEM is fundamental when modelling environmental processes. Special attention needs to be paid to both measurement campaign and interpolation technique. DEM quality is a function of the input point quality, point density and the spatial distribution of points (Lane et al. 1994). Heritage et al. 2009 analysed the influence of the interpolation model on DEM quality. Interpolation model choice is unique to each study. The trend of surfaces will not change regardless of the interpolation technique as the measured points are the main constraint in DEM surfaces (Heritage et al. 2009).

The aim of this study is to map the topography and bathymetry of the Sheskinmore Lough and wetland and create a high resolution grid raster DEM. A secondary aim is to map the superficial sediment and to explore different water volume scenarios in the wetland as well as assessing the performance of the sluice.
Figure 1. An aerial image of the Loughros More Estuary.

Figure 2. A graphic display of the site and influencing features, illustrating in flow and out flow, sluice location, sand dunes, agricultural land and elevation.
1.1. Data Acquisition

DEM's are generated from x, y, z point data. Point data can be collected from various sources, ground surveys, remote sensing techniques and digitisation of paper maps (El-Sheimy et al. 2005). Ground survey techniques include differential global positioning systems (DGPS) and theodolite measurements. Remote sensing includes photogrammetry techniques and the use of LiDAR and RADAR. Digitisation of paper maps is very useful however it results in the creation of a low resolution DEM.

1.1.1. Remote Sensing Techniques

Remote sensing has been used to passively monitor & measure the environment since the early 1930s, allowing a method to monitor large areas, in a frequent and unbiased manner (Dowman, 2009; Baptista et al. 2008). Since then new ways of measuring the environment have evolved through the advancement of sensors and measuring platforms. Nowadays remote sensing can be broken into two categories; spaceborne and airborne. Spaceborne retrieved data has accuracies between 1 and 10 metres, but elevation errors can be much larger (Hutchinson & Gallant, 1999). Recently, spaceborne and airborne lasers have been used to gather elevation data in narrow swaths, resulting in both high and low resolution DEMs. NASA’s Shuttle Radar Topographic Mission (SRTM) provided a global DEM with a horizontal resolution of 30m, and a vertical resolution root mean square error of 7.5m and 16m (Jones et al. 2012). Aerial imagery, in the absence of vegetation, can provide elevation data to sub-metre accuracy, but is usually between 1 and 3 metres (Hutchinson & Gallant, 1999). Stereoscopic methods have been applied to satellite imagery as well as airborne and spaceborne synthetic aperture radar (SAR). Stereoscopic methods use two stereo images and ground control points to determine a vertical axis and elevations for each pixel (Cheng & Chappell, Online). LiDAR can provide elevation data with vertical accuracies of ±0.1m (Rayburg et al. 2009; Schmidt & Persson, 2003). LiDAR’s main limitation is its cost, with smaller studies opting for alternative methods (Baptista et al. 2008; Schmidt & Persson, 2003). Other problems arise with the presence of dense vegetation, water and algae, which result in false returns. False returns are when the sensor receives returns that aren’t from the earth’s surface. Jones et al. 2012 opted not to use LiDAR due to dark peat substrate, standing water, vegetation and periphyton. Other studies which do use LiDAR as their main survey method use other methods (such as DGPS) to collect data in wetlands (Rayburg et al.
In beach monitoring, due to the cost of LiDAR surveys and frequency of surveys required, as well as the morphological changes being relatively small, other techniques are used (Baptista et al. 2008).

1.1.2. Differential Global Position Systems Techniques

Global Navigation Satellite Systems (GNSS), commonly known as global positioning systems (GPS), have been used extensively in geographic research. These systems can provide continuous, accurate, three dimensional positional information to a GPS receiver (Kaplan & Hegarty, 2006). GPS was first used by the US Navy in the early 1960s, it was known as TRANSIT. This was later replaced by GPS, a system developed by the US Department of Defence. The GPS satellite constellation was complete in the late 1980s (Baptista et al. 2008). A GPS receiver is a device that receives a signal from GPS satellites which is interpreted to provide a geographic location. Essentially it is based on the satellites knowledge of its geocentric location, the GPS receiver antennas location and the distance between satellites. A minimum of four satellites are needed to determine the receiver’s position; the first for the x-axis position, the second for the y-axis position and the third for the z-axis position. The fourth is needed to determine the time difference between satellite and user clocks; as they are not synchronised (Kaplan & Hegarty, 2006). A GPS receiver determines its position with an uncertainty of around 10m.

A differential GPS (DGPS) improves the uncertainty, to determining position within the centimetre scale. DGPS works using two GPS receivers, one receiver acting as a base station where its precise position is known and the other acting as a mobile receiver (rover). The rover determines its position from both the satellites and the base station. The base station and rover must be receiving data from the same satellites. As the base station knows its precise position when it receives information from the satellites, it can determine the bias in the measurements. The base station communicates the bias to the rover, through radio links, allowing the rover to correct the position data being received and thus calculate its precise location. Bias is the difference between the base stations position and the positional information being received by the satellites. Bias is a function of receiver noise, atmospheric noise and clock offset (van Diggelen, 1997).
Conducting a DGPS survey provides highly accurate x, y, z data, however it is very time consuming and has terrain limitations. Areas can only be measured if they are visited thus site size can limit the measurement extent. When conducting a DGPS survey for DEM generation, the measurement campaign has a strong influence on DEM quality. The quality of a DEM generated using DGPS is only limited by the effort expended during data collection, the quality can satisfy the requirement of any application (Keim et al., 1999).

1.1.3. Measurement Technique Case Studies

Baptista et al. 2008 conducted a DGPS survey on beach profiles using a DGPS mounted on a vehicle and a traditional pole-mounted DGPS. A vehicle mounted DGPS was used to provide a highly accurate non time consuming measurement campaign that could be easily repeated. In areas where the vehicle could not reach, measurements were taken using a pole-mounted DGPS. The area surveyed in this study was approximately 10,000m$^2$. As beach profiles are relatively smooth features a mesh measurement regime was used. It is noted that profile features should be the base for profile mesh size used. The volume of points should represent the amount of morphological change in the survey site. Increased elevation variability in the site requires more measurement points than a smoother site. However very high resolution meshes may not significantly improve the quality of a DEM, not to mention the increased field work required, but a mesh too wide will not pick up the topographic features in a site. When different mesh sizes were analysed in this study, the highest density mesh provided the best results.

Jones et al. 2012 aimed to survey the full topographic extent of the Everglades region in South Florida, USA. Specified accuracy requirements for the data were a vertical accuracy of ±15cm and horizontal distant between points of approximately 400m. They used a DGPS mounted on a custom built helicopter. The system could measure sub-water and terrain surface heights in a non-destructive manner. The system used a weighted bob that hung from the helicopter that automatically collected data when the plumb line experienced resistance. This method was used after pre-existing height data was deemed too coarse – SRTM-data (Shuttle Radar Topographic Mission) and NED-data (National Elevation Dataset). They explored the use of a dual system using an airboat and foot survey system however it was noted that it would have a negative impact on the ecosystem and accessibility was
limited. The survey was successful and points were measured along an evenly spaced grid. They assessed the accuracy of the system against regional bench marks, hovering at heights of 3 and 6 meters, the mean error was -6.2 cm and 0.6 cm retrospectively. This satisfied the accuracy required for the study.

Rayburg et al. 2009 assessed the quality of DEMs derived from LiDAR, DGPS and spot heights taken from a 1:100,000 topographic map. The study area was Narran Lake Ecosystem in north western New South Wales, Australia. The DGPS survey consisted of 20,000 points with a spatial resolution of approximately 1m along survey lines and 200m between survey lines. LiDAR survey consisted of a dataset of approximately 650,000,000 data points, with a spatial resolution of 1m² and a vertical accuracy of 8 - 11cm. All DEMs were created using the kriging interpolation model. As the context of the site was known, the best form of quality assessment of the DEMs was visual interrogation to determine how well each represented the study area. The LiDAR-derived DEM represented a wide range of topographic features that other methods missed, even features in the magnitude of 10cm. The DGPS-derived DEM provided considerably less detail, but did yield similar results to the LiDAR in some areas. The coarse DEM produced from the topographic map poorly represented the area, with large features missed. LiDAR- and DGPS-derived DEMs differ by a minimum of 25cm and maximum of several metres in areas. The DGPS survey did represent the major features in the site but did over-simplify them. DGPS-derived DEM is of varying quality as considerable fewer points were measured compared to the LiDAR survey. The limitation of survey points was mainly due to the challenges associated with ground surveying, as the terrain was difficult to navigate. Features are only represented if they are measured, thus every feature deemed important needs to be measured and this includes spot heights, breaks of slope, toe of slope and ridges. The LiDAR-derived DEM provided the best results as it was not restricted to the ground surveying complications. This resulted in the representation of a lot more features including macro- and micro-channels, flood plains, clay pans, sand dunes, and subtle variations in lake topography.

Heritage et al. 2009 analysed different measurement techniques and interpolation models and their influence on DEM quality. Their study site was focused on a 9900-m² area of point bar on the River Nent at Blagill in the North Pennine uplands, Cumbria, UK. Point measurements were taken using theodolite total stations (accuracy of ±5mm). Although this
measurement instrument will not be considered for this study, the sampling method can be compared to DGPS sampling methods. Four sampling regimes were examined: (i) cross section; (ii) bar outline (in order to highlight the issue of low survey density within a geomorphic unit); (iii) bar and chute outline and (iv) bar and chute outline with spot heights on uniform surfaces. A fifth was used to act as control data, this was surveyed using a terrestrial laser scan (TLS) data that was degraded to mimic LiDAR. The control surface derived from TLS provided the best results, which coincides with Baptista et al. 2008, who noted that the higher density regime provided the best results. In the cross section survey errors were lowest close to the cross section points and highest in areas where there was no measured data (between the sections). It was noted that survey point location holds the biggest influence on DEM quality and measurement campaigns should be sensitive to the morphology under consideration. Increased vertical error is usually experienced at breaks of slope, unless the top and base of a slope are measured and thus represented by the interpolation model. More data is required where relatively large changes in elevation occur over short distances e.g. breaks of slope, peaks in height. This paper noted that to accurately survey river beds a morphological measurement approach proved best where morphological outlines, breaks of slope and inclusion of spot heights on uniform features reduced DEM error. Surveying these features provided DEMs with a similar error to grid-based surveys such as those obtained from aerial LiDAR.

1.2. Interpolation

Interpolation is a procedure for transforming point data into a continuous surface. There are two approaches; global and local. Global models use all available points when interpolating a point, while local models work within a local neighbourhood when interpolating a point, only values in its prescribed neighbourhood are used in the calculation (Burrough & McDonnell, 1998). Local interpolation models can also be categorised as exact and inexact. Exact models ensure the interpolated surface passes through all measured points, while an inexact model does not (El-Sheimy et al. 2005). The influence of interpolation models on DEM output has been widely researched, with some papers agreeing that measurement regime is the main influence on DEM quality, with the interpolation model choice being less influential (Heritage et al. 2009; Aguilar et al. 2005).
1.2.1. **Inverse Distant Weighting**

Inverse Distant weighting (IDW) is a commonly used interpolation model in surface modelling. It is an exact and local method (Aguilar et al. 2005). It uses known points within a local neighbourhood and applies linear weights to them to predict unknown values. The method is based on each local point being weighted by its distance to the unknown value. The significance of these points is determined by the pre-defined power. IDW performance in DEM generation has been thoroughly researched and has been found to be a consistently poor performer amongst studies that concern small sites (approx. <4ha) and presumably lower cell size (Baptista et al. 2008; Heritage et al. 2009; Aguilar et al. 2005; Kienzle, 2004). Performance increases as site and cell size increase. This is evident in Guo et al. 2010 where IDW is the worst performer compared to splines, natural neighbour, ordinary kriging and universal kriging models when cell resolution is 0.5m, however as cell resolution increase to 1m, 5m and 10m IDW gradually becomes the best performer. Binh & Thuy 2008 supports this result, in their study of large sites (211ha – 14,000ha). They advised IDW be used to generate a DEM for hilly and flat sites if the data source is digital photogrammetry, noting that if the data source is total stations or GPS then IDW is only recommended if the study site is large.

1.2.2. **Minimum Curvature Splines**

Minimum curvature splines (MCS) is an exact interpolator that estimates elevations based on a surface that passes through all measured points, minimising the curvature of the output surface (Binh & Thuy, 2008). Historically, rubber rulers were used to achieve the local fitting curves determined by visual means, the ruler was held in place by weights as the curve was drawn – MCS is the mathematical equivalent of these rubber rulers (Burrough & McDonnell, 1998). There are two spline methods; regularised and tension. Regularised splines create a smooth surface that regularly minimises the curvature while still passing through input (measured) points, this can result in estimated values that may lie well outside the input data range. Tension splines create coarser outputs than regularised splines, as the surface values are constrained by the input data range. The main parameters in spline models are weight, increasing weight in regularised splines results in a smoother surface while in tension splines it results in coarser output (Binh & Thuy, 2008).
In the literature splines performance is inconsistent. Splines never seem to be the best performer in DEM generation. Binh & Thuy 2008 recommend splines if the data source is digital photogrammetry, however when the data source is GPS or total stations, especially when the site is hilly or flat, the method should be avoided. Heritage et al. 2009 discovered that it was consistently the worst performer for each sampling regime in modelling a point bar. Baptista et al. 2008 note that MCS and TINs provide the lowest errors, but recommend TINs instead of MCS as it is stated “MCS is not an exact interpolation method”. Surfer Software was used to compute the interpolation and it is noted that the MSC method can only be computed as an inexact interpolation, contradictory to the software used in this study – ARCMAP 10.1 where output surface passes through all of the input points. (ESRI ARCGIS Online Resources).

1.2.3. **Kriging**

Kriging is a geostatistical interpolation method that assumes the distance between the interpolation point and input points reflect a spatial relationship that can be used to mathematical explain the variation of a surface. It is a multistep process that is computationally expensive; statistically analysing the dataset, variogram modelling and creating the surface. It is similar to IDW as the weighting is a function of the distance to local input points; however unlike IDW the weights are also a function of spatial arrangement. The spatial arrangement is based on the use of semivariograms; there are two types of semivariograms to choose from ordinary and universal (Bing & Thuy, 2008; Burrough & McDonnell, 1998). Ordinary kriging assumes the dataset is not constrained by a structural component. Universal kriging assumes that the dataset is constrained by a structural component (i.e. drift), a spatially random correlated component and random noise representing the residual error (Guo et al. 2010). Ordinary kriging semivariograms include: circular, spherical, exponential, Gaussian and linear, while universal kriging semivariograms include linear drift and quadratic drift. Many studies opt for alternative interpolation techniques due to the computational time required with kriging (Guo et al. 2010; Schmidt & Persson, 2003; Baptista et al. 2008). Binh & Thuy 2008 recommends kriging ordinary with exponential model of variogram when modelling small areas when the data source is total stations or GPS. Peralvo & Maidment, 2003 noted that kriging does produce good results when modelling drainage patterns, as river junctions are not well represented. Kriging works
better at finer resolutions, while at coarser resolutions the interpolation model used has less influence on DEM quality (Guo et al. 2010). Kriging results in ‘streaking’ problems, also experienced with IDW and splines, however they are usually less pronounced. Streaking occurs with irregular input point geometry (Schmidt and Persson, 2003). Baptista et al. 2008 and Heritage et al. 2009 also concluded that kriging was not an ideal interpolator in their studies as resulted in high error and was not as reliable as other methods.

### 1.2.4. Natural Neighbour

Like all interpolation, natural neighbour is also based on the idea that an unknown value depends more on data values that are nearer rather than further. Natural neighbour differs as it incorporates the idea of ‘neighbourhood’ in its interpolation; neighbourhoods are formed in a natural way and are quantified and measured by ‘neighbourliness’ of a position. The dataset is partitioned into neighbourhoods by joining neighbouring data which results in a triangulation of the dataset, known as the Delaunay triangulation (Sibson, 1981). Natural neighbours of a point are those associated with the neighbouring Voronoi polygon. It is a local model that assumes constraining trends and will not lead to the creation of peaks, pits, ridges or troughs that are not represented by the data. It is an exact interpolator. It works with irregular and regular spaced data (Garnero & Godone, 2011). Baptista et al. 2008 found natural neighbour interpolation to be moderately successfully however it produced larger differences than TINs and minimum curvature splines.

### 1.2.5. Australian National University Digital Elevation Model (ANUDEM)

The ANUDEM interpolation model uses a locally adaptive interpolation algorithm that generates a hydrologically correct DEM. The algorithm was developed by Hutchinson, 1981. It couples a drainage enforcement algorithm (that removes spurious sinks and pits) with a finite difference interpolation model based on a terrain specific roughness penalty (Hutchinson, 1989; Peralvo & Maidment, 2003). The ANUDEM is based on a thin plate spline technique with additional input data: point elevation data, sink point data, streamline data, coastline data, contour line data, lake boundary data, cliff line data and mask boundary data (Kienzle, 2004). The model reads all data and clips to the mask boundary and then generalises the data to the predefined grid resolution. Line data is generalised by only accepting one line per cell, and lake polygons, coastlines and cliff data are essential divisions between values (Hutchinson et al. 2011). The algorithm ensures good shape and drainage
structure in the output DEM in five main ways: By imposing the drainage algorithm it removes pits and sinks that are evident in simple interpolation techniques, this results in a DEM that performs better in hydrological analysis; Incorporating stream data directly imposes surface drainage constraints; By precisely reading ridges and streams from input contour data; Using cliff data to break the continuity of the output DEM and ensuring compatibility of lake boundaries with elevations from connecting streamline data and lake boundary DEM points (Hutchinson, 2011). Criticism comes from the algorithm honouring the original data points too much, sometimes oversampling the contour data (Wise, 2007). However, as there are varied types of input, ANUDEM results in a grid based DEM that realistic represents the site (Gousie & Franklin, 2003; Kienzel, 2004).

1.3. Sediment Mapping

A secondary aim of this study is to map the superficial sediment of the site. The site’s superficial sediment is a mix of sand encroaching from the extensive sand dune system to the west, while peat encroaches from inland to the north, east and south east. A thin layer of Calcareous grassland is draped over much of the sand dune (Shaw & Carter, 1994). Different sediments have different drainage patterns. Peat is one of the most water retaining soils (along with clay), having both a high surface water flow and subsurface water flow (Haslam, 2003). Sands are not good at retaining water, with high water conductivity and low moisture content (Hiscock, 2009). Most studies that analyse soils, aim to retrieve cores for laboratory analysis, thus the need for soil samplers with encasing tubing is needed (Schmidhalter, 2005; Lewis et al, 1994). Lewis et al. 1994 note that when choosing the equipment certain factors have to be considered; site limitations, soil characteristics and number of samples need. They note that this will be unique to each study.

1.4. Surface Water Mapping

DEMs are commonly used to map surface water, using hydrological derivative maps calculated from the DEM (such as flow direction, flow accumulation surfaces) (Jain & Singh, 2005; Camporese et al. 2010). These perform well on larger mountainous areas; however with flat landscapes they don’t perform well. In future studies, as mentioned before, the hydrological extent will be accurately modelled using a MIKE SHE model. The aim of mapping the surface water is to analyse the success of the sluice and to investigate the potential effects of climate change on the water in the Lough.
2. Methodology

2.1. Study Site

The study site is Sheskinmore Lough and wetland, a 835,644m$^2$ wetland in the Co. Donegal, North west Ireland. The wetland is mainly covered in thick reeds, with open water extending approximately 51,450m$^2$. There are two inflow streams, one to the north east and one to the east. The sluice is located on the outflow stream to the south. The sediment is mainly sand and peat is also present, overlaying a granitic bedrock.

2.2. Data Acquisition

Elevation points will be collected using a DGPS. This was favoured over an airborne LiDAR survey because of the cost of such a survey as well as the nature of the site: where thick vegetation and surface water would lead to large errors in derived elevation heights. In addition to a desired high resolution DEM that LiDAR may not achieve (Baptista et al. 2008; Jones et al. 2012; Rayburg et al. 2009; Schmidt & Persson, 2003). A Leica GPS1200 (base station) and a Leica GS15 (rover) will be used to conduct the survey. The rover can be set to measure automatically, measuring every metre in the horizontal axis or 20cm change in the vertical. A small boat will be used to take bathymetry measurements in the Lough where the rover will be mounted on a pole. Depending on the water levels in the Lough, if high a sonar system will be utilised to measure Lough depths, if low the pole mounted DGPS will be used everywhere within the Lough. When conducting a DGPS survey the strategy campaign is very important as it influences the DEM quality greatly. The survey strategy planned was to measure 20m parallels recording points every 1-2m. As well as measuring points along morphological outlines, i.e. spot heights, morphological outlines, cut banks and breaks of slope, as well as measuring Lough outline.

2.3. DEM Generation

The following workflow will be used to generate the DEM. The software used to compute the DEM will be ESRI ArcMap 10.1. All GIS analysis will be undertaken using the Irish National Grid (TM 65) projection system. All elevations in this study are relevant to the Malin Head ordnance datum.
### Table 1. The outlined approach to generating DEM. Adapted from Jones et al. 2012.

<table>
<thead>
<tr>
<th>Step</th>
<th>Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>FILTERING.</strong> Filter input elevation points, removing outliers. Outlier’s description described below.</td>
</tr>
<tr>
<td>2</td>
<td><strong>RANDOM EXTRACTION.</strong> Randomly extract 10% of all input points and withhold them from the interpolation (step 3) and use as ground control points (GCPs) to validate interpolation models.</td>
</tr>
<tr>
<td>3</td>
<td><strong>INTERPOLATE.</strong> Interpolate points creating a DEM using interpolation various models: Inverse distant weighting (IDW), Natural Neighbour, Splines, Kriging and ANUDEM.</td>
</tr>
<tr>
<td>4</td>
<td><strong>OPTIMISE.</strong> Optimise parameters in each model by comparing output DEMs to GCPs.</td>
</tr>
<tr>
<td>5</td>
<td><strong>TRUE VALIDATION.</strong> Choose best interpolation method from optimised models, based on the error compared to GCPs.</td>
</tr>
<tr>
<td>6</td>
<td><strong>DEM PRODUCTION.</strong> Generate DEM using ‘best’ interpolator models, and all input elevation points.</td>
</tr>
</tbody>
</table>

Outliers will be detected if position and height accuracy is above 1m, they lie outside of the maximum and minimum heights (1.71m and 13m retrospectively) and, by visual interrogation in places where the there is evidence of human error, i.e. unnatural measurements for that area. Interpolator models have numerous parameters. In IDW the power variable has the greatest influence on the final surface, splines are controlled mainly by the weight and whether they are regularised or with tension, kriging is determined by the type of variogram used, ANUDEM roughness penalty and discrete error are analysed, and natural neighbour has no variable parameters in ArcMap 10.1. The power in IDW controls the importance of nearby points in the interpolation, the higher the power the less the influence further points have. The weight in splines influences the character of the output surface, with regularised splines a higher weight results in a smoother output, while with splines with tension a higher weight results in a coarser output. The main parameter in kriging is the type of semivariogram used, which controls the description of spatial dependence. The main parameters in ANUDEM are; the discrete error parameter that controls the smoothing of the surface, the higher the value the smoother the output and a roughness (ArcGIS, online). Interpolation models performance is analysed by comparing the estimated elevations to the measured elevations (GCP). Elevation values from the output DEM are extracted using the Gdal Library in Python (Bury, 2010). Once values are extracted they are compared to the GCPs. Root mean square error (RMSE) is used to analysis the difference between estimated and measured.
2.4. **Sediment Mapping**

Soils will be sampled using a stainless steel auger to a depth of 50cm. The handheld sampler consists of a 50cm tube that is open at the bottom and on one side. Soil type and depth of change will be recorded as well as geographic location. Cores will not be kept. This will give us an idea of the extent of the superficial sediment across site. Soil modelling will conducted in Golden Software Surfer 8 or Voxler 3.

2.5. **Surface Water Mapping**

Different scenarios will be modelled with the final DEM, to assess the influence of the sluice on the Lough. The water level was measured in 2012, when the sluice was closed; the sluice will be open when the field study is conducted and will be measured again. These water levels will be model in conjunction with the DEM generated. The modelling is conducted by firstly mapping the extent of the water heights on the DEM and calculating the volume of the water retained by the Lough in both scenarios. Future scenarios will be examined, with water levels being derived from the IPCC AR4 report that discusses water resources. The water levels modelled will be based on 5%, 10% and 15% increases to the water volumes of the Lough when the sluice is closed and open. These values are based on the projections for runoff in northern Europe, and are rough estimates. This section will also help analyse the performance of the DEM through application (Jones et al., 2012).
3. Results

3.1. Data Acquisition

The topographic survey was conducted over four days and resulted in 26,821 measured points and 134 bathymetry points. Due to human, systematic and random error it was important to filter the results. After filtering the input data 1,066 points were rejected; 575 were rejected for having a position/height accuracy value that did not satisfy the threshold of 1m and a further 492 were rejected as they lay outside the maximum and minimum elevation for the site, a minimum of 1.71m and a maximum of 13m. A further 239 were deleted through visual interrogation, resulting in 25,516 points being used for interpolation. 10% of the points were not used in the preliminary interpolation investigation, acting as control points for validation. It is evident that filtering the dataset reduced the error considerably, reducing the overall position quality by 0.5m.

Figure 3. Illustrates the points collected from the topographic and bathymetric survey.
Table 2. Descriptive statistics of point quality before and after filtering the dataset. Shows statistics for horizontal (X, Y) position, vertical (Z) position, and combined position (X, Y, Z). All statistics in metres.

<table>
<thead>
<tr>
<th></th>
<th>MEAN</th>
<th>MIN</th>
<th>MAX</th>
<th>MEDIAN</th>
<th>ST. DEV</th>
<th>1st Q.</th>
<th>3rd Q.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X, Y</td>
<td>0.278</td>
<td>0.001</td>
<td>1302.612</td>
<td>0.006</td>
<td>15.949</td>
<td>0.005</td>
<td>0.008</td>
</tr>
<tr>
<td>Z</td>
<td>0.453</td>
<td>0.002</td>
<td>2173.116</td>
<td>0.009</td>
<td>26.611</td>
<td>0.007</td>
<td>0.012</td>
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<tr>
<td>X, Y, Z</td>
<td>0.532</td>
<td>0.003</td>
<td>2533.364</td>
<td>0.011</td>
<td>31.024</td>
<td>0.009</td>
<td>0.014</td>
</tr>
<tr>
<td>Filtered</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X, Y</td>
<td>0.018</td>
<td>0.000</td>
<td>1.287</td>
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<td>0.061</td>
<td>0.005</td>
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<tr>
<td>Z</td>
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<td>0.000</td>
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<td>0.007</td>
<td>0.012</td>
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<td>X, Y, Z</td>
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<td>0.000</td>
<td>1.827</td>
<td>0.011</td>
<td>0.095</td>
<td>0.009</td>
<td>0.014</td>
</tr>
</tbody>
</table>

3.2. DEM Generation

Table 3. List of error statistics from six optimised interpolation models. Statistics are based on RMSE between estimated and measured GCP. Statistics are ranked by standard deviation. Minimum is not included as they are all 0. All statistics in metres.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>MAX</th>
<th>MEDIAN</th>
<th>STDEV</th>
<th>1st Q.</th>
<th>3rd Q.</th>
<th>Vol. m³</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Neighbour</td>
<td>0.0724</td>
<td>1.0888</td>
<td>0.0488</td>
<td>0.0720</td>
<td>0.0164</td>
<td>0.1214</td>
<td>2016281.1</td>
</tr>
<tr>
<td>IDW</td>
<td>0.0861</td>
<td>1.0382</td>
<td>0.0609</td>
<td>0.0854</td>
<td>0.0201</td>
<td>0.1405</td>
<td>2052248.1</td>
</tr>
<tr>
<td>Spline Tension</td>
<td>0.0917</td>
<td>1.9125</td>
<td>0.0512</td>
<td>0.0987</td>
<td>0.0153</td>
<td>0.1683</td>
<td>8890214.1</td>
</tr>
<tr>
<td>ANUDEM</td>
<td>0.0999</td>
<td>1.0515</td>
<td>0.0558</td>
<td>0.0996</td>
<td>0.0183</td>
<td>0.1852</td>
<td>2019468.0</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>0.0937</td>
<td>1.3351</td>
<td>0.0777</td>
<td>0.1025</td>
<td>0.0334</td>
<td>0.1147</td>
<td>1776014.0</td>
</tr>
<tr>
<td>Spline Regularized</td>
<td>0.0850</td>
<td>4.8313</td>
<td>0.0603</td>
<td>0.1402</td>
<td>0.0194</td>
<td>0.1271</td>
<td>48257552.0</td>
</tr>
</tbody>
</table>

The six interpolation models were optimised, highlighting the best parameters to be used in the interpolation. The optimal interpolators are:

- Inverse distance weighting with a power of 3.0,
- Ordinary kriging using a Gaussian variogram,
- Regularised splines with a weight of 0.5,
- Splines with tension with a weight of 0.1,
- ANUDEM with a discrete error factor of 0.5 and a roughness penalty of 0.5,
- Natural Neighbour didn’t have any variable parameters within ArcMap 10.1.

The statistics of the each optimised interpolator model are in Table 3; all statistics from the interpolator parameter analysis are in Appendix 1. Statistically, natural neighbour preformed the best, IDW (power of 3.0 used) and spline with tension (weight of 1.0 used) came second and third retrospectively. Spline with tension and kriging were the worst interpolators for this study.
Figure 4. Illustrative plots of DEM results from 6 interpolation methods, (a) ANUDEM, (b) Natural Neighbour, (c) Regularised Spline, (d) Spline with Tension, (e) IDW and (f) Ordinary Kriging with Gaussian variogram.

Splines resulted in interpolated values that lay well outside the sites natural elevations, with regularised spline elevations reaching a low of -53m and a high of 102m, and splines with tension reaching a low of -6m and a high of 15m. The minimum measured elevation was 1.71m and the maximum was 13m. Kriging and inverse distant weighing resulted in stripping features that occur between the measurement parallels, these give the surface a ‘streaking’ feature. Figure 4 illustrates the problems with the different interpolation models. It is clearly evident that splines create an unnatural surface producing spontaneous peaks and pits. The lines represented on IDW and ordinary kriging are the ‘streaking’ features.
Figure 5. Illustrative displays of final DEM generated using the ANUDEM interpolation model, (a) 2D display, (b) 3D display looking north and (c) is the generated DEM nestled in a low resolution DEM.

ANUDEM was selected as the best interpolator despite not producing the best statistical results. However, after visual examination ANUDEM outperformed the other interpolators in terms of realistically representing the site. One main benefit was its representation of the streams. ANUDEM allows extra data types to be used in the interpolation, stream lines and break lines helped to realistically model site. It is clear in Figure 5 (b) that peaks and pits are
present along the surveyed lines. This is due to the high density of points along the lines, resulting rough features along these lines and smooth features between. Figure 6, illustrates the elevations of four transects.

**Figure 6.** An illustrative plot of four transects across the site, (a) is transect A-B, (b) is transect C-D, (c) is transect E-F and (d) is transect G-H. Significant features are highlighted in the plots. Note the x-axis is in metres and represents the transect.

**Figure 7.** An illustrative display of the transects displayed in Figure 6.
3.3. Sediment Mapping

Figure 8. Illustrative plot of sediment across the site at, (a) the surface (including soil core locations), (b) 10cm depth, (c) 20cm depth, (d) 30cm depth, (e) 40cm and (f) 50cm. Cores interpolated with IDW.

The interpolated soils reinforce what would have been expected, with some areas incorrect due to the lack of measurements. The entire site, expect for the Lough, and some patches were covered in a peaty soil, to the west this was very thin laid over the dune sands. At 10cm depth down to 50cm the sand reaches the centre of the site, where it is met by peat. It should be noted that in the east, the soils for 30cm to 50cm, is incorrect. It is shown as sand but in reality it is peaty soil, this error is due to the inability to sample saturated sediment.
3.4. Surface Water Mapping

Figure 9: Illustrative displays of water coverage when, (a) the sluice is open (measured 2013) and (b) the sluice is closed (measured 2012). The elevations were 2.47m and 3.05m retrospectively.

Modelling the two measured water scenarios based on measurements, provided confidence in the DEM, as it truly represented what was observed at the site visits. Illustrating that the sluice was working in the wetland, as it is evident that the ground water extent was greater in Figure 9 (b) when the sluice was closed than (a) when it was open. Water volume statistics are provided, along with the six scenarios based on IPCC future run off predictions.
Figure 10. 6 different water scenarios, (a) Open sluice with 5% water increase, (b) closed sluice with 5% water increase, (c) open sluice with 10% water increase, (d) closed sluice with 10% water increase, (e) open sluice with 15% water increase and (f) closed sluice with 15% water increase.

Table 4. Measured and estimated water volumes based on the measured water volumes for open and closed sluice scenarios and IPCC predictions.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Water Volume m$^3$</th>
<th>Illustrated in</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured Open Sluice 2013</td>
<td>13318.6</td>
<td>Figure 9 (a)</td>
</tr>
<tr>
<td>Measured Closed Sluice 2012</td>
<td>158939.1</td>
<td>Figure 9 (b)</td>
</tr>
<tr>
<td>Open Sluice with 5% water increase</td>
<td>14032.2</td>
<td>Figure 10 (a)</td>
</tr>
<tr>
<td>Open Sluice with 10% water increase</td>
<td>14645.7</td>
<td>Figure 10 (c)</td>
</tr>
<tr>
<td>Open Sluice with 15% water increase</td>
<td>15288.2</td>
<td>Figure 10 (e)</td>
</tr>
<tr>
<td>Closed Sluice with 5% water increase</td>
<td>166914.3</td>
<td>Figure 10 (b)</td>
</tr>
<tr>
<td>Closed Sluice with 10% water increase</td>
<td>174848.6</td>
<td>Figure 10 (d)</td>
</tr>
<tr>
<td>Closed Sluice with 15% water increase</td>
<td>182772.0</td>
<td>Figure 10 (f)</td>
</tr>
</tbody>
</table>
4. Discussion

4.1. Data Acquisition

When the survey was conducted, parallels walked did not strictly conform to the evenly spaced 20m parallels proposed, varying from a minimum of approximately 10m to a maximum of approximately 80m. Topographic outlines were prioritised when measurements were taken, i.e. breaks of slope, spot heights etc. The proposed regime was not kept due to the nature of the site; the wetland is covered in thick reeds that are approximately 2 metres tall and the surface is a wet muddy mixture of peat and sand. This meant navigating the terrain was difficult and time consuming. Numerous pools of water were also too deep to cross in waders. As the site was difficult to navigate stumbling, falling and sinking was common resulting in numerous incorrect measurements. In addition to this the antenna was rarely kept at a constant height, this results from the surveyor’s natural movement. This noise is in the region of millimetres but should be noted. The rover lost connection to the base station once, this occurred to the north east of the site. Post processing was done to correct any heights that were not corrected in real time. This was done using Leica Geo Office GNSS Post Processing software. It is essential in any means of surveying to filter the measurements as there are numerous sources of error: human error (as described above), systematic error and random error. Filtering the dataset by their accuracy quality and clipping the extreme values improved the mean accuracy, removing inaccurate measurements. This removed a certain amount of the outliers; however points were examined visually to remove any points resulting from human error. This was a time consuming task but a vital task. It reduced the mean uncertainty by 0.503m, providing millimetre accuracies. It is very important to visually inspect and reject points, using statistics works on rejecting the obvious outliers, however as Rayburg et al. 2008 suggested, visual inspection is better, as the topography of the site is known from the field study. It is easy to determine if a point is a true measurement or an outlier. It was carried out in this study by identifying point clusters, and examining then. Clusters usually represented areas where human error occurred. Filtering was successfully concluded when all clusters were examined. Preliminary DEMs created showed that certain features were missed (streams), to represent these features extra points were included to add constraints in these areas. It is an estimation process used to fill areas that need ‘measurements’ to represent the features.
It was carried out on the river banks and river beds only, to represent the rivers in a realistic manner. This technique has not been used in any of the literature. It is a very useful process but it should be done with caution. The points added should be estimated from the nearby measured values. This method significantly improved the representation of the streams in the resulting DEMs.

4.2. DEM Generation

Six different DEMs were generated using six different interpolation models: IDW, kriging, splines with tension, regularised splines, ANUDEM and natural neighbour. It must be noted that the cell size used in all interpolations was 1 metre, meaning a pixel represented 1m². A smaller cell size not only improves the quality of the DEM, but also DEM derivatives, for example slope maps (Smith et al. 2006; Kienzle, 2004). Kriging was the most computationally expensive and time consuming model, while the remaining models interpolated the points relatively efficiently. Statistically all models preformed similarly, natural neighbour was the best interpolator with an error standard deviation of 0.0720m and the worst interpolator was regularised splines that had an error standard deviation 1.402m. Average RMSEs were all similar, varying from 0.0724m to 0.0999m. There is a flaw in the statistics, they are grossly biased. For a true validation of the techniques, the GCP used should be independent of the measurement campaign. By extracting them from the dataset; the GCPs are situated along survey parallels, in areas where point density is high. This meant that the GCP location did not have much freedom to be interpolated; there were numerous points in the area creating lots of constraint on the possible values for that point. The interpolated value would not deviate that much between each model.

![Figure 11. An illustrative display of volume area curve for all of the interpolation models. Note how except from regularised splines, all interpolation methods yield similar results.](image-url)
This is confirmed by studying the statistics along with the resulting DEMs, splines with tension are ranked the third best interpolator but on inspection it is clearly evident the DEM misrepresents the site – producing a completely unnatural surface. IDW is ranked second but the ‘streaking’ features are clearly evident on the surface, creating a step like feature, again an unnatural surface. It is highly recommended that if parallel survey regimes are used, GCPs must be recorded independently, otherwise the statistics calculated from them will hold little meaning. Numerous papers stated that visual inspection was best when considering DEM quality, as the site has been visited and overall topographic trends are known. When visually comparing each DEM, both types of splines, regularised and tension, were immediately rejected. Both resulted in extreme elevations. Regularised splines resulted in elevations of 102.8m and -53.7m. Splines with tension were not as extreme, values calculated were still unnatural for the site, high of 15.5m and a low of -6.4m. Kriging and IDW, were both rejected because of ‘streaking’ features, these occur between the survey lines. Figure 11 illustrates the volume area curve of all the interpolation models. It is evident that they are very similar except regularised splines. Regularised splines differ due to the extreme maximum and minimums in the DEM. This figure further illustrates the theory that interpolation holds little influence on DEM generation and quality. Although visually the DEMs differ, the overall trends of the site do not, and change between DEMs is minimal, except regularised splines.

The final two DEMs for consideration, natural neighbour and ANUDEM, yielded very similar results, both accurately represented the terrain. However, natural neighbour underrepresented the streams, where ‘bull’s-eye’ features occurred. Bull’s eye features are where peaks and pits form around points that are not of a similar value to ones in the local neighbourhood. ANUDEM allows for extra data types to be used in the interpolation, stream lines, cliff lines, contours etc. This allows for realistic representation of the terrain. Streams and stream banks were represented using stream lines and cliff lines, allowing for the streams to be accurately represented. ANUDEM has a drainage enforcement feature that allows for the drainage patterns to be represented, however it was not used in this study. The drainage algorithm in basic terms locates sink points and finds their lowest adjacent saddle point that leads to a lower sink point or edge or data point, and forces a drainage chain from the sink to the lower point via the intervening the saddle (Hutchinson, 1989). In
this study, this algorithm resulted in drainage channels that were not present in reality. No other interpolation model examined allows for additional features to be incorporated, this is mainly due to the fact that ANUDEM was specifically created for creating raster grid DEMs. ANUDEM was selected as the best performing interpolation method. One feature of the resulting DEM was a roughness along the survey lines, evident in Figure 5 (b).

Roughness along survey lines occurred because points along the line were spaced every 1m or less, but distances between the survey lines were 10 to 80m, resulting in a smooth surface between the surveyed lines and rough surfaces along the lines. To solve this problem three different methods were explored. The first method was linearly smoothing the input data. The measurements were sorted chronologically (by their timestamp) and smoothed, by calculating a rolling mean. This was achieved using the rolling mean function in the Pandas library in python, Figure 12 illustrates this. The smoothing did work in the wetland area, however in areas where the elevation varied the parallels became more pronounced, especially using 5 and 10 elements to calculate rolling mean, resulting in a ‘smearing’ like feature. Using 3 elements in the calculation did provide promising results in the wetland, however did create some peaks that were not evident in the original. The main criticism was that smoother continued over measurement breaks, where a different area was sampled after a break (i.e. lunch break or day break). Meaning areas where smoothed with values that were not representative of that area.
Figure 12. Illustrative plot of 100 measured elevations (solid line) against smoothed elevations (dashed line) using, (a) a 3 window smoother, (b) a 5 window smoother and (c) a 10 window smoother, (d) illustrates the location of the elevations on the site used in the illustration.

Figure 13. Illustrative plot of the three DEMs generated from smoothed input data with, (a) a linear window size of 10, (b) 5 and (c) 3.
The second method was to smooth the final DEM using a Gaussian filter of varying window sizes, three filter sizes were used; 3 x 3, 7 x 7 and 11 x 11. The smoothing filter works by the window moving through the image, pixel to pixel. It results in a loss of the outer pixels, this happens because to compute the new value of a pixel, it needs to be surrounded by enough pixels to satisfy the window size. This has many advantages, and hydrological modelling favours smoothed DEMs, as hydrological derivatives are easier to compute i.e. flow direction and flow accumulation. Smoothing the original DEM reduces random error and filters out peaks and troughs, smoothing tends result in the topographic data becoming closer to the mean elevation of the site (Vieux, 1993). In certain areas of quick elevation change the features become less defined. This occurred at the streams and at the small dunes to the north west of the site. Figure 14 illustrates the difference between an 11 x 11 smoothed DEM and the original DEM, highlighting the areas where there were significant changes. It is clear that changes mainly occurred at the streams and the dunes. Little change occurs across the site with small increases and decreases, all major change occurs at larger features. It did not improve the roughness along the survey lines.

Figure 14. Illustrative of the difference between, (a) the original DEM and (b) the DEM smoothed with an 11 x 11 Gaussian kernel. (c) Illustrates the changes between the two DEMs. Note that the main changes in DEMs are along the two streams and there banks, minimal changes along survey lines.
The final method used to reduce roughness along survey lines, was subsampling the data. Three variations were explored, selecting every 5th, 10th and 50th element from the dataset. Reducing the number of points used in interpolation puts less stress on the interpolation model, giving it less requirements to satisfy. Selecting every 10th and 50th element produced over simplified DEMs, while selecting every 5th element resulted in an improved DEM. This method reduced the roughness along the survey lines, Figure 15 illustrates the change.

Figure 15. Illustrative of the difference between, (a) the original DEM and (b) the DEM created from the subsampled dataset using every 5th element. (c) illustrates the changes between the two DEMs.

Figure 16. Illustrates the smoother DEM (a) compared the original DEM (b); most of the roughness along the survey lines has been removed.
Figure 16 shows a more detailed display of the smoothing effect, illustrating that most of the pits and peaks are removed. After the three methods were analysed, it was decided that the most realistic was using the subsampled data selecting every 5th point. Although fewer points were used than measured, it created a better DEM. This does not contradict Heritage et al. 2009 and Baptista et al. 2008 who noted that higher density points used create the most accurate DEM. As they also note that in relatively flat ‘feature less’ areas, less points are needed.

Figure 17. The final DEM created by subsampling the original dataset, selecting every 5th element to be used in the interpolation.
4.3. **Sediment Mapping**

Sediment influences subsurface water flow therefore accurately mapping them is essential in our understanding of the hydrology of a wetland. This was successfully undertaken showing divisions of sand and peat. In certain areas the sediment was not sampled, as the sediment did not retain in the auger. This problem occurred in areas where the sediment was saturated, which was to be expected. An alternative soil auger was not viable as the sites nature was difficult to navigate. Golden Software Voxler 3 was used to interpolate the 50cm cores into a 3D grid, allowing us to analyse the extent of the two soil types. The interpolation model used was inverse distant weighting. It should be noted that these are estimates and approximately represent the terrain, capturing the overall soil trends. The outputs displays peat covering most of the surface, thin to the west and deeper to the east, except at the Lough were sand was present. At a depth of 50cm this has reversed, sand extending most of the site, except the north east. Mapping these soils was successful, however if the study was repeated it would be recommended to take soil cores on a regular grid, to fully map the extent of the site. The under sampling in areas of the site creates uncertainty.

4.4. **Surface Water Modelling**

Human management at Sheskinmore Lough has been undertaken to maintain the sites characteristics in response to climate change and other influences. The stream to the north east and south west, have been channelled, this coupled with other drainage works, has led to a decrease in water levels in the Lough. A sluice was installed on the outflow stream (south east) to maintain the water levels in the Lough. One of the aims of this study was to assess the effectiveness of the sluice. The water levels were recorded in June 2012 when the sluice was closed and June 2013 when it was open, the water heights were 2.48m and 3.05m retrospectively. It should be noted that there was considerable more rainfall in 2012 that in 2013, with a sharp increase in local River flow from the 7th to the 9th of June; the field work was carried out from the 11th to the 17th of June 2012. The total rainfall for June 2012 was approximately 137mm, and for June 2013 was approximately 86.5mm (values are calculated means from Finner weather station and Malin Head weather station) (Met Eireann Online; Owenea Fishery 2013 Newsletter, 2013). Couple this with the fact that the
sluice was closed explains the very high surface level. Mapping of surface water was achieved by reclassifying the DEM, replacing elevation values below the measured water height, with the value of the measured water height. The mapped water surface for June 2013, Figure 9 (a), is accurate based on what was observed during the field trip. Using surface volume analysis in ArcMap 10.1, the water volume retained was calculated, this was 13,318.6 m$^3$. The water surface for 2012, when the sluice was closed, is far greater than that of 2013, however this is partly due to the weather, the Lough held 158,939.1 m$^3$. This is only partially due to the weather in 2012; it is quite conclusive that the sluice is having some effect. The IPCC predicts an increase of 5 to 15% in run off in Northern Europe by the 2020s, and 9 to 22% by 2070, Figure 10 shows six different scenarios of increased water level. Due to the lack of flow and precipitation data, it is assumed that runoff directly influences the water volumes in the Lough, thus the projections were based on the approximation that if runoff increases this directly increases water volume in the lake. It is evident that the sluice is working; clearly showing that water extent between the two scenarios is drastically different. With IPCC projections, runoff will increase thus leading to increased water in the wetland. The IPCC does note that precipitation events may become less frequent but precipitation events will become more intense, leading to an increase in flooding. These changes to the water cycle could be problematic for wetlands as periods without precipitation increase. In dry periods soils become hard and less permeable, resulting in less water infiltrating soils when precipitation events occur, increasing runoff (Price, 2003). This could lead to quicker through flow, less retention time, in the Lough if the sluice is open. The sluice will be a key player in the health and management of the wetland in the face of climate change.
5. Conclusion

This study used a differential GPS survey to model the surface of a wetland in North West Ireland, resulting in a very accurate dataset that other measurement methods would not have provided. After filtering the dataset a mean vertical error of 2.3cm was achieved with a horizontal accuracy of 1.8cm. DEM comparison using a variety of interpolation models was assessed using both statistical and visual methods, allowing for the following comments to be made. Input data’s spatial distribution and quality has the most significant influence on DEM quality. In DGPS surveys morphological outline should be prioritised, to ensure they are represented in the final DEM. Choice of interpolation model is less important, but is still very important in DEM quality. ANUDEM provides the most realistic results as it allows alternative data types to be included, and is the only interpolation model made for DEM creation. Other models all performed poorly, except natural neighbour who’s only negative was it inability to incorporate other data forms like breaks. Point density measured can prove problematic in DGPS surveys using parallels as survey regime; this study explored three possible methods for correcting the roughness along surveyed lines. Smoothing input data and using a Gaussian smoothing kernel were both rejected and subsampling the dataset was used. This proved the best method, as the others resulted in either unnatural features or oversimplified surfaces. Overall DEM performance is hard to assess except through application, and may need to be altered to satisfy the application.

Forty seven sediment samples were measured providing data on the sediment type to a depth of 50cm across the site. This confirmed what was already expected, showing that peat covered most of the surface except of the Lough, with sand encroaching from the west and peat from the east. Illustrating a complex mix of sand and peat in the subsurface sediment. The sluice is working based on the mapping of water extent under different sluice conditions, open and closed. Clearly showing that Lough retains significantly more water when the sluice is closed, it is hard to quantify how much, due to Lough water volume being a function of precipitation, the sluice and temperature. However it is clear that the sluice is working. In the future the IPCC predict increased runoff in northern Europe, this can be misleading as this means more intense precipitation events and longer dry periods. The sluice will play an important role in the health of the wetland in the face of climate change.
6. Auto-Critique

This study was chosen as I have always had an interest environmental processes and modelling. The idea of modelling topography through the creation of high resolution digital elevation model excited me, as well as the chance to gain valuable experience in surveying during field work.

The main strength of this work was the successful generation of a high resolution digital elevation model, created using a differential GPS. This is particularly impressive when you consider the nature of the site, a wetland covered in thick reeds, and the fact that other high resolution measuring techniques were unfeasible. The main criticism of the study is the lack of true validation the ground control points need to be independent of the study. Meaning any error statistics calculated were optimistically biased. Sediment modelling did not truly represent the entire site as certain areas were under sampled. This was due to saturated soils not being sample as the auger didn’t capture the sediment. Additional to this parallels proposed in the methodology were not used, in future I would explore the ability to upload parallel coordinates to Leica hardware to aid a more systematic approach while surveying. This would hopefully lead to a more spatially distributed dataset.

The data used in this study will be used in future studies to accurately model the site’s hydrological processes. I would recommend accurately measuring elevation at numerous points across the site with a pole-mounted DGPS, that will act as control points to truly validate and quantifying the error of the DEM.
7. References


Dowman, I. Image maps and three dimensional data from satellite sensors, 2009.


Garnero, G., & Godone, D. (2011) Optimal Methodologies of Interpolation for the DTMS.


### 8. Appendix

#### 8.1. All Interpolation Statistics

| Table 5. Descriptive statistics of all DEMs generated by different models, and their varied parameters. |
|---------------------------------------------------|------------|------------|------------|-----------|----------|----------|
| Model                                              | RMSE     | MIN       | MAX       | MEDIAN    | ST DEV   | 1ST Q    | 3RD Q    |
| Spline Tension Weight 0.1                         | 0.0917   | 0         | 1.9125    | 0.0512    | 0.0987   | 0.0153   | 0.1683   |
| Spline Tension Weight 0.2                         | 0.0922   | 0         | 1.7977    | 0.0509    | 0.0994   | 0.0151   | 0.1700   |
| Spline Tension Weight 0.3                         | 0.0971   | 0         | 5.1477    | 0.0510    | 0.1731   | 0.0150   | 0.1710   |
| Spline Tension Weight 0.4                         | 0.0926   | 0         | 1.7348    | 0.0508    | 0.0996   | 0.0149   | 0.1718   |
| Spline Tension Weight 0.5                         | 0.0946   | 0         | 1.7190    | 0.0507    | 0.1123   | 0.0149   | 0.1723   |
| Spline Regularized Weight 0.1                     | 0.0902   | 0         | 5.8971    | 0.0670    | 0.1554   | 0.0196   | 0.1317   |
| Spline Regularized Weight 0.2                     | 0.0881   | 0         | 5.8045    | 0.0648    | 0.1545   | 0.0196   | 0.1291   |
| Spline Regularized Weight 0.3                     | 0.0866   | 0         | 5.5468    | 0.0632    | 0.1507   | 0.0194   | 0.1273   |
| Spline Regularized Weight 0.4                     | 0.0856   | 0         | 5.2085    | 0.0611    | 0.1457   | 0.0191   | 0.1271   |
| Spline Regularized Weight 0.5                     | 0.0850   | 0         | 4.8313    | 0.0603    | 0.1402   | 0.0194   | 0.1271   |
| ANUDEM Discrete Error 0.5                         | 0.1000   | 0         | 1.0568    | 0.0560    | 0.0996   | 0.0182   | 0.1855   |
| ANUDEM Discrete Error 1.0                         | 0.1121   | 0         | 1.1540    | 0.0583    | 0.1148   | 0.0187   | 0.2069   |
| ANUDEM Discrete Error 1.5                         | 0.1211   | 0         | 1.2825    | 0.0606    | 0.1243   | 0.0189   | 0.2257   |
| ANUDEM Discrete Error 2.0                         | 0.1211   | 0         | 1.2825    | 0.0606    | 0.1243   | 0.0189   | 0.2257   |
| ANUDEM Rough Value 0.5                            | 0.1012   | 0         | 1.0889    | 0.0551    | 0.1039   | 0.0175   | 0.1848   |
| ANUDEM Rough Value 1.0                            | 0.1019   | 0         | 1.0732    | 0.0556    | 0.1044   | 0.0178   | 0.1867   |
| ANUDEM Rough Value 1.5                            | 0.1025   | 0         | 1.0608    | 0.0565    | 0.1047   | 0.0182   | 0.1882   |
| ANUDEM Rough Value 2.0                            | 0.1029   | 0         | 1.0505    | 0.0576    | 0.1049   | 0.0186   | 0.1891   |
| IDW Power 0.5                                      | 0.0978   | 0         | 1.2384    | 0.0905    | 0.0966   | 0.0301   | 0.1408   |
| IDW Power 1.0                                      | 0.1023   | 0         | 1.1487    | 0.0788    | 0.0958   | 0.0267   | 0.1635   |
| IDW Power 1.5                                      | 0.1026   | 0         | 1.1830    | 0.0708    | 0.0983   | 0.0234   | 0.1717   |
| IDW Power 2.0                                      | 0.0975   | 0         | 1.0507    | 0.0646    | 0.0935   | 0.0213   | 0.1660   |
| IDW Power 2.5                                      | 0.0921   | 0         | 1.3778    | 0.0619    | 0.0940   | 0.0198   | 0.1549   |
| IDW Power 3.0                                      | 0.0861   | 0         | 1.0382    | 0.0609    | 0.0854   | 0.0201   | 0.1405   |
| Kriging Ord. Circularr                             | 0.1014   | 0         | 1.1735    | 0.0500    | 0.1046   | 0.0157   | 0.2004   |
| Kriging Ord. Exponential                          | 0.1014   | 0         | 1.1735    | 0.0499    | 0.1046   | 0.0157   | 0.2005   |
| Kriging Ord. Gaussian                              | 0.0937   | 0         | 1.3351    | 0.0777    | 0.1025   | 0.0334   | 0.1147   |
| Kriging Ord. Linear                               | 0.1014   | 0         | 1.1735    | 0.0500    | 0.1046   | 0.0157   | 0.2004   |
| Kriging Ord. Spherical                            | 0.1014   | 0         | 1.1735    | 0.0500    | 0.1046   | 0.0157   | 0.2004   |
| Kriging Uni. Linear Drift                         | 0.1133   | 0         | 2.9192    | 0.0892    | 0.1113   | 0.0292   | 0.1826   |
| Kriging Uni. Quadratic Drift                       | 0.0990   | 0         | 18.7281   | 0.0486    | 0.3959   | 0.0256   | 0.0761   |
| Natural Neighbour                                 | 0.0724   | 0         | 1.0888    | 0.0488    | 0.0720   | 0.0164   | 0.1214   |
8.2. Python Smoothing Input Data Script

This program smooth’s a list of data, based on moving averages and outputs the smoothed list into a text file.

def smoothPoints(filename):
    
    This program smooths a list of points, using a moving average. It smooths with using 3, 5 and 10 elements. It saves the new lists to a text file.
    
    # Load in X,Y,Z data
dataset = np.loadtxt(filename, skiprows=1)
    # Defines x, y, z
    x = dataset[:,0]
y = dataset[:,1]
z = dataset[:,2]

    # Number of values to be used in moving mean
    movingmean = (3, 5, 10)

    # Loop through moving average values
    for i in movingmean:
        # Smooth Z values
        Zout = rolling_mean(z, i)
        # Define output text file contents
        dataout = column_stack((x,y,Zout))
        # Save text file
        np.savetxt('Smooted%s.txt' %i, dataout, delimiter=',')
8.3. Python Subsampling Script

This program selects every 5th, 10th and 50th element from an X, Y, Z list and saves the subsampled data to a text file delimited by commas.

```python
def subsample(file):
    
    This program subsamples an X, Y, Z list three times, choosing every 5th, 10th and 50th element. Saving each new list into a text file.
    
    # Load text file
    dataset = np.loadtxt(file, skiprows=1)
    # Set up x, y, z from text file
    x = dataset[:,0]
y = dataset[:,1]
z = dataset[:,2]

    # Elements to select
    element = (5, 10, 50)

    # Loop through different elements to select
    for i in element:
        # Subsample each list
        xout = x[::i]
yout = y[::i]
zout = z[::i]
        # Define output text file contents
        dataout = column_stack((xout, yout, zout))
        # Write text file
        np.savetxt('Sub%s.txt' %i, dataout, delimiter=',')
```

8.4. **Python Smoothing DEM Script**

This program was written in Python. It smoothes an image using a different sized Gaussian kernels and saves the image, a 3 x 3, 5 x 5 and an 11 x 11.

```python
def Smooth(Imagefile):
    '''
    This program smoothes an image using Gaussian blur, with a 3x3 window, a 5x5 window and 11x11 window.
    Code has been adapted from Dr. P Lewis, UCL, London.
    URL: www.geog.ucl.ac.uk/~plewis/geogg122/pythonmodel.html
    Accessed on: 20 July 2013
    '''
    import Image
    from scipy import signal

    #Load image
    im = Image.open(Imagefile)
    #Change to an array
    dem1 = numpy.array(im)

    #Define window size
    kernels = (1,2,5)

    #Loop through kernel sizes
    for i in kernels:
        #Sets x size
        sizex = i
        #Sets y size
        sizey = i
        #Creates grid
        x, y = np.mgrid[-sizex:sizex+1, -sizey:sizey+1]
        #Changes grid to a Gaussian grid
        g = np.exp(-0.333*(x**2/float(sizex)+y**2/float(sizey)))
        # Creates filter
        filter = g/g.sum()
        #Smoothes the DEM
        demSmooth = signal.convolve(dem1, filter, mode='valid')
        # Arranges data for Saving
        outImage = Image.fromarray(demSmooth)
        # Saves image
        outImage.save('Smoothed_%s.tif' %i)
```