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Scaling up of peatland methane emission hotspots from small to large scales

Abdulwasey Mohammed

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University of Edinburgh

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Declaration

I declare that this thesis is of my own composition, and that it contains no material previously submitted for the award of any other degree. The work reported in this thesis has been executed by myself, except where due acknowledgement is made in the text.

A handwritten signature in blue ink, appearing to read 'Abdulwasey Mohammed', with a stylized flourish at the end.

Abdulwasey Mohammed

Abstract:

Methane is an important greenhouse gas that is relatively long-lived in the atmosphere, and wetlands are a major natural source of atmospheric methane. Methane emissions from wetlands are variable across both space and time at scales ranging from meters to continents and a comprehensive accounting of wetland methane efflux is critical for quantifying the atmospheric methane balance. Major uncertainties in quantifying methane efflux arise when measuring and modelling its physical and biological determinants, including water table depth, microtopography, soil temperature, the distribution of aerenchymous vegetation, and the distribution of mosses. Further complications arise with the nonlinear interaction between flux and drivers in highly-heterogeneous wetland landscape. A possible solution for quantifying wetland methane efflux at multiple scales in space ('upscaling') is repeated observations using remote sensing technology to acquire information about the land surface across time, space, and spectra. These scaling issues must be resolved to progress in our understanding of the role of wetlands in the global atmospheric methane budget from peatlands.

In this thesis, data collected from multiple aircraft and satellite-based remote sensing platforms were investigated to characterize the fine scale spatial heterogeneity of a peatland in south-western Scotland for the purpose of developing techniques for quantifying ('upscaling') methane efflux at multiple scales and space.

Seasonal variation in pools such as expansion and contraction was simulated with the LiDAR data to investigate the expansion and contraction of the lakes and pools that could give an idea of increase or decrease in methane emissions.

Concepts from information theory applied on the different data sets also revealed the relative loss in some features on peatland surface and relative gain on others and find a natural application for reducing bias in multi-scale spatial classification as well as quantifying the length scales (or scales) at which important surface features for methane fluxes are lost.

Results from the wavelet analysis demonstrated the preservation of fine scale heterogeneity up to certain length scale and the pattern on peatland surface was preserved. Variogram techniques were also tested to determine sample size, range and orientation in the data set. All the above has implications on estimating methane budget from the peatland landscape and could reduce the bias in the overall flux estimates. All the methods used can also be applied to contrasting sites.

Key words: *upscaling, methane, peatland, remote sensing, GIS, climate change, wavelet, quadratic interpolation, DEM, information theory, Shannon entropy, Kulback-Leibler distance, heterogeneity, pixel averaging, wetland, Water logger*

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Abbreviations

ATM	Advanced Thematic Mapper
AVHRR	Advanced Very High Resolution Radiometer
ARSF	Airbone Research and Survey Facility
ATM	Airborne Thematic Mapper
ARSF	Airborne Research and Survey Facility
ATM	Atmospheric Thematic Mapper
CO ₂	Carbon dioxide
CFCs	Chlorofluorocarbons
CoA	Coefficients of Approximations
CIR	Color Infra Red
DGPS	Differential Global Positioning System
DEM	Digital Elevation Model
DP	Digital Photography
DP	Digital Photograph
DMRWA	discrete Multi Resolution Wavelet Analysis
DWT	Discrete Wavelet Transform
DPHA	Dorothy Hodgkin's Postgraduate Award
ETM	Enhanced Thematic Mapper Plus
EL	Eriophorum Lawn
FTIR	Fourier Transformed InfraRed
GC-FID	Gas Chromatography-Flame Ionization Detector
GPS	Global Position System
GWP	Global Warming Potential
GHGs	Greenhouse Gases
HRMSI	High Resolution Multispectral Image
HRPANI	High Resolution Panchromatic
HIPAN	High resolution panchromatic
HRV	High Resolution Visible
HHL	Hummocky Heather Lawn
IC	Information Content
IC	Information Content
IT	Information Theory
IFOV	Instantaneous Field of View
HIS	Intensity Hue Saturation
IPCC	Intergovernmental Panel on Climate Change
D _{KL}	Kullback - Liebler Distance
LiDAR	Light Detection and Ranging
LRMSI	Low Resolution Multi Spectral Image

MATLAB	Mathematics Laboratory
CH ₄	Methane
MSE	Microstructural Elements
MSEs	Microstructural Elements
MSE	Microstructural Elements
MAUP	Modifiable Areal Unit Problem
MRA	Multi Resolution Analysis
MRDWA	Multi Resolution Discrete Wavelet Analysis
MRA	Multiresolution Analysis
NOAA	National Oceanic and Atmospheric Administration
NERC	Natural Environmental Research Council
N ₂ O	Nitrous oxides
PAN	Panchromatic
PSNR	Peak Signal To Noise Ratio
PPT	Precipitation
QI	Quadratic Interpolations
QT	Quick Terrain
RGB	Red Blue Green
RESSys	Regional Ecosystem Simulation System
RHESSys	Regional Hydro-Ecologic Simulation Systems
RS	Remote Sensing
SPOT	Satellite Pour l'Observation de la Terre
T _s	Soil Temperature
SSSI	Special Scientific Investigations
SPECIM	Spectral Imaging
WTD	Water Table Depth
wv	Wavelet Variance

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1. Introduction

1 Greenhouse gas Methane and its global warming potential

The atmospheric greenhouse gases (GHGs) such as methane (CH_4), carbon dioxide (CO_2), water vapour, nitrous oxides (N_2O), ozone and chlorofluorocarbons (CFCs) increase the earth's surface temperature by some thirty degrees from an atmosphere-free state by controlling in part the planetary energy balance, a phenomenon known as the greenhouse effect, IPCC (2007). If GHGs continue to increase in concentration and the temperature rises as per the IPCC (2007) predictions, alterations to the climate system will result, thus the net impact of global change is arguably negative as human infrastructure, species ranges, and other features of the combined human-planetary 'anthroposphere' are conditioned on the current climate.

Methane is a colourless and odourless gas that has doubled its concentration in the atmosphere over the last two hundred years (Khalil and Rasmussen, 1989) with much of the post-industrial emission being caused by human activities (Prather et al., 1995, Leliveld et al., 1998). Globally, the atmospheric methane concentration is 1.8ppm as compared to 360 ppm for CO_2 , but each molecule of methane has a potential to contribute about 25 times as much greenhouse warming as each molecule of CO_2 (Lashof & Ahuja, 1990; Albritton et al., 1995). As per IPCC (2007) report the radiative efficiency of methane is $3.7 \times 10^{-4} \text{ W m}^{-2} \text{ ppb}^{-1}$ when compared to CO_2 ($1.4 \times 10^{-5} \text{ W m}^{-2} \text{ ppb}^{-1}$) in one year, giving a global warming potential (GWP) of methane with respect to one year of CO_2 of 21 years. GWP of methane indicates the amount of heat a certain mass of methane gas traps in the atmosphere in comparison with the same amount of mass of CO_2 calculated over a specific time interval, commonly,

20, 50, 100 years. The GWP of CO₂ is standardized to one. For example, if the same amount of methane is released into the atmosphere, then the GWP of CH₄ is 86 factors higher in trapping heat than CO₂ over the next 20 years.

The spatio-temporal variations and interactions among the physical, chemical and biological subsystems results in earth system process complexities. Getting an insight into these dynamics has taken immense importance in the context of current environmental change and the portent of even larger global change. Integrating data and models from different disciplines and different spatio-temporal scales is a difficult task and requires appreciation for the concept of scaling. In particular, biophysical and ecological information derived at micro-level scale (< 1 m) must be extrapolated to the regional and global scales (100's m to 100's Km) of climate models. Complex spatial variations and nonlinearities in dynamics across landscapes make the whole procedure extremely challenging.

Peatlands presents one such challenge for measuring the GHG such as methane emitted from various methane hotspots within the landscape. They are mainly due to the nonlinear variation in emissions across space and time.

Wetland methane emission estimates as reported in the IPCC reports.

From the (table1) below it is evident that during the last three decades the global budget of methane emissions from wetlands shows a range of values with the difference between as high as more than 100% in the bottom up approach and more than 50% range reported in top down approach. Such uncertainties are primarily due to the aggregations made using mean values of the deriving factors of methane across the landscape.

Tg(CH ₄) yr ⁻¹	1980–1989		1990–1999		2000–2009	
	Top-Down	Bottom-Up	Top-Down	Bottom-Up	Top-Down	Bottom-Up
Natural Sources	193 [150–267]	355 [244–466]	182 [167–197]	336 [230–465]	218 [179–273]	347 [238–484]
Natural wetlands	157 [115–231]	225 [183–266]	150 [144–160]	206 [169–265]	175 [142–208]	217 [177–284]

Table 1: Natural sources and sources from wetlands of CH₄ emissions from the last three decades (source: IPCC AR5-WG1 report, Chapter 6, page # 507)

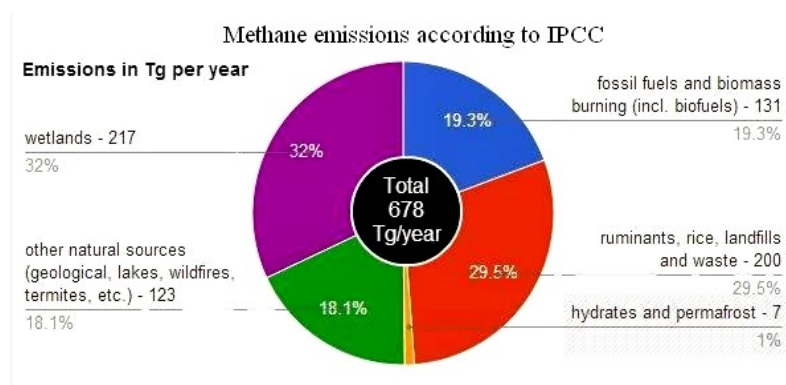


Figure 1: Various sources of methane emissions as reported by IPCC in AR5 2013

Overall aim and specific objectives

The overall aim of this project is to investigate scaling issues from hyperspectral and LiDAR techniques from micro to macro scales in the assessment of methane from peatland. Blanket peatlands are complex landscape units that show distinct heterogeneity in surface elevation and vegetation/land cover at scales ranging from 1 to > 1000s m. Peatland hydrological and biogeochemical processes are both intimately related to heterogeneity in surface structure at the micro scale (1-100 m). The development of remote sensing techniques for quantifying surface attributes at the micro scale is the first, crucial step that will enable routine monitoring of peatland response to environmental change and the accurate estimation of peatland contributions to regional and global CH₄ emissions. Specific objectives of this project are as follows:

1. Characterise the spatial scale-dependency of peatland methane emission hotspot, and to develop novel numerical methods for treating non-linear scaling in order to understand:
 - A) how do the structural changes in micro-topography, such as expansion and contraction of pools during summer and winter, influence the changes in CH₄ emissions?
 - B) is there a well-defined scaling relationship between CH₄ emission controlling factors and different remote sensing data and if there is, then is it possible to scale up from fine resolution to coarse resolution?
 - C) How do changes in scale bring changes in pattern on peatland and in doing so affects vital information to estimate CH₄ emissions?
 - D) Is scale dependency in pattern and hence CH₄ emissions continuous? If not, where do scale breaks occur?
 - E) Is there a single method of aggregation that can be applied across contrasting sites?
2. Quantify surface characteristics and heterogeneity that are key parameters in process-based models of peatland CH₄ emission.

Background and context

According to IPCC 2007, wetlands account for about 32% of natural methane emissions, (figure 1). Peatlands account for about 40 % of global emissions of methane, (Wang et al., 2004) and may hold over half the global reservoir of soil organic carbon, (Gorham 1991). Hence, peatland response to climate change has the potential for strong feedback on the global climate system, (Gedney et al., 2004). In addition to their globally important role in the carbon cycle, peatlands are of high conservation value, particularly as habitat for rare or endangered species of plants, invertebrates and birds. Globally and within the UK, these functions are threatened by climate

change, land-use change and nitrogen deposition. At present, global estimates of peatland carbon stores and fluxes are extremely uncertain because of high heterogeneity at small spatial scales and the difficulty of quantifying peat depths over large areas. Environmental and habitat changes on peatlands are difficult to track, because sites are extensive and remote, and vegetation responses occur on the scale of metres, a spatial scale that is too coarse to detect by rapid ground survey and too fine to detect by conventional remote sensing. Blanket peatland, a globally rare ecosystem type that in Scotland covers over 1 million ha, about 10 % of the world total, (Lindsay et al., 1988).

An estimated 2.3 million hectares (9.5% of the UK land area) is covered by bog peatlands (JNCC 2011). Scotland has about 60% of the UK's peatlands, and 4% of Europe's total peat carbon store (UKCCC 2011). Today around 1.8 million hectares (over 20% of Scotland's land area) is covered by blanket bogs alone (JNCC 2011), comprising about 15% of the global total for this habitat (Scottish Government 2010a). Blanket bogs are rare on a global scale, and those in Caithness and Sutherland are some of the largest and most intact in the world today (JNCC 2011). Silver Flowe blanket bog are similar in nature to the Flow Country peat bogs. Further, it is reported that the Silver Flowe bogs also resembles the bogs 'Kermihnochmoors' of Finland and the 'string bogs' of North America (Boatman, 1983). Thus, the methods developed in this research would be significant for translating to other sites. According to the author of the book, "Peatland and Environmental Change", Dan J. Charman, the peatlands of hyperoceanic areas such as some of the systems on the Pacific Canadian coastal areas and the Southwest Newfoundland on the east coast of Canada are also the closest in resemblance to the Silver Flowe peatland. Hence, the methods developed and presented in this research are significant in terms of applications to other areas of the globe.

Recent developments in hyperspectral sensor and high-resolution Lidar technologies offer new possibilities for routine collection of detailed attributes of peatland surface structure over broad spatial extents, enabling a step-change in the quality and quantity of data available to conservation organisations and modellers of the global carbon cycle.

Surface structure and ecosystem function of peatlands

The peatland landscape is complex and extremely heterogeneous, but can be viewed as a hierarchy of landform units exhibiting distinct hydromorphological characteristics, (Ivanov 1981; Lindsay 1995):

- *Microforms* are individual microtopographic features (~ 1–10 m in horizontal scale) that are the elemental units of the surface pattern (e.g., a high ridge with a peat surface ~ 50 cm above the water table or a permanent pool in the order of 100 cm deep).
- *Microtopes* are uniform areas (~ 10 – 100 m in scale) of distinctive vegetation and physical structure, which may be composed of a mosaic of specific microform types (e.g., a low ridge–*Sphagnum* hollow complex or a high ridge–permanent pool system).
- *Mesotopes* are the basic hydrological entities (~ 100 – 1000 m in scale), encompassing all inputs, outputs and internal fluxes of water for normal system dynamics (e.g., an unconfined raised bog with a central high ridge–permanent pool system and a peripheral low ridge–*Sphagnum* hollow complex).

- *Macrotopes* are the highest level of the hierarchy (generally > 1000 m in scale), denoting landscape units of two or more mesotopes that are hydrologically connected (e.g., a mire complex composed of unconfined raised bog, valley side mire and ladder fen).

Microforms are characterised by plant species that differ in functional traits along two main gradients: height above the water table and peat forming ability. Microforms may be terrestrial, aquatic (i.e., with surface water year-round) or semi-aquatic (i.e., seasonally flooded). Regional differences in climate affect the range of microform variation, (Yabe & Uemura 2001) and the abundance of functional plant types such as dwarf shrubs (Lindsay et al., 1988).

As a result of differences in surface structure and functional traits of the vegetation, microforms differ greatly in ecosystem processes. For example, methane (CH₄) emissions can vary by two- to four-fold across microforms that may be separated by only a few metres (Moore et al., 1990; Huttunen et al., 2003) and also show large seasonal variation (Waddington & Roulet 1996). This fine-scale and short-term variability creates problems for estimating current fluxes and for predicting future emissions under a changed climate. Highest rates of emission occur from aquatic and semi-aquatic microforms with seasonal to permanent surface water and abundant cover of aerenchymous plants that can transport CH₄ directly to the atmosphere through their vascular systems. Upscaling emissions from the microform to landscapes and regions is highly challenging because the relationships between controlling factors and CH₄ emissions are non-linear and vary across cover types. Existing process-based models of methane emission (Kettunen, 2003) are quite successful as long as water-table depth and aerenchymous plant cover can be provided as input. A promising approach involves linking a process-based model (Kettunen 2003; Walter et al., 2001) to remotely-sensed estimates of

these key model drivers. So far, airborne and satellite remote sensing of peatlands has focussed on coarser-scale issues of delineating major peatland types (Bubier et al., 2005).

Peatlands respond to environmental change through shifts in the diversity and abundance of microforms and their associated plant species, (Belyea & Malmer, 2004). Throughout the Holocene, hollow–lawn and lawn–hummock margins have expanded and contracted on time scales of 10s to 100s of years, apparently in response to shifts in climatic wetness (Barber, 1981). Even with weak climate forcing, major switches in vegetation and divergence of surface structure into hummock-hollow complexes can occur rapidly, having large effects on peatland carbon cycling (Balyea & Malmer 2004). Anthropogenic nitrogen deposition also leads to changes in vegetation composition (i.e., increased cover of vascular plants and decreased cover of *Sphagnum* mosses) that have knock-on effects on carbon cycling (Berendse et al., 2001). Monitoring peatland responses to environmental change requires rapid acquisition of detailed information on micro-scale vegetation composition and surface structure (i.e., microform and microtopo attributes). Although cameras mounted on kites (Aber et al., 2002) or balloons in (Miyamoto et al., 2004) may provide data at the necessary spatial resolution, these methods are not practical for extensive surveys. Airborne remote sensing, using a combination of multispectral, hyperspectral sensors and high resolution LiDAR, may offer a solution because these technologies allow for the separation of distinct cover types at the micro scale and at repeated spatio-temporal frequencies.

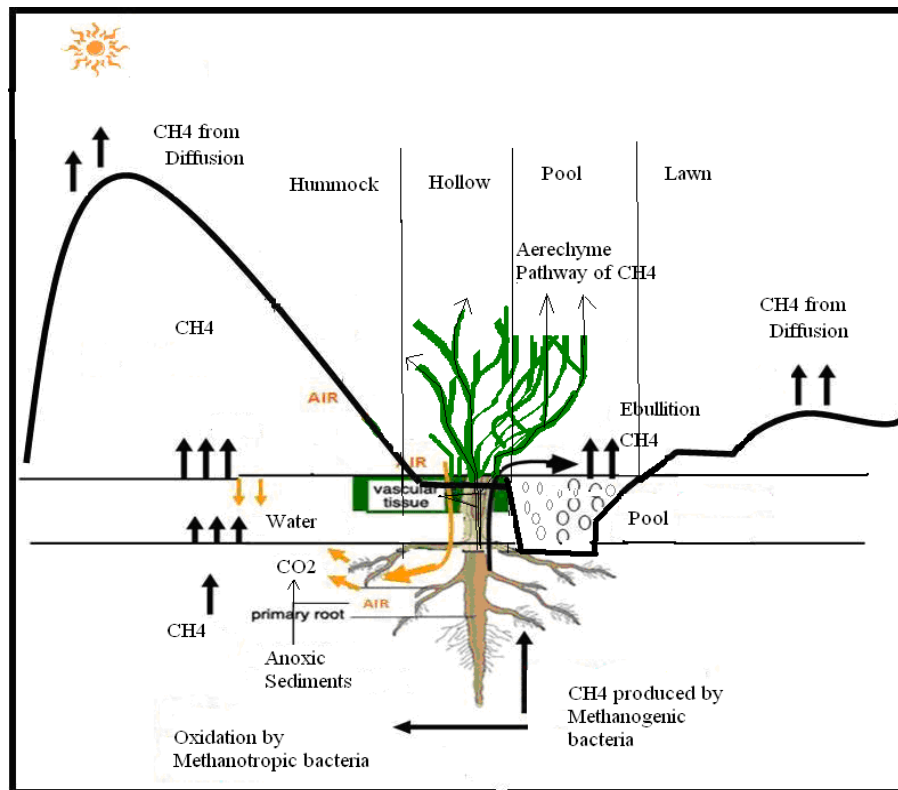


Figure 2: A schematic of methane production, oxidation and release into the atmosphere from different microstructural elements (MSEs) in a peat bog. (Adopted and modified from Kettunen (2002) and Schuetz et al., (1991).

Peatland methane transport to the atmosphere

Once produced, the transport of the methane gas into the atmosphere occurs by diffusion through water-/air-filled soil pores, ebullition to the water table, and plant mediated transport from layers below the rooting depth (figure 2). Plants supply carbon to the peat matrix. In hummocks, carbon is supplied to the unsaturated layers where it may accumulate or be respired. In pools the rate of supply is somewhat lower due to sparse vegetation cover. On lawn surfaces, low vascular plant cover results in lower methane fluxes due to lack of substrate. Consequently, methane flux increases with an increase in vascular plant coverage

given anaerobic conditions, until an oxidative environment is created, often through root growth. Methane is also directly released into the atmosphere by ebullition to the water table.

Peatland microtopography and its effect on methane emissions

Peatlands surface display a complex structural microtopography that includes hummocks, hollows, lawns, drought sensitive pools and permanent pools (Lindsay et al. 1988) and each such structure contributes to the heterogeneity in methane emissions. Peatland microtopography is extremely heterogeneous at the centre of the bog and displays more homogeneous surfaces near the bog margin. Thus in contrast to bog margin, the bog centre displays a striking range of patterns consisting of alternating terrestrial and aquatic microforms (figure 2). Lindsay et al. (1998) characterized these features as terrestrial and aquatic zones, which are considered as two main classes. These classes are further characterized using remote sensing data to assess the peatland spatial heterogeneity and to do up-scaling in the present work. The selected study site at Silver Flowe in Scotland has most of these features arranged into patterned areas, (figure 3), in various combinations forming bog expanse and bog margins. In the present work the terrestrial class is further characterized into Hummocky lawn, *Eriophorum vaginatum* and *Calluna vulgaris*.

As a result of differences in surface structure and functional traits of the vegetation, the ecosystem processes that occur within microforms differ greatly. For example, methane (CH₄) emissions can vary by two- to four-fold across microforms that may be separated by only a few meters (Moore et al., 1990; Huttunen et al., 2003) and also show large seasonal variation, (Waddington and Roulet, 1996). The range of surface patterns contributes significantly to variability within and between sites and the distribution and abundance of particular zones in

areas of patterning provides one level of variation, but in addition the form and orientation taken up by the patterns are an important factor (Lindsay 1995, page 28).

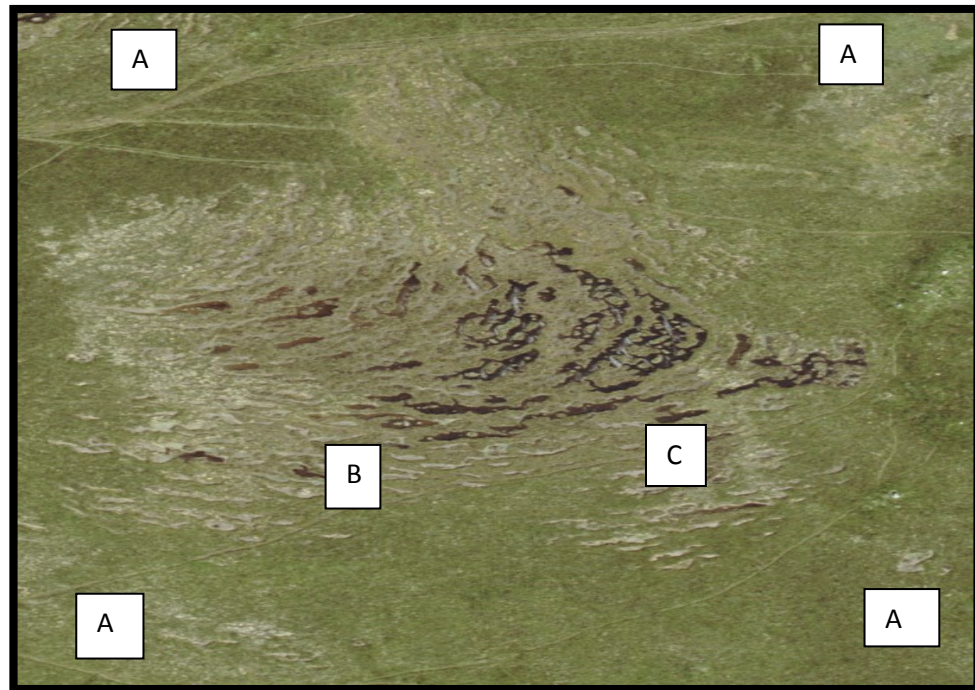


Figure 3: Digital photo with pixel resolution of 0.25 m of Brishie bog centre in Silver Flowe showing complex microform arrangement of permanent hummocks, hollows, pools, drought sensitive pools, mud bottom- and Sphagnum filled hollows and lawn. The complex microform marked as (C), the bog centre is marked as (B) and the bog margin is marked as (A).

The common method used by (Mathews and Fung, 1987; Asselmann and Crutzen, 1989; Bartlett & Harris, 1993) for estimation of global CH₄ emissions from wetlands was simply to multiply the flux rates by the area of the wetland distribution. As previously mentioned, this method introduces errors in regional and global estimates of CH₄ emissions as the fine scale heterogeneity which is the dominant controlling factor is invariably lost.

Peatland effects on carbon (C) cycling involve changes in both large-scale structure and community composition. The rate of C sequestration declines as the peat deposit accumulates

in depth, and methane emission increases as wet microhabitat expands in area (Belyea & Baird, 2006). The postglacial development and expansion of northern peatlands has resulted in transfer from atmosphere to the soil (peat) of large amounts of carbon (270 to 370 Pg); (Turunen et al., 2002), mainly over the past 5000 years (Gajewski et al., 2001). The long term role of peatlands carbon storage, however, contrasts with their present role as significant sources of atmospheric CH₄ (Wang et al., 2004) and exporters of dissolved organic carbon to the oceans (Hope et al., 1994). Present rates of emissions are controlled largely by water table position below peatland surface, temperature and supply of readily decomposed substrate (Christensen et al., 2003). As a result vegetation and microtopography are strong predictors of emission rates (Bubier et al., 1995), and fluxes can vary more within a few meters than across peatland regions (Moore et al., 1998).

As mentioned earlier that the deterministic properties such as water-table position, peat temperature and aerenchymous wetland plant community influence the methane flux, the large spatial and temporal variation in methane emissions is one reason for the wide range of estimates available for CH₄ emissions from peat lands, and regional differences can be significant even when the sites are similar in climate, vegetation and topography (Sebach et al., 1986; Crill et al., 1992). Spatiotemporal variation in methane emission rates is high between peat land types (Yavitt et al., 1988; Windsor et al., 1992) and even between microsites on the same peat land (Svensson & Rosswall 1984; Moore et al., 1991; Bubier et al., 1993) within 10s of meters. Moore *et al.*, (1990) reported emission rate from a fen site in Canada during the early summer from 30 to 40 mg CH₄ m⁻² d⁻¹, rising to > 50 mg CH₄ m⁻² d⁻¹ later in the summer, further identifying the major differences in magnitude of methane emissions between hummock (<20 mg CH₄ m⁻²d⁻¹), hollow (10 to 100 mg CH₄ m⁻² d⁻¹) and pools sites (< 200 mg CH₄

$\text{m}^{-2} \text{d}^{-1}$). Large variation in CH_4 emissions within a similar site in Finland were reported by (Saarino et al., 1997) and (Ketunnen et al., 2000). Results from a Canadian site (Strack et al., 2004) where chambers were deployed within a few tens of meters distance of each other to measure CH_4 emissions concluded that the pools and lawns containing vascular plants emitted the highest amount of CH_4 with water table, sedge cover and microtopography having a strong influence of emissions rates. Therefore it is evident that field-based chamber measurements are useful in defining fluxes as point sources from the individual microforms, and also to identify the significant spatial variations and uncertainties in the overall methane budget across plots. These point sources could also compliment in landscape regional and global scale estimates. When characterising peatland microsites using remote sensing data, care is required to ensure proper classifications of such hotspots as any misclassification would lead to a biased estimate of net flux of methane. There is therefore a need for a novel up-scaling method to estimate peatland methane emissions across multiple spatial scales. Hence the present work is focused on applying novel methods that preserve the landscape patterns and fine scale heterogeneity across the landscape when up-scaling from small to larger scales.

Common methods of peatland methane emissions measurements

At the moment there is no single method that is widely recognised as the standard method to measure annual average methane emissions from peatlands. As mentioned earlier, the main challenge in measuring methane emissions from peatlands is the spatio-temporal variability of emissions, along with the sheer size and treacherously risky landscape.

Limitations with the most common field methods

Some of the commonly adopted techniques for measuring methane emissions from peatlands are 1) Soil core measurements, 2) Closed chamber measurements, 3) Eddy correlation measurements.

Common techniques that are adopted for *in situ* measurements of methane from wetlands such as the chamber systems gives the point source which is then extrapolated across the landscape to estimate the total emissions from the landscape, (Macdonald et al., 1998; Beckwith et al., 2003; Glaser et al., 2004; Pelletier et al., 2007; Denmead 2008; Forbrich et al., 2011). This is the most frequent method applied to measure methane from peatlands, Duenas et al. (1996). In this approach, gasses that accumulate in the headspace of a closed chamber are sampled and analysed, usually by GC-FID (Gas Chromatography-Flame Ionization Detector). This approach is sensitive, with a minimum detectable flux of $\sim 0.6 \mu\text{mol m}^{-2} \text{h}^{-1}$ (Duenas et al. 1996), which is well below a 'typical' wetland methane flux of $20 \mu\text{mol m}^{-2} \text{h}^{-1}$, (Moncrieff et al., 1998). Closed chamber method is easy to understand and requires no analytical equipment beyond a common FID or an IR-analyzer. The method is able to detect small fluxes of methane and is not sensitive to other sources of methane near the landscape. However, it has several disadvantages. Because they require an accumulation time, chamber methods cannot be used to make continuous, real-time measurements and may be affected by non-steady-state diffusion. Installation of chambers disturbs the habitat and can sometimes lead to artificially high emission rates (Chasar et al., 2000). Chambers must be placed over a small area that is unlikely to be representative of the entire ecosystem. This is perhaps the largest draw-back of closed chamber measurements because to obtain a reliable methane emission estimate, large area sampling is required perhaps using a systematic grid sampling technique that are

proposed in (Saarino et al., 1997; Kettunen et al., 2000; Spookas et al., 2006). The heterogeneous emission hinders the reliability of average methane emission estimates from the landscape and sometimes the episodic emissions from the hotspots may also be completely missed out. In addition, installation and monitoring chambers is labour-intensive and is not amenable to remote operation. These factors make it difficult to utilize chambers to comprehensively determine methane emission dynamics from heterogeneous wetland ecosystems, especially those found in remote, high-latitude environments. All the above mentioned techniques give methane estimates but also involve lot of time and labour due to the challenge peatlands possesses for traversing across its landscape.

Similarly, eddy covariance measured from the flux towers (Hendriks et al., 2007; Rinne et al., 2007; Denmead 2008; Zona et al., 2009; Schrier-Uijl et al., 2010; Kroon et al., 2010; Long et al., 2010); are used over the kilometre range helps in measuring methane estimates over the landscape as well as regional scales. However, the eddy covariance method also has a wide array of limitations, such as it is most applicable over horizontally homogeneous area, in flat terrain and in atmospheric steady-state conditions. It has been suggested that the measured total fluxes can be underestimated during night-time low turbulence conditions due to the large CH₄ concentration build-up in the nocturnal boundary layer (Long et al., 2010). Other techniques used are FTIR (Fourier Transformed InfraRed) method in which a transect across the landscape is used to measure methane emissions.

Recent developments in satellite remote sensing have supported advanced programmes to estimate trace gasses in the atmosphere. SCIAMACHY (Scanning Imaging Absorption Spectrometer for Atmospheric CHartography) is an imaging spectrometer whose

primary mission objective is the global measurements of trace gases in the troposphere and in the stratosphere. The solar radiation transmitted, backscattered and reflected from the atmosphere is recorded at relatively high resolution (0.2 nm to 1.5 nm) over the range 240 nm to 1700 nm, and in selected regions between 2.0 μm and 2.4 μm . Total column quantification of CO, CH₄, CO₂ and N₂O retrieved from SCIAMACHY nadir observations in its near-infrared channels have been compared, in a number of studies, to data from a ground-based quasi-global network of Fourier-transform infrared (FTIR) spectrometers (Dils et al., 2006). These studies have highlighted that the individual SCIAMACHY data obtained with the initial versions of the algorithms have been significantly improved, but that the quality requirements, for estimating emissions on regional scales, are not yet met. In another study, (Bloom et al., 2010) used gravity anomalies as proxy to water table depth at the continental scale to assess the methane emissions from the wetlands and rice paddies. But, the estimation of areas using satellite techniques at such a large scale has numerous errors. It would be extremely difficult to estimate the percentage corresponding to the global coverage area of these ecosystems at 3 degrees pixel size, particularly if the ecosystem is small such as the present case of Silver Flowe, it would not appear in the pixel at all. Similarly, there are chances of mixed pixel classifications confusing with other classes such as forest and agriculture might be classified as wetland. For example, a global process-based model, (Walter et al. 2001) to study climate-induced variations in methane emissions with model forcing including soil temperature, NPP (Net Primary Productivity), and water table based on global wetland distribution, based on global vegetation distribution map from 1°x1° grid cell (Mathews and Fung, 1987). But this global wetland distribution map misclassified some of the areas as wetlands which are not primarily wetlands in the vegetation map of *Wilson and Henderson-Sellers (1985)*.

Most of these challenges with mixed pixels and misclassifications, at least at a regional scale could be overcome by using very high resolution, multi-spatial remote sensing data collected over the landscape. Studies must be carried out highlighting short-range spatial heterogeneity including areas of the Earth that are virtually unknown as yet. Hence, bottom-up (incubation chambers, surface drifters, remote sensors, eddy covariance towers) and top-down (inverse modelling) measurements must be combined to enhance the global estimation of methane emissions to the atmosphere. The significance of methane as a greenhouse gas (IPCC, 2007) makes these improvements essential if a better and more accurate picture of global emission is to be found, which is a precondition to reducing methane emissions worldwide.

Scaling issues

Recent investigations in this field of vegetation and semi-natural vegetation species use complex mathematical–statistical methods and models for rescaling to quantify land surface variables (Garrigues et al. 2006, 2008; Tarnavsky et al. 2008). According to Malenovský et al. (2007) and Wu (2009), there are still no truly suitable methods available at present to derive land surface variables such as global NDVI products from remote sensing data from different spatial and spectral resolutions and therefore from scaling. Wu (2009) states the reasons for this: “The research on scale, the effect of different scales, scale transition and methods of scaling in remote sensing are still at

the very beginning. There are many reasons why the transfer of information over different scales is so difficult:

(1) Different remote sensing instruments have a different field of view (FOV) and types of lenses that correspond to different spatial resolutions.

(2) Instruments of a comparable target measurement have different technical designs and acquisition parameters.

(3) The earth's surface processes are highly nonlinear and can create quite unexpected patterns.

(4) The calibration and validation of models is generally characterized by specific spatial and spectral data characteristics.

(5) There is a large discrepancy between the observation scale, the model scale and the land surface process scale.

(6) Different factors, such as funding, the time of data recording and available manpower, constrain the choice of scale and the mode and intensity of airborne and even satellite-based observations. Hence, a data product may not be exploited to its full potential".

A serious barrier to airborne- or satellite-based characterisation of peatland surface structure is the mis-match on both spectral and spatial scales. Spectrally, there is a mis-match between the resolution of hyperspectral airborne sensors (e.g. ~200 bands) and

the resolution of conventional multispectral satellite sensors (~2 to 6 spectral bands). Spatially, there is a mis-match between the spatial scale of peatland microforms (e.g., 1 m), airborne sensors (e.g., ~3 m) and satellite sensors at ~10 – 1000m.

Since peatlands exhibit extreme heterogeneity in surface attributes at distinct scales over a large spatial range, the scale dependency of spectral reflectance is likely to be non-linear. Comprehension of the scale dependencies within peatland systems is required in order to understand and overcome the institutional fit and scale discordance problems posed by (Cash & Moser 2000) where the scales of the environment and assessment fail to match those at which process-based modelling and management are applied. If dependencies are non-linear, traditional aggregation methods of scaling up are unlikely to work, so this project will investigate alternative approaches, such as information theory, fractals & geostatistics and wavelets, applied to multi-sensor air and space borne RS data.

Scale, Spatial heterogeneity and aggregation of peatland methane emission hotspots

Firstly, in dealing with scale in ecological research applications, we need to appreciate and understand how changing the scale of observation affects research results and their interpretation. Much work has been done in this area, for instance, “the modifiable areal unit problem” (MAUP), or “scale effects” where scale can be grain or extent in space or time unit (for example, Marceau 1999, Jelinsky and Wu 1996).

However, it is not clear whether the effect of changing scale is an artefact due to improper use of the analysis methods, an indication of scale multiplicity of ecological systems or neither of the two or a combination of the two (Wu & Qi, 2000).

Second, if the ecological systems like peatlands, are multiple-scaled or hierarchically structured (Belyea & Baird, 2006) then identifying characteristic scales and hierarchical levels becomes extremely important for understanding and predicting an ecological phenomenon like methane emissions. Although studies exist, the issue of characteristic scales and hierarchical levels is not without controversy. However, the presence of scale-dependent heterogeneity is important in two main contexts: 1) defining a suitable scale range which would reveal for instance the variation of interesting structures such as pools, lawns, hummocks and hollows, and 2) characterising the nature of the spatial variation of these structures so that the scale of measurement may be changed, meaning that the data may be up-scaled. This is the crux of the present work explained further in the following sections. Similarly, (King, 1991) recognised two main challenges for problems which show spatial heterogeneity: 1) the definition of spatial heterogeneity, and 2) the correct integration and aggregation of data.

It is generally accepted that nearly all environmental problems are scale dependent (Davis et al., 1991; Davis & Simonett 1998). Different scales of measurements reveal variables to be homogenous at one scale yet heterogeneous at another, (Atkinson & Tate, 2000). High resolution data would capture fine scale heterogeneity and spatial variability across the landscape better as more detailed information is available.

Heterogeneity can also be increased by increasing the spatial extent of the study area (Haining 1989; King 1991). In the context of landscape ecology, (Milne,1991) suggested that a key to understanding heterogeneity was to conduct the analysis across a wide range of measurement scales and extract parameters that are robust to changes in scale.

Spatial aggregations of raster data based on the majority rule have been typically used in landscape ecology (Turner et al., 1989a, 1989b; Moody and Woodcock 1994, 1995; Benson & MacKenzie 1995, Mladenoff et al, 1997). These studies observed that dominant classes become more dominant and minor classes decrease and in some cases disappear entirely from the landscape.

Aggregation of a classified TM imagery across broad spatial scales (30-990 m) may be based on a majority rule or a random rule. The majority rule finds the majority value for the specified cells of the input grid and records that value in the corresponding aggregated cell of the put grid, while the random rule assigns the value for the output cell by randomly picking a value among the specified cells of the input grid (He et al., 2000). The aggregation was sequential starting from 30m to 990m with an increment of 30m; hence no division of pixel was necessary. This study revealed that the results from random rule-based aggregation showed less distortion and more stability while retaining cover type proportions, than those from majority rule-based aggregation. The majority rule based aggregation caused distortions of most common and least common cover types by clumping most common cover types and eliminating the minor classes.

Working with the Regional Ecosystem Simulation System (RESSys) model over a 150-km² mountainous forested watershed in Glacier National Park to find out whether the model scaled linearly in complex terrain when changing resolution from Landsat TM (30m) through AVHRR (1Km) resolutions, (White & Running, 1994) found that the above ground NPP and photosynthesis remained stable across scales. However, they observed that evapotranspiration predictions changed with change in scales. As grasslands are very sensitive to moisture availability, it is reasonable to assume that if their study were repeated in Grasslands National Park, it would be more difficult to scale net productivity (Mitchel et al., 2005).

Zhu & Mackay (2001) looked at the effect different levels of detail had on predicted streamflow and photosynthesis using The Regional Hydro-Ecologic Simulation Systems (RHESSys), and found that detailed spatial soil information and distributed parameterization were important when there was moisture stress, but not at other times. Mackay & Band (1997) and (Creed & Band 1998) both demonstrate examples (also using earlier versions of RHESSys) where small pockets in the landscape that are disconnected hydrologically can produce very different dynamics from their surroundings, and that this behaviour is significant within the context of the landscape, but the ability to capture it is lost with aggregation that averages out the local soil water content. All of these studies demonstrate specific instances where issues of aggregation or details about landscape representation can have important impacts on the ability to predict ecosystem dynamics, (Mitchell et al., 2005).

Up-scaling peatland methane emissions hotspot is one of the most fundamentally important objectives in this research. As a result of differences in surface structure and functional traits of the vegetation, microforms differ greatly in ecosystem processes (Belyea & Baird 2006). This fine-scale and short-term variability creates problems for estimating current fluxes and for predicting future emissions under a changed climate (Belyea & Baird 2006). Highest rates of emission occur from hotspots such as pools and drought sensitive pools with seasonal to permanent surface water and other microforms with abundant cover of aerenchymous plants that can transport CH₄ directly to the atmosphere through their vascular systems (Moore et al., 1990). For example, methane (CH₄) emissions can vary by two- to four-fold across microforms that may be separated by only a few meters (Moore et al., 1990; Huttunen et al., 2003) and also show large seasonal variation (Waddington & Roulet 1996). As mentioned earlier that up-scaling emissions from the microform to landscapes and regions is highly challenging because the relationships between controlling factors such as water table depth, temperature and vascular plant cover and CH₄ emissions are non-linear and vary across cover types, the existing process-based models of methane emission (Kettunen 2003) are quite successful as long as water-table depth and aerenchymous plant cover can be provided as input. A promising approach involves linking a process-based model (Kettunen 2003; Walter et al., 2001) to remotely-sensed estimates of these key model drivers from the hotspots. So far, airborne and satellite remote sensing of peatlands has focused on coarser-scale issues of delineating major peatland types (Bubier et al.,

2005). Undoubtedly, methane emissions being non-linear across spatial and temporal scales due to high degree of heterogeneity, the real challenge in this research is to incorporate the non-linearity in processes and forms across different spatial scales by preserving the fine scale information which otherwise may be lost in aggregation from small to large scales. Hence it is envisaged that multiple data sets with multi-sensor and multi-spatial resolution data could be scaled up using different schemes such as wavelet multiresolution analysis (MRA) and quadratic interpolations (QI) that is expected to give improved estimated of peatland methane emission hotspots. Such standalone and independent data is also free from the bias due to resampling of pixels in case single data is used.

Remote sensing and peatland methane emissions

This research work utilizes multiple remote sensing (RS) data sets based on both space borne and air borne platforms. Airborne data acquired from ARSF (Airborne Research and Survey Facility) during spring and early summer from ATM (Advanced Thematic Mapper) and high resolution hyperspectral sensor systems (from SPECIM, Spectral Imaging Ltd., Finland) such as AISA's EAGLE sensor and satellite based IKONOS data would be tested against plot and landscape scales. LiDAR data is used to model the seasonal changes in the pool complexes while the optical RS data delineate the emission hotspots and for up-scaling.

The expansion and contraction of pools due to precipitation and other seasonal variations cause changes in the net effective wet area. As the methane emission hotspots are wet areas that has varying water table depth that triggers methane due to rise in temperature, it would be an interesting analysis to investigate the expansion of wet areas due to the rising water table and precipitation. This was possible using LiDAR data. Digital Elevation Model (DEM) developed from LiDAR is used to simulate the pool area expansions. In order to get an idea of fluctuation in water table depth from different microsites in different seasons, field measurements of water table depth (WTD) were recorded using water table depth loggers that were designed and installed in the peatland subjectively from March to October of 2007 and 2008. WTD fluctuations were measured on the monthly frequency. During winter and post winter the site was inhospitable for field work. The accuracy of DEM was ascertained by correlating the DEM with the surface elevation measurements recorded using a precision Total Station from two plots demarcated in the centre of the bog.

When coarse resolution data such as ETM+(Enhanced Thematic Mapper Plus), MODIS (The Moderate Resolution Imaging Spectroradiometer) or NOAA AVHRR (National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer) is used, the inevitable problem of mixed pixels or mixels due to limited spectral separability and instantaneous field of view (IFOV) would affect the classification of peatland at plot and landscape levels. Takeuchi et al, (2003) investigated a scaling up technique using two different pixel resolutions, a 20m SPOT HRV (Satellite Pour

l'Observation de la Terre, High Resolution Visible) and a 1.1km NOAA AVHRR sensor data for the estimation of methane emissions from Western Siberian wetlands. The underlying concept in their approach is the fusion of data with different spatial resolutions. HRV data were geometrically corrected and overlaid onto AVHRR such that one pixel of AVHRR covered a rectangular block of 55x55 SPOT pixels giving an RMS error between two images equal to 0.68 pixels in AVHRR size. A supervised classifier was trained by 30 in-situ training areas selected for each class on the basis of GPS (Global Position System) locations to classify the HRV data. A linear mixture model was used to un-mix each pixel in low spatial resolution data of AVHRR into four different categories by deriving the end members such as open bog, forested bog and birch forest and conifer forest types. Takeuchi et al., (2003) used chamber technique and reported mean rate of CH₄ from forested bog and open bog averaged 21.1 and 233.1 (mg CH₄/m²/day), respectively. The CH₄ emission from the area was estimated by multiplying these average CH₄ emission rates and the fractional coverage in each AVHRR pixel. The total CH₄ emission over AVHRR coverage was estimated to be 9.46 (10⁹ g CH₄/day) and the mean value over the AVHRR coverage was calculated as 59.3 (mg CH₄/m²/day). Hence overall result is crude and inconsistent with in-situ measurement which is reported in an earlier investigation Tohjima et al. (1994) at the same sites in which the average methane flux was 83 (mg CH₄/m²/day), which is about 1.4 times larger than above mentioned results.

There are many drawbacks in the method described by (Tekeuchi et al., 2003). Firstly, the assumption that all the classified SPOT HRV pixels into four classes that were superposed on AVHRR pixels are treated as pure pixels neglecting the mixels that would contribute for significant errors. Secondly, only vegetation cover is taken in to consideration and variation in water table depth (WTD) is overlooked. Since the spatio-temporal variation in WTD and vegetation cover cause non-linear effect in CH₄ emission flux rates (Barlett et al., 1988; Moore et al. 1990; Saarino et al. 1997; Walter et al. 2001; Strack et al. 2004; Wahlen S.C. 2005), further research is needed to address these issues to answer any scaling problem more accurately.

The landscape pattern within peatlands is highly heterogeneous, and fine spatial resolution data set would help discern plot level heterogeneity from both spectral signatures which distinguish between peat forming mosses and vascular plants (Bubier et al., 1997) and spatial resolution in further characterizing the microform features. It has been reported that CH₄ flux could not be related to the overall coverage of herbaceous plants or sedges, but on a finer scale the occurrences of vascular plants in wet sites were indicators of high methane flux (Bubier et al., 1997). Bryophytes have been found to be more sensitive to water table depth than were vascular plant, which makes bryophytes good predictor of methane emissions. Data from high resolution hyperspectral sensor systems (from SPECIM, Spectral Imaging Ltd., Finland) such as AISA (EAGLE due to the narrow contiguous bands would be useful to discern such peatland finger prints, but they also suffer from lack of wide area coverage. This would

lead to both spatial and spectral mismatch necessitating more research on up-scaling methods. The present work is focused on spatial scaling, thus improving the understanding of the complexity in which the forms and process in peatland methane emissions changes from plot to landscape and regional scales.

Problem Statement

Spatial scaling of land surface processes, such as land surface atmosphere exchanges of water and carbon, has been recognized as one of the most difficult and challenging issues in environmental sciences, (Bonan et al., 2002; Chen, 1999; Jarvis, 1995; Kimball et al., 1999).

There is a wide range of global budget reported by various sources and collected in the AR4-WG1 of IPCC (2007) and also recently updated reports shows big difference in the range of methane emissions from the wetlands as shown in the table 1.

One of the main sources of error in the regional and global estimates of CH₄ emissions from peatlands is loss of fine scale heterogeneity in the main controlling factors such as water table depth; aerenchymous plant coverage and peat temperature. At larger scales, individual process-level controls on CH₄ production and emission frequently shows non-linear interaction in the wetlands, that are characteristically variable with respect to environmental drivers of CH₄ emission at time scales ranging from hours to years and spatial scales of <1m, (Whalen & Reeburgh 1990). Extrapolating point source emissions measured from *in situ* chambers, to landscape and regional scales using

process based models (Walter et al., 2001) by assuming mean water table and mean surface temperature would introduce bias in the final values leading to erroneous results. Peatland *in situ* measurements over vast areas presents an extremely difficult and challenging task. Repetition of measurements is equally challenging and also expensive both in terms of time and resources. Remote sensing (RS) can overcome this challenge. Very high spatial resolution optical RS data and Lidar data could help quantify the fine scale details such as water table depth in flooded pools and water logged areas, aerenchymous vegetation etc., but often suffers from wide area coverage due to narrow swath. Moderate resolution RS data has a wide coverage, but it is unsuitable to discern detailed information of the heterogeneous surface of peatland, thus, pose the problem of spatial and spectral mismatch. Hence, it was the objective of this project to determine whether utilising different RS data, if any well-defined scaling relationship exists between different spatial data from fine to coarse resolution, if available then what issues would one faces, such as whether there would be loss of information, preservation of pattern and fine scale heterogeneity and if the methods are transferable to other study areas.

Thus, the aim of this project is to scale up peatland methane emission hotspots using multiresolution earth observation data and address the issues in upscaling. "Scale" is used to refer to the size or spatial extent of the study area (plot, landscape, region and geographic extent) and also to the degree of detail e.g. pixel size or pixel resolution (fine resolution (0.25 m-1 m) to coarse resolution (>1 m-1 km). Peatland methane

emission estimates from plot scale are often measured by using chambers of size 25 cm² to 50 cm² (Scheutz et al.,2009) (in the present work remote sensing equivalent of Digital photograph of pixel size ≤ 0.25 m-0.5 m) and then emission estimates are derived at the landscape (ATM, EAGLE and IKONOS pixel size >1 m ~ 5 m), regional (SPOT HRV, ETM+ pixel size ≥ 20 m) and global scales (for example MODIS, AVHRR) by multiplying flux rates that have been averaged across major peat land types by remote sensing based estimates of areas of peat land cover (Takeuchi et al., 2003, Becker et al.,2008). If the peatland surface is homogeneous and the methane emission processes are linear with respect to the water table depth and peat temperature, then averaging is justified. But the peatland surface is normally highly heterogeneous and the processes are non-linear, therefore simple averaging gives biased estimates of methane emissions. Hence in the present work, a Scottish peatland site which has a series of microforms such as the classical hummock-hollow-pool systems (Boatman 1983) is investigated to understand scaling issues to compliment the accurate estimates of peatland methane emissions.

Up-scaling here refers to the aggregation of key drivers of methane emission, such as water logged areas and pools within the bog area and lawns with vascular plant coverage, from very fine resolution to coarser resolutions. Up-scaling is required to expand knowledge from a fine to a coarser resolution.

Natural wetlands have been identified as the largest source of methane to the atmosphere (Walter et al 2001) and figure 1, IPCC (2013). Lelieveld et al (1998)

reported that 76% of methane emissions from all the natural sources are contributed by natural wetlands. In sharp contrast to the former, (Galchenco et al., 1989) reported that natural wetlands release about 20% -30% of total annual global methane emissions. The large spatial and temporal variation in methane emissions is one reason for the wide range of estimates available for methane emissions from peat lands, and regional differences can be significant even when the sites are similar in climate, vegetation and topography (Sebacher et al., 1986, Crill et al., 1992). Climate change modellers need accurate statistical information on the variables deriving peat land CH₄ emissions in the investigations for global carbon cycle.

The major sources of methane in the atmosphere have been identified table 1 and figure 2, IPCC (2007), but many are poorly quantified and characterised, introducing considerable uncertainty into model predictions of future trends in atmospheric methane, (Whalen 2005). The approach taken in the above mentioned studies does not take into account the small to large scale dependent interactions that occur between processes and spatial variations in drivers like water table depth and peat temperature. Such spatial averaging would also results in the loss of pattern on peatland leading to biased area estimates of hotspots (Mohammed et al, 2009). The up-scaling of ecological processes requires a simplification of landscape complexity. Such a simplification is a critical issue in land surface modelling as ecosystem model simulations depend closely upon the representation of land surface heterogeneity, (El Maayar et al., 2006). Peatlands display such an extreme heterogeneity causing

difficulties in accurately quantifying variations in factors controlling methane emissions. Therefore, a scaling method is needed that preserves the pattern on the peatland whence up-scaling, thereby reducing the bias in area estimates of hotspots caused by simple averaging with a minimum loss in the information in every step of resolution degradation.

Data set used for investigation

Aircraft and satellite based remote sensing imagery is used. The data collected by NERC's ARSF from the aircraft are Digital photography (DP), Airborne Thematic Mapper (ATM) Multispectral data, AISA's EAGLE hyperspectral data, LiDAR data. The IKONOS data from the GeoEye's satellite platform with its native ground sample distance (GSD) of 0.82 x 3.2 m was purchased was obtained with the output resolution of 1 m x 4 m pixel size. ETM+ was freely downloaded from internet with the pixel resolution of 28.5 m. The spectral range of ATM and AISA's EAGLE sensors is shown in Figure 4. Table 2 shows the initial pixel size of different data set used before applying any upscaling techniques.

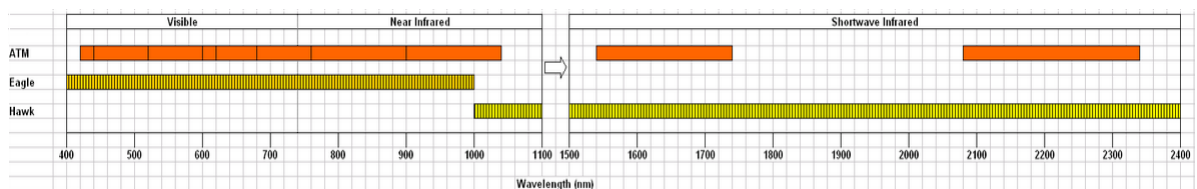


Figure 4: Spectral wavelength range of ATM and Eagle data (adopted from NERC's website)

Name of the Sensor	Pixel size in square meters
Digital Photography	0.25
ATM	1.5
LiDAR	1 , 4
IKONOS	1, 4
EAGLE	5
ETM+	28.5

Table 2: List of different aircraft and satellite remote sensing data used in this project

Thesis outline

The overall aim of this Thesis is to scale up peatland methane emission hotspots such as pools, hummocks, and lawn with shunt species from small to large scales from a Scottish peat bog area, Silver Flowe, using multi-resolution multiple sensor remote sensing data.

Chapter one (this document)

This is an overall introduction chapter which describes the problem statements, aims & objectives of the entire project. It also describes the arrangement of the entire thesis. Traditional method of thesis writing has been avoided. It is the intention of the Author from the start to produce independent standalone papers publishable in peer review journals. Therefore, all the chapters are independent but complete in the context of the thesis and each one is addressed to one or a combination of the overall thesis aims and objectives. As such the readers will find some part of the introduction repetitive in

each of the papers. It makes sense when every paper is seen as a standalone independent chapter in itself.

Paper I

In this chapter we applied wavelet theory to understand the up-scaling behaviour peatland surface features that are considered as hotspots of methane emissions. The hierarchical phenomenon with its information about the dominant and average pattern across spatial scales has been shown to be lost using pixel averaging but preserved using quadratic interpolation. This phenomenon in which the position and location of the microforms is preserved could also be integrated using wavelets. This capability of wavelets which preserves the location and position of a detected pattern and enables interpretation of the individual patterns within its ecological concept is investigated here.

Paper II

This chapter demonstrates the impacts of different remote sensing products and spatial aggregation techniques on the quantification of peatland features. Applying concepts from the information theory such as Shannon entropy and information transfer such as Kullback- Liebler distance, the transfer in information is quantified from fine scale to coarser scale. The analysis using quadratic approximations improved multi-scale estimates of the spatial extent of important peatland microstructural elements. These elements were not well preserved by mean aggregation.

Paper III

This chapter describes *in situ* water table depth measurements carried out at monthly intervals during the March-November of 2007 and 08. It discusses the hydrological investigations using LiDAR data. The expansion of pools due to increased precipitation and their area after inundation is calculated using a DEM from LiDAR data.

Paper IV

In dealing with scale in ecological research applications, it is necessary to understand and appreciate how changing the scale of observation affects research results and their interpretation. The presence of scale-dependent heterogeneity is important in two main contexts, particularly when the results are interpreted at large coarse scales, ETM+ data with 28 m pixel resolution was downloaded from USGS website for : 1) defining a suitable scale range which would reveal for instance the variation of hot-spot structures such as pools and lawns and other structures such as hummocks and hollows, at such large scales and 2) characterizing the nature of the spatial variation of these structures so that the scale of measurement may be changed, meaning that the data may be up-scaled with the implication on regional scale modelling. In this chapter geostatistical technique such as variogram analysis and fractal analysis is examined and combinations of object based techniques with spectral and statistical techniques were discussed.

Summary and overall Conclusions and Outlook

This chapter draws conclusions from all the above four papers and collates them together into a common conclusion. In outlook, it also discusses and criticizes the present work and proposes future work that is required to further improve our understanding of the complexities involved in scaling up the peatland methane emission hotspots.

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Multiresolution wavelet analysis of spatial pattern distribution on peatland from multi-sensor data to up-scale landscape heterogeneity

Abstract

The importance of spatial heterogeneity in peat landscapes which are scale dependent and their influence on estimation of gas fluxes has been long recognised. However, little attention is given to determine appropriate techniques to preserve the pattern on such landscapes especially when remote sensing (RS) techniques for scaling up from plot to landscape and regional scales for the assessment of regional and global methane emission estimates. An interesting question that needs to be addressed: How do changes in scale bring changes in pattern on peatland and does this affect estimates of CH₄ emissions? The pattern of pool complexes and other terrestrial microforms on the bog centre and their spatial variation controls the CH₄ and this detail information has to be preserved. In the present work, an approach based on 2-D discrete wavelet analysis is presented in which the hotspots responsible for methane emissions, such as pools, lawns with hummocks and vascular vegetation, with multi-scale features of different remote sensing (RS) data are quantified and their spatial variation with increasing coarseness in pixel resolution is analysed. This paper presents four different RS data sets taken from aircraft and satellite platforms with the pixel resolutions from 0.25 m to 5 m to upscale and characterise pattern on peatland using 2D discrete wavelet multiresolution analysis on the classified imagery. We then computed the wavelet variance on different levels of wavelet decompositions. Our results show that wavelets preserve the surface patterns to some order of up-scaling and reveal that the peatland surface shows scale breaks after some level of wavelet decompositions. Further the variance analysis suggests that high resolution data show steep decadence in lower levels of wavelet decompositions while coarse resolution data shows a shallow rate of decay in variance with increasing scale. The wavelet variance gives scale by scale variance analysis. Thus, our analysis clearly shows the scale dependencies in patterns on peatlands and demonstrates preservation of pattern which is crucial in the accurate assessments of methane from peatlands.

Key words: *heterogeneity, methane, multiresolution analyses, peatland, spatial pattern, up-scaling, variance, wavelet*

Introduction

Detection and quantification of ecological phenomenon over multiple scales and often at large scales is a very complex issue. Ecological investigations are made simple (Wiens, 1989) primarily due to limitations in time and resources required for data gathering. With the improvements in remote sensing technologies, it is now possible to collect a number of long terms; large aerial data coverage repeatedly for performing statistical analyses in both domains. Thus, proper interpretation in spatial domains would lead to closer approximations of the way ecological relationships naturally exist. Such analyses would aid further in our understanding of the contributions made by heterogeneous land surfaces in the assessment of emission fluxes and helps in selecting sampling resolution with appropriate scale.

Peatland is one such ecological system that shows non-linear variation in variables that affect methane emission fluxes. In the assessment of gas fluxes from peatlands, important variations in peatland microtopography, and thus variability in water table mean position, are often unaccounted for (Walter et al. 2001). The quantification of peatland methane emissions are typically conducted on small scales ~ 0.25 m using chamber based methods (Strack et al., 2004), but the climate change due to green house gasses (GHGs) models and general circulation models are usually on large scales (XIE Jiangbo et al., 2007), there is a clear need for scaling. Understanding the correlations and dependence of spatial patterns with scales is necessary for spatial heterogeneity analysis which in turn is necessary for up-scaling of methane fluxes from the peatlands. As such any method that is sufficiently detailed to detect patterns at multiple scales and yet practically easy to implement is required to properly extract

information from the complex data. The technique used should preserve information in the form of spatial pattern when moving from fine scale to a coarse scale. Many conventional methods have been proposed to describe the heterogeneity in the peatland topography with scales and spatial pattern distributions (Saunders et al. 1998; Broszofski et al. 1999; Redding et al. 2003; Wang et al. 2004). Work carried out by (Becker et al., 2008) showed that when the pixel value is aggregated from 6 cm to 100cm using a simple mean value, the carbon budget would be underestimated by about 9.3%. Brunsell & Young (2007) investigated wavelet signal on the precipitation and reported how the signal is transferred into soil temperature and vegetation signal. They quantified the statistical distribution of both normalized difference vegetation index NDVI and soil temperature field that are directly due to spatial variability of precipitation and how this relationship varies with spatial resolution. In the present work, an approach based on 2-D discrete wavelet analysis is presented in which the hotspots responsible for methane emissions, such as pools, lawns with hummocks and vascular vegetation, with multi-scale features of different remote sensing (RS) data are quantified and their spatial variation with increasing coarseness in pixel resolution is analysed. Wavelet techniques are ideal for decomposing nonstationary variation across space into the frequency domain, for robust analysis of the patterns of variation at the landscape level that contribute to the structure, and thus function, of the wetland ecosystem investigated here. The results contribute in understanding how the methane emission hotspots affect the emission fluxes from plot scale to landscape and regional scales. The aerial classification of such hotspots has a direct bearing on the net flux estimates in peatland. The present paper aims to describe the methods from wavelet theory applied to peatland ecology domain of Silver Flowe in southwest of Scotland. Of particular interest is the addressing the question of how do different spatial

scales affect the peatland heterogeneity when upscaled from fine to coarser resolutions. When looked through fine scale data, one could see that the pools are clearly demarcated. However, if the pixel resolution is enhanced to some coarser resolution then how will be the emerging pattern? And would the original pattern is preserved during up-scaling or the smoothing caused by wavelet functions alters the pattern on peatland, if so then at what scale? And how do these changes affect the emission fluxes from plot scale to regional scale. However due to lack of temporal data sets available, this analyses is limited only to spatial domain.

Wavelets have good space-time localization, can represent data parsimoniously, and can be implemented with fast algorithms (Cho & Chon 2006). Wavelet transformations approximate a data series by linear combination of functions (wavelets or small waves) with specific scales (resolutions) and locations (positions along the data series) (XIE Jiangbo et al., 2007). Two dimensional wavelet analyses is novel in its ability to detect and quantify the boundaries and internal structures of the ecological data set at multiple scales (Csillag and Kabos, 2002; Anthony J.A., 2004). Identification of multi-scale patterns of landscape using IKONOS PAN Image (Sun, 2003) has also been performed using wavelet analysis. In another study, wavelets have been used to model remotely sensed spectra for noise reduction as well as for detection and extraction of characteristic features from the spectral signatures (Carvalho, 2001). Bruce & Li (2001a) and Shimidt & Skidmore (2003) showed how wavelet transforms can be used to smooth spectra before further analysis. Their approach provides an effective way of selecting appropriate width for the smoothing filters (Carvalho, 2001). Bruce & Li (2001) have also pointed out the significant gain in computation time achieved by the method. In another study (Koger et al., 2003), the authors demonstrated that features extracted from wavelet transforms were superior to the original spectral bands and to features extracted with principle

component analysis for discriminating between weed-free soybean crops and soybean intermixed with pitted morning glory. Automated detection of hyperspectral targets was also tackled by Bruce et al. (2001) and Bruce et al. (2002a) making it a powerful tool for the detection of constituent's absorption bands within hyperspectral signatures.

Another application of wavelets is in image edge detection. Edge detections and linear features are effectively characterized from images using wavelet transforms. In fact, edge detection was one of the first applications of wavelet transforms in image processing (Mallat & Zhong, 1992). The first scale of decomposition and the respective modulus maxima curves provide an efficient framework for the detection of linear features such as agricultural field boundaries, streets and roads (Ji, 1996; Dong et al., 1997).

Ecological data such as Silver Flowe peatlands shows concentric patterns of pools (hotspots for methane) from bog centre to the bog margin together with other micro-structural elements (MSE) such as hummocks, hollows and lawns that show heterogeneity forming the part of the bog expanse (bog centre). This hierarchical phenomenon with its information about the dominant pattern across spatial scales has been shown to be lost using pixel averaging but preserved using quadratic interpolation (Mohammed et al., 2009). This phenomenon in which the position and location of the MSEs is either lost or preserved could also be integrated using wavelets. This study investigates whether wavelets are capable of preserving the location and position of pattern, and therefore, quantifying the multi-scale spatial patterning of Silver Flowe peatlands. The results of the different remote sensing (RS) imagery for the purpose of characterizing heterogeneity of peatland surface features and upscale methane flux hotspot estimates is described.

Materials and Methods

Overview

In this research, four different remote sensing imagery were first classified using pixel based unsupervised technique into six classes. The spatial resolution of the multispectral IKONOS image was enhanced by fusion with the high resolution panchromatic image before classification. Concepts from wavelet theory are applied to scale up the six classes to find change in pattern on peatland and also to find out the dominant scale and dominant orientations with respect to the scale. The uncertainty analysis was performed using both qualitative and quantitative methods. Finally the discussions were followed by conclusions and outlook.

Wavelets Analysis

A wavelet transform divides the signal in to its frequency components and then study the component with a resolution matched to its scale (Daubechies, 1992). Analysis of data from such complex landscapes by wavelets allows one to capture the spatial pattern on the landscape with its fine scale details. The present work is restricted to the analysis spatial aspect of the peatland landscape as the RS temporal temporal data was not available.

A wavelet transformation converts the data in an orthonormal basis generated by a dilation and translation of a father and mother wavelet (Li et al., 2002). A function $\psi(x)$ is called a mother wavelet such that:

$$\{\psi(2^j x - m), i, k \in \mathbb{Z}\}$$

in an orthonormal basis of function space $L^2(\mathbb{R})$, and a function $\phi(x)$ is called a father wavelet or a scaling function such that

$$\phi(x) = \sum_{m=-\infty}^{+\infty} a_m \phi(2x - m).$$

Wavelets functions satisfy certain requirements, i.e., they have compact support; they are orthogonal and have vanishing moments¹. As each wavelet is supported on a finite interval, the wavelet function is constrained to be zero outside the finite support. This implies that with a compact support the processing of the region of data with the wavelet does not affect the data outside of this region and hence wavelets are localized. The property due to vanishing moments ensures that the data are denoised and also reduce dimensionality. The vanishing moments also ensures distinguishing essential information from noise and using some threshold one can eliminates the noise.

For any particular application, the choice of mother wavelet is an important precondition for satisfactory results, but there is no known and standard method for the selection of a particular wavelet and mostly the decision is based on trial and error methods. However, a general suggestion is that the important properties of a wavelet filter to be considered are compact support, symmetry, orthogonality, regularity and the degree of smoothness (Grgic & Grgic, 2001).

The raster data from remote sensing is an approximation of the sensors field of view of the target integrated to a square pixel. The Haar wavelet and Daubechies db1 wavelet has the shape that corresponds to the shape of a raster data pixel besides meeting the criterion discussed above. Hence, in the present work, db1 wavelet is applied to study the scaling behaviour of the classified images using a two dimensional multiresolution discrete wavelet analysis.

2D Multiresolution discrete wavelet analysis (2D-MRDWA)

Discrete wavelet transform (DWT) was developed to efficiently compute the time-scale representation of non-stationary signals (Poliker, 2006). A basic and comprehensive introduction as well as advanced concepts on DWT and multiresolution analysis (MRA) can be found in (Gonzales and Woods, 2002; Boggess and Narcowich, 2001; Goswami and Chan, 1998; Polikar; Daubechies, 1990; Strang and Nguyen, 1997). Two dimensional multi-resolution discrete wavelet transform is analysed as 2D and represents spatial variability in complex data sets (such as images in this case) by linearizing and approximating the pixels in horizontal, diagonal and vertical directions (Daubechies 1992, Bruce & Gao 1996). In a 2D DWT (Gonzales and Woods, 2002) a 2D scaling function, $\varphi(x,y)$, and three detailed wavelets $\psi^H(x,y)$, $\psi^V(x,y)$ and $\psi^D(x,y)$ representing the horizontal, vertical and diagonal directions respectively are required that produce a separable scaling function as follows,

$$\varphi(x, y) = \varphi(x)\varphi(y) \quad (1)$$

and wavelets in the three directions,

$$\psi^H(x, y) = \psi(x)\psi(y) \quad (2)$$

$$\psi^V(x, y) = \varphi(x)\psi(y) \quad (3)$$

$$\psi^D(x, y) = \psi(x)\psi(y) \quad (4)$$

Each directional wavelet measures the variance of the images along horizontal ψ^H , vertical ψ^V and diagonal ψ^D directions respectively (Gonzales and Woods, 2002).

The scale (a) and translated (b) basis functions are then defined as

$$a = \varphi_{j,m,n}(x,y) = 2^{j/2} \varphi(2^j x - m, 2^j y - n), \quad (5)$$

$$b = \psi_{j,m,n}(x,y) = 2^{j/2} \psi^i(2^j x - m, 2^j y - n), \quad (6) \quad i = \{H,V,D\},$$

the index i defines the direction of the wavelets in the above equations.

Thus the discrete wavelet transform of a function $f(x,y)$ of size $M \times N$ (in this study four contrasting image data sets in table 1) is then, (eq. 7) and (eq.8) below,

$$W_{\varphi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \varphi_{j_0,m,n}(x,y) \quad (7)$$

$$W_{\psi}^i(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \psi_{j,m,n}^i(x,y) \quad (8)$$

$$i = \{H, V, D\}$$

where j_0 is an arbitrary starting scale and eq. 7 is the approximation of $f(x,y)$. Eq. 8 gives the coefficients in the three directions for the scales $j \geq j_0$. Once we obtain the information in eq. 7 & 8, we get $f(x,y)$ via the inverse discrete wavelet transform in eq.9 below:

$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_{\varphi}(j_0, m, n) \varphi_{j_0,m,n}(x,y) + \frac{1}{\sqrt{MN}} \sum_{i=H,V,D} \sum_{j=j_0}^{\infty} \sum_m \sum_n W_{\psi}^i(j, m, n) \psi_{j,m,n}^i(x,y). \quad (9)$$

In the above equation n is the number of wavelet decompositions.

Multiresolution analysis (MRA)

The 2D discrete wavelet transformation (DWT) analyzes the input signal at different frequency bands with different resolutions from an analysis filter by decomposing the signal into one coarse approximation (eq.7) and three detailed coefficients (eq.8) in the three directions as

mentioned above, and shown in Figure 1 below with the example of ATM data. Each section of the wavelet transform contains the coefficients in different directions for that scale. The width of the section corresponds to the number of observations it contained. The larger the section, the more the observations and hence the finer scale. The smaller sections represent less observations and coarser scales. For up-scaling we need only the smoothed approximations, while the details coefficients together with the smooth approximation are required for reconstruction of the synthesized image. This is computed by taking the inner product of $f(x,y)$ and the 2D scaling and wavelet functions, that are associated with the low pass filter and high pass filter respectively, in eq. (1) through (4) followed by a subsampling by two in each dimension. The wavelet coefficients are the inner product of the original signal and the wavelet (Mallat 1989). Thus low pass filtering halves the resolution, but does not change the scale. Once the signal is subsampled by two, this doubles the scale (Polikar, 2006). The total number of decompositions possible is determined by sample size (N) according to the rule $\log_2 N$, which means that the number of scales we could possible analyze for a given imagery is restricted by the domain size of the study area or image (Percival, 2000). Table 2 below shows the different levels of wavelet decompositions for all the image data in this study.

Thus in a discrete wavelet transform, the image is discretized along the square pixels spacing Δ (table 2). The scale parameter a is evaluated by $2^{j-1}\Delta$, where $j = 1, 2, 3$, are the levels at which the wavelet transform is computed. So, for level $j=1$, the wavelet transform is analysed at scale $a=2$ that is translated to $b = [2\Delta, 4\Delta, 6\Delta \dots]$. At level $j=2$, it is analysed with a wavelet of scale $a = 4$ that is translated to $b = [4\Delta, 8\Delta, 12\Delta \dots]$ and so on. In general, for a scale parameter $a = [2\Delta, 4\Delta, 6\Delta \dots 2^j\Delta]$ the shift or translation parameter is evaluated for $b = [2a, 4a \dots]$.

Methods:

Study site

The study area is located in south west Scotland in the Galloway forest reserve, U.K. It is declared as the site of special scientific investigations (SSSI). The total area of this landscape is approximately 192 ha. The pool complexes are located on the centre of the bogs and are concentrically aligned parallel to the contour lines forming a spatial pattern in the bog centre. The landscape becomes plane as one move from the central part to the edges of the bogs. This patterned landscape is termed “Silver Flowe” which has a series of bogs very similar in surface characteristics. Detailed description of individual bogs and their characteristics are described in (Boatmann 1987). A plot is demarcated on the northern side of the bog encompassing the patterned hummock, hollow and pool complexes as shown in the Figure 1 for the analysis from each data set and results are outlined below.

Table 1: The table below describes the four images and their corresponding scales and decomposition levels.

Scale $2^{j-1} \Delta$	DP ($\Delta=0.25$ m)	ATM ($\Delta=1.5$ m)	IKONOS ($\Delta=1$ m)	Eagle ($\Delta=5$ m)
L0; J=1	0.25	1.5	1.0	5.0
L1; J=2	0.5	3.0	2.0	10.0
L2; J=3	1.0	6.0	4.0	20.0
L3; J=4	2.0	12.0	8.0	40.0
L4; J=5	4.0	24.0	16.0	80.0

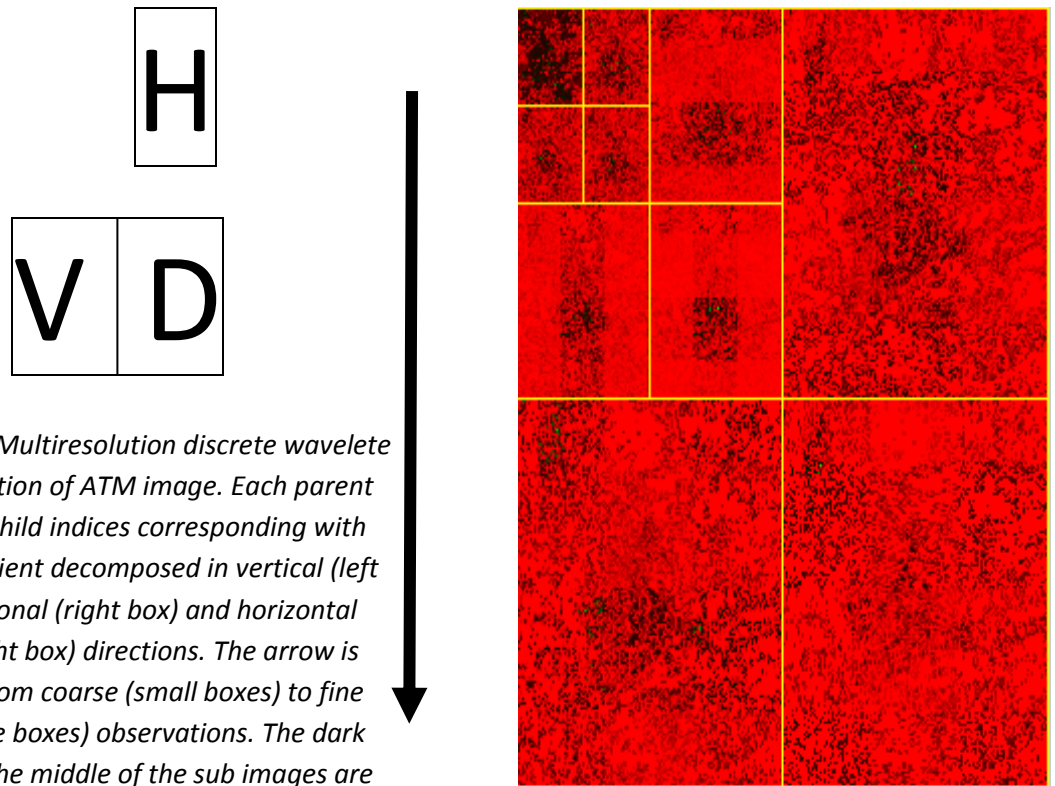


Figure 1: 2D Multiresolution discrete wavelete transformation of ATM image. Each parent has three child indices corresponding with each coefficient decomposed in vertical (left box), diagonal (right box) and horizontal (upper right box) directions. The arrow is pointing from coarse (small boxes) to fine scale (large boxes) observations. The dark regions in the middle of the sub images are the hummock and pool complexes.

Remote Sensing data:

In July 2007 airborne ATM and Eagle sensor data along with LIDAR data was acquired. The satellite based multispectral and panchromatic IKONOS data was also purchased during the same time. The data sets were pre-processed for atmospheric and geometric corrections using ATCOR4 (Richter 2007) and AZGCORR (Azimuth Systems 2001) respectively. A digital photography is also obtained over the study site. A subset of the color infrared band combination of the ATM, EAGLE and IKONOS data set from the study site is shown below besides the digital photography in Figure 1. The concentric and complex pattern of pools can be viewed in the centre of the Figure 3A-D. The table 1 below describes the subset and resolution details for all the data set as shown in the Figure.

Image Fusion

To better identify natural and built objects from a low resolution images, a merging technique known as image fusion is used to improve the quality of the low resolution images. The term quality depends on the application (Wald, 1999). Due to some technological constraints the optical remote sensing images acquired from satellites may have good spectral resolution but lack in spatial resolution, while other satellites sensors could identify the objects spatially, but not spectrally. But new satellites carry dual resolution data scanned in both panchromatic mode as well as multispectral mode. IKONOS sensor has such high resolution panchromatic image with 1 m resolution along with a multispectral four band low resolution image of 4 m pixel size. The 1 m PAN image is very good to discern small sub-meter features on the peatland surface such as hummocks and small sub-meter size pools as compared to the coarser 4 m image. However, the spectral information associated with multispectral data would be useful in distinguishing vegetation, aquatic and other non-aquatic features. When the two data sets of IKONOS are merged using image fusion techniques, a better results is expected from the combination of high spatial (1 m) and low resolution multispectral data, Figure 2 below.

There are many methods that are available to carry out image fusion to combine the two images. For a comprehensive review see (Pohl and Genderen, 1998). Other methods that compare IKONOS imagery is very well described in (Wang et al., 2005). The fusion of IKONOS PAN and multispectral image is carried out using the ENVI image processing software (ENVI Version 4.5 August 28, 2008, The Environment for Visualizing Images, Research Systems, Inc., Boulder, CO USA). The low resolution multispectral data is resized by a factor of 4 to get the pixel size of high resolution PAN 1 m data. The fusion method in ENVI uses intensity hue saturation (IHS) value technique that is based on human colour perception parameters that

separates the spatial and spectral components of the RGB image. The ENVI model has the hues in the range of 0 to 360 degrees where red is zero degrees, green is 120 degrees and blue is 240 degrees. The saturation ranges from 0 to 1. In the transformation, the multispectral LRMSI bands produce the hue and saturation parameter while the HRPANI produces black to bright white values. The IHS transform converts LRMSI bands from RGB colour space to the IHS colour space. The spatial details of high resolution PAN image are then introduced to the RGB transform of the low resolution multispectral image by replacing the spatial component of low resolution multispectral image. The resulting image is a high resolution multispectral image (HRMSI) (Wang et al., 2005).

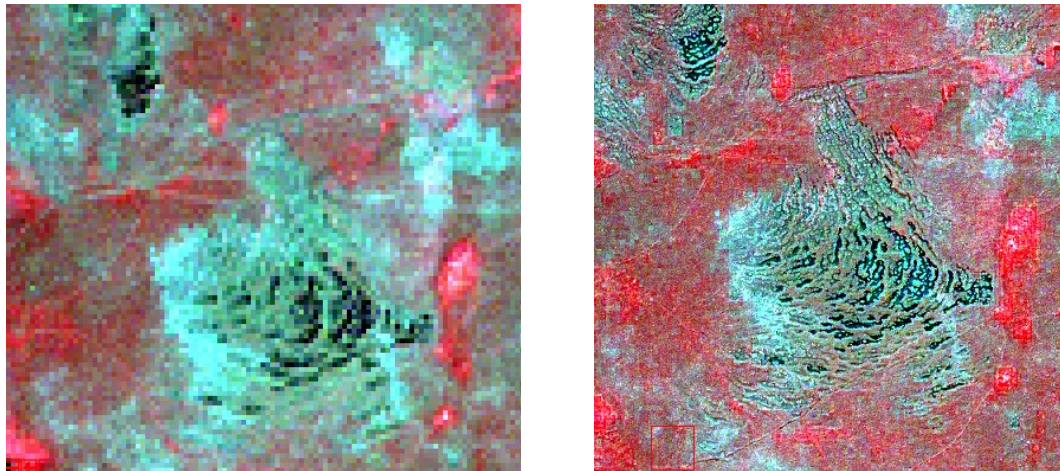


Figure2: Pan fusion IKONOS image. On the left is the 4m multispectral CIR image and on the right is the panchromatic 1m image fused with the multispectral 4 m image to obtain a 1m multispectral sharpened image.

Classification of data sets

All the images used here were classified using a unsupervised classifier available in the standard classification tool (ENVI 4.5 @ 2008, ITT Visual Information Solutions) into aquatic and non

aquatic regions and therefore, . A differential global positioning system (DGPS) was used to record the coordinates of the pools, hummocks, *Eriophorum vaginatum*, *Calluna vulgaris* and *Molinia* dominant areas on the ground. Their location was identified on the imagery by transferring the DGPS recorded coordinates to empirically validate the classification results. As the main objective was to analyse how the heterogeneous spatial pattern on the peat bog changes with the decrease in resolution of the original imagery from fine to coarse resolution, and to find out upto what length scale the pattern on the bog centre is preserved, the classified maps were directly used into the 2D DMRWA without any further post processing. The classification results from the digital photography with 0.25 m pixel resolution was considered as ground truth. The unsupervised classification results with six classes from all the four data sets is used for the wavelet analysis. The classification results were empirically tested by comparing with the digital photograph classification results based on evidence from the site visits, and considered as the representation of the pools, hummocky lawns, *Eriophorum vaginatum* lawns, *Calluna vulgaris* lawn, *Molinia* lawn and other sedges on all the data sets.

Discrete wavelet transformation of classified data

The objective was to analyse the spatial variation of the peatland surface heterogeneity and determine spatial pattern of the upscaled peatland surface. It has been demonstrated that with the mean pixel averaging the peatland surface pattern is lost leading to highly biased estimates of the surface features , while a quadratic approximation would not only preserve the surface pattern but also gives accurate estimates of the classified features (Mohammed et al; 2009). However, in the present work it is intended to assess and demonstrate the power of 2D DWT

and MRA on the Silver Flowe peatland in particular and recommend generalisation of this approach for any type of wetland studies.

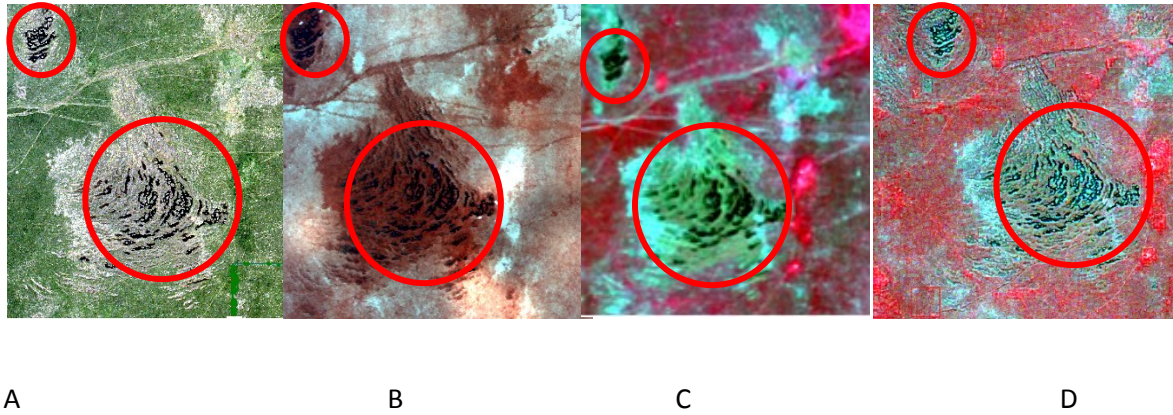


Figure 3: Silver Flowe bog centre images taken from different sensors: A) digital photograph and color infra red band combinations of B) ATM, C) Eagle and D) IKONOS sensors. The resolution (pixel size) of DP is 25cm, ATM is 1.5m, Eagle is 2.5m and IKONOS is 4m respectively. The red circles indicates the main pool complex on the bog centre and one on the N-W region of the peatland. The small black concentric regions are the pool complexes in the centre of the bog which are clearly seen in A and blurred in D with the change in the spatial resolution (black spots). Hummocky heather ridges are concentrated around the pool structures. Rest of the image has scattered *Culluna vulgaris*, *Eriophorum vaginatum*, *Molinia* and sedges

Table 2: Data source and subset size

Image source	Resolution (m)	Sample size (subset) N	Domain Area in m ²
Digital Photograph	0.25	1024x1024	65536
ATM	1.5	512x512	147456
Eagle	5	96x96	230400
IKONOS	1;4	256x256	63356

Uncertainty estimates using image quality and quantitative measures:

Percentage deviations

Any up-scaling procedure used would affect the quality of the image due to the smoothing effect caused by the up-scaling window across the image domain. Subsequent wavelet decomposition reduces the resolution of the image while at the same time increase the size of the pixel. Thus, two different methods were used to compute the uncertainty caused by db1 wavelet up-scaling. One is more local and quantitative at individual class level. This is done by determining the percentage deviation of the ratio of area of each class to the total area of the domain of the data at every level of decomposition,

$$(A_{i0}/T_{j0} - A_{i1}/T_{j1}) * 100$$

where A_{i0} is the area of the class ($i=1:6$) at level $j0$ and T is the total area and A_{i1} is the area of the class ($i=1:6$) at level $j1$ computed for all the six classes.

Results

All the four image data set were scaled up using the wavelet scheme explained in the previous sections. The upscaled data and their variances are plotted against scale show the change in areas of the classes after each upscale step. Inferences are drawn from the graphs about dominant scale and also any scale breaks along the up-scaling ladder.

Scaling of the six classes with different imagery is shown below with highlighted values in yellow boxes showing the possible combination of results that may be compared due to similar pixel sizes.

Digital Photography (DP)

As shown in the table 1 above, the 0.25 m pixel resolution DP that was used to classify the image into six classes had an area of 65,536 m² with the initial size of the image being 1024x1024 pixels. After the first level of Daubechies db1 wavelet decomposition the pixel numbers halved to 512x512 while the size of the pixel doubled to 0.5 m. The initial classified image had 10.25 % of the total domain as pool area. With the first level of decomposition the pool area was reduced to 8.78 % and a further level of wavelet decomposition left the total pool area almost unchanged to 8.79 %. The next level of wavelet decomposition resulted in new domain that is half the previous one and equal to 256x256 pixels resulting in new pixel size of 1 m.

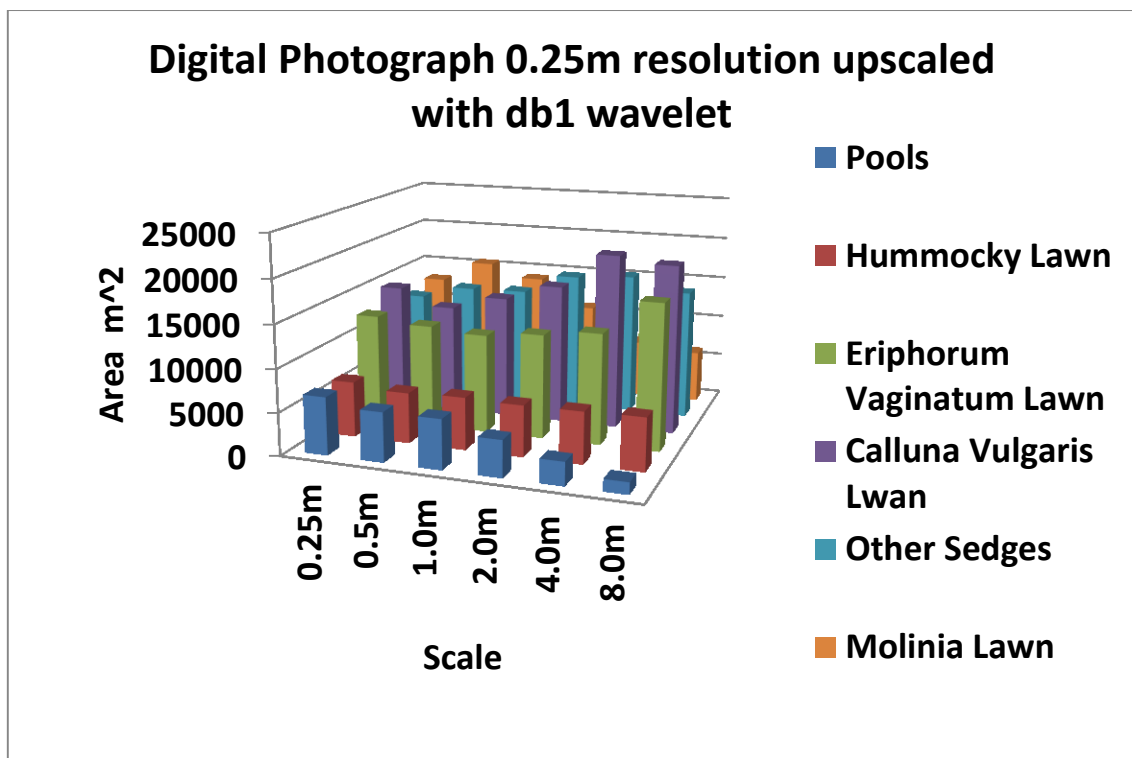


Figure 4: Area of the six classes plotted as histogram bars against the resolution for all the four sets of the digital photography

The decomposition scheme follows the rule $j = \log_2 N$ where N is 1024 for the digital photograph. The above process could be repeated until ten decomposition levels according to the scheme. However, in the present analysis, only $j = 5$ levels of decompositions were done. At the 3rd level of wavelet decomposition, as the domain size was 256x256 pixels, the percentage change in pool area was reported as 6.5 % and the new pixel size was 2 m. The next two decomposition levels of the DP reported a reduction in a total pool area of 4.1 % and 2.05 % for pixel sizes of 4 m and 8 m respectively at the fourth and fifth decomposition levels.

In contrast to the above, the total vegetation coverage of the DP domain increase from 89.75 % to 97.95 % from the first level of decomposition to the fifth level of decomposition. A histogram of all the classes was plotted with a bin size equal to six and multiplied by the area of each pixel at the respective decomposition level to compute the area of all the upscaled images. The changes in areas of all the six classes with respect to the pixel resolution as a bar plot are shown in the Figure 4.

ATM data

The 2D multiresolution wavelet analysis using Daubechies db1 wavelet upscaled the ATM data with 512x512 size, following the same scheme as above with total levels that are possible was $j=9$. Only five steps were analyzed from 1.5m scale to 24m each time doubling the previous scale and reducing the resolution of the upscaled imagery by half. Figure(5) shows successive up scaling of the ATM classified image with six classes from an initial smooth approximation, to a final upscaled image that has the size equal to 32x32. The class pools with an initial area of 11,113 m² prior to up-scaling starts to increase with decrease in resolution from the first level of wavelet decompositions when the pixel size changed to 3 m. When the resolution degrades to 6m, the area of pool decreased by 0.34 % from the previous step but still higher than the

original pool area value computed from the original resolution of 1.5 m. The percentage increase in pool area from the initial condition compared to the first decomposition level was 3.5 %. Further up-scaling of the data from 6m to 12 m and 24 m increased the total pool area from 10.64 % to 11.62 % and 13.3 % respectively.

Other land cover classes showed some fluctuations in upscaled values while some class areas decreased with decreasing the resolution or increase in scale. Hummocky lawns decreased from 11.9 % at 1.5m resolution to 9.4 % at 24 m resolution. *Eriophorum vaginatum* showed marginal fluctuation between 20 % and 19 % as the imagery is degraded due to coarse resolution. Whilst the area of the class *Culluna vulgaris* decreased when the resolution changed from 1.5m to 24m, the class Molinia and other Sedeges showed fluctuations between the fine and coarse resolution data. The histogram of classes is plotted against the resolution for each of the upscaled imagery and is shown in Figure 5. The PAN sharpened IKONOS image with 1 m resolution was classified into six classes as described above and had a total domain size of 256x256 pixels. The first level of wavelet decomposition

PAN fusion IKONOS imagery

produced a matrix of size 128x128 and increased the pixel size to 2 m. Subsequent wavelet decompositions changed the domain to lower matrices while at the same time doubling the pixel size at each step of up-scaling. The first level of the up-scaling (j0) resulted in a consistently decreasing trend in pool areas from the initial resolution of 1 m to a resolution of 8m, i.e, up to 3rd decomposition level. The pool areas decreased from 14.9 % to 7.3 % almost 50 % reductions from initial measurements. With further degradation in the resolution, when the pixel size was 16 m and 32 m, the pool area increased to 15.6 % of the total domain size. In contrast to pool class, the *Eriophorum vaginatum* class increased with every level of up-scaling.

Whilst, the other three classes, Hummocky lawn, *Calluna vulgaris* and other sedges had fluctuations, the class *Molinia* area first increased from 1 m to 2 m pixel size, but then consistently decreased from 15.8 % at 2 m to 7.8 % at 32 m resolution. The results are reported in a histogram plot below in Figure 3.

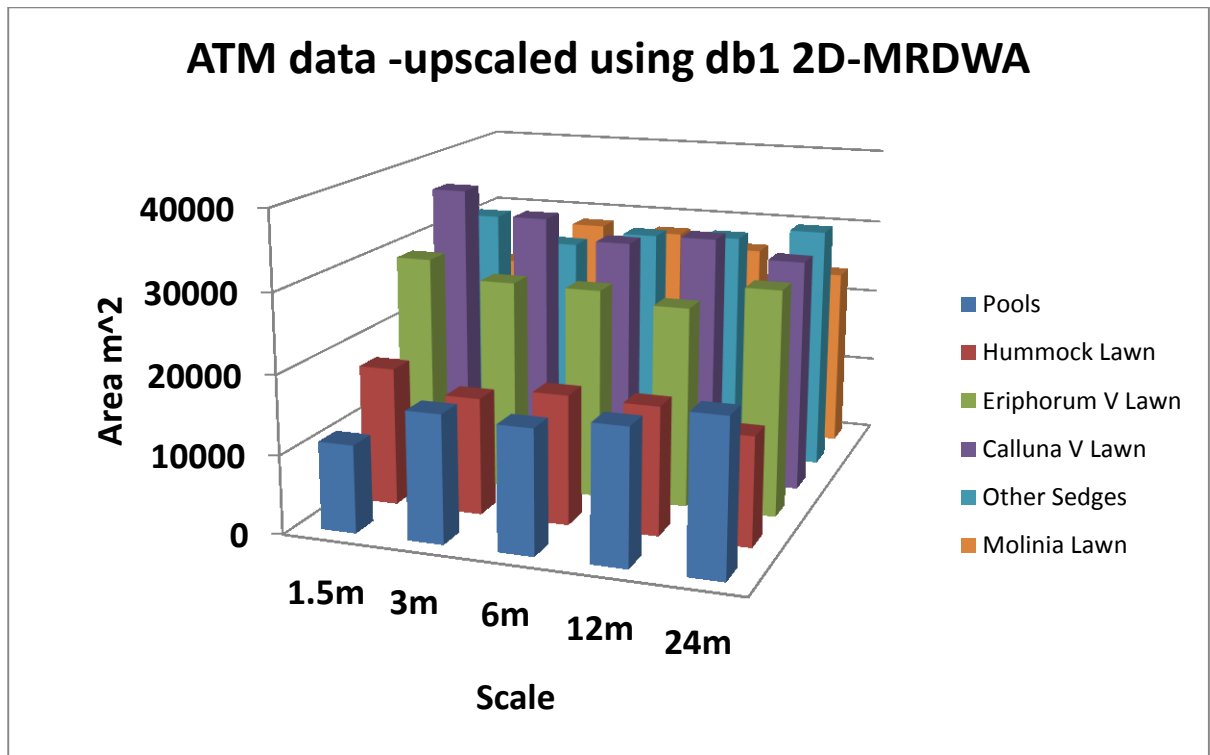


Figure 5: Figure 1: Area of the six classes plotted as histogram bars against the resolution for all the four sets of the ATM data

Eagle data

The original Eagle data had an initial pixel size of 5 m. The size of the domain for wavelet analysis was 96x96 pixels giving a total area of 2,30,400 m². The total decomposition levels that are possible with this data set was ($j=\log N_2$), six levels. The total decomposition levels analyzed were five ($j=0-4$), so that the final domain size was 8x8 pixels with each pixel size equal to 80 m.

The j1 level of decomposition resulted in pool area increasing from 10775 m² to 15200 m² that corresponds to an increase of 2 % of the total domain size. The j2 level decreased pool areas to 5.7 % of the total area while the subsequent decomposition levels j3 & j4 enhanced the pool area to 7.6 % and 8.3 % respectively.

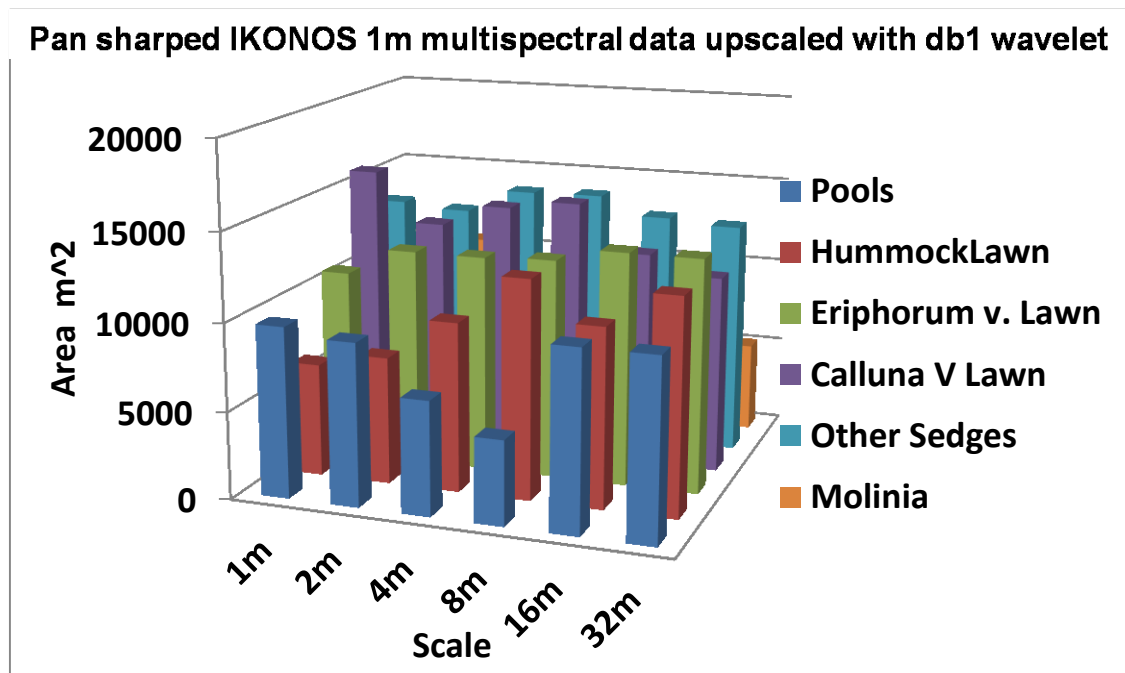


Figure 6: Figure 1: Area of the six classes plotted as histogram bars against the resolution for all the four sets of the IKONOS data

The upscaling of vegetation class *Calluna vulgaris* decreased in size. The total area of *Calluna vulgaris* lawn decreased from 36 % to 25 % at the resolution from the decomposition level j0 to the decomposition level j4. The pixel size at j4 level was 80 m. The other vegetation classes fluctuated between the five decomposition levels. All the results are plotted as histograms

against the resolution in the Figure 8. All the above histogram computations and plots were done in Matlab programme.

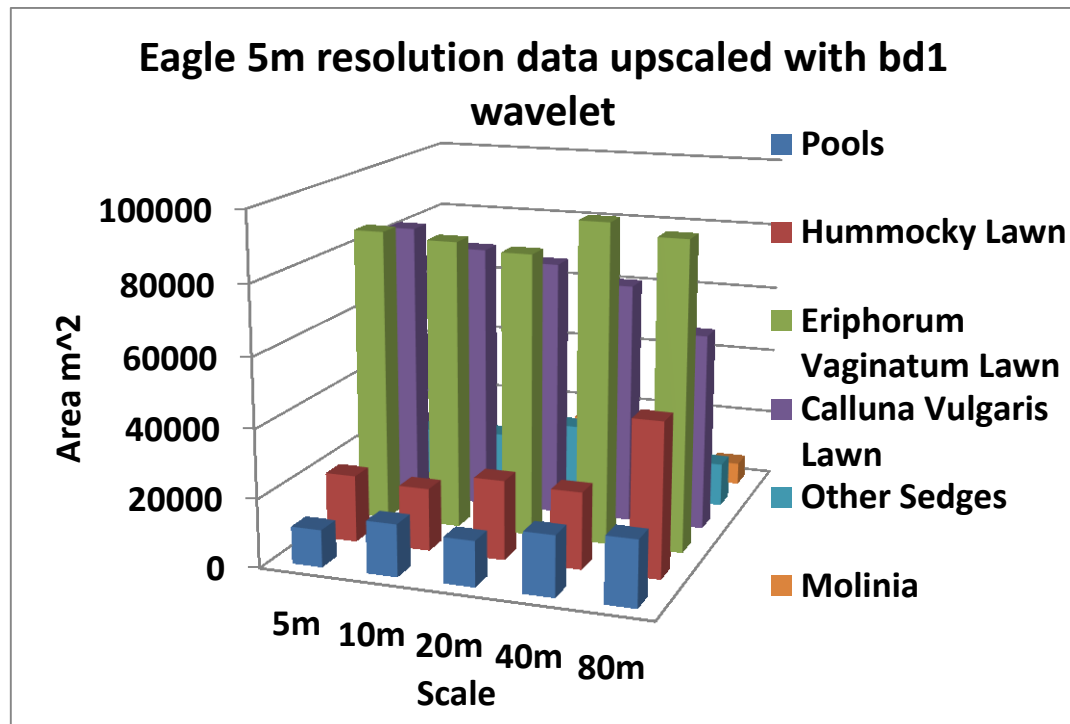


Figure 7: Area of the six classes plotted as histogram bars against the resolution for all the four sets of the Eagle data

Wavelet variance (WV) of Coefficient of Approximations

The wavelet transformations of the four classified images have provided information about scale, location and directionality. If the relative influence of the scale on the overall pattern is to be determined, then one way of doing this is by computing WV and plotting it against the scales. Thus, one number defined by the variance that collapses the information of the wavelet transform at each scale describes the measure of the contribution of the energy of each scale component to the overall pattern in the images. In Figure 9, (wv) is plotted against the scales corresponding to the level of decomposition to show scales that are important contributors to

the potential methane emission process variance. After the wavelet decomposition obtained from 2D-MRDWA db1 analysis, the resulting coefficients of approximations (CoA) were normalized to compute the wavelet variance. The wavelet variance for each of the normalized CoA was computed and then histograms with six bins were calculated. The results from histograms were multiplied by the size of the pixel ($2^{j-1} \Delta$) at their respective decomposition levels j , where Δ is the size of the pixel at the initial resolution of the image, and plotted against the scale as shown in the Figure 9 for all the four classified images.

The Figure 9A highlights the wavelet variance of the digital photography. All the classes show highest variance at scale of 0.25 m except pools. The pools variance decrease initially and then increase at 1.0 m resolution, then decrease with further increase in the resolution. This is analogous to the classification results where the upscaled values from 0.25 m to 0.5 m decreased and then increased at 1.0 m and then again decreased all the way down to 8 m. Highest variance is obtained by *Eriophorum vaginatum* at all scales, except at 8 m where Hummocks are slightly higher than the rest. The overall wavelet variance demonstrated high heterogeneity at fine scales from 0.25 m up to 1 m except for pools. Pools have highest heterogeneity at 1 m and further coarsening of the resolution decreased the variance of all the classes approaching to homogenous patches. Compared to all other classes Molinia with its homogeneous patches showed low variance from the start. This could be explained simply as the total coverage of Molinia in the DP subset was very low compared to the other classes. For all the classes except pools the variance decreased almost by half from fine scale resolution to next coarse resolution Figure (9a). The variance pattern in all the classes is fairly similar along the scales except in pools that demonstrate highest heterogeneity at 1 m and then again showing behaviour similar to the other classes with further increase in resolution beyond 1 m.

In Figure 9B the wavelet variance of ATM image is plotted against resolution. All the classes demonstrate a decrease in the variance from the fine resolution to the coarse resolution except *Molinia* that has some undulation between 2 m and 6 m scales. Highest variance was obtained by other Sedges at 1.5 m but with every upscale step, a very steep decrease in the wavelet variance of Sedges was observed until when the pixel size was 24 m. Though the initial variance of *Eriophorum vaginatum* was less than the Sedges, a trend similar to Sedges was observed in *Eriophorum vaginatum* lawn, Figure 8B. This was in contrast with the less steep trend observed in variance for the classes pools, *Calluna vulgaris* and Hummocky Lawns. *Molinia* had a small range between the scales 1.5 m and 6 m and the resulting variance curve is almost flat.

The wavelet variance of the pan fusion IKONOS image is shown Figure 9 C. Ikonos data showed the highest variance for the class *Calluna vulgaris* lawn, however the variance from a high of 83 % at 1 m scale drops to 12 % as the pixel value change to 3 m. The trend for *Calluna vulgaris* was almost stable between the scales 4 m and 6 m. The wavelet variance of pools rapidly decreased from 1 m to 4 m and from 8 m to 32 m the decline was almost flat. The least variation is demonstrated by hummocky lawn between 1 m and 32 m. *Calluna vulgaris* had an asymptotic fall in the variance between 1 m and 4 m and the behaviour is very consistent between 8 m and 32 m. Similar pattern was observed in *Molinia* between 1 m and 4 m and subsequent fall in variance was very flat from 8 m to 32 m. *Eriophorum vaginatum* had the steepest gradient between 1 m and 16 m but little change was observed at 32 m. Pattern similar to *Eriophorum vaginatum* was also observed in other sedges.

Finally, the wavelet variance in all the six classes was computed from Eagle image that had 5 m initial pixel size. The subsequent upscaling reduced the resolution to a maximum pixel size of

80 m. The pool structures showed rapid oscillation between the scales of 10 m and 20 m and between 40 m and 80 m with overall trend being shallow. The other classes showed very steep decrease in the variance between the initial pixel resolution of 5 m and final upscaled pixel resolution of 80 m.

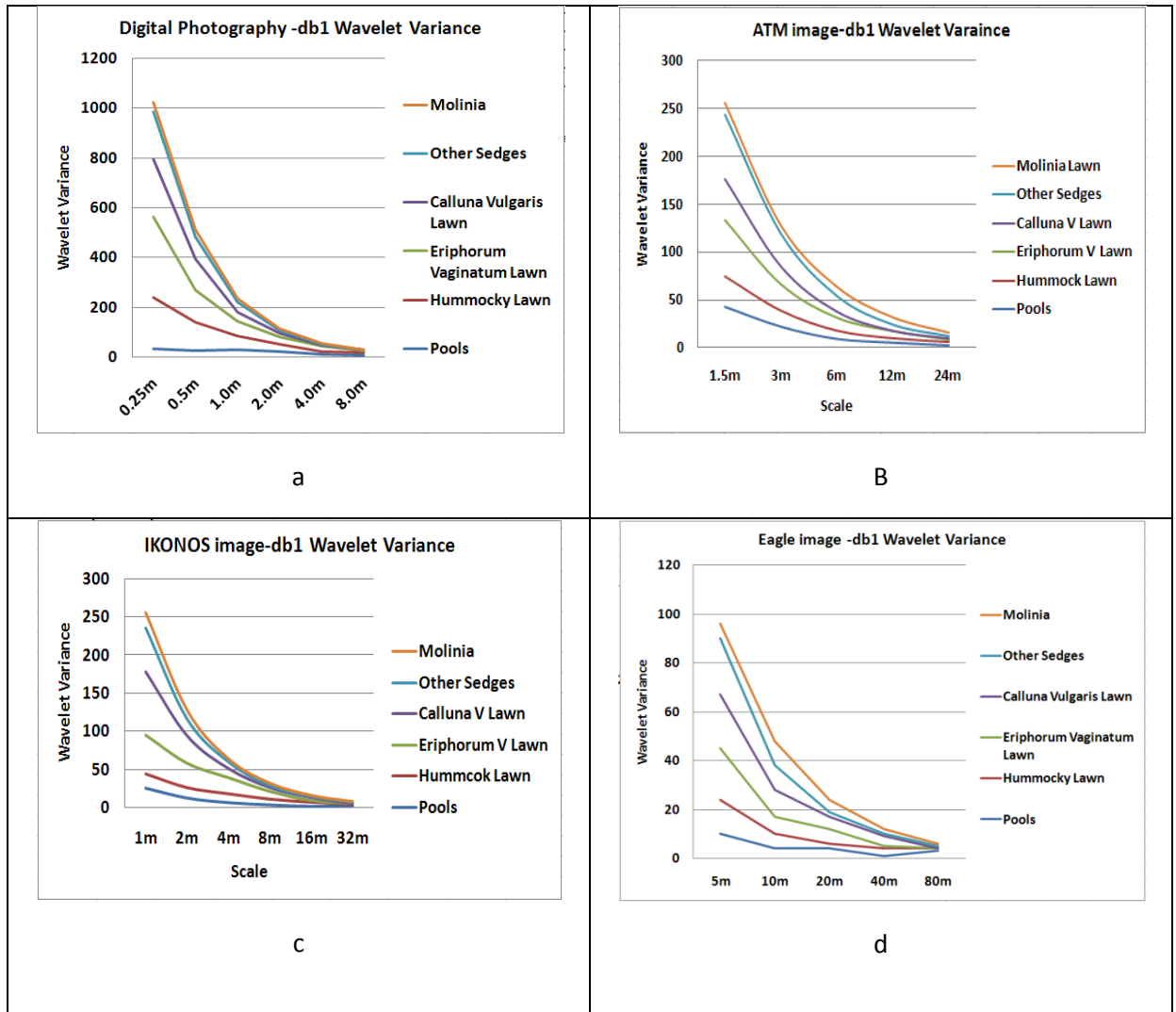


Figure 8: A) wavelet variances of the DP Photography B) ATM image C) PAN Fused IKONOS image and D) Eagle Image. (Note the line colour is same for a particular class in all the four plots)

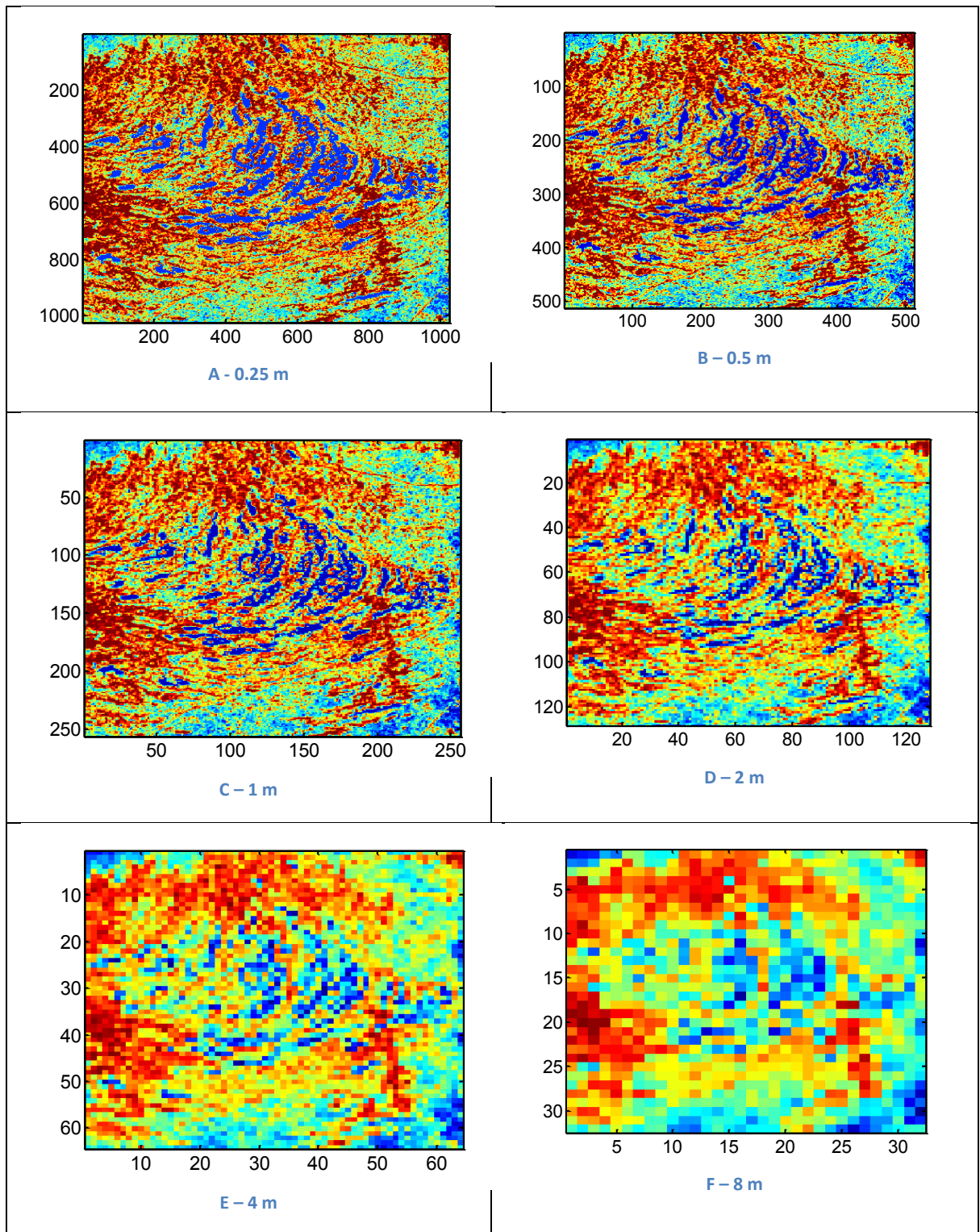


Figure 9: 2D-MRDWA using db1 on classified digital photography. Starting from top left a) original 0.25m data and top right is b) upscaled 0.5m ,middle left c) upscaled 1.0m, middle right is d) 2.0m bottom left is e) 4m and bottom right is f) 8.0m upscaled version of DP.

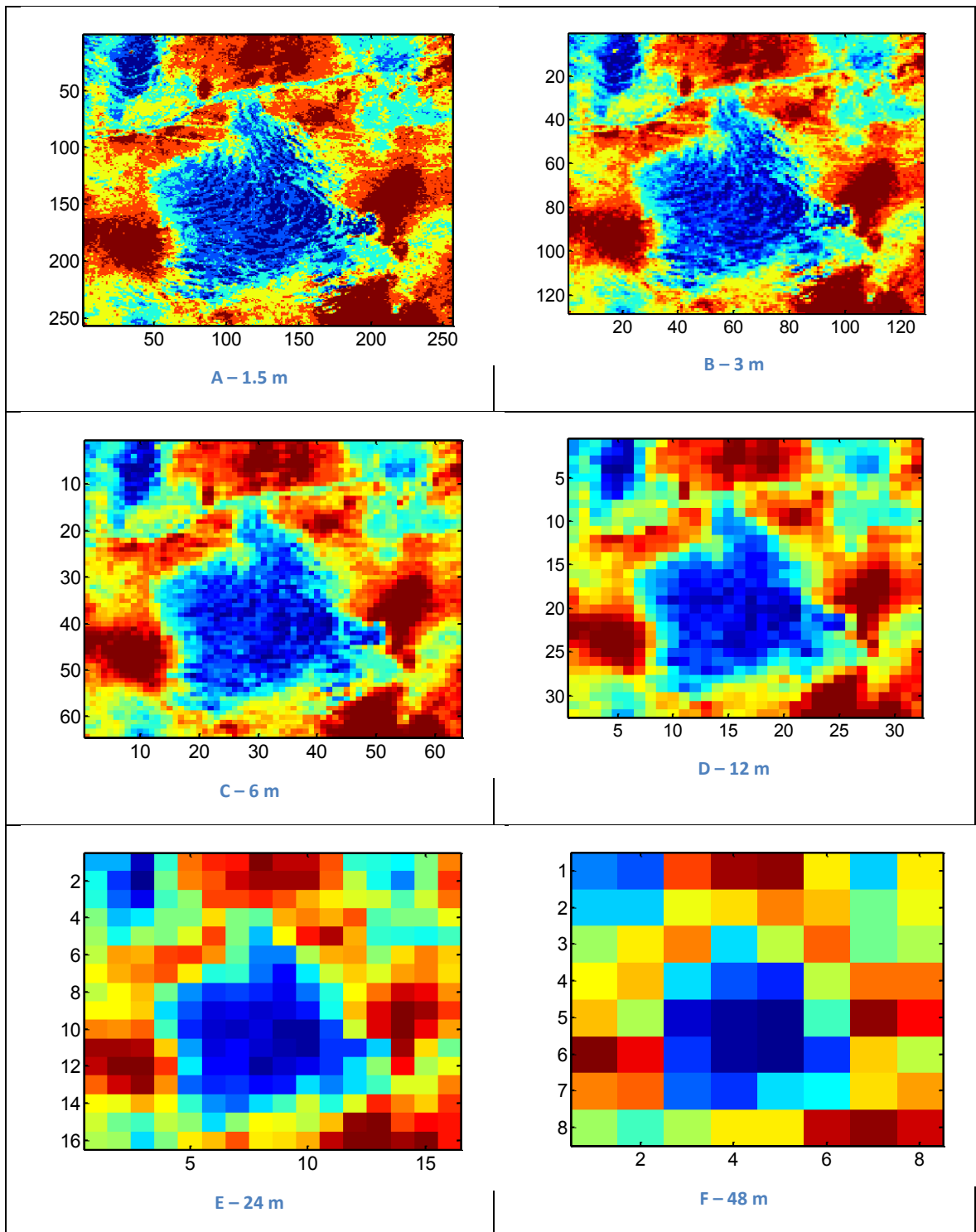


Figure 10: 2D-MRDWA using db1 on ATM classified image. Starting from top left a) original 1.5m data and top right is b) upscaled 3m ,middle left c) upscaled 6m, middle right is d) 12m bottom left is e) 4m and bottom right is f) 24m upscaled version o f ATM.

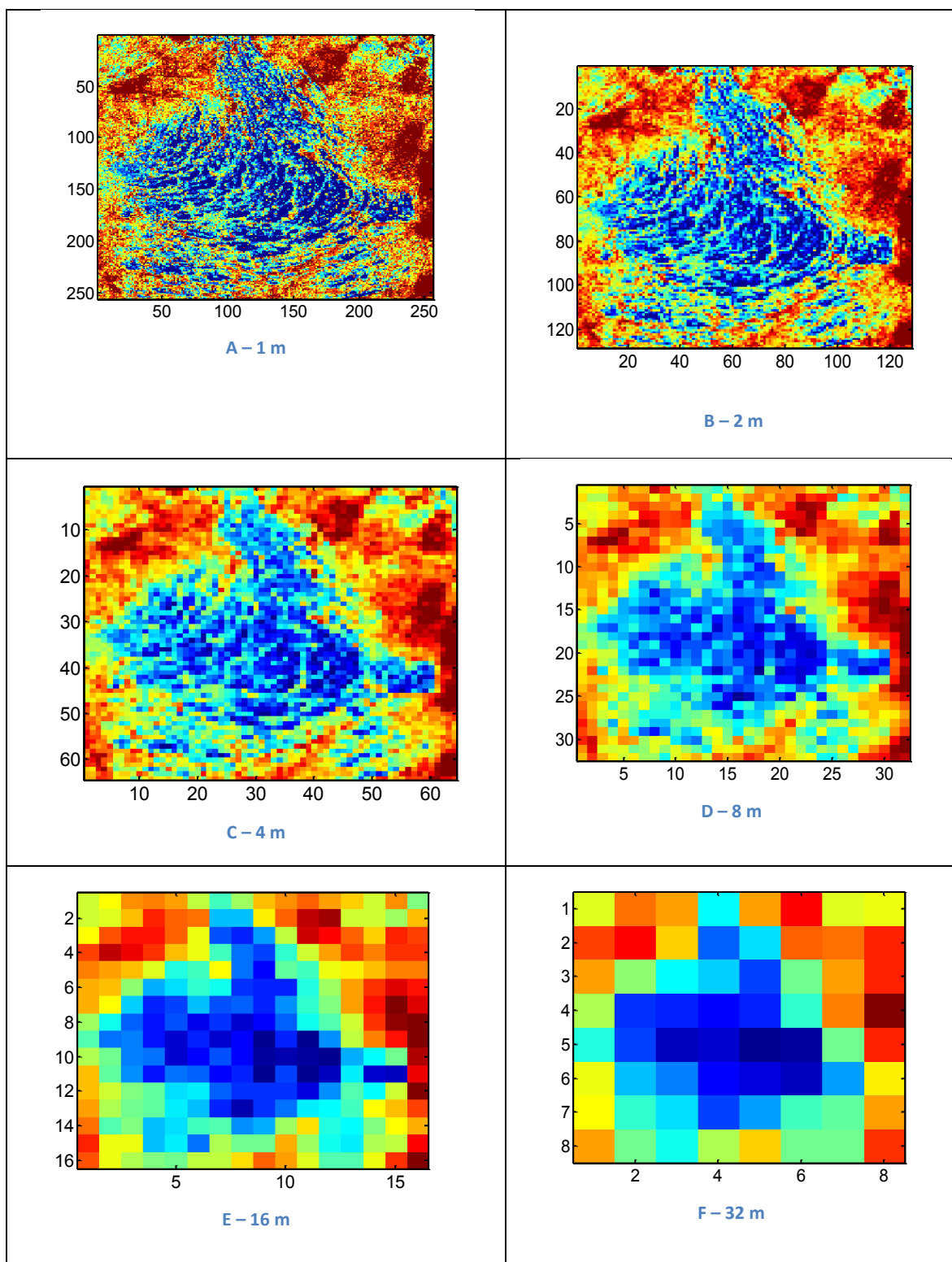


Figure 11: 2D-MRDWA using db1 on pan sharp IKONOS classified image. Starting from top left a) original 1m data and top right is b) upscaled 2m ,middle left c) upscaled 4m, middle right is d) 8m bottom left is e) 16m and bottom right is f) 32m upscaled version o f IKONOS.

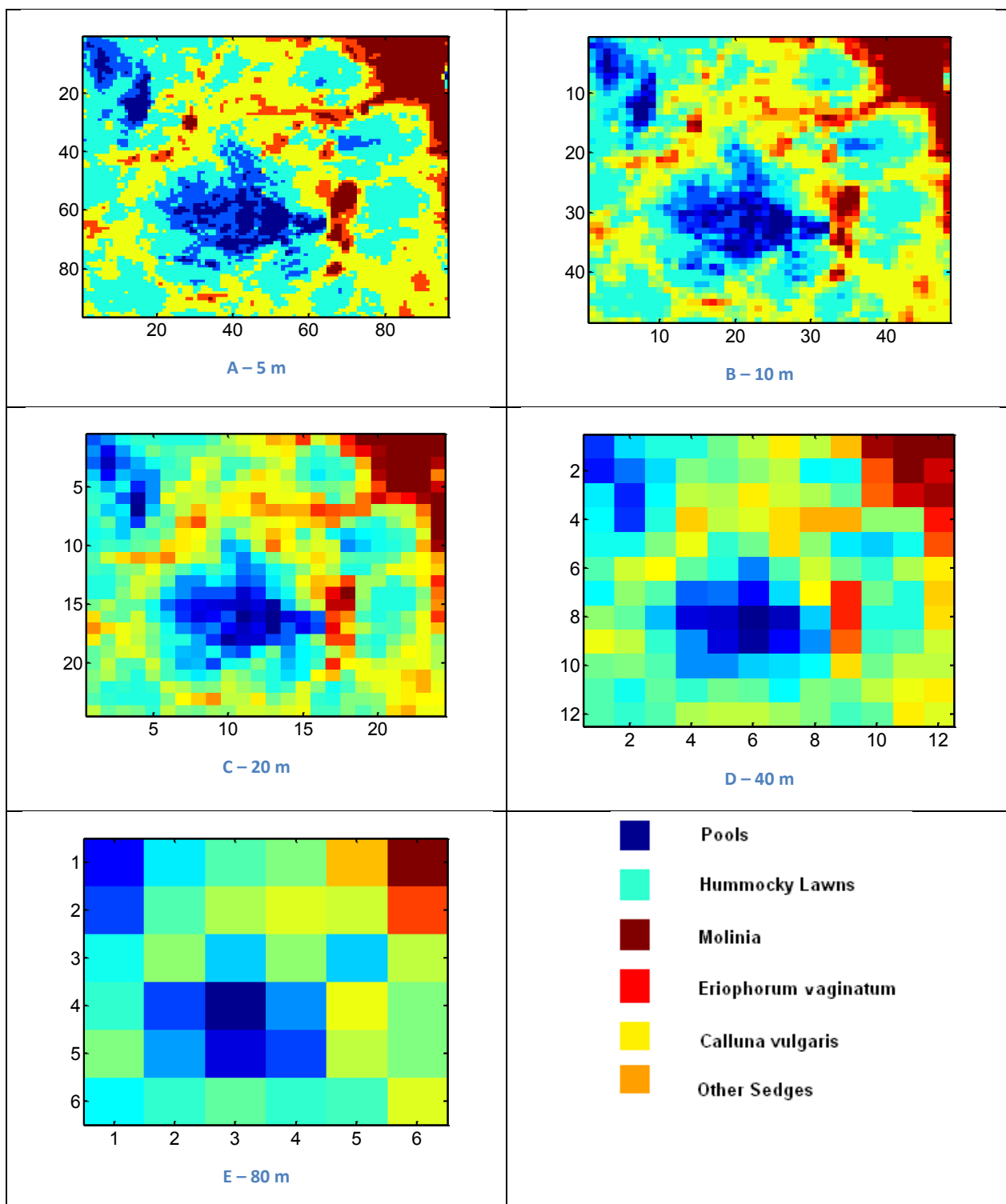


Figure 12: 2D-MRDWA using db1 on Eagle classified image. Starting from top left a) original 5m data and top right is b) upscaled 10m ,middle left c) upscaled 20m, middle right is d)40m bottom left is e) 80m upscaled version o f Eagle data

Discussions

Multi sensor implications on classifications

The reflectance spectrum of a material is a plot of the fraction of radiation reflected as a function of the incident wavelength and serves as a unique signature for the material. In principle, a material can be identified from its spectral reflectance signature if the sensing system has sufficient spectral resolution to distinguish its spectrum from those of other materials. In the current research we used two airborne and one satellite based imagery. ATM and EAGLE were taken from airplane while IKONOS was taken from satellite platform. The different bands for each of the data set are schematically shown in figure 13 below.

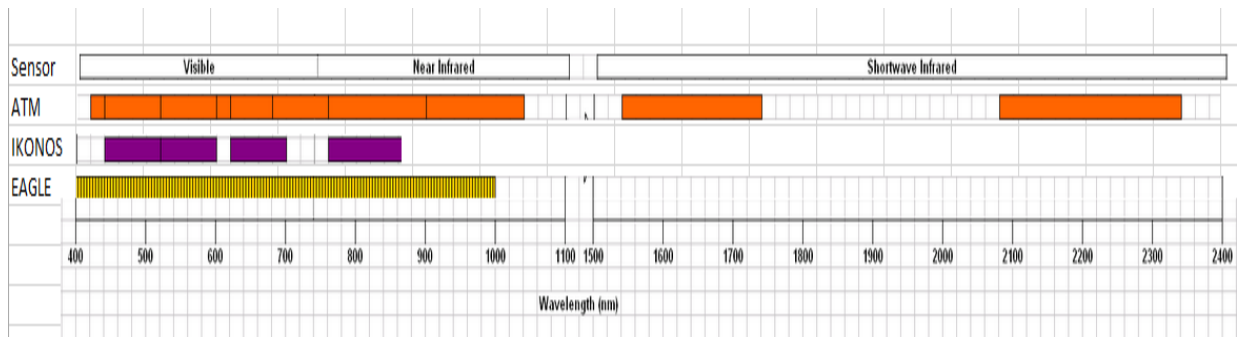


Figure 14: Spectral band distribution across the EM range of three different sensors.

The reflectance of clear water is generally low. However, the reflectance is maximum at the blue end of the spectrum and decreases as wavelength increases. Hence, clear water appears dark-bluish. Turbid water has some sediment suspension which increases the reflectance in the red end of the spectrum, accounting for its brownish appearance. The reflectance of bare soil generally depends on its composition. Hence pools are detected and classified in all the three data set.

Vegetation has a unique spectral signature which enables it to be distinguished readily from other types of land cover in an optical/near-infrared image. The reflectance is low in both the blue and red regions of the spectrum, due to absorption by chlorophyll for photosynthesis. It has a peak at the green region which gives rise to the green colour of vegetation. In the near infrared (NIR) region, the reflectance is much higher than that in the visible band due to the cellular structure in the leaves. Hence, vegetation can be identified by the high NIR but generally low reflectance.

Very high spatial resolution Remote Sensing (RS) such as 1 m from ATM data would help quantify fine scale details but lacks wide area coverage. Its EM range is wide from 400 nm to 2340 nm with some gaps in INR and SWIR. But for a more rigorous classification of the various vegetation types on the peatland surface, Eagle data with its very fine spectral bands could be utilized but only for those classes whose end members are extracted within the EM range from 400 nm to 1000 nm, any vegetation class beyond this range will be missed out due to absence of EM data in the Eagle image. Moderate resolution RS data has a wide coverage such as PAN sharpened IKONOS data, but it is unsuitable to discern detailed information of the heterogeneous surface of peatland.

The reflectance of vegetation in the SWIR region (e.g. band 5 of A TM and band 4 of INONOS sensors) is more varied, depending on the types of plants and the plant's water content. Water has strong absorption bands around 1.45, 1.95 and 2.50 μm . Outside these absorption bands in the SWIR region of ATM, reflectance of leaves generally increases when leaf liquid water content decreases. This property can be used for identifying tree types and plant conditions from remote sensing images. The SWIR band can be used in detecting plant drought stress and

delineating burnt areas and fire-affected vegetation that occurred in the Silver Flowe during the research project.

Wavelet Variance

Wavelet variance decomposes the variance of certain stochastic processes on a scale by scales basis and hence has considerable appeal to scientists who think about physical phenomena in terms of variations operating over a range of scales (Percival et al., 2004). A plot of wavelet variance computed from db1 2D DWA versus scales (pixel size) indicates which scales are important contributions to the methane emissions processes. The scales where the fine scale peatland heterogeneity is preserved in the upscaled model is considered as important scale.

Reduction in wavelet variance of the microstructural elements of the peatland is observed with the reduction in the scales of observation by an order of magnitude, possibly giving reduced methane budget estimates at the coarser scales. As explained earlier that the methane emissions are connected to pools and vegetation cover at the plot scale, any reduction in the resolution of the pixel in the image that causes class pools wrongly assigned to the class vegetation would result in reduced estimates of methane budget. On the contrary, if the class vegetation is wrongly assigned during the upscaling process to the class pools, then the result may be an over estimation of the CH₄. In the present study, results from EAGLE data demonstrates such a tendency where the hummocky lawn is misrepresented as pools right from the original 5 m resolution image and continues to its upscale versions.

Similarly, if the upscaling process assigns pools to non-aquatic classes, then the methane budget estimates would be lower than expected. For example, the level 4 upscaling of the

digital photograph at J5, Table 3, showed deviation of class pools by almost 80%, thus significantly reducing the contributions from the class pools at the pixel size of 8 m.

Pattern on peatland surface and effect on fine scale heterogeneity due to spatial scaling

The aim of this study was to upscale peatland surface heterogeneity and investigate the change in pattern on peatland using different remote sensing data. Different results are obtained from the environmental models when applied at different scales (Zang et. al., 2002). The difference is reported global CH₄ budget from the wetlands in the fifth assessment report of IPCC (2013) shows an order of magnitude which may be due to many reasons such as inadequate data, inadequate modelling or improper extrapolation procedures from plot to global scales. Many processed based models (Cao et. al., 1995, Segers & Leffelaar 2001a, 2001b; Walter et. al., 2001a, 2001b) do not incorporate fine scale site specific heterogeneity factors that are linked to the methane fluxes (Kettunen et. al., 2000) that are well documented in (Wickland et. al., 2001).

The loss of information in peatland fine scale heterogeneity associated with the degradation of the pixel resolution in spatial scales provides a substantial obstacle to large scale modelling of CH₄ as each model parameter is affected in a different way (Walter et. al., 2003).

Many conventional methods have been proposed to describe the heterogeneity with the scales and spatial pattern distribution (Sanders et al., 1998; Brostofke 1999; Redding 2003; Wang 2004). Any successful upscaling method should capture the important details of the fine scale. This implies that relatively heterogeneous structures of peatland should remain heterogeneous at large scale. Spatial heterogeneity could be qualitatively described as complexity that contains the spatial information of the heterogeneity distribution (Li and Reynolds, 1995). In

the present work the effect of spatial scaling from db1 wavelet on the surface pattern of peatland is discussed. This has been described through visual inspection by plotting the upscaled maps of the data Figures (10 - 13). Wavelet analysis quantifies the influence of pattern at each scale within the data series as a function of location along a transect (Percival et al., 2004). This technique allows the analyst to assess patterns in the data set at multiple scales concurrently (Grays 1995).

The effect of smoothing due to db1 wavelet is examined on the four data sets for generating robust responses to up-scaling. In this context, robustness is referred to the extent to which the pattern on peatland surface changes significantly or remains similar from the previous level of decomposition as judged by visual inspection on the six classes. A more quantitative measure that is used here to assess the information loss is by computing the peak signal to noise ratio (PSNR) plotted for all the upscaled versions for all the four data sets to compare information transfer (loss) between the original pixel resolution data and the upscaled data.

The 2D discrete wavelet transform could be applied as recursive filters where the original classified map of all the four different data sets are decomposed into a smooth upscaled coefficient of approximations and the eliminated details in the three directions, Figure (1). Thus, in the present work, upscaling is smoothing of the original six classes classified image to a coarser resolution. Smoothing is one form of correlation (Wickerhausen, 1994), therefore, an upscaled smooth image shows a better correlation between the six classes as shown in all the variance plots Figures 9A-9D where the six classes have almost constant variance near the coarser pixel resolutions. As the resolution decreased with increase in pixel values, notice how the image becomes smoother, eliminating fine scale details and represents the entire study

area by a weighted average of the finer scales. Thus the scaling effect causes the heterogeneous surface to become gradually homogeneous. This also implies that the opportunity to scale up homogeneous surface patterns is higher than upscaling heterogeneous surfaces without significant loss of information during the smoothing process.

Tekeuchi et. al., (2003) attempted to measure CH₄ from the Siberian wetlands by incorporating 20 m HRV classified pixels overlaid on the 1.1 km NOAA AVHRR grid size pixels assuming that all the four classes of the classified HRV pixels as pure pixels but neglected the mixels (mixed pixels) is bound to give significant errors. As evident from the results in the present study, the fine scale heterogeneity is preserved only up to a pixel size of 10 m in almost all the four data sets. Hence it is argued that subpixel analysis as described by Tekeuchi et. al., (2003) would introduce bias due to loss in fine scale heterogeneity at the grid scale. The wavelet analysis would be able to help in deciding at what coarse scale the detailed fine scale heterogeneity is still intact and thus be able to incorporate such information in the global change models for more accurate assessments of CH₄ from peatlands. The dichotomy of each data sets and their plotted surfaces with their upscaled images are discussed below.

Digital Photography

In order to appreciate the upscaling of the peatland surface heterogeneity using db1 wavelet, the original very high resolution, 0.25 m pixel size digital photography is shown. The 2D-MRDWA performed on the digital photography upscaled the peatland surface classified into six classes and produced an upscaled map for the j=0-5 levels of wavelet decompositions. The observation from visual inspection suggests that the pattern of hummock-hollow-pool complexes remains nearly intact from the initial pixel resolution of 0.25m at level j0 up to the

second j1 (pixel 0.5m) and third level (j2, pixel resolution 1.0m) of decomposition of the data, Figure (10 A,B,C).

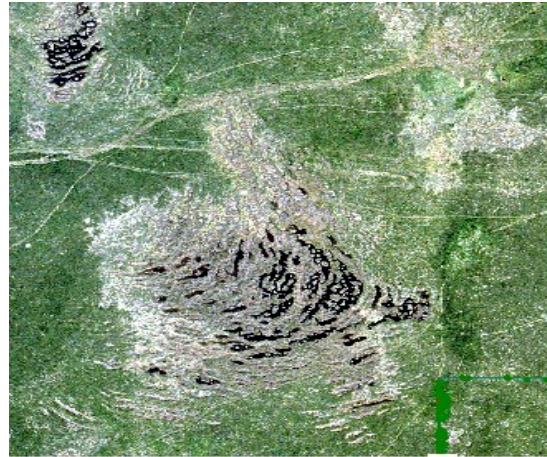


Figure 14: A Digital photograph with 25 cm pixel resolution taken over Silver Flowe bog centre.

Further, the smoothing process up to the j2 level shows clear demarcation between pools (blue colour) and neighbouring class pixels. At level j3 when the pixel size is 2m, the peatland pattern started to change Figure (10 D). At this level, there is some transfer of fine scale heterogeneity into coarse pixels that begin to show the blurring effect due to the smoothing caused by the bigger window size of the scaling factor.

Table 3: Percentage deviation of pools and relative percentage change in all the classes obtained from the upscaling of the digital photograph using db1 wavelet

J level- Total Area	% Pools	% Hummocky Lawn	% Eriophorum Vaginaturn Lawn	% Calluna Vulgaris Lawn	% Other Sedges	% Molinia Lawn	% deviation of pools
J0-65536	10.24	9.86	19.26	22.30	18.54	19.77	0
J1-65536	8.77	8.98	18.31	19.36	20.82	23.71	14.30
J2-65536	8.79	9.31	17.59	21.89	21.04	21.36	14.15
J3-65536	6.46	9.10	18.60	24.85	24.59	16.37	36.84
J4-65536	4.10	9.17	19.77	31.25	25.36	10.32	59.96
J5-65536	2.05	9.37	25.97	30.17	23.14	9.27	79.98

At this scale the percentage deviation of pools from the original resolution increased to almost 37%. Further up-scaling to level j4 has changed the pattern significantly when the resolution decreased to 8m, Figure (10F) and increased the percentage deviation to 60%. Finally, the last j5 level of decomposition completely changed the pattern on the hummock-pool complex with many false alarms blue colour pool pixels emerging at the south east corner of the peatland. This result implied that the uncertainty increased with the loss of structural information of class pools from fine resolution to coarser resolutions when the pixel size reach 4 m with the digital photograph. The results from 0.25 m pixel size (Fig. 10. A) is important as it could be compared with the field based chamber measurements. Similarly, the results (Fig. 10: A-D) are also important as they can be compared with ATM image results and pan sharpened IKONOS image results as baseline with the implications on the landscape and regional studies.

The db1 wavelet preserved the pattern on the landscape as it remained intact as long as the pixel size was increased to 4 m, Figure (10 A-E). The pattern was fairly intact when the pixel resolution was further decreased to 8 m, Figure (10F). This is a very significant improvement from the results of simple averaging methods in which a shifting trend in the peatland surface heterogeneity was observed as the levels of upscaling progressed and at one stage the complete pattern was lost (Mohammed et al 2009). Hence, for the assessment of methane emissions, the upscaled image from the digital photograph with the pixel size of 4 m could give fairly accurate results as the fine scale heterogeneity is fairly preserved. Any results adopted from the upscaled image data beyond 4 m is likely to introduce bias in the assessments of methane as the pattern starts to loose and mixing of the peatland surface structural elements is evident in the subsequent degradation of the resolution.

ATM Data

Figure (11 A-F) shows the results of db1 wavelet upscaling of airborne Atmospheric Thematic Mapper (ATM) image with the classification map at its original pixel size of 1.5 m Figure 11 A. Subsequent upscaling of the data to 3 m pixel resolution, Figure (11 B) had preserved the surface pattern. The dark blue pixels representing pool structures are clearly distinct from the light blue colour pixels that represent hummocky lawns. Subsequent degrading of the resolution due to coarsening of the pixels at bigger scales have coalesced the pattern on the centre of the bog where the pools and hummocky lawns are mixed up. However, the patterns at the centre look distinct from the other surface structures around the pool complexes. When the pixel size was increased to 6 m, Figure (11 C) the fine scale heterogeneity between pools and hummocky lawns is still fairly preserved with a clear pattern still remains intact over the landscape. At 12 m pixel size, Figure (11 D) the smoothing effect is so strong that it is hardly possible to discern pools from the hummocks. Beyond 12 m, there is also shift in the structure from their original positions. Any further upscaling beyond 12 m has very strong smoothing and shifting effect on the fine scale heterogeneity and the resulting patterns in Figures (11 E & 11 F) shows complete loss in the structural pattern. The most important features such as pools that are the hotspots for methane emissions has been mixed up with the other non-aquatic structural elements such as hummocky lawns, *Calluna vulgaris* or *Eriophorum vaginatum*.

At the higher scales of 24 m and 48 m, the non-aquatic structural elements such as the earlier mentioned shunt species also get intermixed thus any input taken from an upscaled ATM image beyond 6 m would lead into biased estimates in the methane emissions.

Table 4: Percentage deviation of pools and relative percentage change in all the classes obtained from the upscaling of the ATM data using db1 wavelet

J-Level Total Area	% pool	% Hummock	% Eriophorum	% Calluna	% Sedges	% Molinia
J1-147456	7.54	11.94	19.85	24.66	20.97	15.04
J2-147456	10.99	10.12	18.35	22.59	18.79	19.17
J3-147456	10.64	11.18	18.29	20.87	20.14	18.87
J4-147456	11.62	11.04	17.38	21.78	20.41	17.77
J5-147456	13.28	9.38	19.53	20.31	21.48	16.02

PAN Sharpened IKONOS Data

The classified and pan-sharpened IKONOS 1 m resolution image taken from the satellite shown in Figure 12 A resembles close to the airborne digital photography in Figure 10 A with respect to the detail fine scale heterogeneity and the surface pattern in the distribution of the pools and non-pools structural elements. The db1 wavelet has distinctly preserved the pattern on the surface up to the scale length of 8 m, Figure 12 D and arguably until 16 m, Figure 12 E. The advantage of high resolution fine scale panchromatic image fused with the low resolution multispectral image of the IKONOS data is clearly visible from the surface plotted after every level of upscaling. The smoothing effects as a result of upscaling at 16 m and very strong smoothing effects beyond 16 m is visible from the images in Figure 12 D and 12 E.

As satellite data have a wide spatial coverage but lacks fine scale spectral resolutions, the pan-sharpened imagery could be used for regional studies with the combination of spectral and spatial fused images that helped in discerning important fine scale features such as pools as well as preserved the pattern on the peatland surface fairly well up to 16 m pixel size. When the pixel size was increased to 32 m there was a shift in the patter and a complete loss of fine scale surface heterogeneity.

Table 5: Percentage deviation of pools and relative percentage change in all the classes obtained from the upscaling of the Pan Sharpened IKONOS data using db1 wavelet

Level-Total Area (m ²)	% Pools	% Hummock Lawn	% Eriophorum v. Lawn	% Calluna V Lawn	% Other Sedges	% Molinia
J0-65536	14.86	9.84	16.45	24.33	20.43	14.09
J1-65536	14.14	11.08	18.87	20.00	20.03	15.88
J2-65536	9.91	14.75	18.87	21.97	22.14	12.35
J3-65536	7.32	19.04	19.14	22.75	22.27	9.47
J4-65536	15.63	15.63	20.31	18.75	20.70	8.98
J5-65536	15.63	18.75	20.31	17.19	20.31	7.81

It is fair to argue that in this case the IKONOS data upscaled to a length scale of 8 m could be used with strong confidence for the assessments of regional estimates of methane from the peatland. At length scales of 32 m and beyond, the likelihood of bias in the methane emissions estimates will be very high.

EAGLE Data

The last data set investigated for the upscaling of the peatland surface heterogeneity was EAGLE data with the initial pixel size of 5 m, Figure 14 A. There were issues with EAGLE data quality as it was delivered with poor binning as well as poor atmospheric corrections. The idea was to have a fine resolution EAGLE data with pixel size equal to 1.5 m to 2.5 m that can be compared with ATM and PAN sharpened IKONOS data. Since EAGLE is very strong in spectral resolution, an equally high spatial resolution would have benefited in scaling the fine scale peatland heterogeneity due to the combination of high spectral and spatial resolutions capturing the greater fine scale heterogeneity from the peatland surface. Post processing of raw EAGLE data resulted in a stable pixel size of initial value of 5 m. It is classified into six

classes and upscaled with db1 wavelet. The resulting patterns from the start showed total elimination of microtopography in hummocky lawns and most of the pool complexes were dominant over the hummocky lawns along the periphery of the pools in the initial classified image, Figure 14 A.

Table 6: Percentage deviation of pools and relative percentage change in all the classes obtained from the upscaling of the Eagle data using db1 wavelet

Level-Total area (m ²)	% Pools	% Hummocky Lawn	% Eriophorum v. Lawn	% Calluna V. Lawn	% Other Sedges	% Molinia
J1-230400	4.68	8.52	37.28	35.98	6.15	7.39
J2-230400	6.60	7.94	36.63	33.85	6.51	8.46
J3-230400	5.73	10.07	35.76	32.64	8.68	7.12
J4-230400	7.64	9.72	40.28	30.56	5.56	6.25
J5-230400	8.33	19.44	38.89	25.00	5.56	2.78

Further degradation of the resolution resulted in more loss of the fine scale heterogeneity and beyond 10 m pixel size, the smoothing effects were strongly visible on the surface patter, Figure 14 C. Next level of upscaling starting from 20 m to 40 m and finally 80 m pixel size resulted in complete shift in the pattern on the peatland. Such results are not of much use in the accurate assessment of methane from the peatland. But with stable pre-processing, and good quality geometric and atmospheric corrections, EAGLE sensor has the potential to give much better results.

Conclusions

Spatial heterogeneity of the measured surface property depends on its observational scale (Cao and Lam, 1997; Quattrochi & Goodchild, 1997; Tian et. al., 2002, Garrigues et. al., 2006; Zhang et. al., 2014). The upscaling of four independent remote sensing data to investigate the changes in pattern on peatland spatial heterogeneity using 2D-DWT db1 wavelet was

successfully demonstrated in this study. The investigations demonstrated the length scales that would preserve the fine scale pattern in peatland surface from the four different data sets. The variations in the fine scale heterogeneity are very well captured upto a length scale of 8 m in the digital photographs. ATM data preserved the fine scale details upto a length scale of 12 m, while IKONOS data demonstrated preservation in the surface pattern up to the length scale of 8 m. Eagle data showed preservation in pattern up to the length scale of 10 m. These spatially complex images, Figures (10-13) answer how much spatial detail is necessary at different resolutions to map the features of a wetland that are important for methane efflux. In this sense this is an empirical upscaling because the processes that dominate at different scales are not considered, merely features that are present at different scales after wavelet decomposition which is still an important objective.

Outlook

The results can be improved by adopting more rigorous classification techniques taking the spectral information from the remote sensing data in general and hyperspectral image data such as from EAGLE data in particular to discern fine scale surface characteristics. Some of the Bryophytes and mosses are linked to microstructural elements (Granath, 2012) in the peatland that are considered as proxy for CH₄ emissions (Belyea, 1996) but would not be possible to capture in spatial domain and requires spectral domain of very high resolution. This can be mapped using the high spectral resolution of EAGLE data and the output from this classification upscaled using wavelet techniques as applied in this study. This is expected to give improved results. Hence any future research would be focused in this direction.

In the future, a rigorous field data should be collected at variable scales and compared with the results obtained from remote sensing analysis above to establish some validation of the existing results.

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Information Preservation and Change Detection across Spatial Scales in the Assessment of Global CH₄ Emission Estimates from Wetlands

Abstract: *The accurate estimation of methane, a greenhouse gas, from natural sources such as peatlands is vital for overall assessment of global climate change. Investigations that rely on process-based models that derive CH₄ emissions from natural wetlands as a function of variables such as soil temperature, water table depth and aerenchymateous vegetation measured at plot scales may produce biased results when extrapolated to landscape, regional and global levels. This is because assumptions such as average water table depth, vegetation patchiness, and microclimate that must be 'scaled up' from the plot to larger scales. Heterogeneity is an inherent characteristic of wetlands, and the relationships between CH₄ and variables deriving methane emissions are non-linear. These limitations can be overcome by independent remote sensing data with multi-spatio-temporal resolutions acquired from different sensors and platforms. This paper discusses novel techniques from information theory applied to preserve the information content of edaphic and vegetative characteristics of a peatland ecosystem in Scotland. Our results demonstrate shifting patterns in the information retrieved as the pixel resolution decreases. We report the changes in processes and patterns across different scales which would help improve the overall performance of the process based models at global scales.*

Keywords: Methane, Peatland, Up Scaling, Heterogeneity, Information theory, Shannon entropy, Kulback-Leibler distance, Quadratic approximation, Remote Sensing, Spatio-Temporal Resolution, Global Change.

Introduction

Wetlands are spatially complex and temporally dynamic ecosystems that emit the important greenhouse gas methane (CH₄) into the atmosphere. Methane creates a significant radiative forcing and is dynamically active in atmospheric photochemistry (Whalen, 2005). Though CH₄ is relatively short lived in the atmosphere, *ca.* 20 years, as compared to CO₂ which is active for 100 years (IPCC, 2007), it traps more heat than CO₂ and hence is more effective in contributing to global climate change. There are many natural and anthropogenic sources of atmospheric

methane, of which wetlands contribute about 20% of the total global efflux (Table 1, Prather et al., 1995; Cao et al., 1996; Harris et al., 1993; Mathew and Fung 1987; Lelieveld et al., 1998; Wang et al., 2004; Fung et al., 1991). Wetlands tend to be sources of methane and sinks for CO₂, which often accumulates as soil organic carbon (Gohram 1991), particularly in peatlands. The Northern peat forming wetlands and tundra regions contain ~30% (200 Gt) of the total global C pool in soil (Joabsson et al., 1999, Post et al., 1982) such that wetlands are critical components of both global pools and fluxes of carbon. Accurate estimates of methane flux from wetlands are required for a comprehensive understanding of the role of the land surface in the global carbon cycle and radiation balance, but the challenge of applying direct methane flux measurements at small scales in space to larger global and regional scales has not been fully resolved.

Though methane emission models based on *in situ* measurements at plot scales have been directly applied to estimate emissions at larger scales (Bartlett & Harris 1993; Walter et al., 2001a), it is difficult to be confident in these estimates as the variation in net emission reported is large among the different methods employed (Table 2). The difference between the methane upscaling results in Table 2 is more than double, and newer estimates tend to be greater than previous estimates. Such differences may result from many factors such as inadequate data from measurement plots, lack of a good physical model to extrapolate and 'upscale' CH₄ flux (Walter et al., 2001) or a combination of reasons, which are not yet clear. Paramount to accurate flux estimates are accurate representations of the physical and biological determinates of methane production.

Sources	Efflux (Tg CH ₄ yr ⁻¹)
Natural	
Wetlands	115 (Northern+Tropics+Other)
Termites	20
Oceans	10
Freshwater	5
Geological	10
Total Natural	160
Anthropogenic	375
Total Source	535
Total Sinks	515
Atmospheric increase	30

Table 1: Estimated sources and sinks of atmospheric methane after Prather et al. (1995)

Methane is produced by methanotrophic bacteria under anaerobic conditions (e.g. Schlesinger, 1997).

Global CH ₄ Emissions (Tgy ⁻¹)	Reference
260	Walter et al., 2001
150-250	Prather et al., 2001
111.1	Mathews and Fung 1987
110	Galchenko et al., 1989
109	Bartlett and Harris 1993

Table 2: Published Global Annual CH₄ flux Estimates from Wetlands

This methane, once produced, is then released into the atmosphere through different

biological and physical pathways that include direct release through the soil matrix, through gas bubbles via ebullition, and also through the vascular root and shoot system of aerenchymous plants (Figure 1). Quantifying spatial variability in both biological and physical characteristics of wetlands is critical for accurate estimates of methane efflux across different scales in space (Christensen et al., 2003).

It is demonstrated in Figure 1 how species composition and land cover classification, particularly the distribution of aerenchymous vegetation, pools and hummocks, are critical controls on methane efflux. For example, Frenzel and Karofeld (2000) reported the highest emissions from plots in a raised bog in Estonia in a hummock-hollow complex with *Eriophorum vaginatum* and *Scheuchzeria palustris*. Spatial variation in vegetation type and landform, and thus methane emission rates, also tends to be high in peat bogs (Yavitt et al., 1988; Windsor et al., 1992) and even between microsites (Svensson & Rosswall 1984; Moor et al., 1991; Bubier et al., 1993a, b) within a distance of tens of meters or less. For example, major differences in the magnitude of methane emissions were observed between hummocks ($<20\text{mg CH}_4 \text{ m}^{-2}\text{d}^{-1}$), hollows (10 to $100 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$) and pools ($< 200 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$) within a small spatial extent (Moore et al., 1990). Preserving the spatial extent and pattern of vegetation and land cover type are thus critical for the accurate determination of methane flux as one moves from smaller to larger scales in space.

Complicating multiscale methane flux estimates, and contributing to the challenge of spatial complexity, is the nonlinear interaction between methane emissions and its drivers, including water table depth, and its controls on anoxic microenvironments and plant distribution, and soil temperature with its control on the rate of biological processes (Prather et al., 1995). The up-scaling of such complex ecological patterns necessarily requires simplification, because

computationally expensive ecosystem model simulations depend closely upon the representation of land surface heterogeneity (El Maayar and Chen, 2006). Simultaneously, naive aggregation of surface features can incur substantial errors if the transfer function

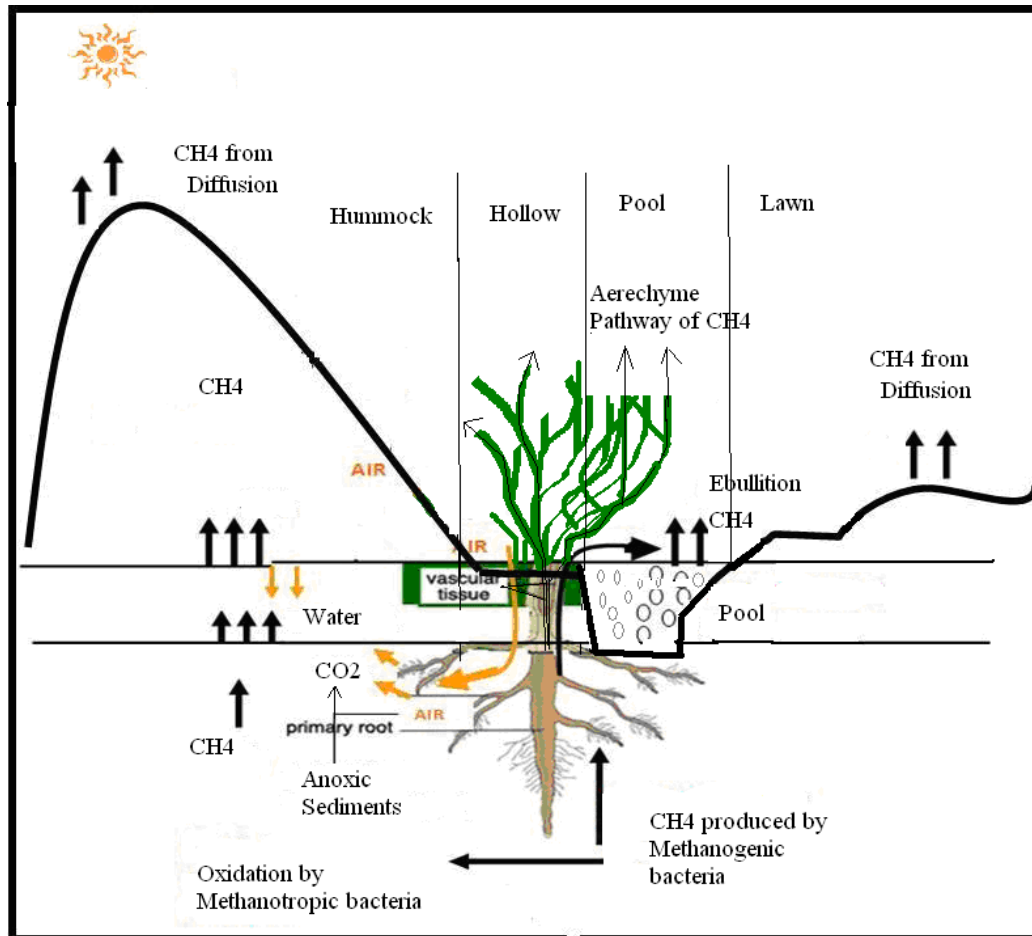


Figure 1: A schematic of methane production, oxidation and release into the atmosphere from different microstructural elements (MSEs) in a peat bog. Plants supply carbon to the peat matrix. In hummocks, carbon is supplied to the unsaturated layers where it may accumulate or be respired. In pools the rate of supply is somewhat lower due to sparse vegetation cover. On lawn surfaces, low vascular plant cover results in lower methane fluxes due to lack of substrate. Consequently, methane flux increases with an increase in vascular plant coverage given anaerobic conditions, until an oxidative environment is created, often through root growth. Methane is also directly released into the atmosphere by ebullition to the water table. (Adopted and modified from Kettunen, 2002 and Schuetz et al., 1991)

between driver and response is nonlinear (O'Neill and Rust, 1979; Rastetter et al., 1992;

Pelgrum, 2000), and a compromise must be found between simplicity and complexity for computationally feasible representation of the biological and physical processes that control methane efflux.

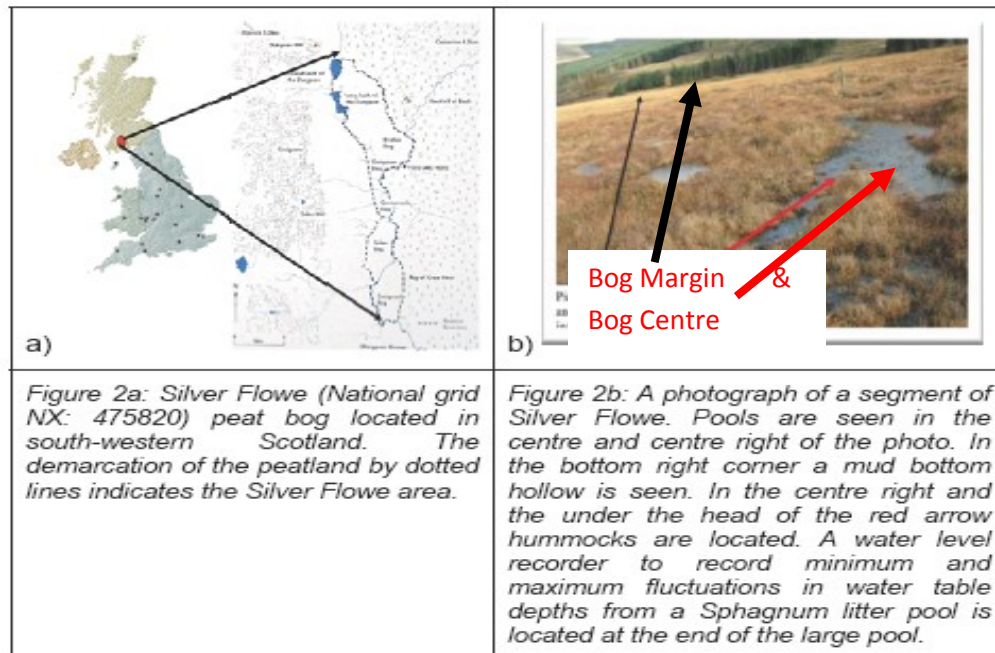
It has been demonstrated that preserving the information content of fine-scale surface features can minimize bias in surface flux estimates for the case of CO₂ while simultaneously simplifying land cover complexity (Stoy et al. 2009), and methane flux estimation presents a similar upscaling problem. To begin progress on the challenge of simplifying spatial pattern in wetlands while retaining accurate estimates of their processes (namely methane efflux), we present a methodology based on multiresolution remote sensing.

We argue that preserving the information content (IC) of high-resolution observations across space and time is critical for obtaining an unbiased upscaled estimate of CH₄ flux. In the present paper we investigate the upscaling of the peatland surface features from fine to coarse resolution by combining inference from multiple remote sensing platforms and spatial aggregation techniques that employ these remotely sensed data from a peat bog in south-western Scotland. We present approaches based on quadratic approximations in which the land surface features responsible for methane are upscaled while preserving the extent and pattern of these features, as quantified using techniques from information theory (IT). Namely, we explore simple aggregation *versus* quadratic approximations, and demonstrate how in the latter the IC is altered less than simple aggregation, leading to improved multi-scale flux estimates. We highlight spatial rather than temporal aspects of methane flux estimation here; extensions of our information conserving approach into the temporal domain as related to future studies are discussed. We focus our investigation on an ombrotrophic (rain-fed) peat bog ecosystem in south-western Scotland that is characteristic of peat bogs in the United Kingdom.

Methods

Study Site

The study site chosen is Silver Flowe (55° 07' 03" N, 4° 24' 08" W), which is located in the New Galloway forest reserve in the Dumfries and Galloway council area, Scotland (Figure 2a). It lies between 230 m-277 m above datum (O.D.) in the Cauldron of the Dungeon, a valley drained by Cooran lane north of Loch Dee in the Stewartry of Kirkcudbright.



Micro-structural Elements of Silver Flowe

Peatland microtopography is generally most pronounced and varied at the centre of the bog, and at is simplest within the bog margin (Lindsay 1995); the margin may consist of a single growth form or vegetation. In contrast the bog centre may display a striking range of patterns consisting of alternating terrestrial and aquatic microforms or elements (e.g. hummock, hollow, pool, Figures 1 and 2).

Typical micro-structural elements (MSE) found in the bogs include pools, hummocks and mud-bottom hollows (Figure 2b). Pools vary from deeply eroded pools; steep sided pools with a bare floor, to shallow pools with partial or complete cover of *Sphagnum* mosses. Herbs and shrubs common to Silver Flowe include *Molinia spp.*, *Erica tetralix*, *Calluna spp.*, *Eriophorum spp.*, *Trichophorum spp.*, *Dorsera rotundifolia*, and *Rhynchospora alba*. Hummocks of varying size are found across the bog. Lawns are wet to dry depending on the proximity to pool complexes and precipitation. Tussocks of *Eriophorum vaginatum* and patches of *Calluna vulgaris* are common on lawns. Overall, Silver Flowe is a typical example of a blanket bog in the UK, and is suitable to investigate the representation of fine scale heterogeneity in upscaled methane estimates.

We selected samples from different images to carry out a supervised classification in ENVI (The Environment for Visualizing Images Research Systems, Inc. 4990 Pearl East Circle, Boulder, CO 80301, USA) program. The samples were selected from scatter plots between green and red bands of the original data sets. The three classes identified were pools, lawns dominated by hummocky heather (HHL), and lawns dominated by *Eriophorum vaginatum* (EL). *Eriophorum* has vascular tissues (aerenchyma) which act like a conduit for methane emissions (Greenup 2000), while pools may release methane directly in to the atmosphere via ebullition (Walter et al., 2000; Frenzel & Karofeld 2000; Moore et al., 1990).

Remote Sensing Data

Optical data was collected from an onboard Daedalus 1268 Airborne Thematic Mapper (ATM) instrument flown by the UK based Natural Environmental Research Council's (NERC) Airborne Research and Survey Facility (ARSF) in April, 2006. And in August 2007 Eagle data was collected by ARSF. These data were delivered in a raw format of level 1b which is radiance data and

required atmospheric correction to be able to obtain reflectance information and subsequent geometric corrections for resampling. For atmospheric correction, ATCOR v.4 (Richter 2000b) was used and geometric corrections were performed using NERC's AZGCORR software. The resulting pixel size was 1.5 m^2 . After this pre-processing, the acquired imagery was further analysed and non-wetland classes including forests, lakes and surrounding mountains were masked.

For IKONOS data collected in August 2007 at 4 m^2 , only atmospheric corrections were necessary as the image was already georeferenced. Post processing, such as a supervised classification of study area was performed using ENVI. Airborne LiDAR data was modelled into a DEM with 1 m^2 pixel resolution using QT Modeler (Applied Imagery, John Hopkins University Applied Physics Laboratory). On board the plane along with other sensors, a digital camera was also mounted to collect a high resolution (0.25 m) digital photography (DP).

Information Theory

Information theory (IT) is a well-developed discipline that cannot be treated fully within the scope of this paper. Briefly, IT quantifies, rather than qualifies, how signals encode information and how information is processed (e.g. reduced, or altered) by systems of any form (Sinanovic & Johnson, 2006), including, for example, the algorithm used for the upscaling procedure (Stoy et al, 2009). Most applications of IT are in the computer sciences, applied mathematics and engineering, and other fields where the communication of information is paramount for creating or explaining a system (e.g. linguistics). IT is employed less frequently in ecology (Ulanowicz, 2002), and especially geoscience, despite the natural application of IT for quantifying information as it is transferred across scale (Chen and Blong, 2002; Stoy et al. 2009).

According to the data processing theorem (DPT, Cover & Thomas, 1991; cited in Sinanovic & Johnson, 2006), a system operating on a signal cannot produce output containing more information than that encoded in its input. In other words information content will be lost or remain static at larger scales with coarser resolutions, but this information loss can and should be minimized while upscaling to avoid bias (Pelgrum 1992). In our context, information metrics can quantify the total change in the areal extent of multiple land cover types, and thus be used as criteria for success when finding optimal techniques to estimate multi- scale CH₄ flux.

Of particular interest is the Kullback-Leibler distance (D_{KL}) which is used to quantify the difference in information between two variables. In our example we used the D_{KL} to quantify how the coverage of micro-structural elements of peatland changes as we scale up from fine resolution to coarser resolutions. For an original probability density function (pdf, or probability mass function, pmf) P and corresponding pdf Q that is the resultant of some processing of P , the discretized D_{KL} for bins (i.e. histograms of land cover classes) quantifies how these histograms change with resolution:

$$D_{KL} = \sum P_i \times \log(P_i / Q_i) \quad (1)$$

The transfer of information can also be compared using the Shannon Entropy ($E_{S,n}$, Shannon, 1948) which can be normalized by the bin size, N such that its value is bounded between zero and one (Wesson et al. 2003).

$$E_{S,n} = (\sum P_i \times \log P_i) \div \log(N) \quad (2)$$

In order to counter the shrinking dimensions of the data series at larger scales (i.e. because the number of data points available becomes small as the length scale becomes large) a bin size of ten was selected in all the computations. Data with uniform distribution takes the

$E_{S,n}$ value equal to one and a Dirac delta function with single-valued support has an $E_{S,n}$ of zero (e.g. Stoy et al., 2006).

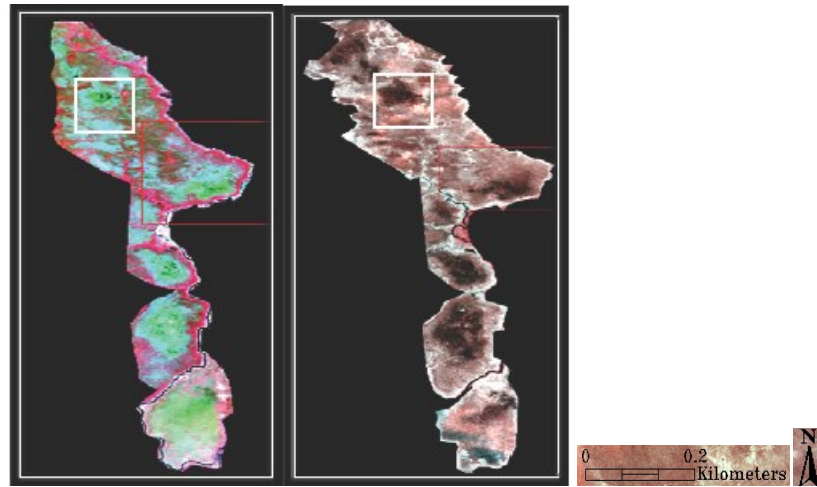


Figure 3: left) Silver Flowe (Figure 2a) in colour infra red (CIR) collected from airborne Eagle Sensor with 258 bands on 28th August 2007. The image is a combination of bands 199, 120 and 71, right) is the CIR (bands :7;G:5;B:2) of ATM imagery collected on 9th May 2006. It is evident that the ATM imagery has more dark regions in the bog centre, which indicates water in pools and hollows. This is due to recent snow melt precipitation in April. The Eagle data has more robust vegetation and sphagnum pools (green areas in the bog centre) due to the maturity of growing season in August. For our analysis we selected one part of the Long Loch bog highlighted in the white box which represents the complexity of the entire bog and it is large enough for the LANDSAT comparison.

Upscaling Methods

The classified image from the original resolution is scaled to coarser resolutions using simple aggregation with square pixels of increasing size and, and is compared against multi-resolution quadratic parameterization (Wood, 1995). Differences among scale and platform are quantified by comparing changes in the spatial extent of multiple land surface features, namely pools, heathery hummock lawns, and *Eriophorum* lawns; these changes are then synthesized using the $E_{S,n}$ and DKL.

Aggregation by mean pixel values (PA)

The aggregate function resamples input data to a coarser resolution based on the mean value aggregation strategy. In this technique, the input data cell values are multiplied by the scale factor and the resulting coarser output cell map the spatial extent of the output onto the input data (Figure 4).

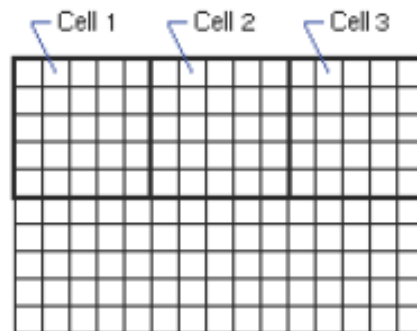


Figure 4: Aggregation Scheme based on mean values of Fine Scale Pixels Encompassing the Desired Coarse Scale Pixel

The resulting aggregation image may have misclassified pixels, which are constrained by applying the majority filter function.

Multi-scale Quadratic Parameterization (QI)

Quadratic approximation is expected to preserve the pattern in peatland as the resulting up-scaled pixel value is a bi-quadratic interpolation within the predefined window size, thus the original pixel resolution remains the same throughout the interpolation. The resulting image will be blurred due to the compression of the image at lower resolutions.

Consider the derivation of the 3 coefficients that define a 2D quadratic trend surface:

$$Z_i = b_0 + b_1x_a + b_2y_a + b_3x_a^2 + b_4x_ay_a + b_5y_a^2 \dots \dots \dots (3)$$

Where x and y represent spatial dimensions and b1-b5 are fitted parameters (e.g. Unwin,

1975; Unwin and Wrigley, 1987; Press et al, 1992)

To solve this expression, the number of points sampled must be at least 6 (e.g. McColy, 1995).

If we limit the sample of cell values to a square window centered around the point of interest, a will be 9, 16, 25, ... n^2 as the local window increases from the smallest size (3 3) to the largest size (n n) determined by the smaller side of the image, where $a = 9$, the resultant quadratic expression will be identical to the quadratic derivation as explained by Evans (1979, p. 28) and adopted by Wood (1996).

To solve the general case, the unknown coefficients are expressed as a set of 6 simultaneous equations, or *normal equations* (Unwin, 1975): If all observed values z a are taken from a local window with dimensions n by n , where n is an odd number, a local coordinate system can be defined with the origin at the central cell and a grid spacing of g . Thus for a 5 by 5 window in figure 5 below, the coordinates of each cell become,

$(-2g, -2g)$	$(-2g, -g)$	$(-2g, 0)$	$(-2g, g)$	$(-2g, 2g)$
$(-g, -2g)$	$(-g, -g)$	$(-g, 0)$	$(-g, g)$	$(-g, 2g)$
$(0, -2g)$	$(0, -g)$	$(0, 0)$	$(0, g)$	$(0, 2g)$
$(g, -2g)$	$(g, -g)$	$(g, 0)$	(g, g)	$(g, 2g)$
$(2g, -2g)$	$(2g, -g)$	$(2g, 0)$	$(2g, g)$	$(2g, 2g)$

Figure 5: Kernel window of size 5x5 which interpolates the values in the window and assigns to the central pixel before shifting to the next pixel (from Wood, 1996)

The symmetry of the coordinate system reduces all expressions without even exponents to zero (as observed for the linear case by Unwin & Wrigley, 1987, p. 352). This matrix expression

may also be reordered using Evans' notation in (3), above. The reordering of the normal equations so that the coefficients of the constant f (or b_0) lie in the last row and column make computation of the matrix inversion much simpler as explained in constrained quadratic approximation below. By expressing the reordered and simplified normal equations in matrix form we are left with the constrained quadratic approximation in which all other cell values in the local window are expressed as relative changes from the central value. Once this coordinate system has been adopted, the trend surface is forced through the origin by dropping the quadratic coefficient f (or b_0) and all relevant elements of the normal equations (the bottom row and right-hand column of the matrix of cross products) resulting in a new expression, (modified from Wood, 1996).

Note that computationally, the solution of this matrix expression can be achieved through the lower and upper triangle LU decomposition and back substitution using the full 6 × 6 matrix (Wood, 1996). The algorithm for such a multiresolution parameterization is implemented by Wood (1996) in the software “Landserf 2.3” and is freely available at <http://www.landserf.org/>.

$$\begin{pmatrix} \sum x_i^4 & \sum x_i^2 y_i^2 & 0 & 0 & 0 \\ \sum x_i^2 y_i^2 & \sum x_i^4 & 0 & 0 & 0 \\ 0 & 0 & \sum x_i^2 y_i^2 & 0 & 0 \\ 0 & 0 & 0 & \sum x_i^2 & 0 \\ 0 & 0 & 0 & 0 & \sum x_i^2 \end{pmatrix} \begin{pmatrix} p \\ q \\ r \\ s \\ t \end{pmatrix} = \begin{pmatrix} \sum z_i x_i^2 \\ \sum z_i y_i^2 \\ \sum z_i x_i y_i \\ \sum z_i x_i \\ \sum z_i y_i \end{pmatrix} \quad \dots (4)$$

Results

We present results of land cover classification from digital photography (DP), ATM, and IKONOS data and alterations using square pixel aggregation and multi-scale quadratic parameterization. We used DP as the highest resolution data against which the other platforms are compared. First we compared the classification results of the original resolutions of each data set. We then scaled the original data to coarser resolutions and compared relative information gained or lost. The questions we address are: would the DP results at 0.25m resolution be similar to the results of original ATM or IKONOS sensors when we upscale DP data to the pixel sizes equal to that of ATM and IKONOS pixels using mean aggregations and quadratic approximations? And similarly, would the results from ATM at its original 1.5m resolution be more or less similar to the classification results from IKONOS data, or LANDSAT data at 28.5 m? Although LANDSAT data was not available for this analysis, we present estimates at the characteristic LANDSAT scale to enable future comparisons.

Classification of Data

The DP image over this expanse contained 1536x1536 pixels at a sample resolution of 25 cm (Table 3). The ATM data subset had 256x256 samples with pixel resolution of 1.5m. The EAGLE subset was 128x128 with a pixel size 2.5 m, and the IKONOS image included 96x96 pixels with 4 m resolution. The total area of the subsets taken from DP and ATM was same and was equal to 147456m². The area of the IKONOS image was almost the same as DP but the total area of the EAGLE subset was less compared to the other three, see Table 3, below. The classification results from the supervised classifier with minimum distance algorithm are shown in Table 3, below. The classified images are shown in Figure 6 below.

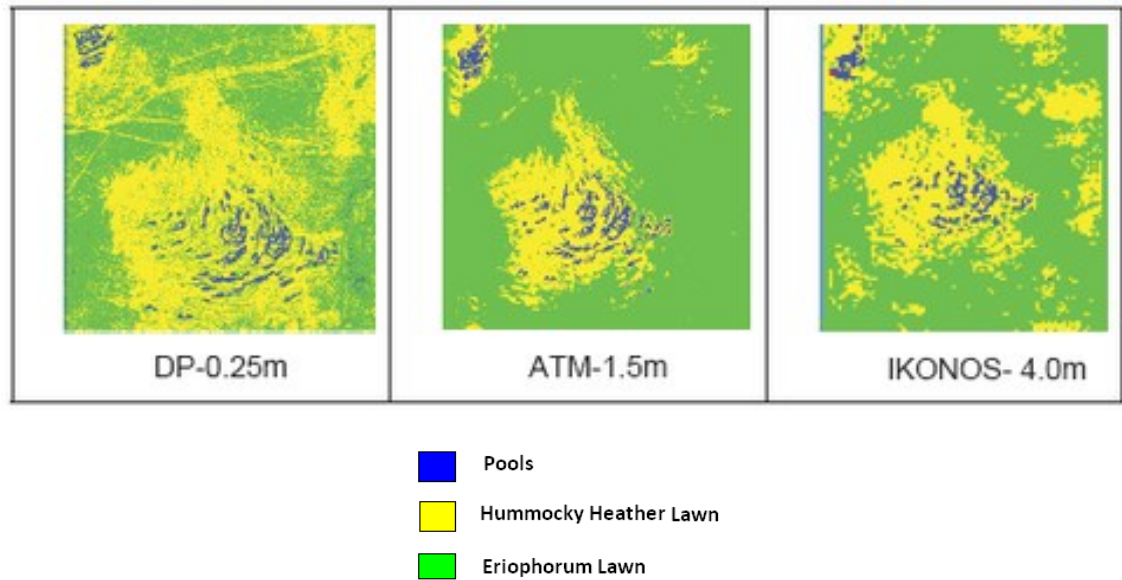


Figure 6 a-c: A classification map for three classes obtained from digital photography (.25m pixel size) is shown on the left. The figure in the middle is the classification map of ATM sensor (1.5m) and on the right is the map from IKONOS sensor (4.0m). Blue corresponds to pools, yellow to hummocky heather lawn (HHL) and green to Eriophorum Lawn (EL. Results from Eagle scene are not displayed.

	Digital Photograph	ATM Image	IKONOS Image
Class	Area m ²	Area m ²	Area m ²
Pools	5352.06	4902.75	4736
Hummocky Heather Lawn	70469.88	28410.75	49760
Eriophorum Lawn	71634.063	114142.5	91424
Total	147456.003	147456	145920

Table 3: Area of the three classes from the figure 6 above.

The area distribution for the three classes with original pixel resolution is shown in Figure 7. We up-scaled the DP classification to the size of ATM, IKONOS and LANDSAT pixels to analyze how the areas of the three classes from the upscaling using both mean aggregations and quadratic approximations would change (Figure 9a & b). We repeated this procedure with ATM and IKONOS data. ATM data was upscaled to sizes 3, 13 and 19 times the original pixel value

(1.5m, Figures 10a & b). Similarly, IKONOS was upscaled to 5 and 7 times the original pixel value (4.0m) in Figure 11 (a & b), to be comparable with the 28.5m LANDSAT scale.

The change in pool area in DP from the original pixel size (0.25m) to 4m was 3.6% to 22.4% of the total area using quadratic interpolations. For the ATM image, the pool area only changed from 3.3% (1.5m) to 3.9% (28.5m). IKONOS data had pool areas increasing from 3.25% (4m) to 22.4% (28m), respectively. Similar alterations to EL and HHL areas were observed (Figure 7).

The pixel averaging method resulted in the pool areas of 3.6% of the total area from the original pixel resolution. The upscaled values (7x & 17x) in this class was 25.5% and 30.44% of the total area, respectively. However, PA clearly lost the pattern on the peatland (see figures 12a-g).

To help summarize these combined changes in the extent of different surfaces, the $E_{S,n}$ is plotted against the pixel resolution in Figure 8. $E_{S,n}$ values increased consistently as resolution increased from 0.25 m to 4 m. The jump from DP (0.23) to ATM was very high, but subsequent entropy values for the coarse resolution data were within 0.6 to 0.67.

The changes in surface pattern as a consequence of mean and quadratic interpolation at different resolutions is apparent (Figures 12 & 13). Figures 12(a-c) represent the patterned areas of the three classes after original DP, ATM and IKONOS data were upscaled, respectively. The results from quadratic approximations are also shown in Figure 13.

Finally we plotted the Kullback-Leibler distances for each data set separately and compared it between the two aggregation methods (Figure 14). The D_{KL} for the DP, aggregated with mean

values is represented as DP (PA) and quadratic interpolation as DP (QI). The pixel averaging method shows an alteration to the information content of the fine-scale image as the scale is increased (blue curve). The D_{KL} from quadratic interpolation shows a loss in information, when the resolution reached the size of ATM, but the information loss between DP and IKONOS is lower than that between DP and ATM.

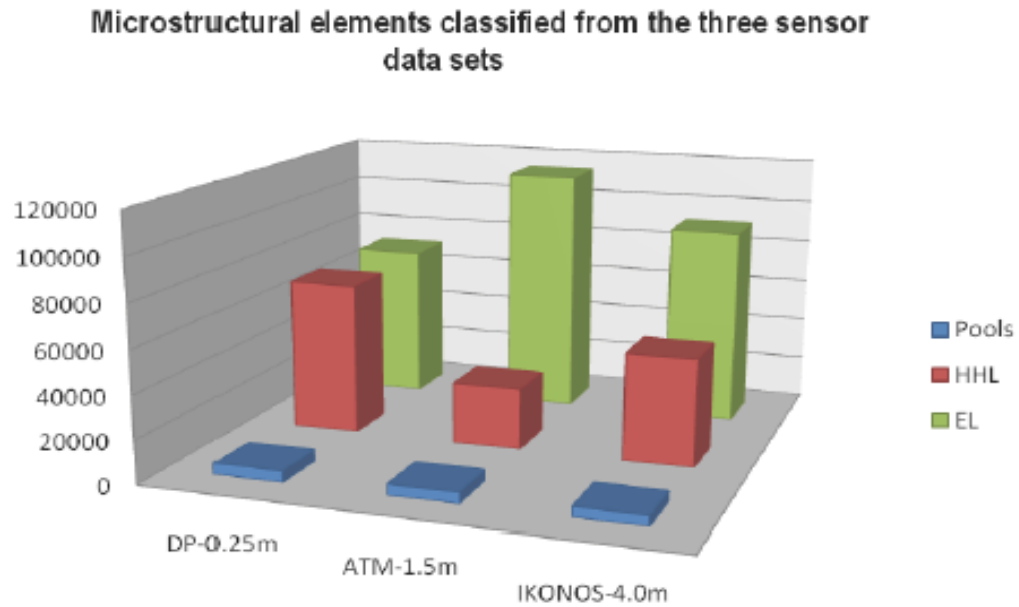


Figure 7: The area (m^2) distribution for the three classes with original pixel resolutions in DP, ATM and IKONOS data from supervised classification method

The alteration to IC upon quadratic approximation of DP to the ATM resolution was lower than PA and had almost preserved the information. In IKONOS data similar results were not reported which may be due to the extreme blurring effect in its pattern, (see figure 13 c & f) as the resolution changes to lower values.

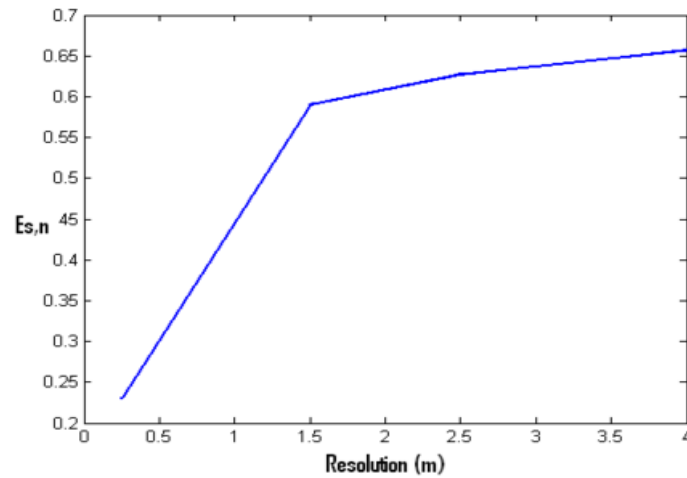


Figure 8: The normalized Shannon entropy (ES,n) of the pdfs for three classes plotted against pixel resolution from the classified images. Whilst DP has the highest information content, the change in information content between ATM data and IKONOS data is minimal. The coarse resolution data becomes more uniformly distributed. See Table 3 for the resolutions that correspond to different imagery

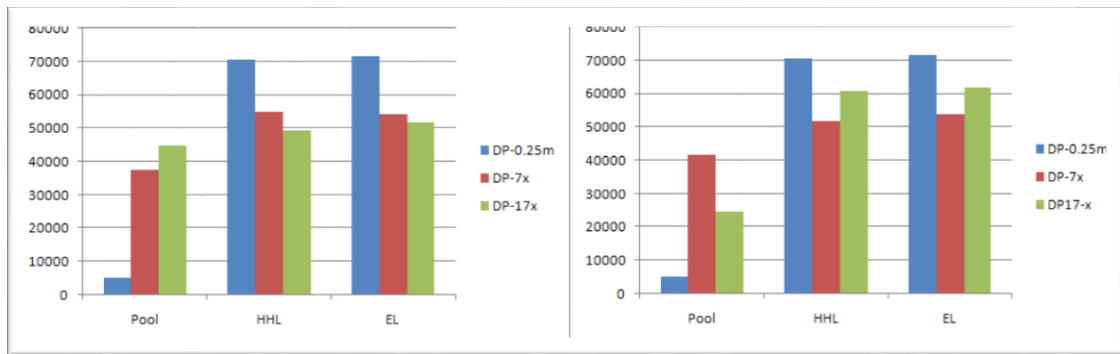


Figure 9: Areas (m^2) of the classes pool, heathery hummock lawn (HHL) and Eriophorum lawn (EL) resulting from mean aggregation (PA) (left) and quadratic interpolation (QI) (right) of the digital photograph (DP)

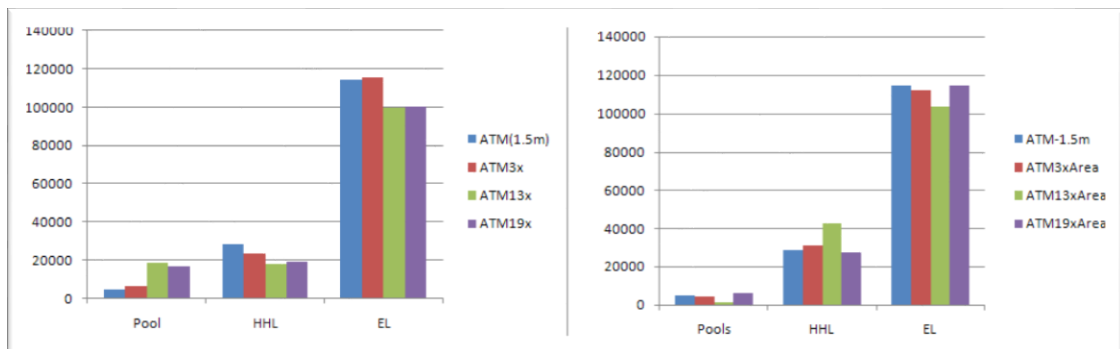


Figure 10: Same as Figure 9 for the Advanced Thematic Mapper (ATM) Image

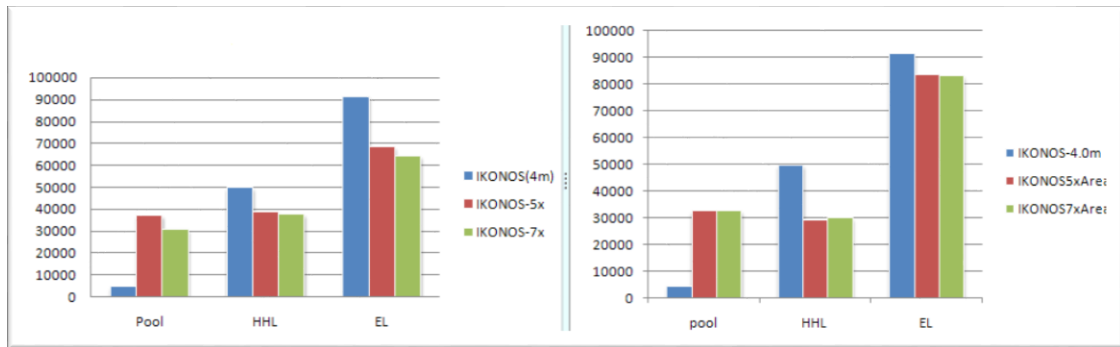


Figure 11: Same as Figure 9 for the IKONOS Image

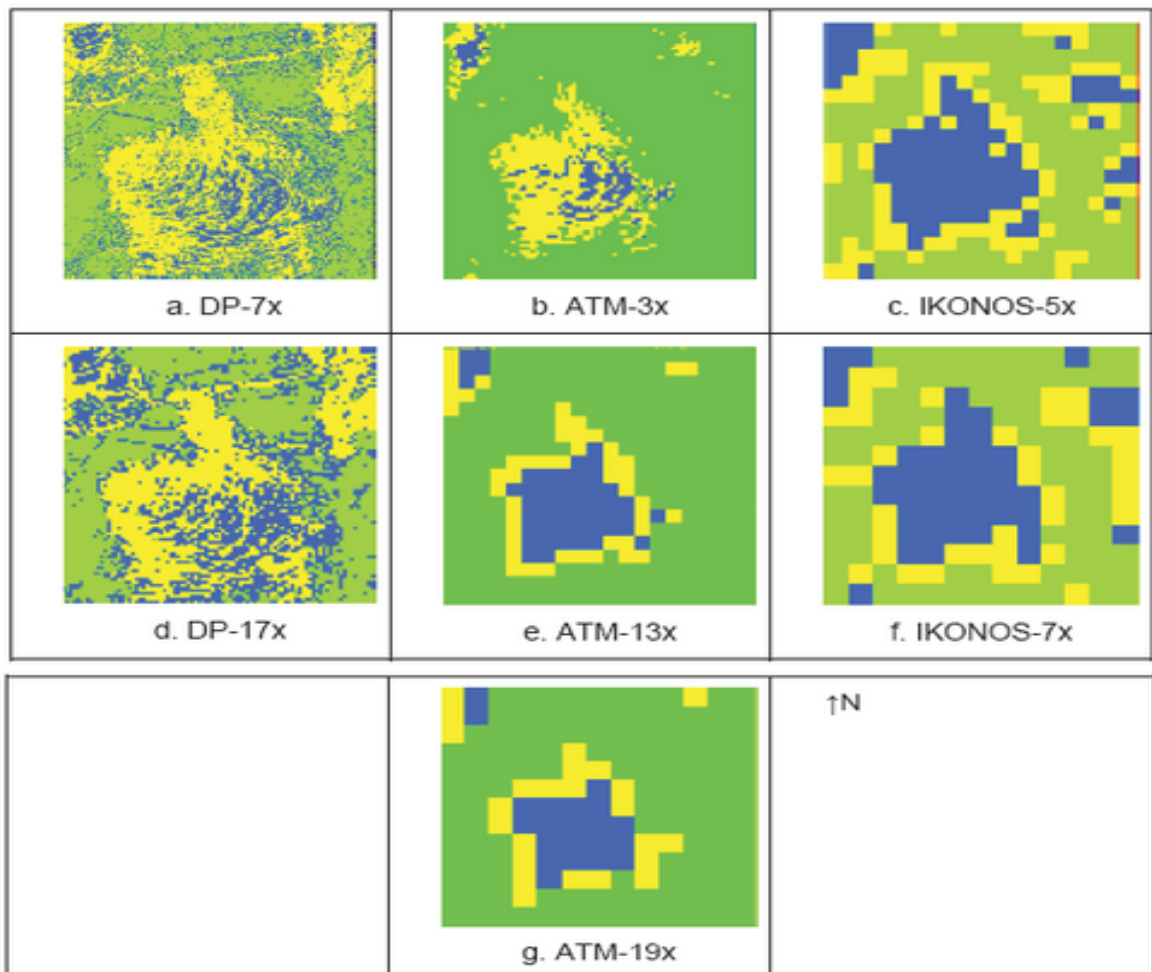


Figure 12a-g: The effect of mean pixel aggregation on the DP, ATM and IKONOS images. As seen, the pool class shows overestimated values in ATM and IKONOS and does not preserve their shape and location at coarser scales. Pool structure in the original classification map in ATM at 1.5m pixel size (dark blue regions) dominate the bog centre from the scene in the coarse scale images. Upscaled IKONOS data overestimated pool extent and misclassified EL in the North-Eastern and South-Western areas of the study domain.

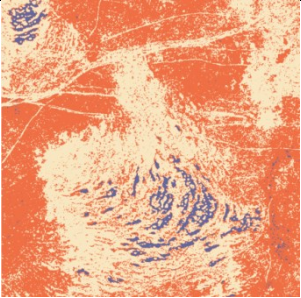
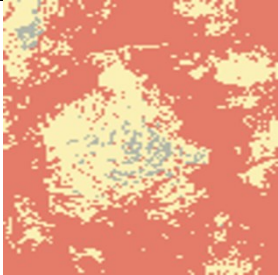
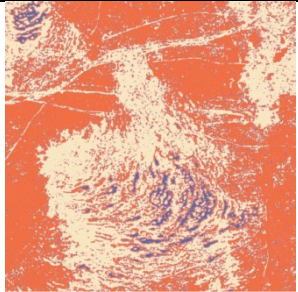
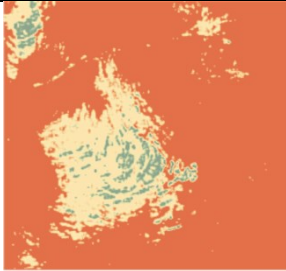
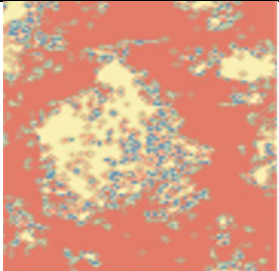
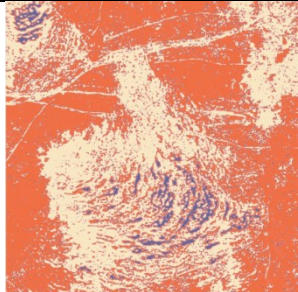
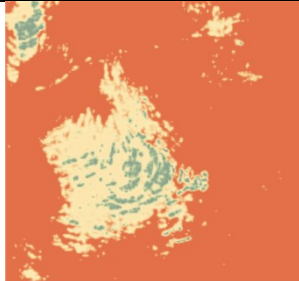
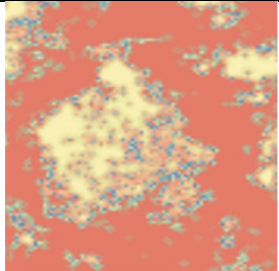
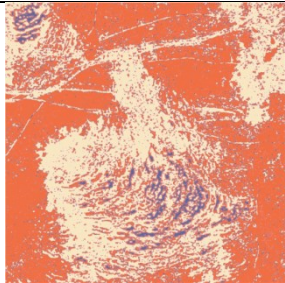
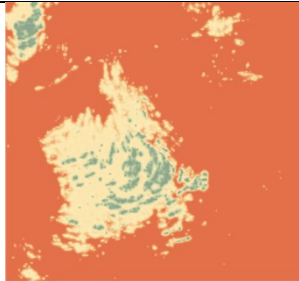
Digital Photograph	ATM Sensor	PAN Sharpened IKONOS
 0.25 m	 1.5 m	 1.0 m
 1.5 m	 4.5 m	 4.0 m
 2.5 m	 7.5 m	 8.0 m
 4.0 m	 10.5 m	 Eriophorum Lawn  Pools  Hummocky Heather Lawn

Figure 13: The effects of the multi-resolution quadratic approximations after progressively interpolating with variable window sizes. The original pixel resolution was unchanged during the interpolation process. In all the scaled up images the pattern on peatland is preserved and also the position of individual microstructure elements are maintained in DP and ATM while in Pan sharpened IKONOS, the pattern is lost.

Discussion

The quantification of methane emissions across space remains largely uncertain (Zhuang et al., 2009), and one of the main sources of error in regional estimates of CH₄ emissions from peatlands is fine scale heterogeneity in the main controlling factors such as water table depth, vascular plant coverage and peat temperature coupled with the non-linear interactions between those drivers affecting emission fluxes and methane. In our example, we explored the effects of different remote sensing imagery and aggregation procedures on the areal expanse and information content of different surface features in a peat bog in south-western Scotland. We quantified how measurements and estimates of land surface patterns change when we scale the original data source to lower resolutions using mean pixel aggregations *versus* aggregation by quadratic interpolations as a means to choose an ideal upscaling procedure and to compare estimates that derive from different images.

Classification of the Images

Our analysis with supervised classification using a mean distance algorithm with original pixel resolutions (Table 3) showed that pool areas decreased by 7.2 % between the DP with 25 cm resolution to the airborne ATM data at 1.5m resolution. The relative reduction in pool area was even higher, 11.5% when DP classification is compared against IKONOS data (Figure 7). The same was true for HHL, which decreased by almost 60% and 30% in total area from DP to ATM, and DP to IKONOS, respectively. Estimates of *Eriophorum* lawn expanse consequently increased by approximately 37% and 27% , respectively, between DP and ATM and between DP and IKONOS imagery (Figure 7). Visual interpretation of the DP results obtained from mathematical averaging (Figure 12) demonstrates that the pool areas were overestimated while the other two classes were underestimated when compared to original classification results (Figure 6). In

the north-eastern and south-western sections of the study area, the *Eriophorum* lawns were misclassified as pools. In the centre of the bog where pools are concentrated, the

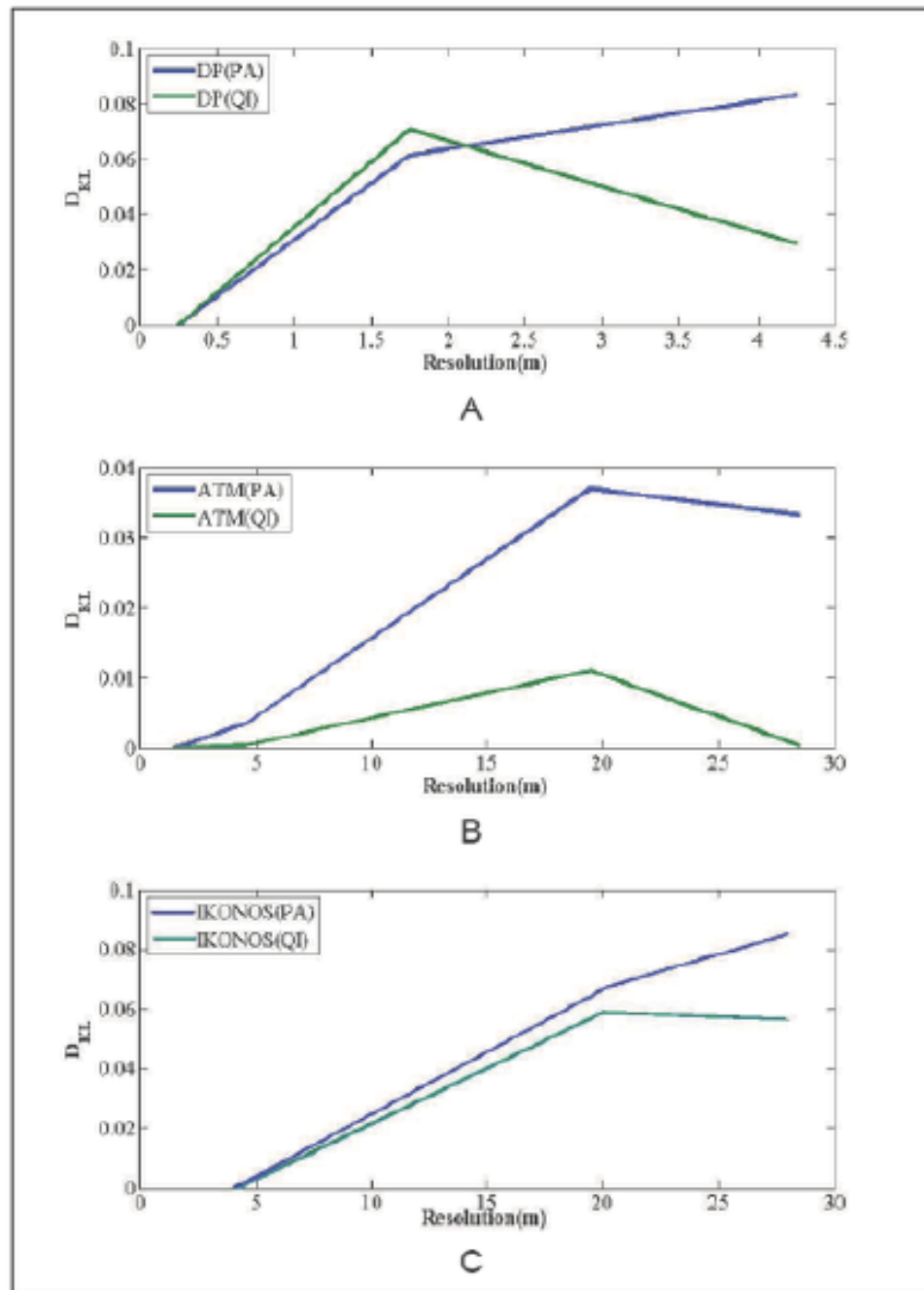


Figure 14: The Kullback-Liebler divergence (D_{KL}) values for aggregating (blue, PA) or interpolating (green, QI) digital photography (DP, A), ATM imagery (B) and IKONOS imagery (C) are shown.

hummocky heather lawn were also misclassified as pools in the upscaled images (Figures 12 a & d). The case of ATM is more severe; pools nearly dominated the bog centre in the upscaled images (Figures 12 e & g).

Elements of the fine scale pattern are also completely lost from the original map (Figure 8) and in the IKONOS image. Becker et al. (2008) recently reported such behaviour when they upscaled peatland microstructural elements from a highest resolution of 6 cm to a lower resolution of 100 cm using nearest neighbour resampling techniques on raw data. They reported loss in pool area by 54% between 6 cm and 100 cm resolution and an increase in hummocks and corresponding decrease in lawns by 21%. Our results from QI show improvements over PA in terms of maintaining the pattern on the bog centre.

Implications of different sensor spectral properties on the classifications

The reflectance spectrum of a material is a plot of the fraction of radiation reflected as a function of the incident wavelength and serves as a unique signature for the material. In principle, a material can be identified from its spectral reflectance signature if the sensing system has sufficient spectral resolution to distinguish its spectrum from those of other materials. Different sensors have different reflectance properties.

This is important because class abundance has been shown to significantly influence the values and scaling behaviour of landscape indices (e.g., Saura and Martínez-Millán 2001). It should be noted that some differences exist in the red (R) and near infrared (NIR) bands for the WiFS and TM sensors, and this has been shown to have some impact on the resultant NDVI values (Teillet et al. 1997). The wavelengths of WiFS bands are 620- 680 nm (R) and 770-860 nm (NIR) while those of TM are 630-690 nm and 760-900 nm (e.g., Chuvieco 1999). The width of the red band

is the same for both sensors, but NIR band is much wider on the TM sensor. There are also slight differences on the center wavelengths for each band, but these differences tend to have opposite effects on NDVI values (Teillet et al. 1997). That is, wider NIR bands tend to produce lower NDVI values, while higher center wavelengths for NIR bands implicate higher NDVI values. As a result of these effects only small differences are expected between the NDVI obtained from TM and WiFS sensors (an absolute difference smaller than 0.02 according to the results presented by Teillet et al. 1997). Moreover, the differences tend to be similar among the different vegetation types analyzed by (Teillet et al. 1997). Thus, the same vegetation types are those with the highest (and lowest) NDVI values both in TM and WiFS data. This is the only assumption required to generate equivalent categorical datasets for both sensors according to the NDVI threshold procedure.

Our objective was to conduct a broad classification of peatland surface features, generally between aquatic and non-aquatic classes and more specifically into pools, hummock-Hollow and vascular vegetation lawns. In our research we used ATM, IKONOS and EAGLE sensor data. ATM has eleven channels with the first eight channels has bandwidth between 420 nm to 1050 nm covering the entire visible and almost the Near Infra Red (NIR) of the spectrum. It has a gap between 1050-1555 nm and between 1750-2080 nm in the Shortwave Infra Red (SWIR) range. Since water has strong absorption around 1450 nm, 1950 nm, these bands are removed.

In case of IKONOS, it has a Panchromatic band from 526 nm - 928 nm and four multispectral bands 445 - 516 nm (Blue), 506 - 595 nm (Green), 632 - 698 nm (Red) and 757 - 853 nm (NIR). The PAN data when fused with Multispectral data gives a high spatial resolution multispectral data of 1 m pixel size, that has been applied in the present research. The ATM sensor has a pixel

resolution of 1.5 m while Eagle has 2.5 m. because of these different spectral and spatial properties of the three sensors, there may be some difference in the classification results.

If the objective is to carry out a detailed classification of species of vegetation from the peatbog then the AISA pair of sensors, EAGLE and HAWK that covers the entire EM range between 400-2400 nm with their narrow contiguous spectral bands are more suitable for extraction of endmembers. But on the other hand the EAGLE/HAWK sensor data may pose redundancy problems due to very narrow contiguous data, thus some kind of spectral filtering or polishing may be desired.

Extracting endmembers for species discrimination is difficult with the other two sensors. ATM channels in the visible, NIR and SWIR spectral range has a broad band and IKONOS has four broad bands in the visible and NIR regions, thus the band ratios makes it difficult to extract endmember of the features of interest from the peatbog.

Since, in the present research, the objective was not about doing any detailed classification of peatland vegetation species but rather only characterizing surface features such as aquatic and terrestrial classes such as pools, hummock, hollow and vegetation lawns, the three sensors classification results on a visual inspection basis had classified the data as desired. But since, in the current study no validation of the classification results was performed, it will be difficult to quantify the exact implication of the sensor spectral bands on the results of the classifications. It is therefore, recognised that any future work on this topic should have a validation method.

Shannon Entropy

The transmission of information has been computationally studied by Shannon by introducing the theory of Information (Shannon 1948). Shannon's entropy is a mathematical index that

measures diversity in categorical data. The main objective of information theory is to evaluate and quantify the information transmitted by a channel. For a given number of categories, the entropy is maximum when each class is present in equal proportions, while for an evenness of distribution the entropy increases with the number of classes. This concept of quantifiable information is done by measuring the entropy that evaluates the degree of diversity of the distribution of the variables such as the point spread functions of the three sensor's classified images in the present research.

Here, we use an information theory perspective to quantify the statistical distributions and information transfer between the remotely sensed fields from three different sensors at multiple spatial resolutions to ascertain the contribution of the various spatial resolutions to the observed signal. We assume that the initial classification result from the digital photography with pixel size of 0.25 m is as good as ground truth information, though no validation is carried out to prove this assumption. This is an empirical approach to determine the nature of methane emission hotspots such as pools, hummocks and lawns with vascular plants classified at larger scales where observations of actual classifications are lacking, but the spatial variability of the surface patterns such as distribution of pools and vascular vegetation is possibly sufficient. Here, we were interested only in the issues of resolution and how the ability to quantify the spatial patterns as a function of resolution impact our ability to determine spatially heterogeneous peatland surface in preserving the information from fine scale to coarser scales. For this, two information metrics were computed, Shannon entropy, $E_{s,n}$ and the Kullback-Liebler Distance, D_{kl} . These metrics have been elsewhere successfully applied to characterize biodiversity as the plot size is increased (Bartha et al., 1995; Juhasz-Nagy & Podani, 1983).

In this case, we use the metrics to examine to what extent the relative importance of the coarse resolution data has on the transfer of classification results from fine scale to coarse scale and hence the pattern on the peatland surface. The spatial entropy as a function of resolution is shown in the figure 8. Larger values of entropy imply more disorder/randomness (i.e. a more uniform probability density function).

As the probability density function becomes more random, the information content is decreased; i.e. an individual sample has less predictive information about any other point. The classified results from Digital Photography have the lowest entropy while that from the IKONOS data has the highest entropy. We used a histogram from the classified image to calculate the entropy, the result is sensitive to the width of the bin, and therefore a kernel-density function approach is advised (Moon et al., 1995). If un-normalized, the entropy is a measure of how complex the dataset is by returning the number of bits necessary to encode the transmission. In this case, we scaled by $\log_2(L)$ in order to calculate a relative measure with a range of 0–1.

Next we investigated the mutual information content from the behaviour of the two different upscaling methods, pixel averaging and quadratic interpolations on the three classes classified from the three different sensors by plotting the Kulback-Liebler distance for each classified data set (figure 14) against the sensors spatial resolutions. This was done to examine how much information is preserved by each of the three sensors classified data set as the sensor resolution is decreased from fine to a coarse resolution. Our results demonstrate that the mutual information is preserved with the quadratic interpolation method better than the pixel averaging method.

Information Content

Changes in aerial extent and thereby pattern among all classes were simultaneously quantified using the ES_n and D_{KL} . The ES_n is lowest for the DP and highest for IKONOS, implying that some categorical information is effectively 'averaged out' in the products with lower spatial resolution. The independent assessment of information transfer between upscaled DP, (Figure 14) ATM (Figure 15) and IKONOS (Figure 16) respectively by mean and quadratic methods further demonstrated the superiority of quadratic approximation for maintaining fine-scale information at coarser scales in space.

Pattern on Peatland

Our investigations demonstrated how the scaling process would influence the resulting patterns on peatland. Results with mean aggregation showed that this method does not preserve the pattern and that pool structures dominated the upscaled versions in all the cases. The distribution of microstructural elements has changed in a zig-zag fashion displaying high positive amplitudes in pools (a gain in area) and high negative amplitude in HHL and EL (a loss in area). In another study, mean aggregation results reported by El Mayar & Chen (2006) lost pattern in lower resolutions before they multiplied by correction factors to compensate aggregation errors due to fine scale heterogeneity in the landscape and nonlinearity in the process based models that they proposed. Such correction factors can improve estimates, but are empirical and likely applicable to a single site or suite of similar sites.

In contrast to the results reported on aggregation by mean pixel values, the preservation of patterns on peatland is better depicted by the quadratic interpolation scheme (compare Figure 12 and 13). The centre of the bog area shows the pool complexes, although the up- scaling had a blurring effect at the coarser scales which is expected in any image

compression. The statistical differences in net areas after approximations are graphically shown in Figures 9b, 10b and 11b. As the quadratic interpolation is designed to retain the original pixel resolution throughout the interpolation process and assigns the interpolated values to the centre pixel, the pattern is very well preserved in the high resolution data and almost preserved in the lower resolution data. This is a considerable improvement on peatland pattern preservation during aggregation to lower resolutions, and we suggest that it could be adopted for regional and global scale estimates.

Conclusions and Future Studies

We demonstrated the impacts of different remote sensing products and spatial aggregation techniques on the quantification of peatland features. Our results using mean aggregations are in confirmation with recently reported analysis by Becker et al. (2008). The analysis using quadratic approximations based on Wood (1996) improved multi-scale estimates of the spatial extent of important peatland microstructural elements. These elements were not well preserved by mean aggregation. If a peatland surface is completely homogeneous and CH₄ emission models are linear then the aggregation can be performed simply by mathematical averaging of the results, but this is not the case here. The Silver Flowe peatland has very high degree of heterogeneity within the spatial distance of less than a few meters (Mohammed & Malthus, 2007), as do arguably most wetland ecosystems.

The overall results clearly demonstrated shifting patterns in peatland with changing pixel resolutions in the remote sensing observations, but not in the quadratic approximation of fine-scale data. We classified the landscape subset into three broad (but important) classes; it would be interesting to quantify how the pattern, and thereby process, estimates change if

more land surface classes are analyzed, and if microtopographical and temporal aspects of peatland heterogeneity are included.

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Simulation of peatland pools by LiDAR to assess the effect of the expansion of pools on the methane emission fluxes

Abstract:

The seasonal changes in the structural microtopography on the peatland surface have its bearing on the net emission fluxes of methane. Water table depth is one of the most important drivers that trigger methane emissions, and bog pools are one of the hotspots for methane emissions in the peatland. Water tables in bogs show seasonal variations with lowest variation in midsummer due to high evaporation. Episodic precipitations also cause short term fluctuations and as a result the pools expand due to precipitation and snow melts post winter, and contract in peak summer due to evaporation. A water logger was designed to capture the seasonal fluctuations in the minimum and maximum water table depth over a period of two growing seasons. Ten water loggers were installed along a 5 m transect on the Long Loch bog centre of Silver Flowe peatland that represented most of the structural microtopography and ten water loggers were installed across the landscape to measure seasonal variations in the water table depth from different microtopographical structures selected subjectively. Airborne Light Detection and Ranging (LiDAR) data from aircraft was acquired and digital elevation models (DEM) were simulated to study the seasonal changes such as the expansion of the pools. Good agreement was found between the field data and LiDAR DEM data with R^2 value 0.89. The LiDAR model simulation revealed the increase in pool areas due to precipitation. The DEM model was sampled at 1 m and 4 m pixel sizes and expansion of pools due to change in volume was simulated. The effective areas from 4 m pixel size were reduced as a result of bigger sampling interval. The computed surface areas from 1 m and 4 m pixel size of the simulation model could be plugged into a methane emission model to estimate the emissions from these hotspots.

Key words: *LiDAR, DEM, water table depth, methane, peatland, bog, water loggers, upscaling*

1. Introduction

Peatland surfaces are typically characterized by structural microforms of aquatic and nonaquatic elements of variable spatial extent, size and shapes. Active peatlands have distinctive structural elements such as hummocks, hollows, and pools complexes (Lindsay, 1995; Belyea and Malmar, 2004) distinguished by a gradient in surface heights above the mean

water table and contains distinctive vegetation communities (Anderson et al., 2010a). These elements are methane emission hot-spots which emit methane into the atmosphere through diffusion, ebullition and plant-mediated transport (Charman et al., 1994; Kettunen, 2000). The factors controlling methane emission are peat temperature; water table depth and vascular vegetation cover (Bubier and Moore, 1994) and some of the physical models used for the estimation of methane emissions from wetlands (Walter et al. 2001) used input parameters like soil temperature, NPP and water table depth. The release of methane from anoxic layers also exhibits seasonal and spatial variations (Clymo and Reddaway 1971). Methane fluxes are controlled by the daily weather (Kettunen et al. 1996), and differences of the order of two in annual emissions have been reported from the same site in consecutive years of a Finnish bog (Martikainen et al. 1995). The depth of ground water table is closely correlated with methane emissions (Moore and Knowles 1989); the large spatial variation in methane fluxes seems to be associated with differences in methane producing bacteria between different micro-sites such as hummocks and hollows (Bubier et al. 1993).

Nutrients, water flow and groundwater table may affect the distribution of vegetation on peatlands and the differential decomposition rates of *Sphagnum* species may be critical in bringing about microtopographic patterns (Johnson and Damman 1991; Belyea and Baird 1996). As a result of these many factors, mire vegetation develops as a mosaic of distinctive microsites (hummocks, lawns, pools and hollows), and the differences in vegetation and in the properties of the underlying peat (Van der Molen and Hoekstra 1988) mean that microsite variation results in considerable spatial heterogeneity in the rate of gas exchange across the peat surface (Alm et al. 1997). Vascular plants provide available substrates for methanogenic bacteria in the form of root exudates and fine root litter (Charman et al. 1994), some species

release methane from peat into the atmosphere through the aerenchyme tissues (Schimel 1995). The height of peatland surface above the mean water table is a key factor for the emissions (Belyea and Clymo, 2001; Belyea and Malmer, 2004) and hence a key variable requiring precise monitoring (Anderson et al., 2010).

The spatio-temporal variation in methane emission rates is high between peat land types (Yavitt et al. 1988, Windsor et al., 1992) and even between microsites on the same peat land (Svensson and Rosswall 1984; Moor et al. 1991; Bubier et al. 1993a,b). Moore *et al.* 1990 reported emission rates, from a fen site in Canada during the early summer, ranged from 30 to 40 mg CH₄ m⁻² d⁻¹, rising to > 50 mg CH₄ m⁻² d⁻¹ later in the summer. And there were major differences in magnitude of methane emissions between hummock (<20mg CH₄ m⁻²d⁻¹), hollow (10 to 100 mg CH₄ m⁻² d⁻¹) and highest in pools sites (< 200 mg CH₄ m⁻² d⁻¹) (Moore *et al.* 1990). This is due to variable water table depth observed at these different microsites within the wetland which is also confirmed by (Walter et al. 2001) in that water table measurements are shown to differ by several tens of centimetres on small spatial scale between hummock and hollow structures (Saarnio et al. 1997). The influence of water table effect on methane emission from peatlands is considerable and has been demonstrated for many different peatland types in many different locations (Charaman 2002). The strong control of water table on methane flux is shown in the figure 1 below with methane flux variation being logarithmic and the mean position of water table explains about 65% of the variation in methane flux across different micro-sites like Lawn, Hollow and Hummock. The control of water table over emission rates is highest especially in lawns and hollows and less strong for hummocks may be due to lower methane production rates or perhaps the consumption rates were higher, even where seasonal water tables were similar to lawns (Bubier *et al.* 1993).

A number of groups (Segers and Leffelaar 2001a, 2001b; Segers et al. 2001) have developed models to describe the dynamic effects of water table regime on methane fluxes unsaturation using a concept of alternative electron acceptors that remain in reduced form and do not affect methane fluxes as long as the environment is water saturated. Accordingly, the lag before CH₄ production begins following a rise in water table depth was the basis for modelling alternative electron acceptor cycle but Kettunen et al., (1999) observed no lag in CH₄ production in peat samples that had been unsaturated from two days to several weeks and instead reported a constant rate of methane production during the first 10 days of incubation. Therefore, alternative electron acceptors are not important control for CH₄ production from northern mires (Kettunen 2002). Similar spatial variations were reported in a study from an Estonian blanket bog (Freznel and Karofeld, 2000) where the pools emitted highest in situ methane followed by lawns with *Eriophorum vaginatum* and *Scheuchzeria palustris* species governed by water table depth. Pools emit methane in to the atmosphere sporadically through ebullition.

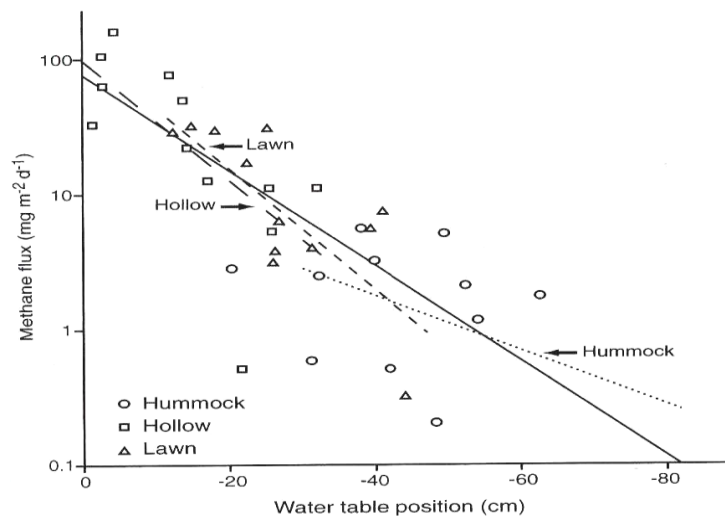


Figure 1: Relationship between the mean seasonal methane flux and the mean seasonal WT position for different microtopographic location at 12 peatland sites in northern Ontario, Canada (redrawn from Bubier et al. 1993)

As the peatland surface is a very heterogeneous landscape, accurately quantifying the variation in factors controlling the methane emission is crucial for the accurate estimation of methane emission from the landscape level, which is a precondition to scale-up estimates of methane to regional and global scales. Heterogeneity of the peat surface therefore makes such scaling a considerable challenge.

Monitoring water table fluctuation on a routine basis is an extremely difficult task as traversing over the bog area is challenging and sometimes risky, time consuming and expensive. Remote sensing technology has potential for repetitive monitoring of the peatlands and could provide fine scale details for the assessment of peatland dynamics (Harris and Bryant, 2009) for characterizing the eco-hydrological structures at fine scales (Belyea, 1996). Characterizing methane emission hotspots such as pools using LiDAR technology could be an alternative, provided an acceptable degree of methodology that can be repetitive and generalized over any contrasting sites is available.

Part of the methane diffuses out of the sediments into the water column or gets converted in to carbon dioxide by methanotrophic bacteria, (Figure 3 after Rudd and Taylor, 1980). Airborne laser altimetry (LiDAR) can provide with vertical accuracies of approximately 10 cm – 15 cm (data collected in this study), and has proven capabilities in spatial characterization of surface and vegetation structure (Hill and Thomson, 2005; Straatsma and Middelkoop, 2007; Straatsma and Baptist, 2008). The objective of this paper is therefore to develop a model using LiDAR data that can simulate the expansion and contraction of pools with some a priori increment in

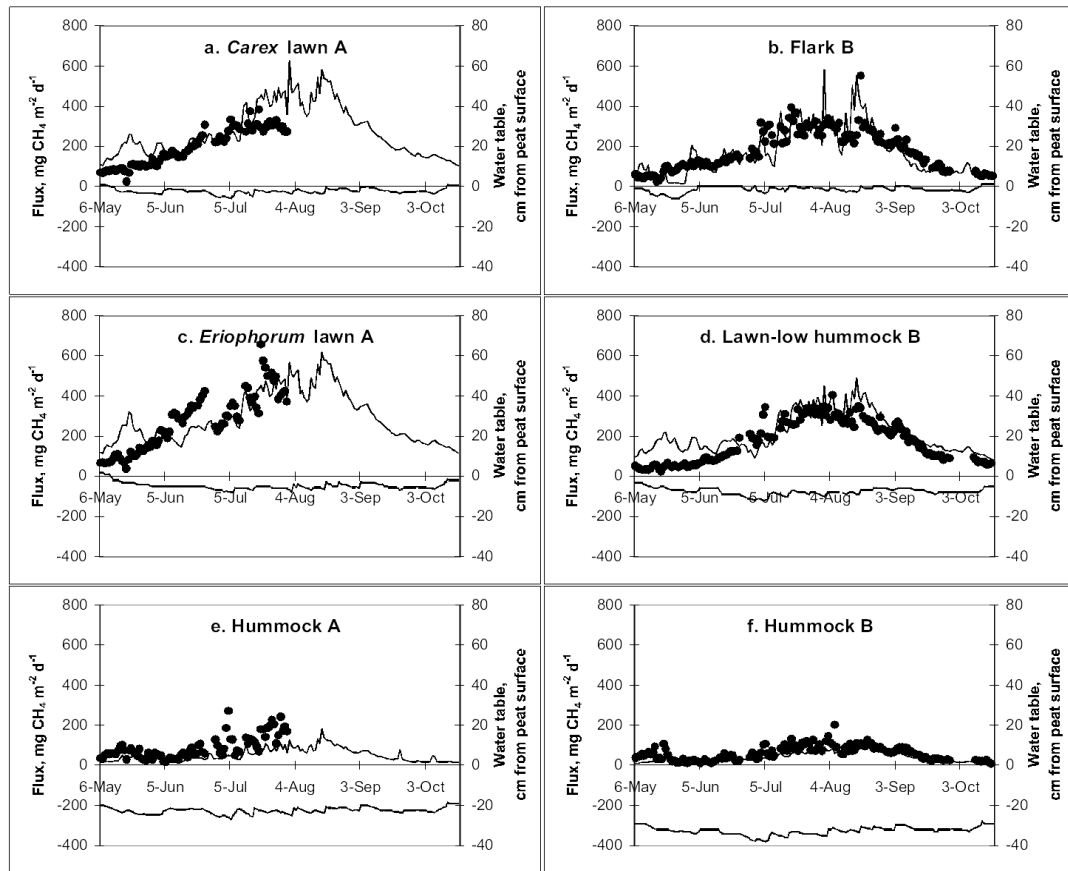


Figure 2: Simulated (solid line and left axis) and measured (circles and left axis) methane flux and measured water tables (solid line and right axis, negative values indicate that water table remains below peat surface) in a. *Carex* lawn A b. flark B c. *Eriophorum* lawn A d. lawn low hummock B e. hummock A f. hummock B. For *Carex* lawn A, *Eriophorum* lawn A and hummock A data were available till the end of July (Redrawn from Anu Kettunen 2003).

volume of water added to a pixel of the pool and analyze pixel by pixel change that occurs in the surface of the neighbouring pixels. Since wet soil triggers emission of fluxes coupled with the soil temperature, any expansion in wet area or contraction thereof would give an estimation of potential emission of methane, thus meaning wet and dry area can be quantified. Statistical analysis was performed between the LiDAR data and field data gathered from the Total station and differential GPS to assess the accuracy of LiDAR DEM model.

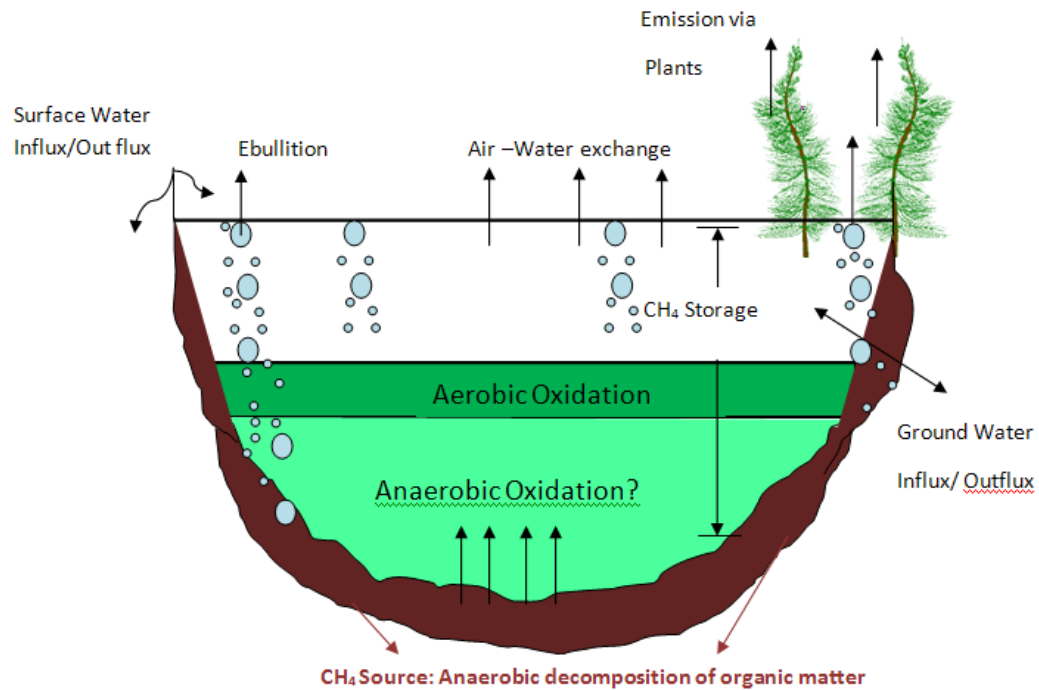


Figure 3: Ebullition process showing bubbling of methane gas escaping from the surface of pool (Redrawn from Rudd and Taylor, 1980)

2. Materials and Methods

2.1 Site Description

2.1.1 Location & Topography

The study site is Silver Flowe (55° 7' 33.8" N, 4° 23' 53.9" W), located in the New Galloway forest reserve, in Dumfries and New Galloway near English borders, in Scotland, Figure 4. This peatland is named as "Silver Flowe" due to the appearance of reflected sunlight on the surface of the system of pools in the bog centre, giving a silvery cast to the whole valley bottom when viewed from top of the hills. On the national map the approximate site location is referred to by the national grid reference NX 475820.

Silver Flowe was declared as a National Nature Reserve in June 1956 and is a blanket bog of international importance. This is reflected in its designation as part of the larger Merrick Kells Biosphere reserve, which is the largest upland area in Galloway unaffected by tree planting, and as a Ramsar site (1999) for the quality of its peatlands and wetlands. The valley runs approximately north-south about 6.5km. The bog area is approximately 8 km². South of the round loch of the Dungeon the valley slopes down into a tongue shaped bog land with the Saugh Burn River flowing on the eastern periphery. On the western side of the bog it is the Brishie Burn which meets the Cooran Lane down slope. Westwards the cliff slope of the Merrick forms the highest peak at 860 m O.D. Both sides of the valley are lined with uneven mounds of lateral moraine, but these are a dominant feature on the eastern side where they form the greater part of the eastern bank of the Cooran Lane (Ratcliffe & Walker 1958) is the site itself is covered with peat-forming vegetation, and the bogs areas are *Sphagnum*-dominated surface with complex patterns of pools and hummock-hollow structures. Lying in a row along the valley bottom areas are *Sphagnum*-dominated surface with complex patterns of pools and hummock-hollow structures. Lying in a row along the valley bottom are seven main bogs of this type, all very similar in their vegetation, but forming a graded series topographically (Ratcliffe & Walter 1957). Out of these seven bogs, further west of the Cooran Lane, four discrete bogs are delimited by marginal draining into it and into the Brishie burn. More detailed description of the individual bogs is given in the sections below.

2.1.2 Climate:

The site is about 45 km from Ayrshire coast and the nearest weather station is located at an altitude of 178 m, in Craigenbay, a farmhouse (Grid Ref. 552785) in the north-eastern side of Clatteringshaws Loch. Rainfall is generally high, with highest precipitation of 1787 mm was

recorded in 2010 . The wettest month is January and the driest months are June and July but although the amount of rain in January is considerably more than twice that in June or July, the number of days with more than 0.2 mm rain is only about 40% higher. Thus a given amount of rain is spread over more days in June or July than in January which might be important for the survival of bog mosses (Boatmann D.J., 1983).

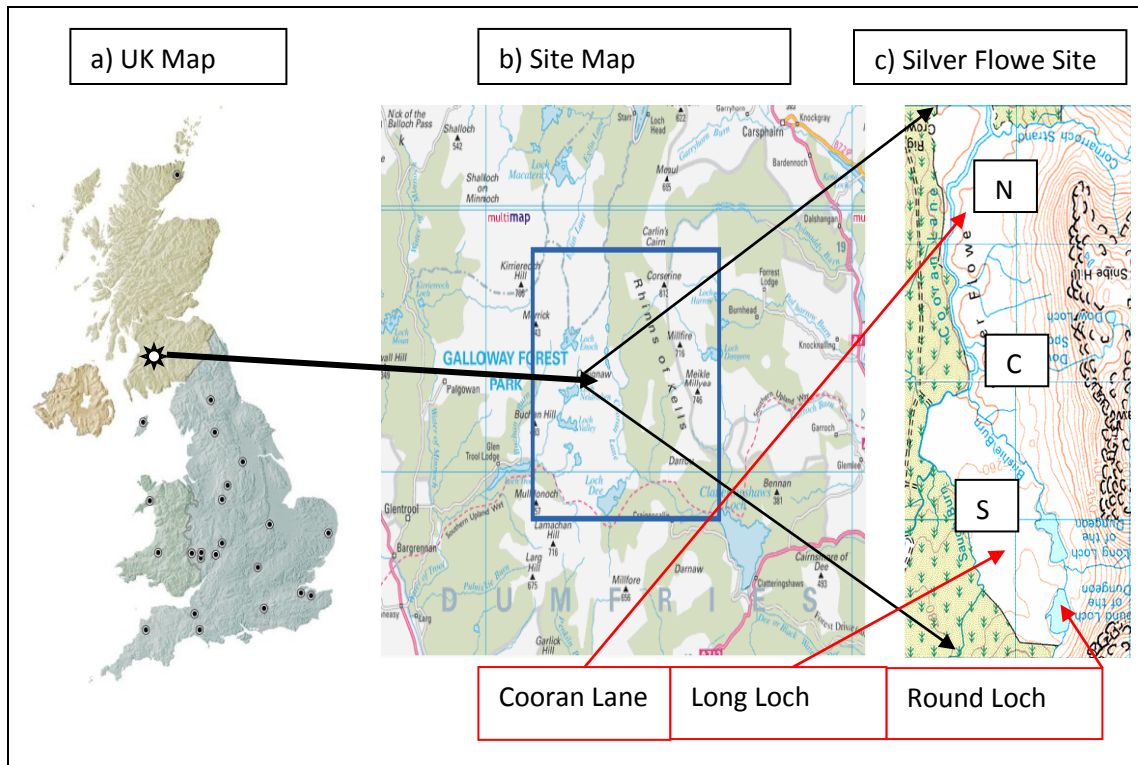


Figure 4: Location of Silver Flowe peatland landscape. Red arrows are pointing to the lakes that are located in the periphery of the Silver Flowe peatland. The dotted red arrow points to the Cooran Lane. Thin black arrows show the extent of the peatland from North to South. N, C and S are the three Zones in the North, Centre and South.

The coldest month is February, when the mean daily minimum temperature is below zero, ice forms on small bodies of standing water. The mean daily maximum temperature in summer rarely reaches 20° C in any month. Minimum temperature less than -12° C have been recorded at Clatteringshaws on five occasions in January 1970, 72 and 79 and in February 1969 & 73. The lowest minimum recorded was -12.8° C in January 1970.

2.1.3 Description of individual bogs

The entire study area consists of a series of eight bogs from North to South, Figure 5. For convenience, these are further divided into three zones. In the Northern zone Round loch and Long loch is located. The Brishie bogs which extends between Brishie Burn and Saugh Burn and the Craignaw bog falls in the Central zone. The remaining three bogs, Craigazeal, Snibe and High Corranoch bogs are part of Southern zone. These zones are indicated by letters N, C and S in the Figure 1.

2.1.3.1 Round Loch Bog:

Named after the adjacent round loch, it is the last of the bogs located furthest to the north of Silver Flowe. This bog has patterned hummock-hollow-pool complexes in the bog expanse (centre) and in general the long axes of the pool and hollows are at right angle to the long axis of the bog. The long axis of the bog is north-east but the bogs slopes toward south-west. A few meters beyond the south-western side of the patterned area, the bog has a steep slope until the round loch where some of channels of the loch headed back tapping the peripheral hollows of the southern bog. Hummocks of variable size and shapes of *Sphagnum* mosses are present and *Molinia caerulea*, *Trichophorum cespitosum* and *Eriophorum angustifolium* are predominant. Pools and hollows are extremely heterogeneous, though pools are found more in the southern part while hollows are predominant in the northern part of the bog.

The ground surface has spongy texture between the pool complexes and one can see infringement of moss carpets within large pools. The pools have gradual gradient along the periphery, thus may expand or contract depending on seasonal changes in contrast to pools which might have vertical or undercut sides. Aerial view of this bog appears as it merged with the long loch bog, though it is at a higher altitude than the long loch bog.

2.1.3.2 Long loch bog:

This is the largest patterned bog-pool complex in the tongue shaped landscape, approx. 0.05sq.Km and lying in the southernmost part of the Long Loch bog (LLB). Pool margins looks eroded due to lowering of the water table. The pools complex forms a concentric shape and coincide the contours.

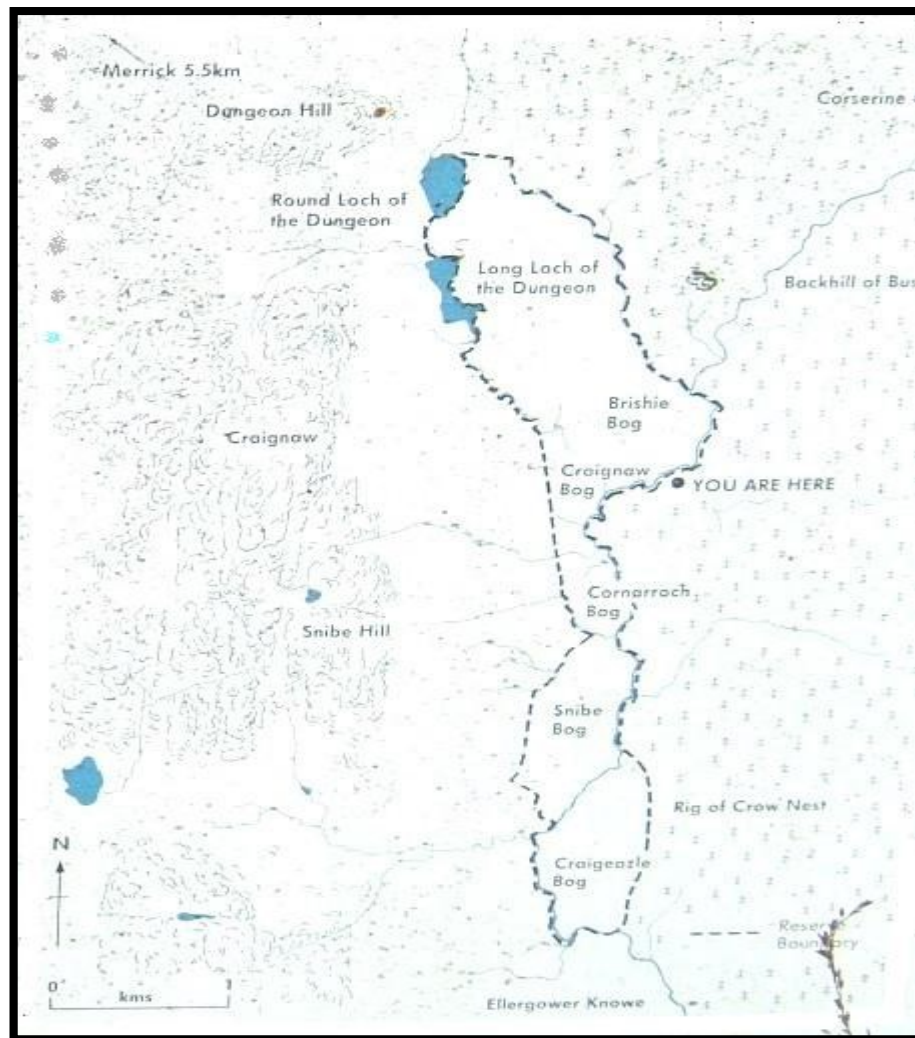


Figure 5: Study area shown in dotted lines of silver Flowe (Photograph taken by the author from the forest reserve facia)

Most of these pools are open pools forming a large network with barely few sphagnum carpets and marginal sphagnum grown on the edges. In March 2007 the fire ignited by some campers torched this bog area severely. This is evident from the fire scars and deterioration of hummocks due to fire damage is obvious. As the underlying surface was still very wet, the damage due to fire was short lived on the lawns and recovery was very quick. But the same is not true with hummocks, as these were dry and took considerable damage and perhaps take much longer periods to heal.

The lawn is dominated by thickly grown *Calluna*, *Eriophorum vaginatum*, *Trichophorum* and *Rhacomitrium*. The sphagnum cover is marginal but the *Rhacomitrium* hummocks are abundant. As mentioned above this bog is the largest and represent all types of bogs available in the Silver Flowe peatland landscape, a subset of the landscape covering almost entire LLB is taken for all the analysis throughout this research work.

2.1.3.3 Round Loch Bog

Compared with Long Loch bog (LLb) this bog has different pool and hummock complexes. The pools are at growing stages, lawns are very active with high water tables. Hummocks are low to medium and unlike LLb, old dry hummocks are scarce in round loch bog. Similar vegetation as in LLb is found here except that the heather is also scarce. *Sphagnum* and tussock cotton grass is visibly abundant. Some pools have scattered *Rhynchospora Alba* and *Menyanthes trifoliata*.

2.2 Remotely sensed Data

First and last returns laser scanning data were acquired from the Leica ALS50 Airborne Laser Scanner by the Natural Environment Research Council, NERC's Airborne Remote Sensing Facility (ARSF: <http://arsf.nerc.ac.uk/>). The Leica ALS50 is a laser-based system for the

acquisition of topographical data for digital surface models and digital images from return signal intensity data. LiDAR data was collected on 29th July 2007. The day was 241 a at approximately 10:08 GMT on board a Dornier 228 aircraft at an altitude of 9017 ft, using a scan frequency of 20 Hz, and repetition frequency of 16 kHz resulting in an approximate spot diameter of 15 and 10 cm. The stated vertical accuracy of these data was 15 cm. This accuracy measure refers to the closeness of fit between LiDAR point heights and independent validation data and is a general value which applies across a range of environments (Anderson et. al., 2010). As the study site has short vegetation and low relief (Boatman, 1983), LiDAR shows increase performance in such terrain as demonstrated by (Clark et. al., 2004).

2.3 Filed Data

2.3.1 *Water level Recorders*

The complex micro-topography would cause water table levels to fluctuate within few tens of centimetres often within small spatial scales (Kettunen, 2000). It is intended to measure the minimum and maximum water table height fluctuations and plot the spatial variability of water table depth over different seasons. This information would be required to understand water table fluctuations in relation to any vegetation changes observed as well as investigate the expansion and contraction of pools in relation to the changes in the water table depth. This would be accomplished by installation of water level range recorders along the 5 m transect, through the main pool system of the Long Loch bog surrounded by hummock-hollow pool complexes, with 50 cm interval to record the minimum and maximum water level every near monthly periods. The location of each instrument will be precisely recorded using an EDM instrument which would record the coordinates of gauge up to 5mm accuracy.

A 2.05 m long water level range recorder made from PVC pipe was designed to record the absolute maximum and minimum water levels in peatlands over discrete time periods based on the water level recording gauge designed by Bragg et al. (1994) to monitor below-ground water tables in bogs. However, the device measures absolute water levels above the bottom substrates of peatlands. In (Bragg et. al., 1994) design the float was an empty one litre coke bottle filled with sand, but the new design presented here using a polystyrene foam of cylindrical shape (76 mm x 64 mm) as a float attached to a 1 m long & 15 mm dia. PVC pipe, at the bottom and a plastic disc 45 mm dia. fixed on the top, the float assembly being enclosed in the 2.05 m long and 67.5 mm inside dia., main PVC pipe.

The plastic disc has a thickness of 2.4 mm carrying a screw that has a hole in its head from the centre of it. Our new design of water level recorder, Figure (6) consists of a commercially available, stainless steel guide wire fixed outside the main PVC pipe (length 90 cm) that runs through the holed screw which guides a large float up and down as water levels fluctuate.

Two markers that are inserted through the SS guide wire, one above the screw and one below the screw record the absolute maximum and minimum water levels in peatlands over discrete time periods. The two markers hold the slides at their last positions. A metre rule is fixed to the main PVC pipe from which the markers position is recorded giving the minimum and maximum water levels. After taking the readings, the two markers are reset to the current water level position that is indicated by the screw position. The difference between the maximum and minimum markers recording gives the information on the water level fluctuation during the time period between installation and the final recording.

2.3.2 Construction of the Water level recorder

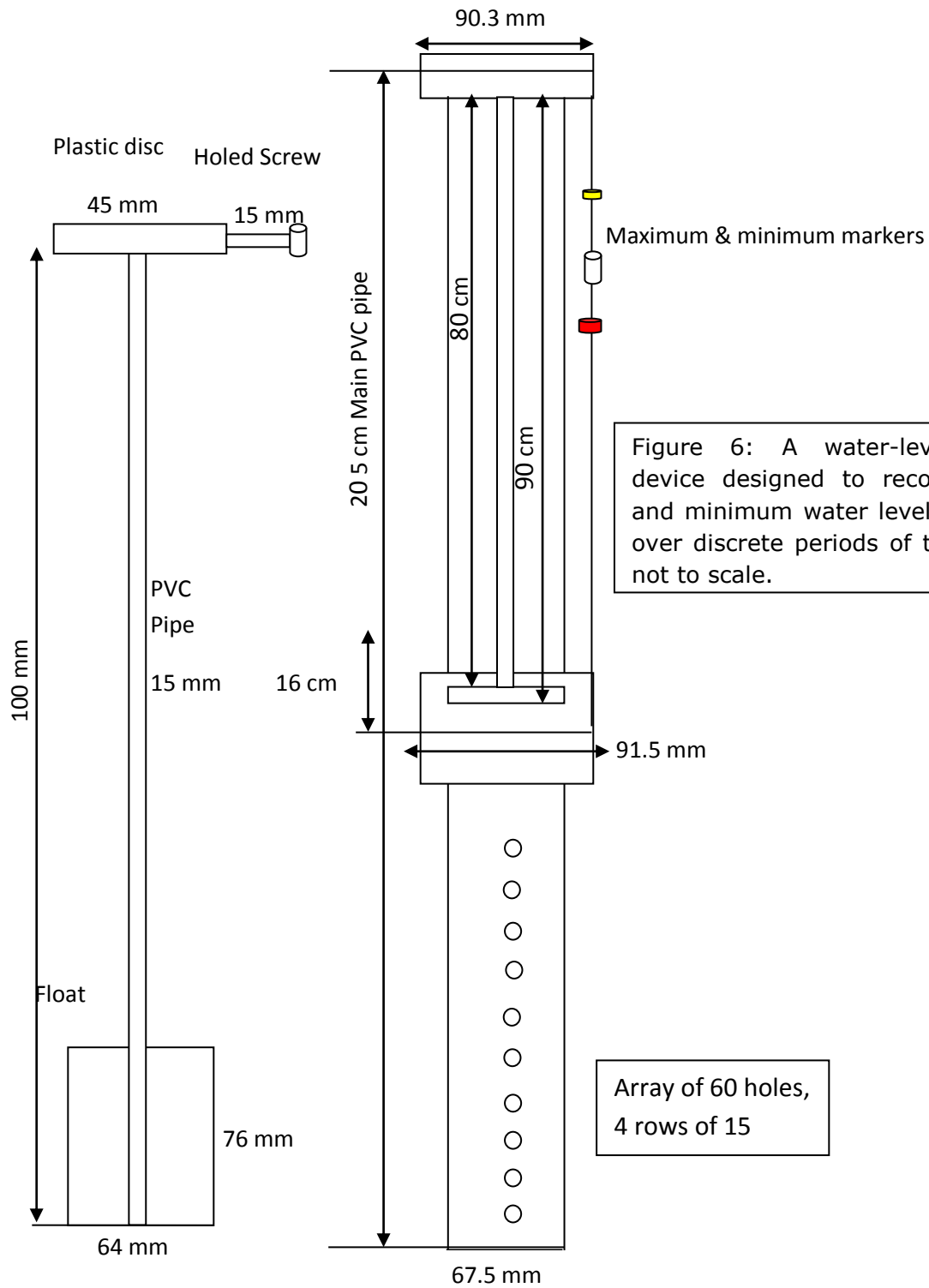


Figure 6: A water-level recording device designed to record maximum and minimum water levels of wetlands over discrete periods of time. Drawing not to scale.

Array of 60 holes,
4 rows of 15



Figure 7: A: Installation of the Water level recorders



B: The Yellow and Red markers showed here at set to the current water table position



C: Fire damaged the Water level recorders



D: water level recorders were severely damaged



E: Long Loch bog landscape with the structural microtopography and a transect with ten water level recorder



F: Replacing the damaged one with the new recorders

The first set of water level recorders were installed in the field in July/August to capture the growing season fluctuation of the year 2006, but has suffered a major setback when the instruments were severely damaged by the fire in the forest that also burnt the water level recorders. In 2007, new instruments were built and reinstalled. The fluctuations in the water table depth were then recorded for the year 2007 and 2008 successfully, Figure 7: A-F.

Transect: A 5 m long transect, Figure 7E was selected from the Long Loch bog, where the structural microtopography represented the variations that included hummocks, hollows, pools and that has maximum variation in the vegetation to record the seasonal variations in water table depth, at a distance of 50 cm c/c . The pools were clear and deep, some of the regions in the pool also had sphagnum carpets and mud bottom hollows in the periphery of the pool.

The recorders were pushed into the pools and soft peat soils vertically down to a depth of 1 m below the surface. One recorder was placed in a permanent pool. A permanent pool is one in which remains throughout the year. The second one on top of the peat mound, the third one on top of the hummock, the fourth one in a permanent pool, the fifth one on the intersection of a hummock and permanent pool, sixth on the top of a hummock, seventh one on the high ridge, the eighth one on the low ridge, the ninth one in the mud bottom hollow and the last tenth water level recorder was placed in a hollow with *sphagnum* carpet. Thus a 5 m transect profile recording the fluctuations in the water table is recorded. The difference between the maximum and the minimum values from these water table records could be plugged into a LiDAR simulation model to investigate the expansion and contraction of the pool surface during drought and precipitation months.

The relative position each water level recorder was determined using a Total station with respect to a fixed datum in the same coordinates in which the LiDAR data collection was planned. The Total station recording were later on transferred to the LiDAR DEM model to show the exact location of these water level recorders on the DEM model. Ten other water level recorders were also placed randomly across the peatland landscape in the Brishie Bog in a “W” fashion to cover the most part of the landscape for the water table fluctuations (not reported here).

2.3.2 Mapping the surface topography using a Total Station

A grid of 10 m x 10 m was demarcated in the Long Loch bog (LLB) near the transect where the water level recorders were placed and hundred elevation points at 1 m centre to centre distance within the grid were recorded using the Total Station from the same fixed datum close to where the water level positions were recorded, Figure 8. The size of the plot was taken as 10 m² as it was previously confirmed by (Ratcliffe & Walter 1957; Boatman, 1984) that the LLB represents the most of the variations in the entire Silver Flowe peatland in terms of microtopographical structural variations, and within the Long Loch Bog a 10 m x 10 m grid would represent most of the structural variations.

2.3. 4 Differential GPS mapping:

From a hand held differential global positioning system (DGPS), the periphery of prominent pools that are easily identified on a 1 m² pixel resolution were mapped and plotted, Figure 9 A., for ground truth information that can be used for validation of the results LiDAR data. Figure 9 B is the classification of the class pools.

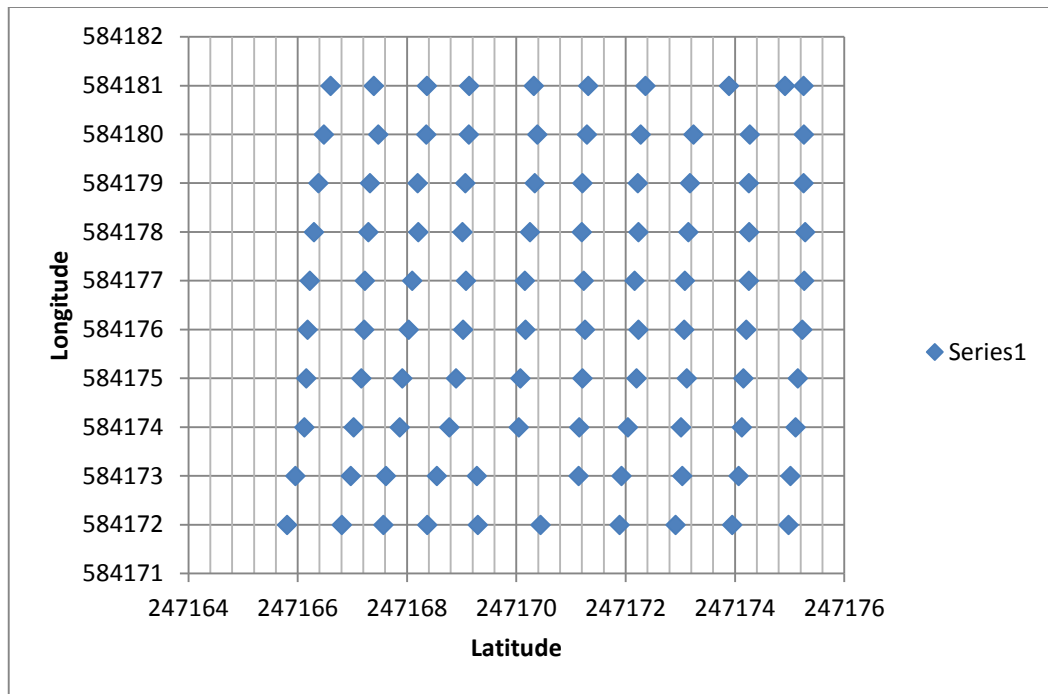


Figure 8: A 10 m x 10 m grid sampling of surface elevations taken from the Long Loch bog with stratified random sampling at an interval of 1 m c/c.

2.4 Airborne LiDAR Data processing:

The aircraft flew five sorties over the catchment area and collected first and last returns. The ASCII point cloud data delivered by NECR-ARSF was converted into a digital elevation model (DEM) from the first return and the last return individually. A DEM model was generated; Figure 10 for the entire catchment area to investigate if any gaps or missing data is present in the LiDAR data. The model was sampled in 1 m, and 4 m resolutions.

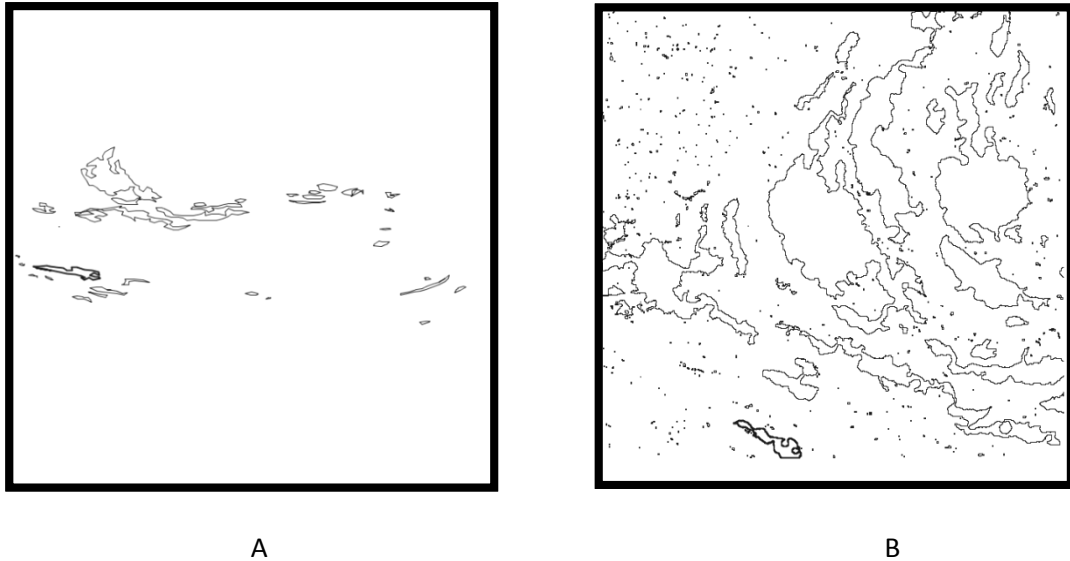


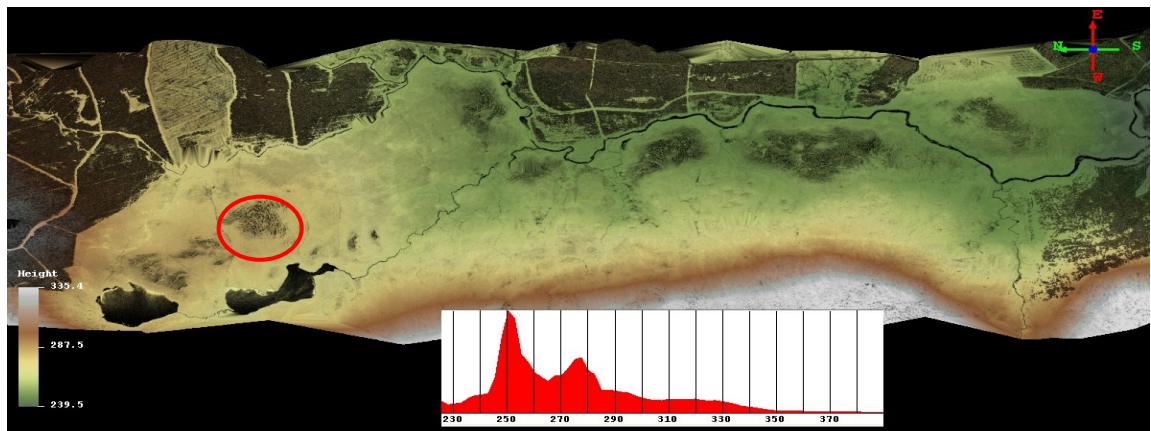
Figure 9) A& B: Pools complexes on the Long Loch bog mapped by walking around the pool periphery using a hand held DGPS. B: Pools mapped from an unsupervised classifier.

The Digital Elevation Model (DEM) is a digital representation of the ground surface topography or terrain represented as a triangulated irregular network (TIN) (Moretti and Orlandini, 2008). The regular DEM grid is convenient for calculations and has relatively simple structure that can be easily applied to topographic analysis and terrain visualisation (Zhu et al., 2013). Many fully and semi-distributed hydrological model structures or parameterisations are based on the DEM, such as the overland flow module in TOPMODEL (Beven et al., 1995). Since the DEM is an approximation to terrain characteristics, the accuracy of the topography and the related hydrological applications will depend on the quality of the DEMs (James et. al., 2006).

The 1 m resolution data is used for the classification of the pools from a small region of interest over the Long Loch pool and the areas of the classified pools was computed from the shape file with the area attribute table. The results were cross checked with the filed measurements carried out from the DGPS and were found to be accurate.

2.5 Simulation of pools expansion: theoretical model

An idealized model is considered with certain assumptions to analyse the expansion of the surface of the pools by increasing the height of water in the pools. We assume that we know a priori the increment of water coming into the pool. We get this information from the water logger's data, that the maximum fluctuation at any level recorder that was recorded during the two years of observation was 60 cm and the minimum value of the water table depth fluctuation was 20 cm, Figure 13.



A

Figure 10: Digital Elevation Model (DEM) of the Silver Flowe catchment area with the histogram of the height data shown in red graph. The elevation range is between 239.5 m to 335.4 m a.m.s.l for the entire catchment area. To the East is the managed forest and to the West are the mountains. The Long lake and Round Lake is in the North West. Highest point on the Silver Flowe peatland is in the North with height 285.7 m and the lowest point is in the South with height 239.5 m. (B) The picture on the right side is the subset of the Silver Flowe highlighted by the red circle, where the experimental work and LiDAR analysis was carried out. The subset region has all the features of a raised bog that contains all fine scale heterogeneity found anywhere on the Silver Flowe. Dark black regions in the centre are the pool complexes.

western Scottish peat bog where the hydraulic conductivity of the peat column was reported to be very low at $5 \times 10^{-6} \text{ cm s}^{-1}$ at 100 cm to $0.7 \times 10^{-6} \text{ cm s}^{-1}$ at 500 cm. Clymo (2004)

calculated mean bulk velocity of pore water to be as low as 1 mm year⁻¹. Pressure in the silty sand below the peat was 180 mbar less than expected, suggesting a thin highly impermeable layer at the peat base (Clymo, 2004). Thus the loss of water is mostly by way of evaporation.

In the proposed theoretical model we calculate the new surface area (S_2) of the pool based on the a priori knowledge of height increment (Δh) in water level, which is equal to the maximum or minimum fluctuations obtained from the water logger, the previous surface area (S_1), the previous height of the water (h_1) and the current height of the water ($h_2 = h_1 + \Delta h$) as shown in the Figure 9. From the classification maps of the LiDAR model we know the previous surface area S_1 and we get the surface height h_1 of the pool surface from the DEM.

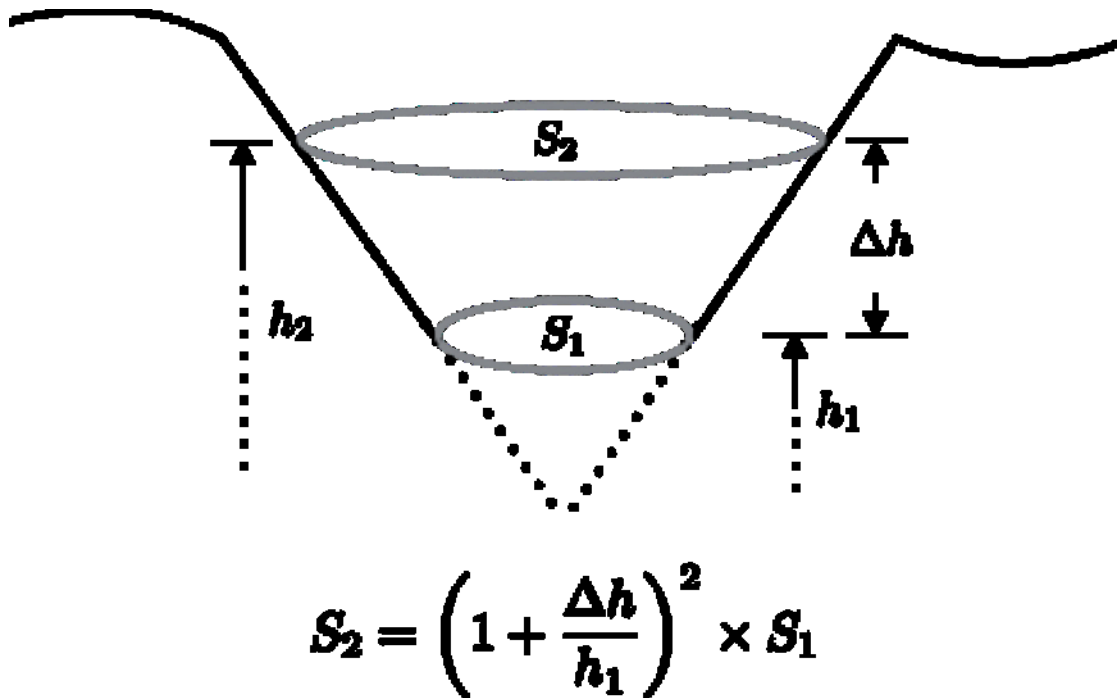


Figure 11: Idealized model of pool surface expansion due to increase in the height of water

We assumed a priori height increment of water in the pool to be 20 cm per step, and calculated the new surface area of the water from the previously known surface area of the pool from the LiDAR data. As the water level increases with the increase in the height of water, the surface of

the pool get bigger with every increment in the height of water. The simulation is performed using a tool Quick Terrain Modeler™, Applied Imagery from Johns Hopkins University Applied Physics Laboratory.

3. Results

3.1 Grid sampling of surface elevations

The grid sampled to measure point elevation data of various surface structures in the field over the LLB area from a Total station were superimposed on the LiDAR data DEM model and a correlation analysis was found in a good fit between the measured and modelled data with $R^2 = 0.89$, Figure 9, thus validating the method of field measurements and LiDAR DEM construction.

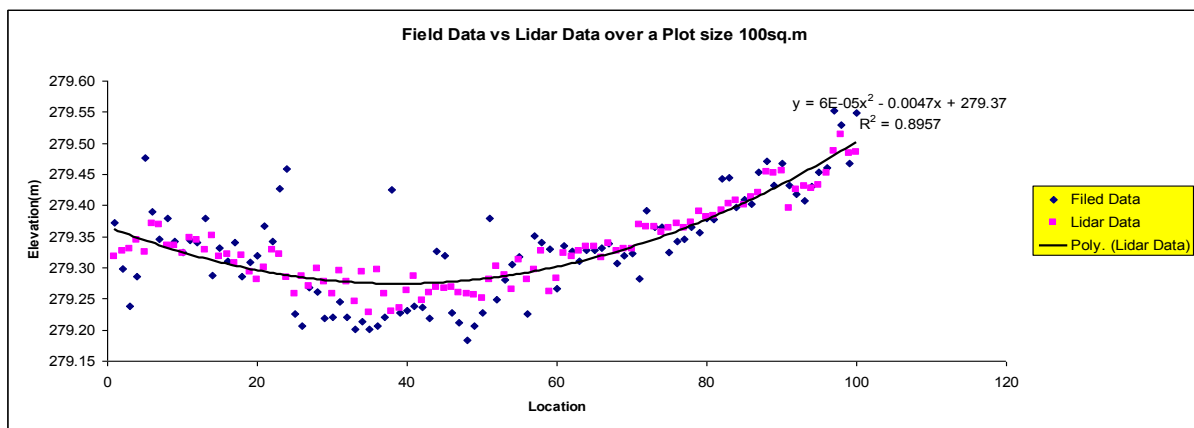


Figure 12: Correlation analysis between measured and modelled surface elevation data from a 10 m² plot from the LLB.

3.2 Water table depth records

The minimum and maximum water table depth recorded over the two growing seasons in 2007 and 2008 are plotted in Figure 12 A & B. Three out of the ten recorders gave erroneous maximum value in the month of April of 2008 and were not included in the plots. It was found that the maximum marker had a free fall and was found at the bottom of the scale. The position of maximum water level recorder for the 3rd level recorder (LR) that was placed in

hummock could have fallen to very low level, but the same was not true for the 7th and 10th recorder as they were placed on a ridge and *sphagnum* hollow, Figure 13 A below:

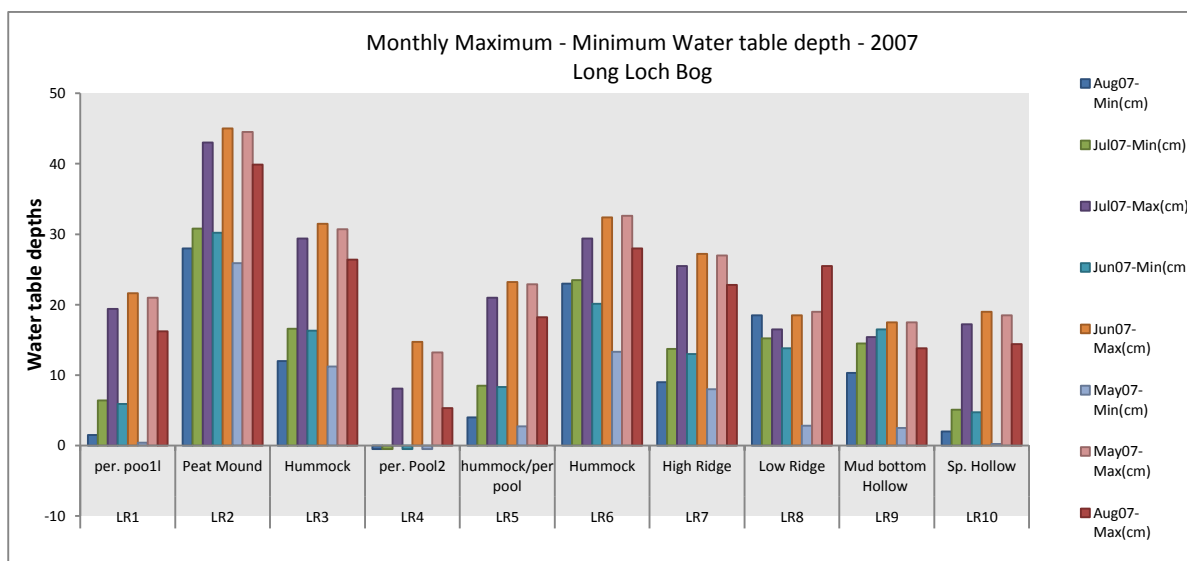


Figure 13 A.

As expected hummocks and peat mounds recorded the highest water table depth below the surface in all the months during the 2007 and 2008 observations. In the year 2008, the water level recorder placed on the hummock at LR 6 recoded highest depth below the surface of the water table at 82.4 cm. AT LR1 in Figure 13 B, the permanent pool recorded sharp drop of 60 cm but we believe it is an error may be due to wind or bird or unknown reason would be responsible for such erroneous value as such sharp drop in its value was not recorded in the previous year. The maximum depth in the water table recorded by LR1 in 2007 from the permanent pool was 21.6 cm. There was no dramatic seasonal shift from 2007 to 2008 in the month of June that could have dropped the water table to more than double the value.

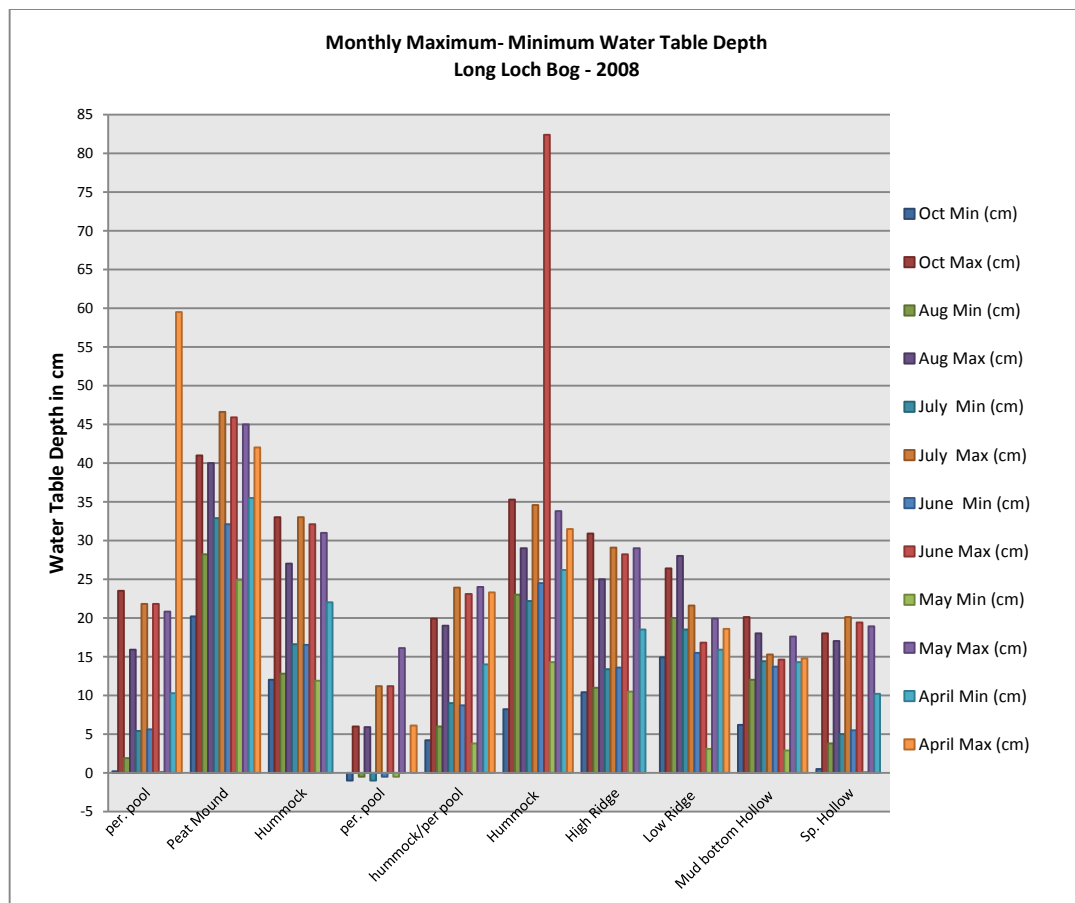


Figure 13 B

Figure 13 A&B: The minimum and maximum water table depth recorded from the ten water level recorder placed at 0.5 m distance c/c in the Long Loch bog along a 5 m transect , A) for the months from May to August in 2007 and B) from April to October in 2008

The permanent pool at LR4 in fact recorded lowest water table depth for 2007 and 2008 and for the month of April and May there was a negative water table depth, meaning water table went above the peat surface of this microsite. One way to explain it is due to the inundation that followed from melting of winter snow. Inhospitable conditions that are prevalent at Silver Flowe during November- March period prevented from site visits during the two years. The difference between the maximum and minimum water table depth give the fluctuation in a particular microsite in that month. This data is plotted for the two years as shown in Figure 14.

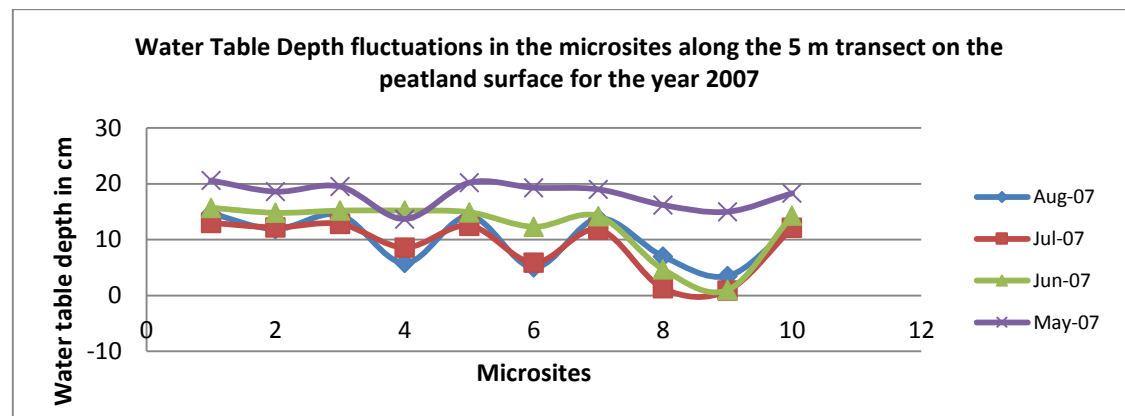
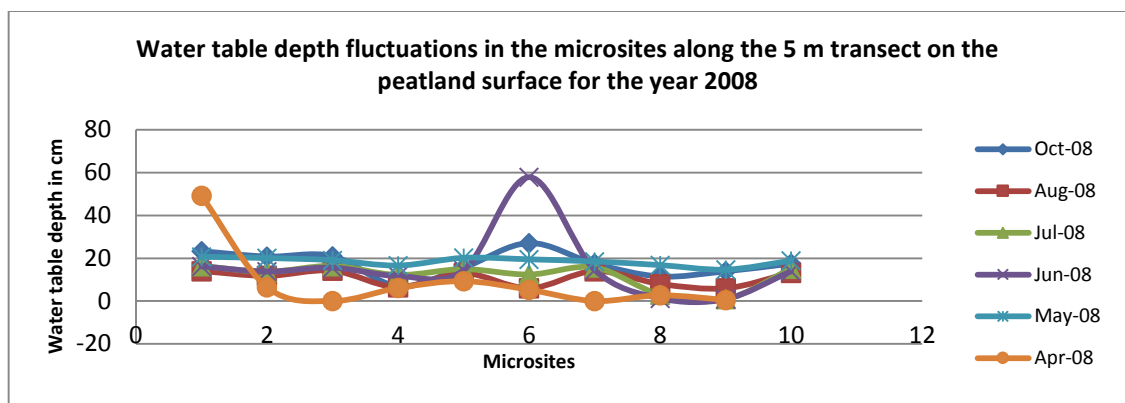


Figure 14: Image showing ten water level recorders along a 5 m transect in the Long Loch bog. The two charts above this photo are the water table depth fluctuations recorded in 2008 and 2007 at this transect.

The maximum fluctuations were observed in the month of June and October for the year 2008 and in 2007 the months of June and July reported the maximum fluctuations. Hummocks reported the maximum fluctuations in the month of June in 2008 and the month of May in 2007. The lowest fluctuations were observed in the mud bottom hollows, near the pool

boundary, during 2007 and 2008 with the water table remaining nearly at the surface. The maximum fluctuation from a hummock in 2008 was 59 cm while for the same year the lowest fluctuation was from the mud bottom hollow at 5 cm. In the year 2007 these values were 20.5 cm from a permanent pool and 0.5 cm from the bud bottom hollow.

The maximum fluctuation of 10 cm of the water table depth from the pool is taken as a step change to simulate the expansion of the pool. The second step of the analysis would represent the simulation of maximum fluctuation recorded in the pools and the fifth step would represent the maximum fluctuations recorded from the hummocks. The intention is not to replicate the fluctuations recorded from the field observations, it was only meant to study the expansion of area under each circumstances.

3.3 Surface elevation of Long Loch bog in different directions for 1 m & 4 m

The original point cloud LiDAR data set was interpolated into the desired DEM resolution, be it 1 m or 4 m or 30 m. This was done in the QT Modeler tool and a DEM of the specified resolution was created. The 4 m model appears blurred in comparison to the 1 m model because the 1 m model has 4 times as many pixel resolutions for every one pixel in the 4 m DEM.

This processing sequence does not involve any aggregation of fine resolution pixels through any algorithm either simple averaging or quadratic interpolations.

The 4 m pixel size changes in the surface characteristics as a result of the degradation in the resolution are plotted in the Figure 15 (A & B). The DEM of Long Loch bog with 1 m pixel size, top left in Figure 14 A and its surface profile along a transect in the SE-NW direction is plotted,

Figure 14 C. The DEM model resampled with 4 m pixel size and its corresponding elevation profile along the East-West transect is plotted over the 1 m DEM for comparison, Figure 15 C. Observations from the 4 m DEM reveal that the smoothing effect had changed the surface profile. At a distance of 16 m, walking from the West, a hummock in the 1 m DEM (pointed by the red bold arrow) is represented as a flat in the 4 m DEM. Similarly, many small hummocks and pools disappeared from the 4 m DEM due to the smoothing effect. Two large pools were formed with a sloping ridge between them in 4 m DEM at a distance between 100 m and 140 m where there are many small hummocks and pool complexes present in the 1 m DEM. At 140 m a high hummock was misrepresented as a sloping ridge (indicated by Red bold arrow). Similar changes in surface structure were observed between 160 m and 180 m. In the one meter pixel DEM, the slope between 230 m and 240 m is very well represented by the 4 m DEM. Thus small features are well represented by fine scale DEM (1 m) and large features are preserved in coarse scale DEM (4 m).

The transect along the East – West direction reveals the similar pattern, Figure 15 D. A ridge with a tall hummock on it between 20 m and 40 m length from West in the 1 m DEM is represented as a flat lawn. The structural changes are stronger between the distances of 60 m and 140 m where a series of pools and hummocky lawn captured by the 1 m DEM is smoothed out with shallow slopes and wide pools in the 4 m DEM. However the steep slopes at 160 m and 200 m in the 1 m DEM are well represented by the 4 m DEM.

3.4 Simulation of Pools expansion.

In the section 2.5 we have explained an idealised model for pool expansion as a result of increase in the height of water. We simulated the theoretical model for with unit area and unit

height as initial values of the pool and took a step size of 0.2 units and plotted the wet area against the height of water, Figure 16.

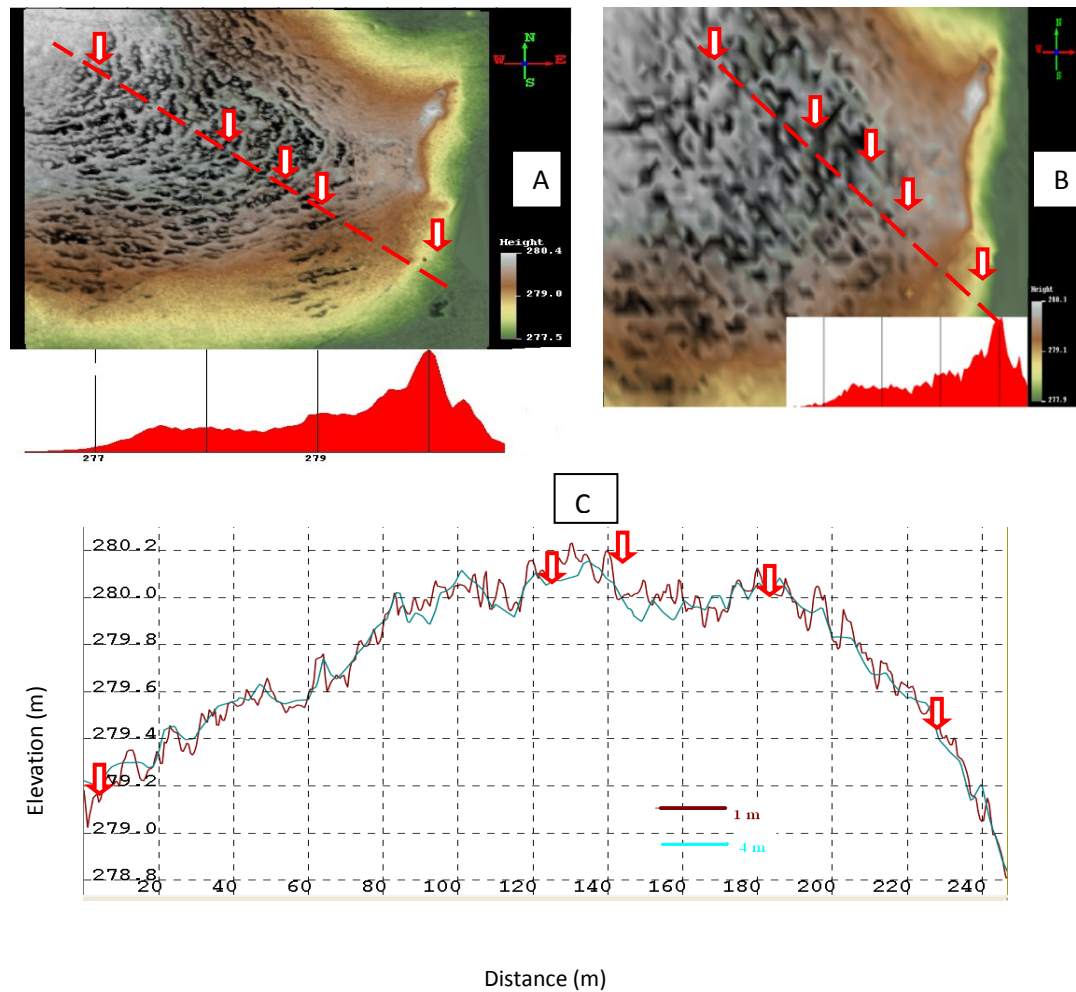


Figure 15 A: Top left is the DEM of Long Loch bog with 1 m pixel size. The red dotted line is a 245 m long transect along the pool complexes on the bog centre in the Southeast-Northwest direction. B) The photo on the right corner is the DEM model resampled with 4 m pixel size. C) The chart shows the comparison between the two DEM elevation profiles along the transect. (Fig. not to scale).

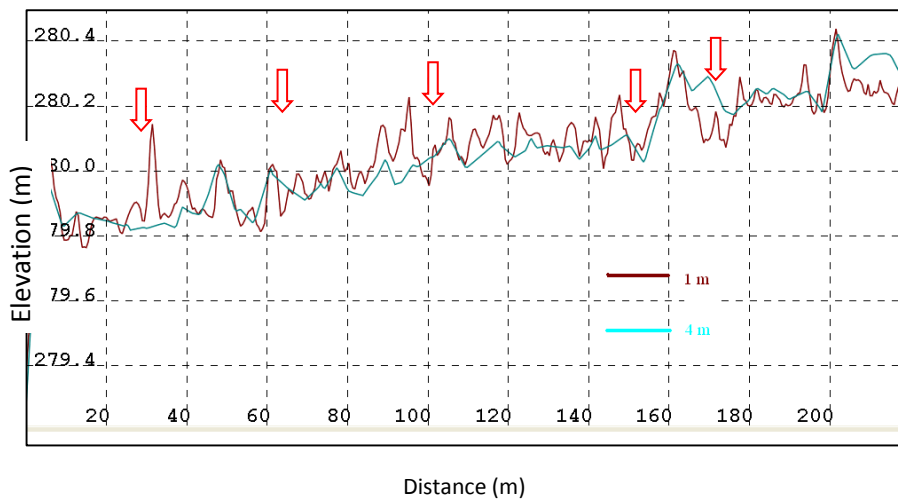


Figure 15D: The transect plotted on the Long Loch bog along the East-West direction

A region of interest (ROI) was selected over the Long Loch bog, Figure 8B, where the maximum pool complexes are located. Within this ROI a drought sensitive pool was demarcated to investigate the affect of flooding by increasing height of water level in the fine scale DEM model of resolution 1 m pixel size. A step size of 10 cm increment in the height of water was applied starting at the surface level at 279.76 m assuming that the surface is dry.

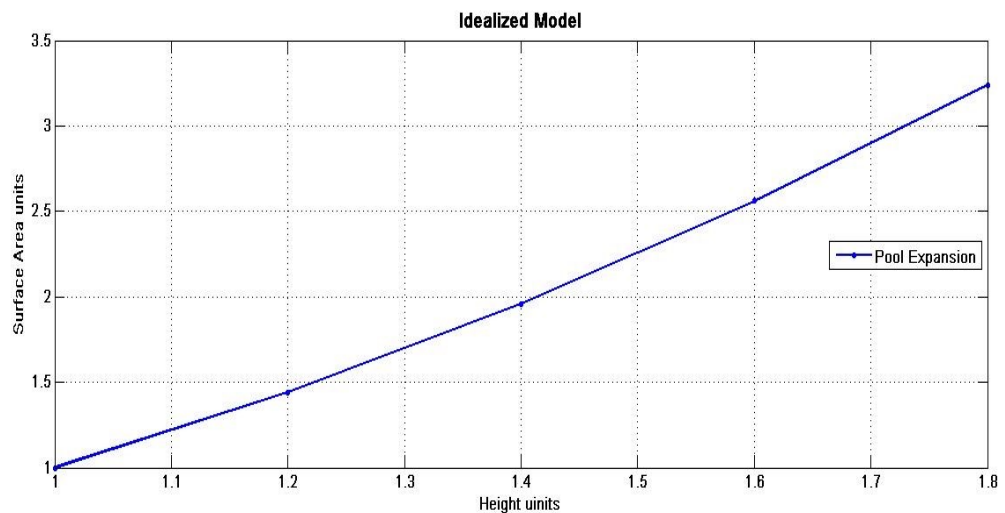


Figure 16: Idealized model simulation of the pool area expansion with the increase in the height of water

The pool was completely inundated and water was allowed to spill over to the neighbouring pixels. At each step increment in the water level, the area under the wet surface was computed by the QT Modeler™. The selected ROI was completely inundated when the height of water was increased to a value of 279.96 m (i.e., 20 cm from the initial value). The wet area recorded at every step increment in the height of water was plotted against the elevation, Figure 17. The entire procedure was repeated with the coarse scale 4m pixel size DEM model upscaled (resampled) from the 1 m DEM and the results were compared. The expansion of the pool complexes due to the simulated wet areas are plotted in Figure 16.

A small subset from this data, Figure 15, was analysed to investigate the expansions of the pool under various water levels. A step size of 20 cm was applied in the QT Modeler™ tool & the expansions of the pool due to inundation were mapped and the new wet area was calculated.

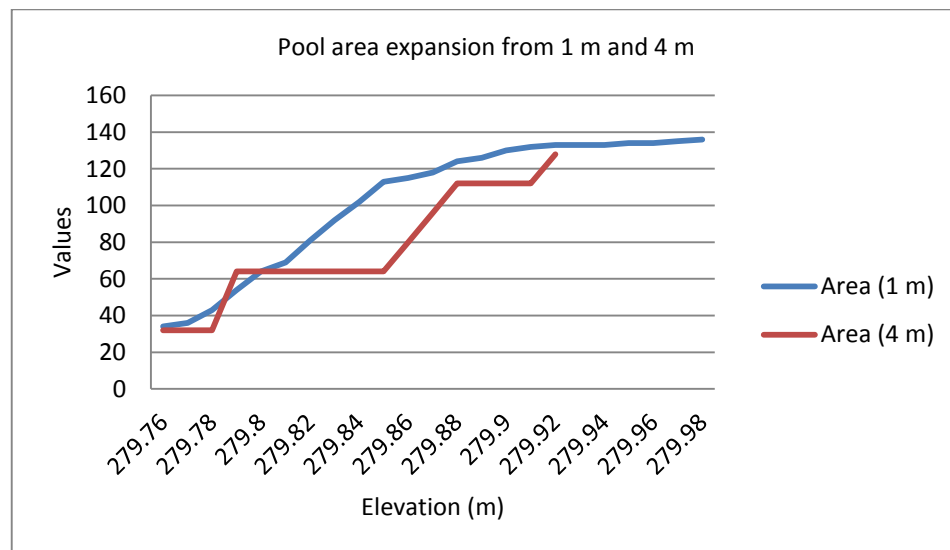


Figure 17: Area estimates of the simulated pool inundated by increasing the height of water level

The resulting area expansion profile, Figure 16 with respect to the increase in height for the pool from the 1 m DEM model resembled the profile that was plotted from the idealized

model, Figure 16. The same step size of height increment value was applied to the coarser 4 m DEM model. The area expansion profile of the 4 m DEM model did not resemble with the 1 m DEM profile and with the idealized profile. The pattern was more like a stair case with alternating platform and slopes. Since the resolution was degraded from 1 m to 4 m, the area of the pixel increased from 1 m² to 16 m² and many small pools got coalesced in to bigger pool in the 4 m DEM. So the same step increment did not bring rapid changes in the surface area that could spread around to new regions of the 4 m DEM as it happened in the 1 m DEM model. The spill over was faster in the 1 m DEM as compared to the 4 m DEM.

The entire procedure was repeated in both the idealized model and DEM models by changing the height increment value to 60 cm and the result was similar to what is shown in Figures 16 & 17, except the fact that expansion was faster and wet area increased which is anticipated. Thus the extreme rise and fall in the water table depths of 20 cm and 60 cm, that were measured from the hummocks at the 5 m transect placed on the Long Loch bog was inserted as fluctuations over the pools due to any seasonal variations and the wet area mapped. The changes on the peatland surface as a result of increasing height over the 1 m DEM was displayed in the Figure 18 above.

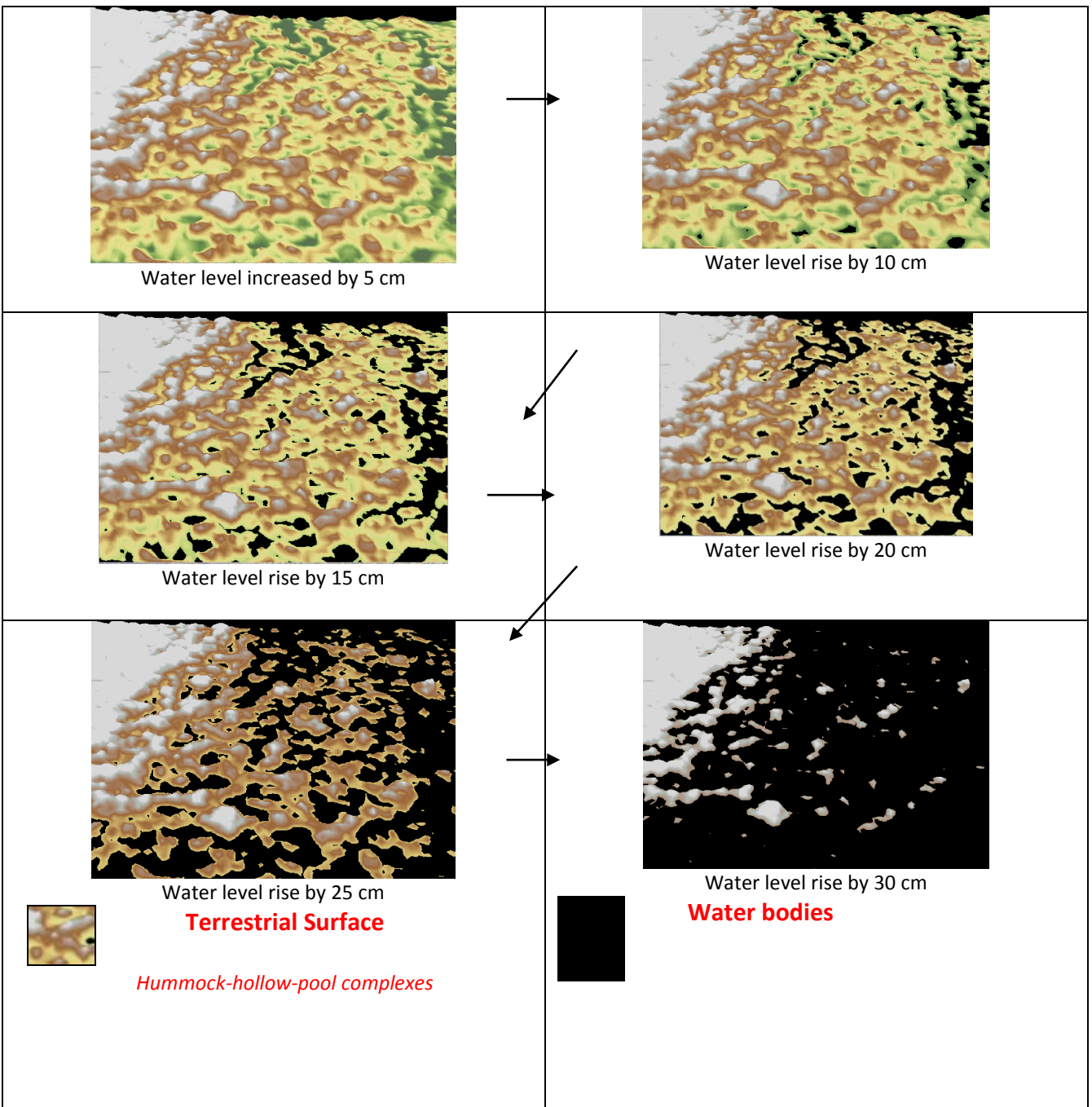


Figure 18: From top left and following the arrows: the first step of the Long Loch bog pool complexes after the first increment of 5 cm in the height of water. The inundated areas are shown in black polygons. The picture on the top right is the new inundated surface when the height of water was increased to 10 cm from 5 cm. Similarly, following the arrows, the step change in the height of water of 15 cm, 20 cm, 25 cm and 30 cm and the respective new expansions in the pool regions are shown.

4. Discussions

Patterned Surface:

The nature of the pattern on Silver Flowe bogs is variable with the variation in the microtopography consisting of vegetation mosaics linked with the microtopography. Among the pool types, there are shallow pools with partial or complete cover of the *Sphagnum* species and the other type of pools are deep eroded pools, steep sided and usually bare floors, with little or no growth of *Sphagnum* species. The sides of these deep pools are vertical or undercut.

The hollows that are elongated alongside pools, often sinuous and generally lie approximately parallel to each other that probably contains free water throughout the year except during the dry summer. Sometimes in some areas they adopt a reticulate pattern so that those parts of the mire above the water level appear as islands surrounded by water.

The shapes of both shallow and deep pools vary from approximately isodiametric to very long and narrow. One such example of isodiametric pool exists in the Long Loch bog with the approximate size of 45 x 28 m, while there are long pools, may be 100 m long and very few metres wide. Where pools lie close together the vegetation of the ridges separating them generally resembles that of flats.

Where the linear pools occur close together, the intervening surfaces form raised ridges and the combination of the pools and ridge resembles that of the 'Kermihnochmoors' of Finland and the 'string bogs' of North America (Boatman 1983)

When rain occurs, the water flows from one pool to another where the ridges are only a few centimetres above the maximum height of water in the adjacent pools. This is seen in the

simulation model with every step increase in the water level increases the volume and the spill over effect is clearly seen in the adjacent pool, Figure 18. After a considerable rise in water level, it is shown that more adjacent pools coalesce to form a big pool. Depending upon the intensity and duration of rain falling on the landscape, the pool area expansion could be significant and cover the entire bog centre, and using the LiDAR model it is possible to map the new expanded wet area.

At some locations right in the centre of the Long loch bog, there are islands that exist in the pools. The sides of the islands are generally vertical or even undercut, suggesting that these could have been formerly hummocks near the side of the pools and have been nipped off by some of the vegetation behind them.

The LiDAR model has captured these details and the effect of water level rise can be clearly seen throughout the landscape. The dark black regions in the images shown in Figure 18 are the expansion of the wet areas due to the increase in the water level. The non-black region in the images is the terrestrial areas that slowly get inundated with the rise in water level.

Since the subsurface lateral water flow is assumed to be zero due to highly impermeable soil and very low hydraulic conductivity, any increase in water level would maintain the level except the loss due to evaporations. The model does not contain a feedback between the water level and evaporation. Any increase in the water table would increase the CH_4 flux by a large magnitude and similarly, any decrease in water table would significantly decrease the CH_4 flux by almost 80 % in magnitude (Roulet et al, 1992). In studies reported by (Moore et al, 1990; Roulet et al, 1992 and Kettunen et al, 2004) it is suggested that CH_4 climate feedback depends upon the peatland physical environments. Hence, one way the CH_4 fluxes could be measured is

by calculating the wet areas and plugging into this area the point source fluxes measured from chambers for the estimation of the landscape scale methane emissions.

Peatland vegetation gradients are controlled by nutrient status (minerotrophic vs. ombrotrophic), position within the peatland (mire margin vs. expanse) and microtopography (ridge/hummock vs. hollow/pool) (e.g. Malmer, 1986). The microtopographic gradient is dominantly controlled by water table position relative to the peat surface with both moss and vascular species distributed based on moisture conditions. Variation of vegetation community types between microforms results in corresponding differences in GEP (Laine *et al.*, 2007a; Riutta *et al.*, 2007) with greatest productivity generally at an intermediate water table/moisture level (Waddington *et al.*, 1998). Any long term water table drawdown may cause shifts of vegetation communities between microforms in response to shifting moisture conditions. At wetter locations, as pools dry out they may be colonized by *Sphagnum* mosses and sedges, commonly present on hollows or lawns, with corresponding shifts in GEP. This has been observed in pools drained naturally by soil pipes (e.g. Foster *et al.*, 1988).

Studies of peat monoliths by Weltzin *et al.* (2000) indicate differential response of bog communities to warming and water table manipulation. Shrub growth was favoured when water tables were lowered whereas sedges and herbaceous species were more productive with water tables at the soil surface. Warming resulted in an increase in belowground biomass relative to aboveground biomass in bog monoliths.

Methane emissions are generally higher from wetter locations. Therefore, in seasonally frozen peatlands, predicted lower water tables will likely reduce methane emissions (Roulet *et al.*,

1992). However, reductions in methane emissions are limited, and fluxes may actually increase, in initially wet locations such as hollows and pools. At these areas, soil subsidence maintains water tables close to the surface and drier conditions may result in increased vegetation productivity. Both of these effects help to maintain high methane fluxes (Strack and Waddington 2007).

Recently, it has been suggested that ebullition may account for as much methane release as diffusive fluxes (Glaser *et al.*, 2004). Because of the rapid release of methane via ebullition, water table position is not as important for controlling this flux in terms of enabling methane oxidation. These fluxes are more closely linked to large changes in atmospheric pressure, drought resulting in groundwater flow reversals, and sudden shifts in water table position. Therefore, future patterns of weather systems, droughts and extreme precipitation events have the potential to greatly impact peatland methane emissions. Rosenberry *et al.* (2006) suggest that thickness and extent of soil ice, which may be altered by changes in the snowpack presence and depth, could affect springtime release of entrapped gaseous methane; but further research is needed to quantify the importance of this efflux. Overall, methane efflux will likely decline from dry locations such as ridges and hummocks and be maintained or increase slightly from wet locations such as pools and hollows. A changing vegetation community can play an important role with more abundant sedge cover enhancing methane emissions at sites that remain relatively wet (Strack & Waddington 2007). Potential changes in methane efflux via ebullition remain unclear and further research is needed to quantify the contributions from this efflux.

5. Conclusions

It has been experimentally demonstrated that pools are the hotspots for methane emissions from the peatland, and releases highest amount of methane (Frenzel & Karofeld, 2000, Kettunen 2002) in to the atmospheric geochemistry. Physically mapping bog pools over land surface is extremely difficult task, although an attempt was made in this project, Figure 9 A to map some of the easily accessible pool using a hand held DGPS by walking around the periphery of the pools. Doing this exercise to record seasonal variations due to drought and precipitations is more challenging in terms of time and resources. High resolution airborne data could rapidly distinguish aquatic structures from the non-aquatic structures. In the present study airborne laser scanner data from LiDAR sensor is recorded over the Silver Flow peatland and a digital elevation model was constructed, Figure 10. The results presented can be used to assess the episodic release in the methane fluxes as a result of precipitation or snow melt.

Many process-based models that connects methane fluxes to site specific factors, water level and vegetation cover and describes the dynamic effects of water table fluctuations on methane flux patterns from natural wetlands have been presented before (*Arah and Stephen, 1998; Cao et al., 1996; Granberg et al., 2001; Segers et al., 2001; Walter et al., 1996, 2001a, 2001b*). A serious drawback of these models is that most of them did not take into consideration the non-linearity of microtopographical influence on the position of WT relative to the soil surface throughout the wetland. Moreover, the authors recognise that a high resolution data sets might help to improve global data sets of model parameters in the future. Expansion and contraction of wetlands due to changes in precipitation are also not considered. Neglecting this change in wetlands could therefore affect modelling results, particularly in the tropics. A

sensitivity test (“micro”) revealed that considering sub-grid-scale variations in water table need to be treated more realistically in the future. Hence using additional precipitation data sources could help reduce this problem in the future. (*Methew and Fung 1987*).

Nevertheless, the existing models do not explicitly describe the connections between the micro site vegetation, water table and methane fluxes, besides these models also do not take into account the dynamic effect of changes in water table patterns on the methane fluxes. Only the models of (*Segers and Leffelaar 2001a, 2001b*) and (*Segers et al. 2001*) presents conceptual ideas of how water table changes should be taken into account, but the model predictions do not match very well to measurements (*Kettunen, 2003*). Most of the previous studies treated average water table depth in the micro site as most crucial factor for methane flux levels (*Morrissey et al., 1993; Waddington and Roulet, 1996; Saarnio et al., 1997*).

In the present study a theoretical model that estimates the expansion or contraction of surface area due to rise or fall in water level was developed and based on this concept a model using LiDAR data was simulated to show the expansion of the pools when the water level increase. The expansion of pools as a result of the increase in water level gives new surface area that can be mapped using the LiDAR model by drawing contours around the periphery of the pools. This information could be used in the estimation of the methane emissions either by plugging into any of the more accurate physical based models discussed above. Another possible way would be to use the point source measurements from chambers interpolated over the pool surface area. Further work is needed to develop spatio-temporal models using time series data to accurately map the pools expansion and contraction over the longer time periods.

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Geostatistical methods to characterize peatland surface heterogeneity using ATM NIR band

Abstract:

An ATM image scene was selected to determine and characterize the surface and spatial heterogeneity of the peatland surface. Peatlands demonstrate inherent fine scale heterogeneity and preserving this information in the assessment of methane fluxes from these landscapes is vital for an accurate assessment of methane emissions. Bands 7 and band 9 from ATM data collected during July 2007 was modelled into a semivariogram and the range was found to be approximately 9 m in all directions. Further it was analysed for spatial heterogeneity using fractal dimensions. The D values ranged between 2.4 and 2.8 and decreased from fine scale model to coarse scale models indicating high spatial correlations at fine scale data. Due to smoothing affect homogeneous large patches resulted from coarse data. The results also pointed to multifractal nature of the peatland surface with scale breaks that appears in the slope of the logarithmic variance versus logarithmic lag plots.

Using a window size of 9 m the textural information such as grey level co-occurrence matrix were computed in the object based fuzzy logic membership functions to classify the data in to aquatic and non-aquatic classes. Nearest neighbour classification rules along with image sub objects and super objects segmentation techniques performed the classifications. Simple average aggregations schemes were performed to demonstrate how the errors propagate when mean values are used for upscaling.

Key words: *Semivariogram, fractal dimension, ATM, NIR, heterogeneity, Object based, fuzzy logic, super object, sub object, spatial variation, peatland, methane, upscaling*

Introduction

It is generally accepted that nearly all environmental problems are scale dependent (Davis et.al., 1991). From an Earth observation point of view, different scales of measurement reveal variables to be homogeneous at one scale and yet heterogeneous at another (Atkinson and

Tate, 2000). Heterogeneity can also be increased by increasing the spatial extent of a given study area (King 1991). In the context of landscape ecology, (Milne 1991) suggested that the key to understanding heterogeneity was to conduct the analysis across a wide range of measurement scales and extract parameters that are robust to changes in scale. The presence of scale-dependent heterogeneity is important when 1) defining a suitable scale range for a given investigation (e.g., a range of spatial resolution which will reveal the variation of interest), and 2) characterising the nature of the spatial variation so that the scales of measurement may be changed (Atkinson and Tate, 2000). Similarly, (King 1991) recognised two main challenges for problems which show spatial heterogeneity: 1) the definition of spatial heterogeneity, and 2) the correct integration and aggregation of data.

Spatial aggregations of raster data based on majority rule have been typically used in landscape ecology (Turner et al. 1996; Moody and Woodcock 1994, 1995; Benson and MacKenzie 1995, Mladenoff et al. 1997). These studies observed that dominant classes become more dominant and minor class decreases and in some cases disappear entirely from the landscape. In one study a general comparison of landscape metrics at variable pixel resolutions was performed (He et al., 2000), in which they compared aggregation of four land cover types from a majority based rule and a random based rule respectively.

Aggregation of a classified Landsat TM image across broad spatial scales (30-990m) based on a majority rule and a random rule was investigated by (He et al., 2000). They found that the majority rule finds the majority value for the specified cells of the input grid and records that value in the corresponding aggregated cell of the output grid, while the random rule assigns the value for the output cell by randomly picking a value among the specified cells of the input

grid (He et al. 2000). The aggregation was sequential starting from 30 m to 990 m with an increment of 30 m; hence no division of pixel was necessary. This study revealed that random rule-based aggregation showed less distortion and more stability while retaining cover type proportions, than those from majority rule-based aggregation. The majority rule based aggregation caused distortions of most common and least common cover types by clumping most common cover types and eliminating the minor classes (Mohammed et al., 2009). There were only four broad cover types in the initial pixel size of 30 m, the technique applied by them have certainly overlooked the mixed pixel problems.

In the present work, we analysed a single? near infra-red (NIR) band 7 and a SWIR band 9 from an airborne ATM image over a site in a Scottish Silver Flowe peat bog taken in July 2007 to characterize the spatial heterogeneity. It also demonstrates how simple averaging introduces bias in the estimation of hot spots for methane emissions when upscaled from fine to coarse resolution. This was done by superimposing pool class from object based classifier on the results from the mean averaging that clearly shows the erroneous estimates of the pools in the upscaled results by averaging method.

Characterization of peatland using geostatistical techniques:

Characterizing the peatland surface would help in designing the field sampling experiments. It may also help in guiding which remote sensing resolution data is most suitable for estimating methane fluxes at landscape and regional scales.

A surface property is heterogeneous if its measurements vary in space (Kolasa and Rollo, 1991). The peatland surface demonstrates spatial heterogeneity by spatial variability of the surface

property over the observed scene and also the spatial structures such as pools and hummocks that repeat themselves independently within an observed scene at some characteristic length scales. (Ratcliffe & Walker 1958) observed that the Silver Flowe peatbogs have spatial heterogeneity and spatial variability that can be captured within a 10 m x 10 m observational plot. Particularly, the spatial variability of the microstructures on the long loch bogs that form the concentric pool structures often distributed into connected as well as independent sets of spatial structures, together with hummocks and hollows being overlaid in the same region are a good representation of landscape spatial heterogeneity. For the accurate assessment of peatland methane emissions a proper characterization of peatland spatial heterogeneity is a very significant step.

There are many geostatistical techniques from simple local variance which are empirical, to mathematical approaches such as wavelet transforms.

Another approach to characterize spatial heterogeneity is by using fractals techniques. Fractals are conceptual objects showing structures at all spatial scales, with a scale-dependent self-similarity (Mandelbrot, 1989). The fractal dimension is determined according to the relationship $N(\epsilon) \propto \epsilon^{1-D}$, where $N(\epsilon)$ is a number measured corresponding to the scale unit ϵ and D is the fractal dimension. There are several methods of measuring the fractal dimension which includes changing coarse graining level, i.e. box-counting methods (Goodchild 1980, Shelberg et. al. 1983), information fractals, etc., using the fractal measure relations, i.e. Area-Perimeter method (Kent and Wong, 1982) and from variogram method by taking the ratio of logarithmic lag versus logarithmic variance (Wood, 1995). The variogram method provides a convenient

means of studying the anisotropy of terrain (Goodchild 1992). This conclusion is also reported by the findings of (Atkinson and Tate, 2000). Hence in this study variogram method is adopted.

Patch hierarchical scaling is another area where fractal applications are used to distinguish hierarchical size scales of patches in nature (Li 2000) such as how to determine boundaries between hierarchical levels and how to determine the scaling rules for extrapolating within each level. (Bradbury et al. 1989) examined the possibility of hierarchical scaling in an Australian coral reef. They used the dividers method in transects across the reef to determine whether D depends on the range of length scales. They found that three ranges of scales correspond well with three major reef structures: 10 cm corresponds to the size of anatomical features within individual coral colonies; 20-200 cm corresponds to the size range of whole adult living colonies; and 5-10 m is the size range for major geomorphologic structures. Hence it can be concluded that the shift in D at different scales appear to signal break-points in the hierarchical organisation of reefs.

For the remotely sensed imagery a well-known technique that is often applied is variogram or semivariogram. It is a probabilistic approach that provides more efficient tools to model the spatial heterogeneity component (Chiles and Delfiner, 1999; Woodcock et al., 1998; Atkinson, 2001). Hence the objective is to characterize the peatland surface heterogeneity using samivariogram and fractal analysis to determine the characteristic length scale.

Classification of peatland landscape using object based fuzzy logic techniques

Object-based fuzzy logic classification technique is a semi-automated, object-based method for image classification. The method emphasizes contextual information based on a hierarchical

fuzzy logic membership function applied on image objects rather than pixels (Baatz et al., 2004; Blaschke, 2005). Very high resolution remote sensing data from satellites such as IKONOS and Quick Bird has led to the development of more sophisticated object-based methods for image analysis (Dissanska et al., 2009) exploiting the spatial context of the image. Unlike spectral based classifiers that rely on pixel statistics, an object based method relies on spatial and functional relationships (Guidon, 1997). The main advantage is that in addition to spectral properties, every single object contains shape, texture, size, sub objects and super objects information and this can relate to the surrounding objects in defining various membership functions.

Materials and Methods:

Remote Sensing data:

Airborne remote sensing data ATM was acquired by NERC - ARSF in March 2007. The pixel resolution of ATM data delivered is 1.5 m. The spectral range of ATM data set is shown in Table 1, below. For the characterization of the peatland surface heterogeneity, we have selected a part of the ATM scene in a) near infrared (NIR) band (Figure 1) and b) short wave infrared (SWIR) band with 400 x 400 pixels centred on the Long Loch bog. The variogram analysis was done in ENVI® tool (Research Systems, Inc., Boulder Colorado). The object based image segmentation and classification was performed using Definiens Professional software, eCognition®.

ATM Band	Spectral range (μm)
1	0.42 - 0.45
2	0.45 - 0.52
3	0.52 - 0.60
4	0.605 - 0.625
5	0.63 - 0.69
6	0.695 - 0.75
7	0.76 - 0.90
8	0.91 - 1.05
9	1.55 - 1.75
10	2.08 - 2.35
11	8.5 - 13.0 μm
12	Spare thermal channel

Table 1: Band characteristics of the Daedalus 1268 Airborne Thematic Mapper (ATM)

Variogram model

A semivariogram provides a concise and unbiased description of the scale and pattern of spatial variability and can be applied to spatial variability and autocorrelation in a region provided that the stationarity hypothesis is valid (Curran, 1988; Şen, 1998; Sertel et al., 2007). For remotely sensed imagery the lag (h) in Eq. (1) is measured in units of a pixel (Berberoglu et al., 2007). The quantity $\gamma(x_i+h)$ is an estimate of the semivariance of $\gamma(h)$ and is a useful measure of dissimilarity between spatially separate pixels and spatial patterns: the larger is the semivariance and the less similar are the pixels (Curran, 1988; Goovaerts, 1999; Sertel et al., 2007). The shape of the semivariogram reflects the spatial structure (Kim et al., 2006). A spherical model was used to fit the computed semivariogram. The parameters, such as lag, sill, range, and nugget, which are used to characterize the spatial variation properties, are illustrated in Fig. 2a & 2b. In a typical semivariogram (Fig. 2), the semivariance values gradually

increase with increasing lags and this diminishes with distance and levels off at a certain point. This distance at which the asymptote is reached is known as the range, signifying the extent of heterogeneity, at which spatial autocorrelation between data point pairs ceases, and beyond which data are stochastically independent (Ettenma & Wardle, 2002). The plateau of the semivariance estimates at the range value is the sill, which is a measure of total population variance, or absolute amount of heterogeneity (e.g. Cohen et al., 1990). The non-zero intercept of the semivariance curve with the y-axis is the nugget, indicating the non-spatial variation due to sampling error (Adams et al., 2008).

For continuous variables, such as reflectance in a remote sensing data in a given wave band, the sample semivariance is defined as half the average squared difference between values separated by a given lag which is a vector in both distance and direction (Atkinson, 1999). Variogram may be obtained for several different orientations to describe the spatial anisotropy in the data set or the surface properties.

A study area with N pixels of a grid has information of a variable Y at each pixel X. The values of Y are generally spatially auto correlated within a range of distances given by a direction which is measured using a semivariogram (Myers, 1997). For continuous variables, such as biomass, leaf area index (LAI), surface moisture content, the sample variance is defined as half the average squared difference between values separated by a given lag or distance intervals h:

$$\gamma(h) = (1/2N(h)) \sum_{x=1}^N [y(x_i) - y(x_i+h)]^2 \dots\dots\dots(1)$$

where $y(x_i)$ and $y(x_i+h)$ are the data of Y at two points x_i and x_i+h separated by distance h which is called lag between the data pairs N(h) (Bian, 1997). The semivariogram can be fitted using a

spherical, exponential or Gaussian model. The semivariogram may be estimated for several different orientations to describe variation that may be anisotropic (Atkinson, 2004).

The semivariogram information was used to determine the optimal window size, based on information on the spatial structure of vegetation. The pixel digital numbers are considered as a function of geographic location, i.e., regionalized variable. The experimental semivariogram measures half of the average squared difference between values $y(x_i)$ and $y(x_i + h)$ of paired pixels separated by a given lag h (Curran and Atkinson, 2002).

Results

To explore and quantify the surface pattern of the peatland, semivariograms were plotted (Figure 2a & 2b). The results have shown that the adoption of the geostatistical techniques on peatland surface pattern revealed several different trends from which pattern forming processes operating at several different spatial scales can be inferred.

The image of ATM and its respective NIR bands are analysed and the histogram plotted in Figure 1. The band 7 of ATM has a NIR wavelength range of 0.76 – 0.9 μm , is less affected by atmospheric influences (Lane et al., 2014), enables broader vegetation segregation due to high reflectance of the vegetation features and strong absorption of the water bodies. In the present research the characterization of spatial heterogeneity would require characterizing hotspots such as pools and vegetation surface using object based classification technique. In object based classification it is possible to base the classification on a single image layer/band in the Multi-resolution segmentation algorithm, one can set the "image layer weights" of the layers/bands one is not interested in to 0 (eCognition user guide). Unlike pixel based classifiers, segmentation classification takes the DN of neighboring pixels into account. There are currently

hundreds of different ways of doing this, but most use just a single band of data a single band is sufficient (Marthe et al., 2012; Shereen et al., 2012; Elmqvist et al., 2008,). In pixel based classification the training areas are selected from the scatter plot of two spectral bands plotted against each other. Thus a minimum of two spectral bands are required If in case pixel based spectral analysis is done. The regions highlighted by red circles are the bog centres of the peatland. The bog centre has a series of concentric pool complexes (red circle) that also has very low reflectance in the NIR due to the absorption by water bodies.

The histogram plot of ATM in Figure 1, has more compact samples with a Gaussian distribution. The bog centre in ATM imagery is brighter; the outlier near the 700th sample in the ATM histogram may be the round lake that is shown as a big bright area in the imagery as compared to the rest of the Silver Flowe peatland. The reflectance is not very bright since the time of flight when ATM data was collected was around 10 am.

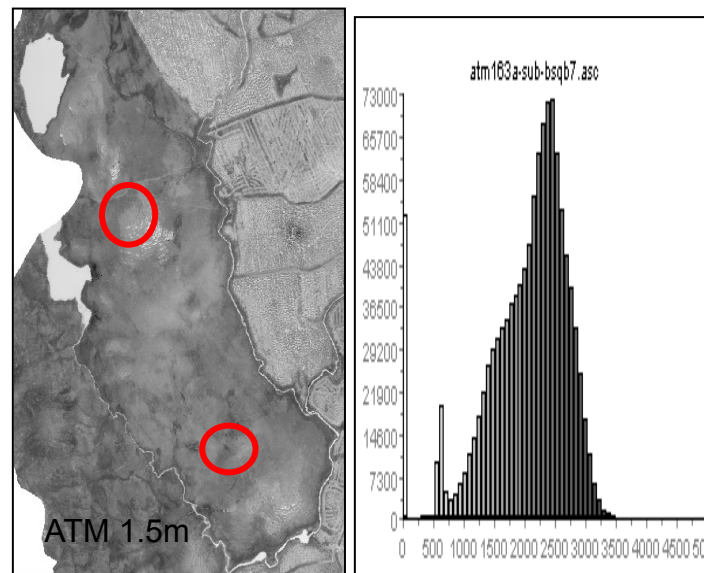


Figure 1: The NIR band 7 of the ATM image with its pixel size showing the bog centres highlighted in red circles and its samples plotted as a histogram shown on its right.

Variogram model and spectral variability

The NIR band 7 of the ATM scene was modelled in ENVI® tool and the resulting semivariogram is plotted in the Figure 2a. The semivariogram models were computed for 400 x 400 pixels subset, representing all possible structural classes within the Silver Flowe peatland. The model behaviour is within the expected

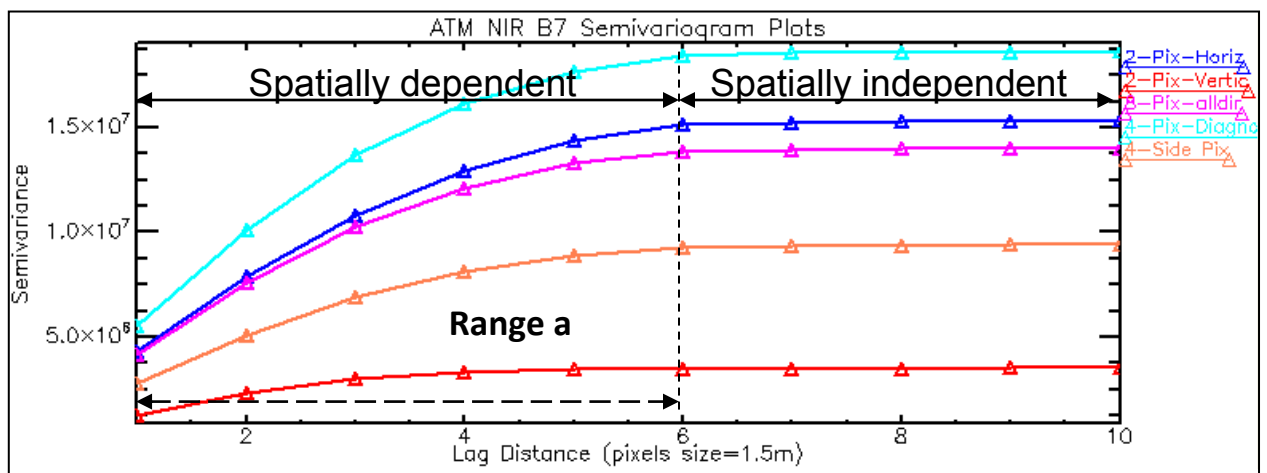


Figure 2a: Semivariogram modelled from ATM NIR band 7 in five different directions

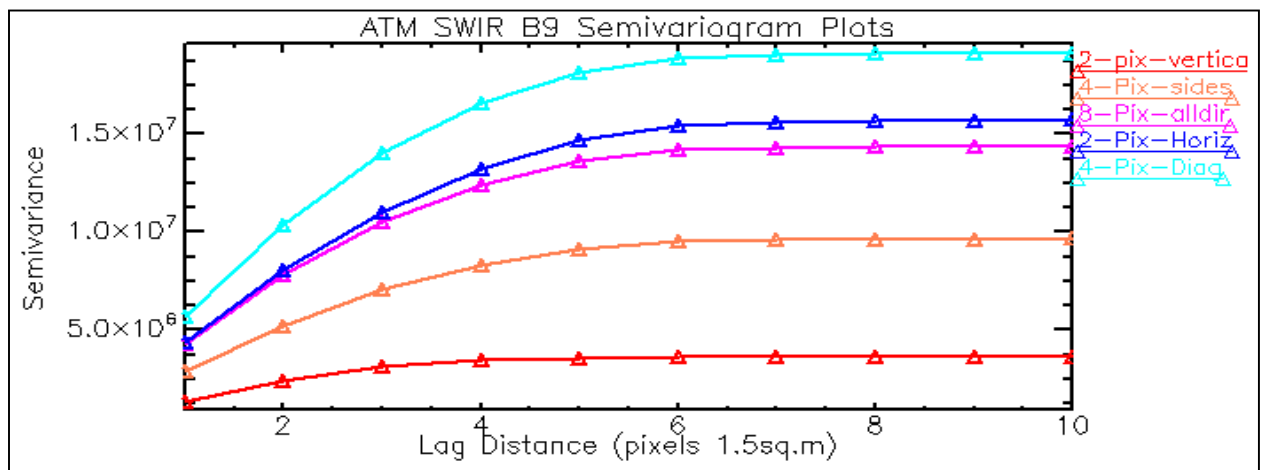


Figure 2b: Semivariogram modelled from ATM NIR band 9 in five different directions

range of 10 m as observed by (Ratcliffe & Walker 1958). The model revealed a range of 6 m in the vertical direction (red curve), while in other directions the range is 9 m. The semivariogram sill provides information on the variability of pixel values and its range indicates the distance within this range the samples are spatially correlated and beyond which there is no spatial dependence of pixels and is associated with the size of the elements within the scene. The range also expresses the extent of the influence of any single sampling point. The pixel size of ATM being 1.5 m, the graphs of the semivariograms resembles those of a continuous data models and therefore, the range for the microstructural elements with this range could be taken directly from the graph.

The semi variogram from NIR band 7 of the ATM band showed different character in different directions thus confirming the anisotropic behavior of the peatland surface pattern. The models in figure 2a are plotted in different directions. In the vertical direction (red curve in Fig. 2a) shows almost zero nugget and a range of 6 m reaching the sill at this distance. This is probably due to the smooth surface of the pools. It also reflects the reduced hummock-hollow complexes and lack of tall tussocky shrub canopy such as heather that are dominant in some part of the Silver Flowe landscape.

Other variogram models in figure 2a, corresponding to different directions has nugget effect where the variogram curves intercept with the abscissa. The range for these models was 9 m before the variogram model reaches their respective sill. Observation of the surface pattern revealed that this was due to the presence of the more pronounced patchy nature of the

peatland surface with heather and sedge canopies. The spatial trend has a length scale of 6 pixel units making the distance of 9 m.

A similar model is constructed using the band 9 from the short wave infra red region (SWIR) of the ATM data, figure 2b. It is almost similar to the behaviour shown in the model developed using the NIR band 7 (Fig 2b).

Fractal Analysis of ATM NIR band 7

It is important to find out at what scales new patterns may emerge so that the image resolution at which the dominant operational scale can be defined. During scaling up these resolutions are where modelling should be conducted (Meetenmeyer, 1989). One way to find out the significant scale that captures the spatial heterogeneity is by fractal analysis. As semivariance based fractal dimension is most appropriate because it measures how data variation changes with sampling interval (Bian, 1997) the fractal analysis of ATM NIR band 7 was carried out and the logarithmic variance was plotted against the logarithmic lag distance.

The initial pixel resolution was 1.5 m, and aggregated pixel resolutions of size 4.5 m, 7.5 m, 10.5 m, 13.5 m, and 16.5 m were computed (Mohammed et al., 2009) for the fractal dimension from the logarithmic lag distance versus logarithmic variance, Figure 3. The fractal dimension is calculated from the relationship (Bian, 1997),

$$D = 3 - s/2$$

The turns on the fractal plots (dotted line) Figure 3, indicate the major operational scales in the data. As evident from the plots, except the model for 4.5 m pixel size that showed the first turn

at 0.3 pixel unit, all others models showed the first turn at 0.6 pixel units. The models also showed multifractal nature of the underlying heterogeneous landscape.

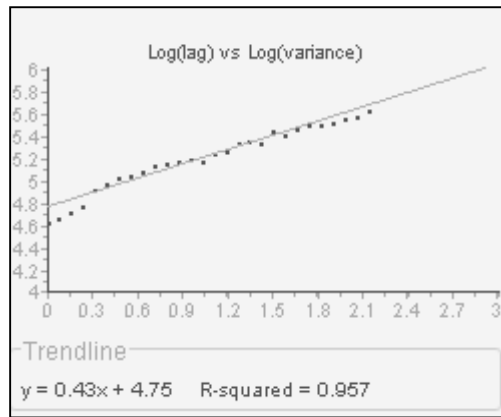
Using the variogram model range of 6 pixel units, the ATM data is classified with a window size of 9 m for computing ancillary information such as texture, entropy, grey level co-occurrence matrix in the eCognition tool.

Classification of ATM image

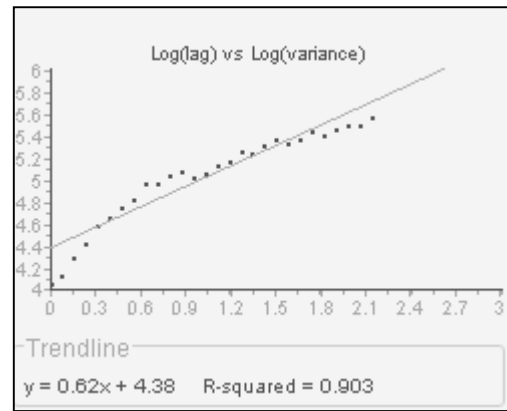
A subset of 400 x 400 pixels image is demarcated on the Long Loch bog. The image is classified to distinguish pools in the bog's centre. Object based hierarchical classification technique in eCognition® was performed at two different levels. The range from variogram model was 6 pixel units so the 1.5m pixel resolution of the ATM data is well within this range making it possible to characterize individual pools and other small scale features like hummocks, hollows and lawns.

The fuzzy logic rules that define membership functions along with the textural information in combination with neighbourhood rules, Figure 4, applied to the multiresolution image objects resulted in a classified image of bog expanse, which is typically a complex of pools, at lower level of segmentation.

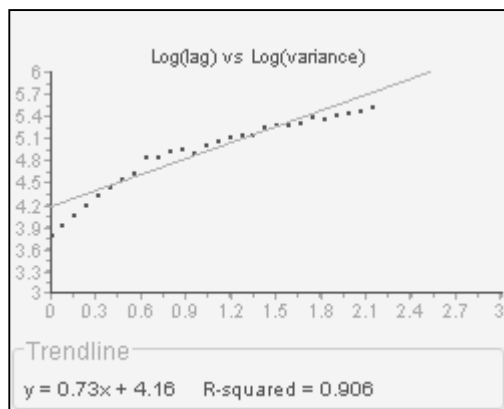
The spectral feature space is supported by additional features axes such as object size, number of neighbouring objects, and number of sub-objects, spectral distance to neighbouring objects, which describes spatial and hierarchical features. While pools were segmented at a lower level the entire peatland area was successfully segmented at a higher level. The resulting polygon features from the segmented images at the two abstraction level were classified by the nearest neighbourhood classifier.



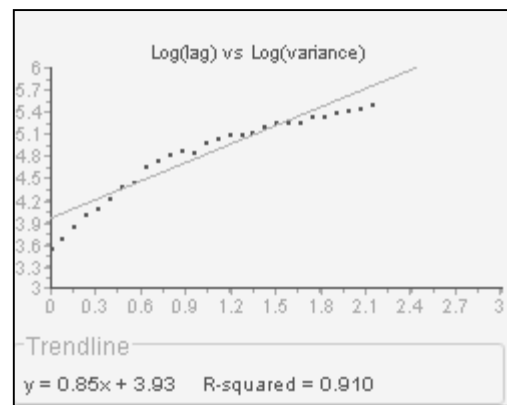
Pixel size 4.5 m



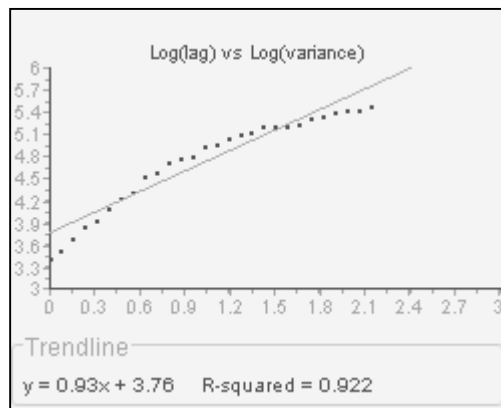
Pixel size 7.5 m



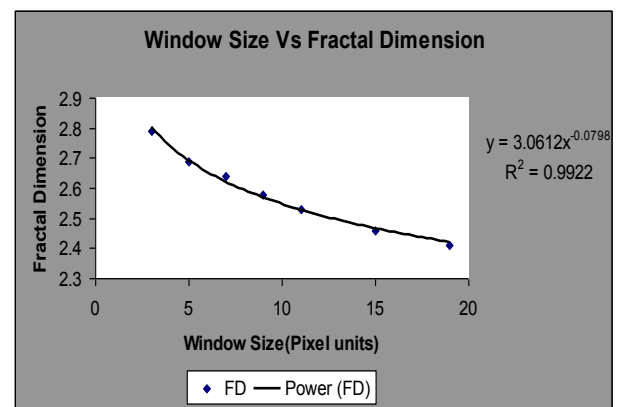
Pixel size 10.5 m



Pixel size 13 m



Pixel size 16.5 m



Scale Vs Fractal dimensions

Figure 3: ATM band 7 image fractal dimensions

The segmentation technique allows selection of super objects and sub objects, Figure 5(A& B), in the eCognition program, resulted in characterizing successfully individual bog pools from the peatland surface. The classification results are displayed in Figure 6.

The classified image at 1.5 m pixel resolution with the classification scheme in Figure 4 is aggregated by simple mathematical averaging up to a pixel size of 4.5m, 9m and 30 m. An empirical analysis of the two results from 1.5 m pixel size and 30 m pixel size that are superposed on each other to demonstrate the errors that occur with the simple averaging techniques are also shown in the Figure 7.

Discussions

Geostatistical techniques offer a means of qualitatively describing texturing features in data such as the degree of spatial continuity in a variable which is useful in the context of the present research because measures of spatial dependency would give an idea of suitable field sampling scheme. The source of variance and their spatial structure within this dataset, a semi-variogram model was produced using

The limitations of using spectral based classifications have been documented in studies of wetland species composition and distributions (Brown et al., 2007), where inaccuracies arise from lack of endmembers for key species assemblages (Thomas et al., 2003), that is, a primary surface with a high

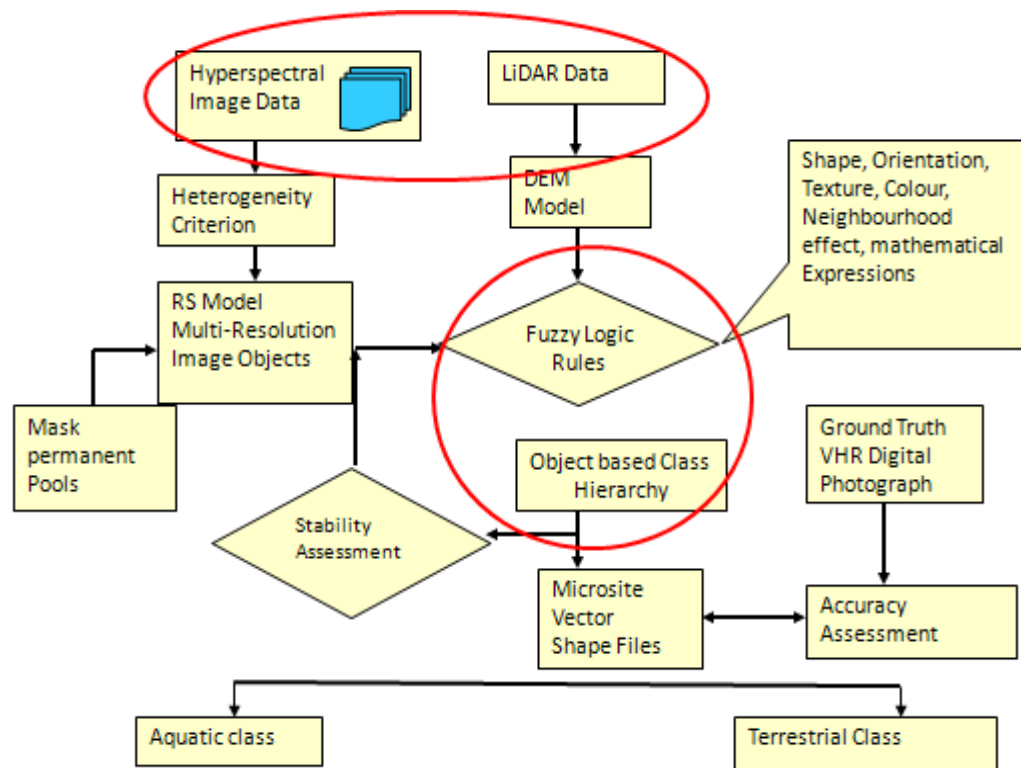


Figure 4: Schematic of Fuzzy logic based hierarchical classification of ATM data

Sphagnum cover may be dominated by an over-canopy of *Calluna vulgaris*, *Erica tetralix*, or *Myrica gale*, which would confuse a spectral-based classifier. Active peatlands have surface microstructural elements such as pools, hummocks and hollows, each distinguished by their water table positions (Belyea and Malmer, 2004) and containing distinctive vegetation communities. Object based fuzzy logic techniques supported with additional textural information are therefore be more useful in achieving greater classification accuracies of the peatbog surface (Anderson et al., 2010).

Depending upon the scale of measurement, the observed magnitude of spatial variation of the methane emissions from peatland may change. Different spatial resolutions reveal information about the distribution of pools, hummocks, hollows and lawns in the landscape (Mohammed et al., 2009) which may be homogeneous at one scale yet heterogeneous at another, continuous at one yet irregular at another. Developing appropriate scaling-up methods to estimate the peatland methane emissions from plot level to landscape and regional scale means resolving the complex peatland surface heterogeneity into a more simplified form (El Maayar & Chen, 2006) and characterizing the parameters like water table depth, sedge cover and peat temperature as input variable for physical based methane measuring models (Walter et al., 2001a).

As methane emission processes are non-linear in both space and time (Yavitt & Knapp, 1998; Moore & Roulet, 1991; Bubier et al., 1993), this means that spatial features, patterns, and processes of variables such as pools, lawns, hollows, and sedge covers and their statistical parameters, spatial distribution, and their variation, should be accurately mapped. The optimal scale differs by variables, which implies existing multiple and hierarchical scales within a complex natural scene (King, 1991; Wu 1999). For these reasons, it was considered important to determine the heterogeneity of such variables to infer spatial data from one scale to another. The semivariance statistics uses the squared difference between the neighbouring pixel values to provide another means of dissimilarity within a data set. Semivariogram helps to understand how the autocorrelation decreases with increasing lag. Such a graph showing how the local variance of a digital image for a scene changes as the resolution of the pixel changes could help in selecting an appropriate image scale (Woodcock & Strahler, 1987). While fractal dimension provide an indication of the breaks in the scales of the data set. The

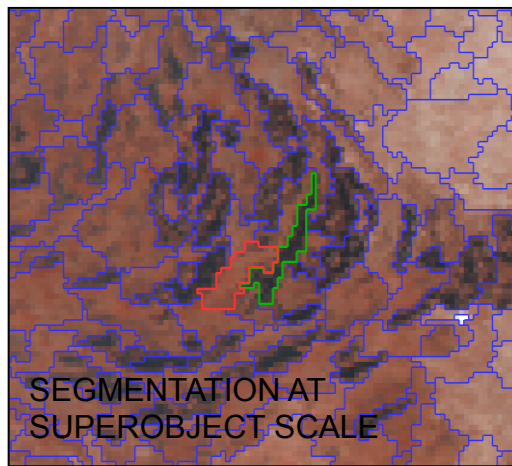


Figure 5 A: Segmentations of image superobjects in the ATM data showing selection of bog structural elements such as pools (green segment) and lawns (red segment).

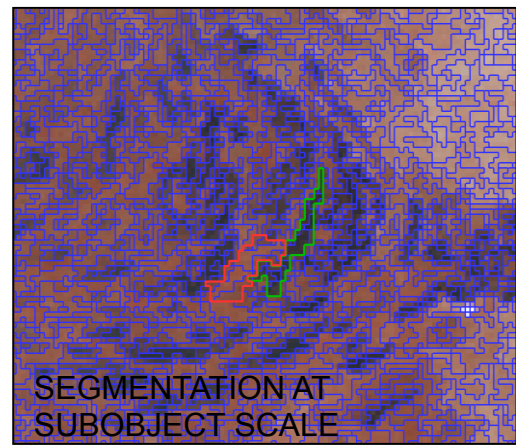


Figure 5 B: Segmentations of image subobjects in the ATM data showing selection of bog structural elements such as hummocks, ridges, hollows (blue) within the pools and lawns.

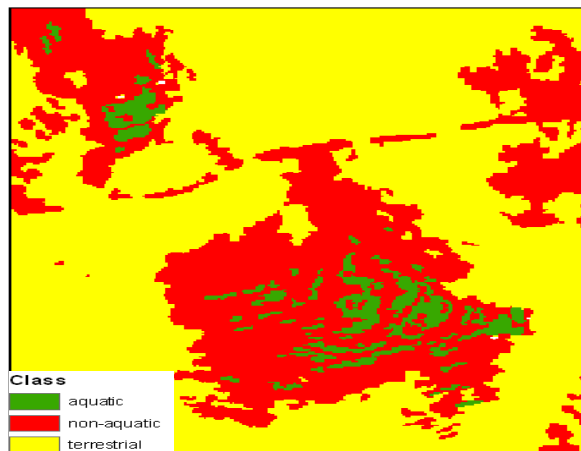


Figure 6: Object based fuzzy logic classification of ATM data into class aquatic (pools), non-aquatic and terrestrial classes

variogram models in Figure 2a & 2b for the ATM band 7 and band 9 in all possible directions with different neighbourhood pixel combinations have revealed a range of four to six pixel units, meaning for the ATM data the samples are spatially dependent within this range, the sampling schemes could be designed within 9 m plot size to capture the spatial heterogeneity

which is within the 10 m distance given by (Ratcliffe and Walker, 1958) on the Long Loch bog of the Silver Flowe peatland. This distance is also in confirmation with the observations made by (Boatman, 1983) and (Anderson et al., 2010). The samples beyond this range are spatially independent.

The high value of fractal dimension at finer scales, Figure 3, shows high spatial heterogeneity and as the D value decrease with increasing coarseness, the pattern on the landscape turn towards bigger patches and attain homogeneous pattern when the length scale reaches 30 m. it also reveals the multiscale nature of the peatland surface, showing scale breaks with the turns in the plotted curves in the log (lag) vs log (variance) plots.

The semivariogram and window size analysis based solely on ATM data provides important information on the structure, amount and extent of spatial heterogeneity of peatland surface surrounding the microstructural elements such as hummocks-hollows-pools. The combination of modeling semivariogram and window size techniques, together with remotely-sensed image data (land cover products) at a fine-resolution (e.g. 1.5 m in this study or less), is therefore a pragmatic approach for assessing the spatial representativeness of the hummock-hollow-pool structures for the measurement of methane emissions.

From the information gathered by variogram model and fractal dimension, a window size of 9 m applied in the eCognition tool to compute the grey level co-occurrence matrix (GLCM) and with well-defined membership rules the ATM data is classified into four classes.

The object oriented classification based on fuzzy logic rules is a promising technique and shows the ability to characterize small scale features such as individual pools at lower level of segmentation and large scale features such as bogs and peatland landscape at higher level of



Figure 7: ATM image classified result aggregated to 4.5 m



Figure 7: ATM image classified result aggregated to 9 m

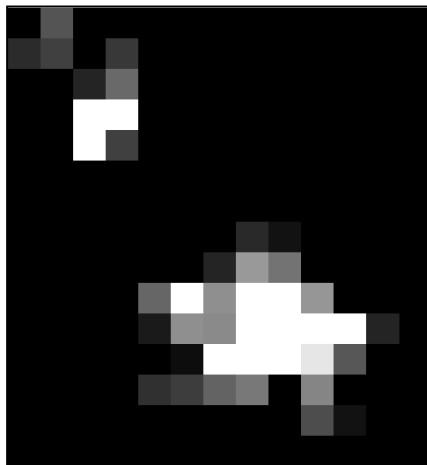


Figure 7: ATM image classified result aggregated to 30 m

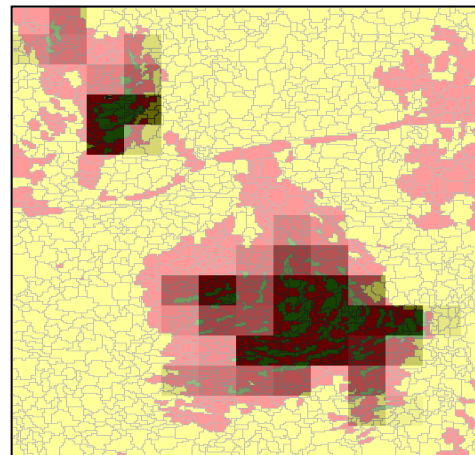


Figure 7: ATM image classified result from 1.5 m pixel size is superposed on the aggregated 30 m classified Image

segmentation within the hierarchy, Figure 5. Thus, results obtained from lower segmentation levels can be applied to aggregate small scale features and the results that are obtained at higher levels of segmentation could be applied for large scale features in a hierarchical way. This possibly reduces the data loss and minimise aggregation errors.

The superimposed results from object based classifier of the ATM 1.5 m data on the 30 m upscaled data from the simple averaging method clearly shows how the entire bog centre is misclassified as pool in the simple averaging method, while the actual pool area is much smaller (Figure 7). Hence if methane budget is estimated at landscape or regional scale using simple averaging method, then certainly it would produce erroneous estimates of the methane.

Challenges across Scales:

It is often challenging to combine data and models at different spatial scales to extrapolate information *between* scales. This challenge is particularly acute for peatland ecology due to its complex and heterogeneous landscape structure. The difficulty is acquiring and then replicating broad-scale experiments and hinders our ability to address the regional processes because of a number of issues: the period during which measurements are taken is obviously not typical for conditions throughout the year, and thus the duration and timing of the measurement period are both of some significance; measurements per hour obtained from a limited period during the year obviously cannot simply be multiplied-up to create a value for annual methane production because methane emissions are likely to vary throughout the year; equally, measurements given for CH₄ production per day cannot simply be divided by 24 to produce equivalent units per hour, because CH₄ production is not uniform throughout the day, being

markedly lower at night because the temperature is lower (Hargreaves and Fowler, 1998; Kettunen et al., 2000), but sampling from closed chambers is sometimes carried out during daylight hours only; comparison between sites is difficult if the sampling periods are not coincident (further complicated by inconsistent use of units); biological factors which are present during some parts of the year but not others (such as emergence, or die-back, of aerial leaves above the water surface) may result in 'step changes' in values which cannot be predicted or detected at certain times of the year.

Remote sensing and geographic information systems can provide information at scales appropriate for analysis by spatially statistical techniques such as semivariograms, fractals, power spectra, multiscale ordination and other geostatistical methods.

The scale problem may not appear in homogeneous systems because process measurements could be integrated directly. However, in heterogeneous systems such as peatlands, process measurements at fine scale cannot be simply summed up directly to produce regional estimates due to the nonlinear influence of the spatial heterogeneity as observed in the peatlands. Peatland spatial heterogeneity poses a challenge in translating information from one scale to another as the change in scale would alter the pattern on the landscape if appropriate scaling techniques are not adopted (Mohammed et al., 2009).

The temporal scale of the methane emission processes must be identified to understand the way in which the controlling factors such as water table depth and soil temperature varies with scale. Once this is achieved then appropriate methods could be developed to translate predictions from one scale to another.

Another area in the present work that would be required to assess the accuracy of the thematic classification maps is the extensive field ecological data that represents true peatland eco-hydrological communities to represent the actual vegetation and microstructural communities. Future studies should include this information to validate the results.

The results presented here have confirmed that a quantitative assessment of the bog surface could be derived from evaluating semivariogram at a variety of lag distances that are known to represent pattern forming processes at different pixel sizes as indicated by the fractal dimensions. Additionally, characteristics of the semi variogram such as sill, range and nugget could be evaluated by a simple variogram. Such numerical indices of pattern would allow automated assessment of surface reflectance over a wide range of sites, allowing user to assess the bog microtopography.

Conclusions:

Semivariogram model from the geostatistics when applied on the band 7 and band 9 from ATM data revealed the spatial range to be approximately 9 m in all directions. Simple average aggregations schemes were applied and the data was upscaled. Further analysis for spatial heterogeneity using fractal dimensions resulted in the D values between 2.4 and 2.8 indicating multifractal nature of the data and the D decreased from fine scale model to coarse scale models in a nonlinear trend indicating high heterogeneity and high spatial correlations at fine scale data. The data became homogeneous with large patches at coarse data due to smoothing affect. Observations also pointed to multifractal nature of the peatland surface with scale breaks that appears in the slope of the logarithmic variance versus logarithmic lag plots.

Using a window size of 9 m the textural information such as grey level co-occurrence matrix were computed in the object based fuzzy logic membership functions to classify the data in to aquatic and non-aquatic classes. Nearest neighbour classification rules along with image subobjects and superobjects segmentation techniques performed the classifications. Object based approach seems promising for future work as a set of routines based of membership functions that could be defined as a template and remote sensing data can be analysed. The problem due to mixed pixels, spectral unmixing and subpixel errors could be avoided with object based methods.

Outlook

The geostatistical methods such as semivariogram and fractal analysis applied on the ATM NIR band 7 resulted in characterising the length scales on the peatland surface. The methods in combination with the object based classification techniques could be explored in more detail with all the other data sets to develop a routine for mapping the peatland surface and apply scaling methods to achieve better results. The future work depends mainly on the higher resolution data from sensors such as AISA, CASI, and IKONOS.

Further work in the present area should consider validation of the proposed method at other peatland sites, where vegetation displays self-organizing patchiness, where the method has real potential for spatially accurate assessment of methane emission hotspots.

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Summary and Overall Conclusions

The aim of this project was to upscale the fine scale peatland methane emission hotspots and investigate the information preservation on the peatland surface heterogeneity due to the upscaling techniques. One of the biggest challenges of carbon modellers is to measure, model and predict methane and its variability over different temporal and spatial scales. The IPCC (2013) reported the global annual methane budget from the wetlands and differences in the methane inventories reported are of the order of the magnitude by more than 50%. The consistency in reporting the wide difference in the methane budget since last several decades is quite evident from the literature as cited in previous chapters. Besides many reasons that could have been possible for such variation and wide range in the reported annual inventories of methane from the natural sources such as peatlands, one reason is the loss in the fine scale heterogeneity that is not well represented at the coarse scale in the global carbon models. The other could be the misrepresentation of the landscape methane emission hotspots by other classes and may well be the underrepresentation of the small pools, lakes and small peatland types on the coarser grid scale in the global carbon budget models. Still among the other reasons as described below, averaging by assuming homogeneity over space would result in biased estimates of the fluxes. In this research it is demonstrated that simple mathematical averaging of remote sensing derived variables (Paper III) would result in biased estimates of the overall fluxes as neither the processes nor the drivers are linearly behaving in time and space.

Measuring methane at plot scale using in situ techniques may be accurate but it is also very challenging both in terms of cost and time and further difficulties arise in repetition of such

methods. Remote sensing provides an alternative option that has been explored by many, yet there are certain issues such as those explored in this thesis.

Global processed based models such as (Walter et. al., 2001) that apply the wetland distribution maps from (Mathew & Fung, 1987) to estimate global methane budget are erroneous due to the misclassifications presented in the global wetland map of Mathew and Fung, where forest is misrepresented as wetlands. Other techniques such as (Takeuchi et. Al., 2003) give rise to the problems of mixed pixels, and moreover, the variation in water table depth is overlooked by them. As water table depth is one of the most significant driver in the emissions of methane from peatlands (Frenzel & Karofeld, 2000; Kettunen, 2000) the results obtained by (Takeuchi et. al., 2003) are biased. Additionally, the non-linear relationship between the methane emission drivers such as water table depth and soil temperature if aggregated by simple arithmetic mean will lead to erroneous estimates of methane budgets from the peatlands. It is therefore, vital to preserve the fine scale heterogeneity when upscaling peatland microstructures from small to large scales before using these as input in any global carbon models.

In the present research an attempt was made to preserve one of the most significant aspects that have strong influence on the way the inventory of methane emission budgets from peatlands are estimated, i.e., the pattern on the peatland with its fine scale heterogeneity on the peatland surface. Applying concepts from the wavelet theory and information theory on different remote sensing data taken above the Silver Flowe peatland located in the South western Scotland, from aircraft and satellites, we have classified the hotspots and upscaled the peatland fine scale heterogeneity from small to large scales. We also investigated the

expansion of drought sensitive pools using LiDAR data and the results are discussed and criticised. Future course of action was suggested in the outlook section.

Multiresolution wavelet analysis of spatial pattern distribution on peatland from multi-sensor data to up-scale landscape heterogeneity

Multiresolution discrete wavelet analysis was successfully applied to the subset of the Silver Flowe peatland to upscale the fine scale surface heterogeneity. The data set taken from four different remote sensing sources was classified and upscaled from fine resolution to the coarse resolutions. The pattern on peatland and its spatial heterogeneity was preserved in all the data sets.

In our analysis the important peatland microform structures such as pools, hummocks and lawns with shunt species were scaled up and the scaling behaviour resembled results from other below mentioned studies using db1 2D -MRDWT. The fine scale heterogeneity was preserved in all the four data sets and the pattern on peatland remained intact up to fourth level of decomposition in most of the data sets used. Thus the methods successfully captured the fine scale heterogeneity up to a length scale 2 m in the digital photography and preserved pattern on the landscape up to the length scale of 4 m. However the pattern and position lost beyond the 4 m scale and the wavelet variance dropped indicating homogeneity due to the smoothing effect.

For the ATM data the scaling affect was observed up to the level 4 when the pixel resolution was upscaled to 12 m and the pattern was preserved at this scale. The wavelet variance dropped rapidly from the original 1.5 m pixel value to the 12 m pixel value and then stabilized beyond 12 m coarsening of the resolution. The PAN sharpened IKONOS data scaled up preserving the pattern and position of the microstructures up to the resolution of 8 m and

beyond 8 m the fine scale heterogeneity is lost at 16 m but the position was intact. Further upscaling beyond 16 m pixel value up to 32 m resulted in the loss of both pattern and position. The wavelet variance decreased indicating considerable loss of information and smoothing affect causing homogeneous surface at that scale.

The wavelet methods were used in directional and multi-scale landscape pattern identification using IKONOS PAN Imagery by Sun Danfeng (2003) over a farmland and found that the tree rows-farm land has three characteristic scales one at 2 m, 128 m and 256 m. In another study, Xie Jiangbo et. al., (2007) demonstrated the applications of wavelets in the scaling of spatial distribution patterns of *Ceratoides ewersmanniana*. They found that the fluctuations between the spatial pattern and spatial heterogeneity was large between the 1 m and 25 m scales of landforms and *C. ewersmannian*, indicating that ecological function and processes of *C. ewersmanniana* were unstable. At scales above 25 m they noticed that the spatial distribution pattern of *C. ewersmanniana* did not change with scales. Hence our results are consistent with what has been reported by other in other ecological applications using wavelet theory.

The EAGLE data used in this analysis lost the pattern and position of the microstructures after the 3rd level of wavelet decomposition dropping the wavelet variance simultaneously. The atmospheric and radiometric corrections of the of EAGLE data was not good; the initial resolution of 5 m pixel had poor classification results. This may be attributed to the poor performance by this data type and also the fact that small hummocks and very small drought sensitive pools < 4 m² size might not be detected by the classifier giving rise to the mixed pixel problems that are not dealt here. Although, EAGLE data has an advantage over the other data used in terms of fine scale spectral resolution that could be very well exploited in combination

with LiDAR data to classify peatland microforms, but this opportunity was both ignored as well as missed. It was ignored as the entire focus was only on resolving spatial heterogeneity and missed due to the poor atmospheric and radiometric corrections. The overall observation of the four data sets seems in compatibility with the results reported elsewhere where the pattern and processes are preserved. Kumar and Foufoula-Georgiou (1993) scaled up the rainfall pattern using wavelet multiresolution analysis on a severe squall line storm which had occurred over Norman, Oklahoma. Their results revealed high fluctuations in coefficients of approximations (CoA) in regions of large intensities and small fluctuations in regions where the intensity was small indicating that the core behaved differently from the anvil region both in mean and CoA, indicating heterogeneity in the processes. This was successfully decomposed using the 2D-DWT into different scales similar to the behaviour of the patterned peat bog that has high heterogeneity at the centre of the blanket bog with the presence of all types of microforms and large patches of sedges and grasses near the boundaries.

The wavelet Coefficient of Approximations (CoA) are a measure of the intensity of the local variations in the signal, for the scale under consideration. The value of the coefficient is large when the size of the wavelet is close to the scale of the heterogeneity in the signal and it will be negligible when the local signal is regular for that particular scale (Ranchin & Wald, 1993). The variance of the wavelet coefficient or the wavelet variance is thus a very useful tool for investigating the spatial scales of variability in remote sensing data (Percival, 1995).

There is no known rule for selecting best wavelet basis for an analysis, and probably it may depend upon the data to be analysed and the overall objectives of the research. We choose db1 as it is similar to the Haar wavelet that has the basis function resembling the shape of the

pixels of the remote sensing data used in this research and like Haar wavelet it captures rapid changes in the data (Mahrt, 1991).

The 2D-MRDWT using db1 wavelet has scaled up the fine scale heterogeneity and had preserved the pattern on the peatland.

Outlook

Further analysis could be carried out by exploring the three detailed components H,V,D to study the orientation and spatial anisotropy on the peatland surface. For this angular wavelets could be explored to detect anisotropy and directional variances. This coupled with the above results is expected to give important information for the GCM modellers in estimating annual methane budget from the peatland landscapes.

Information Preservation and Change Detection across Spatial Scales in the Assessment of Global CH₄ Emission Estimates from Wetlands

In this paper we presented what can be described as proving the null hypothesis in this thesis which can be stated as if the peatland surface is completely homogeneous and methane emission model is linear then the aggregation can be performed simply by the mathematical averaging of the classification results. Fine scale heterogeneity does not simply average out and become insignificant at large scales. Hence any upscaling method should take in to account the spatial heterogeneity on the peatland surface and non-linear interactions between the drivers such as water table depth and soil temperature.

In this paper we explored the possibilities of non-linear aggregation using quadratic interpolations (QI) technique. In quadratic interpolations, the original pixel size remains unchanged and only interpolated values within the window is assigned to the centre pixel. This way the pattern is preserved. We formally quantify the information drift incurred by resolution and aggregation using techniques from IT. Particularly, we demonstrate that the preservation in pattern on peatland compared with mean aggregations that do not conserve information or spatial pattern leads to erroneous upscaled estimates.

According to the data processing theorem (DPT) (Cover & Thomas, 1991; cited in Sinanovic & Johnson, 2006), a system operating on a signal cannot produce output containing more information than that encoded in its input. In other words information content will be lost or remain static at larger scales with coarser resolutions. In our context, to analyze how well the pool area information is processed from fine to coarser scales is an interesting observation. We have drawn conclusions on how pools in bog centre would be preserved to contribute in regional scale estimates.

Our investigations demonstrated how the scaling process would influence the resulting patterns on peatland. Our results with mean aggregation showed that this method does not preserve the pattern and the pool structures have dominated the upscaled versions in all the cases. In contrast quadratic interpolation is retaining the original pixel resolution throughout the interpolation process and it is assigning the interpolated values to the centre pixel, the pattern is very well preserved in the high resolution data and almost preserved in the lower resolution data. This is a considerable improvement on peatland pattern preservation during aggregation to lower resolutions and could be adopted for regional and global scale estimates.

The information metric used such as Shannon entropy gave insight into how energy is transferred between different pdfs and how large entropy values confirm the uniform distribution of the data (Stoy et al., 2006) with class area values becoming more stable once they reach a coarse level. When the coarse scale reached a pixel size of (e.g. 28m), there was not much change between the areas of MSEs reported from ATM and IKONOS, thus making entropy as a good technique to find the most probable pattern of spatial distribution in a system.

Powerful information metrics such as Kullback-Leibler distance D_{KL} are also used to find out mutual information (MI). MI is a statistical similarity measure, quantifying how closely the probability functions of a system input and output agree (Sinanovic & Johnson, 2006). We used this metric and demonstrated the mutual information interchange between the data from the same source and its upscaled values. The implications from our analysis would be a useful contribution in the improved estimation of regional and global assessments in methane from wetlands.

Simulation of peatland pools by LiDAR to assess the effect of the expansion of pools on the methane emission fluxes

One of the main driver considered as the hotspots for methane emissions is a bog pool. Peatlands have many pool complexes and the Long Loch bog of the Silver Flowe peatland has a series of concentric pool complexes spreading out from the centre of the bog. Some of the

pools are deep, may be 20 m in depth and some are shallow. The permanent deep pools have steep edges due to weathering and the shallow pools have a gradient along their edges that make a slope around their periphery with respect to the dry land. Some of the pools are so shallow that during summer months they become dry and with precipitation or snow melt after winter these pools get flooded.

Since the wet areas are known to trigger the fluxes coming out into the atmosphere due to the water table depth and soil temperature causing the methane emissions, those pools that were dry over a short period of time suddenly become strong source for methane emissions when flooded. It is interesting to find out by how much a pool area expands given that the precipitation information is a priori known. This information would help us estimate the methane fluxes released from such drought sensitive pools.

Here we demonstrated how a LiDAR DEM model is used to simulate the flooding after mapping the drought sensitive pools. For the sake of argument, any pool area expansion from inundation can be mapped in this way.

We were able to flood the pools and map the expansion in the wet areas and with this information we can calculate the methane emissions by plugging the fluxes measured *in situ* from such sites or

Incorporate such information in to a physical model. This is significant when an episodic event such a precipitation occurs and by knowing the amount of precipitation, using the LiDAR model, we could compute the methane fluxes assuming that we know the other parameter that goes

into the model. We believe that by this technique a significant amount of time and cost could be saved.

Geostatistical methods to characterize peatland surface heterogeneity using ATM NIR band

Semivariogram model from the geostatistics when applied on the the band 7 from ATM data was revealed the spatial range to be approximately 9 m in all directions. Simple average aggregations schemes were applied and the upscaled the data. Further analysis for spatial heterogeneity using fractal dimensions resulted in the D values between 2.4 and 2.8 indicating multifractal nature of the data and the D decreased from fine scale model to coarse scale models in a nonlinear trend indicating high heterogeneity and high spatial correlations at fine scale data. The data became homogeneous with large patches at coarse data due to smoothing affect. Observations also pointed to multifractal nature of the peatland surface with scale breaks that appears in the slope of the logarithmic variance versus logarithmic lag plots.

Using a window size of 9 m the textural information such as grey level co-occurrence matrix were computed in the object based fuzzy logic membership functions to classify the data in to aquatic and non-aquatic classes. Nearest neighbour classification rules along with image subobjects and superobjects segmentation techniques performed the classifications. Object based approach seems promising for future work as a set of routines based of membership functions could be defined as a template and remote sensing data can be analysed. The

problem due to mixed pixels, spectral unmixing and subpixel errors could be avoided with object based methods.

Future research aiming to shed light on CH₄ fluxes from peatlands must: 1) produce more detailed data on controlling factors; 2) increase efforts to fully characterize spatial and temporal heterogeneity; 3) combine bottom-up (measurements) and top-down (modelling) approaches.

The water table position determines the relative extent of oxic and anoxic horizons within soils and, consequently, the ratio between CH₄ production and CH₄ oxidation, the fundamental microbial processes underlying the CH₄ cycle (Christensen et al., 2001). The effect of the water table position on CH₄ emissions can be compared with an on-off switch. When the depth of water table falls well below the soil surface, microbial CH₄ oxidation is increased and CH₄ emission is hence reduced, as occurs when water table level is increased above the sediment. Methane emissions in water-related ecosystems are partly controlled by water table, a parameter closely related with climate. Rainfall decrease, temperature increase and an elevated extraction of water from groundwater led to decreased water table and increased methane emissions from lakes and wetlands. Ringeval et al. (2010) stated that over the period 1993-2000, the variability in wetland areas strongly influenced the seasonal and interannual variability of CH₄ emissions. On a seasonal timescale, the variable flooded area mainly plays a role in controlling variable fluxes at boreal latitudes (~30 %). The difference with other studies (Shannon and White 1994) is the strength of these relationships. While these authors have

found very strong correlations between water table and methane emissions, world-wide data have shown a much lower statistical relationship.

The factors controlling CH₄ emission in lakes and wetlands are difficult to determine on a worldwide basis. Locally, they have been related to water depth, dissolved organic carbon, total phosphorus and anoxic volume fraction (Bastviken et al., 2004; Juutinen et al., 2009). However, no such relationships hold when studying them on a worldwide basis. Not only do CH₄ emissions from lake environments appear to be more spatially heterogeneous than initially suspected (Bastviken et al., 2010) but also, temporal variations in efflux occur ranging from diel (Bastviken et al., 2010) to interannual changes (Bartlett and Harris, 1993; Pulliam, 1993; Shannon and White, 1994; Hughes et al., 1999). Thus, controlling factors are likely to change depending upon the spatial scale involved. This makes us suspect that the relationship between methane emissions and either water table or sediment temperature are only valid at small scales, for individual study areas. By contrast, when we study an ecosystem type (lake or wetland) at the global scale these relationships disappear, and a more complex relationship may emerge among them.

The latitudinal variability is also striking (Fig. 1), thus preventing meaningful prediction of the factors controlling emissions worldwide. It seems that temperature, organic matter and anoxic conditions may be some of them, but there are not enough data to support this hypothesis on the worldwide scale.

Studies must be carried out highlighting short-range spatial heterogeneity including areas of the Earth that are virtually unknown as yet. Hence, bottom-up (incubation chambers, surface

drifters, remote sensors, eddy covariance towers) and top-down (inverse modelling) measurements must be combined to enhance the global estimation of methane emissions to the atmosphere. The significance of methane as a greenhouse gas (IPCC, 2007) makes these improvements essential if a better and more accurate picture of global emission is to be found, which is a precondition to reducing methane emissions worldwide.

One short coming that is recognised in this work related to the issue of scaling up peatland methane emission hotspots is how to validate the results obtained from small scale by the lack of field based observational capabilities at the larger upscaled support. Hence any future work should address the issue of validation comprehensively.