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DEVELOPING SOIL HEALTH INDICATORS TO INFORM AGRICULTURAL LAND M ANAGEMENT DECISIONS, IMPROVE YIELD QUANTITY AND QUALITY FOR LOWLAND PEAT ECOSYSTEMS

Thesis Submitted for the Doctor of Philosophy in Soil Science

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Declaration:

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Edward Baker

Abstract

Soil is a complex, variable, living medium essential to supporting life on earth through the provision of a range of ecosystem services, yet it is a non-renewable resource. Soil can be identified as the basis for food production, providing us with clean water, hosting biodiversity, cycling nutrients, and buffering against climate change. Anthropogenic pressures to increase productivity to enable food security is damaging these soil systems. The current environmental boundaries for soil systems are being transgressed, leading to the degradation of soil systems globally. This is particularly apparent in peatlands drained for agriculture, where departure from their natural state has caused intense degradation. Peatlands are essential to UK natural capital, food production, and ecosystem service provision. Previous attempts to create metrics to assess soil health and functioning have focused primarily on mineral soils and are not appropriate for assessing the soil health of drained agricultural peatlands. Specific tools to assess peat health were lacking and thus needed to be developed. Here I describe the development of two tools to enable assessment of the health of lowland peat systems using simple indicators that allow farmers to benchmark, compare, and sustainably manage peat health. The first tool created a minimum indicator set to classify peat health though Principal Component Analysis, leading to the development of an Additive and Weighted Peat Health Index approach. These indices were able to effectively distinguish deep peat from wasted peat, as identified by farmers. Additionally, the Peat Health Indices revealed that healthier fields required less farm inputs, indicating a better functioning system. The second tool developed was a Bayesian network. This tool incorporates probability distributions in assessing peat health, enabling the direct assessment of ecosystem uncertainty, and providing an estimated distribution of peat health given the observation of simple on-farm indicators. The network was developed through expert opinion and use of the ECOSSE biogeochemical model. The network was validated through k-fold cross validation, scenario analysis and expert evaluation. This thesis demonstrates the development and application of health assessment tools for drained agricultural lowland peat using easily measurable soil properties. We anticipate these tools to be a starting point for the assessment of peat health across the East Anglian fenland region and lead to the development of a national monitoring network using the Bayesian network approach.

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Chapter 1: Introduction

1.1 Background

The doubling of global food demand projected over the next 50 years will place increasing pressure upon agricultural soil systems reducing the provision of ecosystems services and posing challenges to increasing food production in a sustainable manner (Tilman *et al.*, 2002; Foley *et al.*, 2011). This increasing pressure of agriculture on soils has led to the degradation of these systems, leading to a reduction in their ability to function (Kopittke *et al.*, 2019). Contemporaneously, yield plateaus, or abrupt decreases in gains in yields, have been observed (Grassini, Eskridge and Cassman, 2013). Therefore, a key concern is that the identified degradation of soil systems is leading to a reduction in the provision of ecosystem services and overall functioning, reducing the food security of nations.

Soils are known to provide and regulate a range of ecosystem services, playing an important role in sustaining life on the planet (Pereira *et al.*, 2018). These services are provided through the functionality of soil systems and include; the provision and maintenance of a complex soil structure, the transformation and regulation of elements (including carbon, nitrogen, phosphorous, potassium etc.), the provision of habitat for biological and plant communities, and the control of soil water flows (Bünemann *et al.*, 2018; Pawlett, Hannam and Knox, 2021). A healthy soil allows for the delivery of multiple functions and subsequent supply of associated ecosystem services (Bouma, 2014). Yet soils are complex and spatially differentiated, with high natural variability and differing ecosystem boundaries (Kopittke *et al.*, 2021). Quantitative measurement of the subjective “health” of a soil has proven difficult, particularly given the variation between soil systems (van Bruggen and Semenov, 2000; Cardoso *et al.*, 2013; Maharjan, Das and Acharya, 2020).

Changes to environmental regulation and policy within the UK have moved at pace in recent years with the publishing of the 25 Year Environment Plan and the introduction of the 2021 Environment Act. The current policy aims to encourage and help the natural world regain and retain good health (Department for Environment Food and Rural Affairs, 2018a). The development of tools and metrics to quantify and improve soil health has been highlighted as a key factor to enable sustainable soil management. Further to this, the maintenance and restoration of peatlands within the UK, has been identified as a critical area to improve UK natural capital.

The degradation of soil systems in the UK has led to over 4 million hectares of soil being classified as at risk of compaction and 2 million hectares at risk of erosion. Furthermore, intensive agriculture has caused arable soils to lose between 40-60% of their organic carbon (Environment Agency, 2019). The degradation of soil systems leads to an adverse impact on agricultural productivity, consequently reducing food security, and damaging the environment (Eswaran, Lal and Reich, 2001; Sonneveld, Keyzer and Ndiaye, 2016). UK agricultural production is regionally diverse (Department for Environment Food and Rural Affairs, 2018b). Yet, the lowland fen region in East Anglia (Figure 1) contains rich, fertile areas of peat that that allow the production of horticulture and agricultural crops, accounting for around 7% of England's total agricultural production (Department for Environment Food and Rural Affairs, 2021a). It is increasingly apparent that the sustainable management of lowland fens of East Anglia is necessary for commercial productivity standpoint but also critical to achieve national environmental goals.

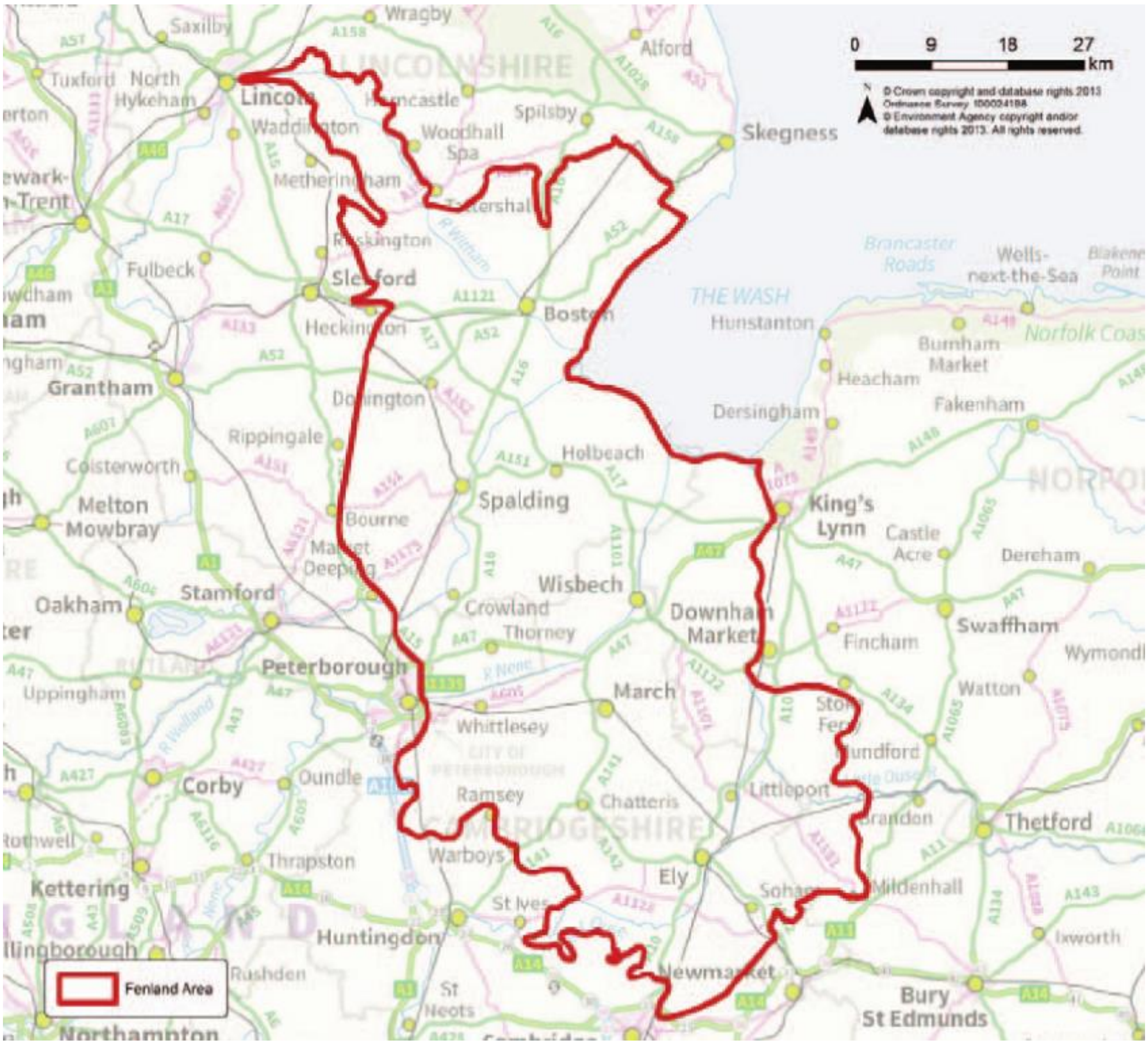

Figure 1: Geographical Map displaying the UK East Anglian fenland area outlined in red. Reproduced from (Redding and Nunns, 2017)

The recent advancements in knowledge of the functioning and services provided by soils has led to a variety of approaches to assess the health of soils. These include the development of national assessments, visual assessment methods, and suites of indicators (Bünemann *et al.*, 2018). However, current methods for assessing soil health are primarily developed with a focus on mineral soils. The development of on-farm indicators and tools to identify soil health specific to lowland drained fens is an urgent and essential requirement to support the sustainable management of these vital agroecosystems.

This project was framed by the research themes of the BBSRC Waitrose Collaborative Training Partnership (CTP). This partnership between BBSRC and Waitrose provided three interrelated research themes; Sustainable Crop Production, Sustainable Soil and Water, and Biodiversity and Ecosystem Services in Agriculture. This project, in theory, could fall under the auspice of any of these themes, but the third theme was deemed most appropriate. Sustainable production systems require a commitment to developing biodiverse systems and multifunctional landscapes to support the delivery of a variety of ecosystem services. The partnership therefore required consideration of the wider context of food production systems, including the concept of food security, the production systems present within the UK, and the development of concepts to assess the functioning of agricultural systems. The thesis work was conducted alongside an industrial CASE partner G's Fresh Ltd, based in Barway, Cambridgeshire who farm over 5,000 ha of land in East Anglia, with a large proportion of this located on lowland fen in the area. This role was directly related to the research project, encouraging the thesis development to be commercially grounded and provide usable outputs for the industrial partner.

1.2 Research Aims and Objectives and Thesis outline

The aim of this study was to develop tools to allow farmers and land managers to measure soil health on farms across the lowland fen region of East Anglia. This required me to identify key physical, chemical, and biological properties that infer the health of lowland peat systems. Two tools were developed to measure the soil health of lowland fen soils. One used a statistical redundancy approach and the other used a Bayesian network approach. After a literature review, two chapters are dedicated to each approach and then the overall thesis findings are discussed in a general discussion chapter. I provide here a short summary of the purpose of each chapter.

Chapter 2 provides a review of the literature concerning food security, the agricultural production systems in the UK, and the role of peatlands in agricultural production. The chapter highlights the ecosystem services provided by peatlands and current approaches to the assessment of soil health.

Chapter 3 describes the development of a Peat Health Index (PHI). The purpose of this exercise was to identify a minimum set of indicators to successfully capture the variance in peat properties across a peat health gradient using Principal Component Analysis. The output from this would allow farmers and land managers to identify differences between health status of their fields and inform sustainable management. Chapter 4 expanded upon the work in Chapter 3. Twenty randomly selected fields (including the study sites used in Chapter 3 to develop the PHI) were assessed using the PHI to validate the index and determine its reproducibility. The scores from this process were compared against farmer's perceptions of soil health and farm key performance indicators (KPIs).

Chapter 5 introduces the concept of using Bayesian networks to model the health of peat soils. The chapter starts with a description of Bayesian networks, how they operate, and how they have been previously used. The chapter then reports a Bayesian network structure created by expert opinion to infer the health of peat systems using simple on-farm available indicators that represent the functions associated with a healthy peat under intensive agriculture. Chapter 6 follows on from Chapter 5 by parametrising and evaluating the Bayesian network to create a tool that can be used to benchmark and compare the health of peat soils. Parameterisation was achieved through using expert opinion and by running simulations using a biogeochemical model. Expert opinion on the probability distributions of the network were gathered using the ACE programme created by Rothamsted Research to aide in elicitation. Expert opinion was combined with outputs from the ECOSSE biogeochemical model to represent carbon and nitrogen cycling. The parameterised network was evaluated through retrospective and predictive propagation, k-fold cross validation and sensitivity analysis. The output enables famers and land managers to assess peat health and consider the uncertainty associated with environmental systems.

The development of the two tools to quantify soil health of lowland drained agricultural peatlands are discussed in Chapter 7 alongside recommendation for future work. The publication strategy for the work presented in the thesis is to combine chapters to create two papers. Chapter 3 and 4 will be combined to describe the creation and validation of the Peat Health Index. Chapter 5 and 6 will be combined to report the creation and evaluation of a parametrised Bayesian network.

Thesis Hypothesis

Chapter 3 Hypothesis

We hypothesised that the health scores from a Peat Health Index (PHI) created with simple indicators will display signification correlation with key farm performance indicators.

Chapter 4 Hypotheses

We hypothesised that the PHI scoring gradient developed in prior work would be reproduceable over time using the indicators developed in Chapter 3

We hypothesised that a significant correlation between PHI scores and farmer subjective opinion on health status of individual fields would exist

We hypothesised that the health scores from a Peat Health Index (PHI) created with simple indicators will display signification correlation with key farm performance indicators.

Chapter 5 Hypothesis

We hypothesised that the Bayesian network structure created through expert opinion would include a range of physical, chemical and biological Peat Health indicator nodes.

Chapter 6 Hypothesis

We hypothesised that the parametrised Bayesian network could distinguished between a (1) deep well structured peat, (2) a deep compacted peat, (3) A Shallow well-structured Peat, and (4) a Shallow compacted Peat.

Chapter 2: Literature Review

2.1 Food Security

Food security occurs when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life (Food and Agriculture Organization of the United Nations, 1996). This concept can be subdivided into four key dimensions; Availability, Access, Utilization and Stability (Simon, 2012). There must be physical availability of food through either domestic production or net trade to meet demands of the populace. The populace must have the ability, both economically and physically, to access the food. The populace must be able to ingest and metabolize the food which requires an adequate and balanced diet, access to clean water, good sanitation, and healthcare to reach a state of nutritional wellbeing. Finally, the last dimension encompasses the former, requiring stability of each to provide continuous security rather than immediate security. Global and UK food security is affected by a range of complex and inter-linked factors that determine whether each dimension can be achieved (Parliamentary Office of Science and Technology, 2017). The importance of food security should not be undervalued. Growth in the agricultural sector is recognised as an important instrument in poverty reduction through four transmission mechanisms; 1) direct impact of agriculture on rural incomes; 2) impact of cheaper food; 3) contribution to growth and generation of economic opportunity and; 4) agriculture's fundamental role in stimulating and sustaining economic transition (Cervantes-Godoy and Dewbre, 2010). Food security also increases a country's global security and stability through self-dependency (Clapp, 2017), encourages economic growth (Timmer, 2000), improves health (Gillespie, 2009) and increases trade opportunities due to expansion of production and population growth in different geographic regions (Godfray *et al.*, 2010).

Food demand is a complex issue influenced by a range of factors from population growth, income growth, urbanization as well as factors including; education, traditions, and development of downstream services (Kearney, 2010). Despite a simple definition, the complexity of achieving food security increases as our environment changes through time and space. It is therefore necessary to explore the pressures that have and will lead to food insecurity. A leading cause of food insecurity will come from the projected population growth (Hall *et al.*, 2017). Historically, global annual population growth rate peaked in 1962 at 2.2% and began a steady decline which is predicted to continue. Whilst the rate of growth is declining, total population predictions indicate global population will reach 10

Billion between 2050 and 2060 (Department of Economic and Social Affairs. Population Division., 2017; United Nations, 2017).

As Malthus stated, "*the power of population is indefinitely greater than the power in the earth to produce subsistence for man*". Despite dissenting views to those of Malthus indicating population growth is controlled by food supply, observations from Africa tend to support these views, with continued population growth despite increasing prevalence of undernourishment (FAO-FAD-UNICEF-WFP and WHO, 2017). The pressures of population growth on food security are multifaceted, perpetual, and go beyond merely production of crops (Brundtland, 1987). For example, urbanisation patterns of growing populations increases demand for a wider assortment of food groups (FAO, 2017), alters dietary patterns, and requires changes to distribution and production infrastructure (Kearney, 2010). However, the influence of increasing population on the consumption and production of food and fodder is not linear. In 2015, UK households wasted around £13 billion worth of food which could have been consumed (Smithers, 2017). Notwithstanding these multifaceted pressures of population growth on food security, current food production is ultimately dependent on land and water supply (Food and Agriculture Organization of the United Nations, 2013) and growing populations will continue to place pressure on production and demand intensification of agricultural practices (Kopittke *et al.*, 2019). As such, food security is directly impacted by downstream influences such as dietary shifts, and upstream effects from climate change, water scarcity and soil degradation. The next four sections will unpack these upstream and downstream pressures in a little more detail.

2.1.2 Dietary shifts

Globally, food production is sufficient to meet population nutritional requirements (Berners-Lee *et al.*, 2018), but waste and demands beyond nutritional needs causes insufficient supply to meet demand. Nutritional demands are influenced by income; wealthier portions of the population tend to increase calorie intake and the portion of resource intensive foods in their diets (Ranganathan *et al.*, 2016). This transition to resource intensive foods increases demand for animal source foods, sugars, fats and oils, refined grains, and processed foods (Hawkesworth *et al.*, 2010). These diets increase health risks (Akbaraly *et al.*, 2013) and impact negatively on the environment through poor carbon, water and ecological footprints (Rosi *et al.*, 2017). The United Nations Sustainable Development Goals acts to promote good health and wellbeing (United Nations, 2015a). Whilst the exact make-up of a balanced healthy diet varies according to cultural traditions, individual's needs, local availability and other factors, World Health Organizations guides recommended a range of fruit, vegetables legumes, nuts and whole grains alongside meats and diary (World Health Organization, 2015). To achieve food security, a population must have access to safe and nutritionally adequate food to fulfil a healthy balanced diet. Fruit and vegetables play an important role in human nutrition providing dietary fiber (Padhy and Behera, 2015) in forms that promote satiety (Slavin and Lloyd, 2012) and improve the health of the populace (Oyebode *et al.*, 2014). Deficiencies in fruit and vegetable intake is correlated with food insecurity, with less frequent consumption in food insecure families, particularly when resources deplete (Grutzmacher and Gross, 2011). Given current drives to increase fruit and vegetables consumption, the benefits of consuming fruit and vegetables, and the negative health impacts associated with current diets, it is likely that there will be a future increase in the demand for fresh fruit and vegetables. It is expected that this future increase in demand will ultimately increase the environmental impact of growing fruit and vegetables, including additional pressures placed on soils.

2.1.3 Climate change

Climate change is likely to directly affect agriculture through changes in rainfall patterns (Piao *et al.*, 2010) and temperature variations (Howden *et al.*, 2007), and indirectly through changes in markets, food prices, and supply chain infrastructure (Gregory, Ingram and Brklacich, 2008). Agricultural systems display a highly sensitivity to climate variations and predicted changes to temperature. Increased frequency of extreme events will likely lead to reduced crop yields and yield stability, accordingly affecting food security (Diacono *et al.*, 2017). Recently published UK Climate Projections by the Met Office indicate a trend towards warmer, wetter winters and hotter, drier summers (Fung *et al.*, 2018b, 2018a). These changes may positively affect crop production through an increase in growing season length. However, they are likely to negatively impact certain crop varieties, create drought scenarios, and, during winter periods, lead to waterlogging, compaction, and decreased land trafficability (Morison and Matthews, 2016). Climate change not only effects food production but may affect food access and utilization via collateral effects on household incomes and loss of access to drinking water (Wheeler and von Braun, 2013). These predicted impacts of climate change on food production highlight a need to alter the current approaches and practices concerning the management of agricultural systems.

2.1.4 Water scarcity

Globally, future increases in crop production will primarily come from intensification of current agricultural land rather than the cultivation of new areas (Gregory and George, 2011). Current demands on water for land associated with agricultural practices are, however, unsustainable (United Nations, 2015b). A host of factors affect water scarcity including; inefficiency of water use, distribution of water resources, depletion of groundwater resources, and degradation of water quality (Wang *et al.*, 2017). Predictions indicate that by 2050, due to climate change, there will be a decline in land suitable for rain fed production in the UK, indicating a future demand for supplementary irrigation (Daccache *et al.*, 2012). This concern has been highlighted in that the South and East of England already requires substantial irrigation (comparing moisture deficits shown in Figure 2a and Irrigation levels in Figure 2b) (Rey *et al.*, 2016), with future drier climates predicted, irrigation will become more crucial to support the UK agricultural sector. However, some areas of the UK are already over-abstracting from water reserves (Figure 2c), indicating pre-existing unsustainable practices.

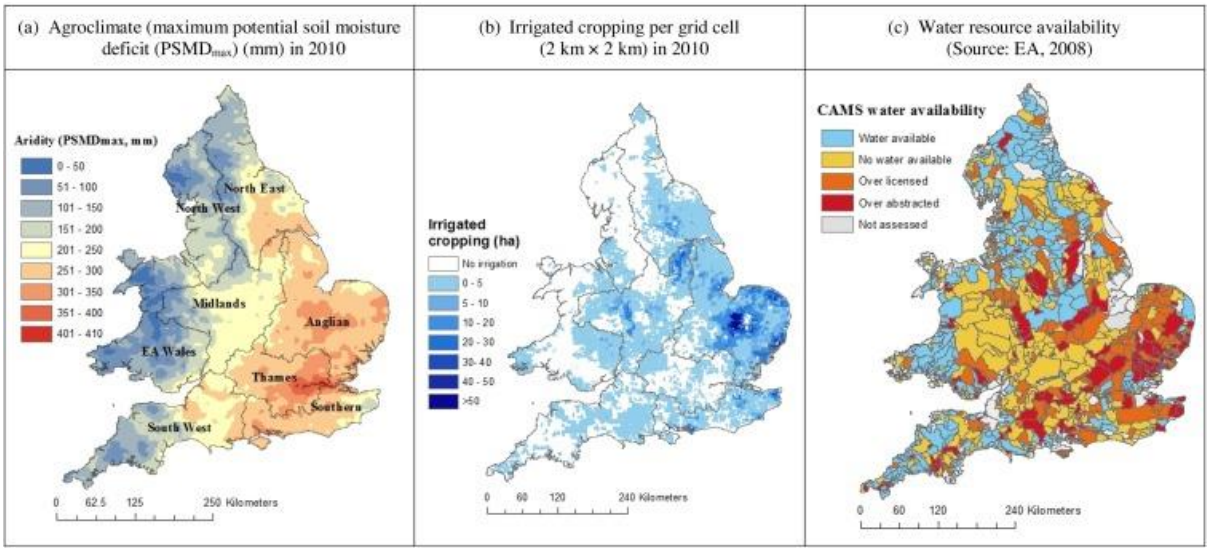

Figure 2: Identifying the spatial variability of agroclimate's across England and Wales in 2010 which was designed to mimic a year characterised by low rainfall and high evapotranspiration). Showing; (a) Maximum potential soil moisture deficit ($PSMD_{max}$) (mm); (b) irrigated cropping (ha); and (c) EA water resource availability for England and Wales, by EA region. Reproduced from Rey et al., (2016).

2.1.5 Soil degradation

Soil, alongside water, is the foundation of agriculture, providing humans with the ability to produce food (Parikh and James, 2012) and it is estimated that 95% of our food is directly or indirectly produced on our soils (Food and Agriculture Organization of the United Nations, 2015). Fertile and healthy soils are essential for sustainable agriculture. However, with expansion of intensively cultivated land, and the management practices associated with it, there has been an increase in soil degradation resulting in a loss of productivity (Horrigan, Lawrence and Walker, 2002; Tilman *et al.*, 2002). Soil degradation as a concept looks at the decline in the capacity of a soil to perform a specified service or function. However, quantifying levels of degradation is challenging due to spatial and temporal scales and global assessments vary due to conflicting methodologies and interpretations (Hatfield, Sauer and Cruse, 2017). Despite difficulties in estimating degradation, the predicted increase in population and intensification of agriculture is likely to; escalate erosion (Prokop and Poreba, 2012; Parliamentary Office of Science and Technology, 2016; Nearing *et al.*, 2017), increase loss of fertility (Brown, 2005), drive the loss of biodiversity (Matson *et al.*, 1997), increase salinization and desertification (McClure, 1998), and increase rates of pollution (Tilman *et al.*, 2002). Apart from the environmental issues associated with degradation, nutritional values of produce are influenced by soil quality, from pH to macro/micro nutrient composition, and degradation is likely to decrease the quality of produce (Hornick, 1992). The Economics of Land Degradation Initiative (http://www.eld-initiative.org/) estimates that, globally, the annual economic losses due to soil degradation are 1.5 – 3.4 trillion Euros. In the UK, quantifiable soil degradation costs have been estimated at £1.2 billion per year, with the majority of costs occurring off-site, and so of limited concern to those who actions may be causing the degradation (Graves *et al.*, 2015). The economic cost of soil degradation is only going to escalate with further demands we place on our soil. Degradation directly effects the soil's ability to produce sustainable and high yields, reducing food security.

2.1.6 Conclusion

Population growth, dietary shifts, water scarcity, climate change, and soil degradation place pressure on farmed soil ecosystems, likely creating vicious feedback cycles. The bourgeoning population, associated nutritional demands, and dietary shifts are the driving force behind anthropogenic changes occurring in our ecosystems. Human activities have begun to exacerbate climate changes and degrade the ecosystems we rely upon for survival. Planetary boundaries for safe operating of humanity are being transgressed which could lead to disastrous consequences (Rockström *et al.*, 2009). Soils provide a variety of ecosystem services and processes that are essential to survival and, as understanding of these has increased, a shift to sustainably manage our soils is observable. The degradation of the soil systems leads to a reduction in production, directly affecting food security, and reducing the capacity of the system to provide beneficial services such as climate and water regulation. The recent publication by the UK Government, the "*25 Year Environmental Plan*" (Department for Environment Food and Rural Affairs, 2018a), sets out the government's ambitions to improve soil management and sustainably manage all farmland by 2030. Within the boundaries of the UK, this will look at developing and testing soil health metrics as well as researching how soil health supports wider ecosystem functioning.

2.2 Overview of Primary Crop Production capabilities

Current global production of crops would be sufficient to provide enough food to feed the population of 9.7 billion in 2050 but would require significant changes to dietary choices (Berners-Lee *et al.*, 2018). Total global production of crops is essential to achieving global food security and trade of food and fodder is vital for both developed and developing countries (Food and Agriculture Organization of the United Nations, 2003) whereas self-sufficiency of a country can be seen as a buffer to market fluctuations (Clapp, 2017). The global cereal and vegetable production rates have steadily increased over the period of 1970's to mind 2010's (Ritchie and Roser, 2013) . However, available fertile land is a finite resource, implying that increasing pressure is being placed upon existing agricultural systems.

Sourcing food from a diverse range of regions, alongside domestic supply, enhances food security (Department for Environment Food and Rural Affairs, 2010). However, around 70% of cropland which supply the UK, and the associated greenhouse gas emissions, are located abroad, indicating a reliance on external resources and displacing environmental degradation (De Ruiter *et al.*, 2016). Sustainably increasing UK production would reduce the reliance on overseas food producers and the offshore degradation natural assets. While increased local food production may improve food security, it would additionally require consumers to follow nationally recommended diets (Behrens *et al.*, 2017). With advances in technology, investment, education, and improved farm management, agricultural production in the UK has risen steadily since 1961 (Department for Environment Food and Rural Affairs, 2010). The yields of cereal crops have in general seen steady increases over the last thirty years, yet vegetable production has decreased remarkably over a similar period (Figure 3). The increasing demands from population, and the rapidly increased momentum to increase vegetable intake, further anthropogenic pressures are likely to be placed on already degraded systems.

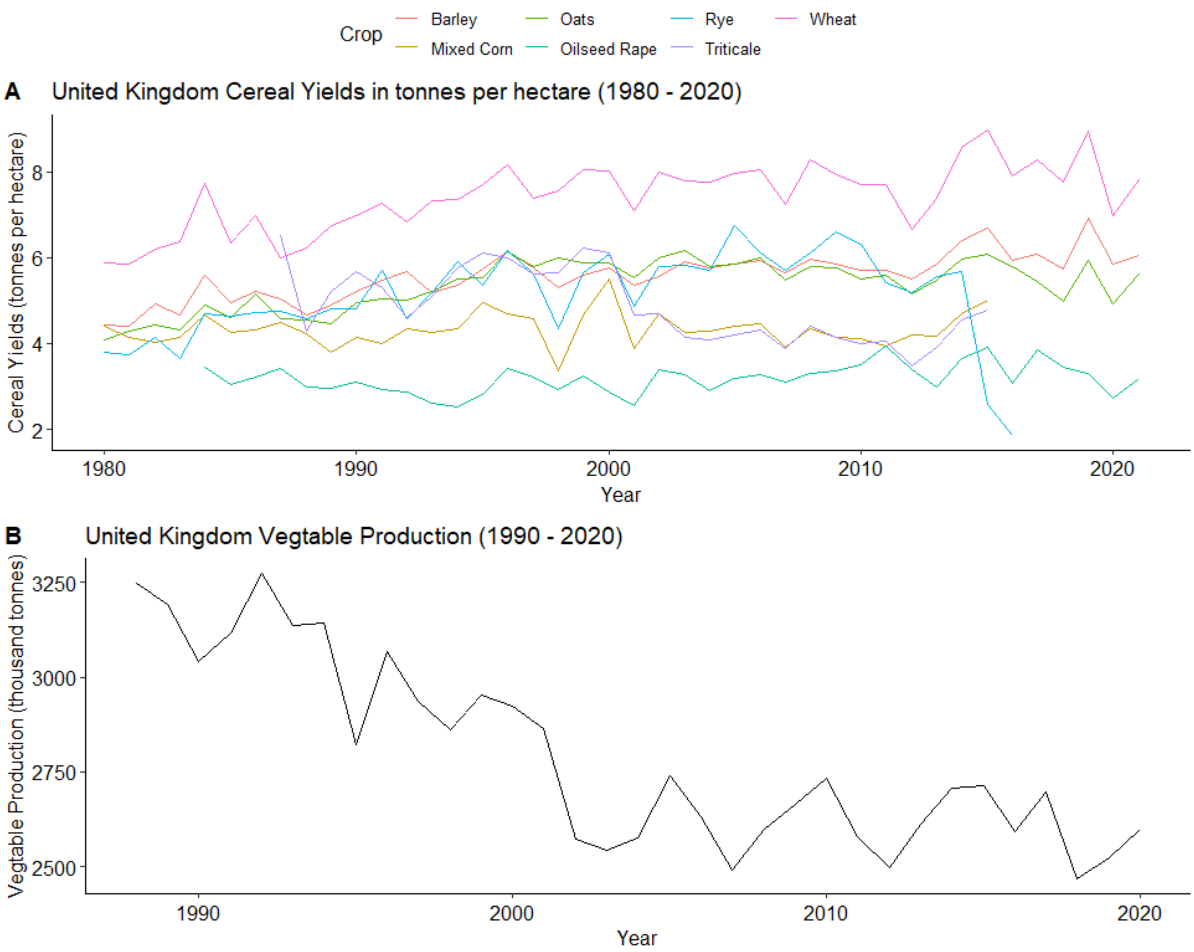

Figure 3: Displaying cereal steady increase and vegetable decline in production across the UK in the last 40 years A) Total cereal yields in tonnes per hectare from 1980 to 2020. Data from DEFRA *(Department for Environment Food & Rural Affairs, 2021)*. B) Vegetable Production in thousand tonnes across the entire UK from 1990 to 2020. Data from DEFRA (Department for Environment Food and Rural Affairs, 2021c).

Within the UK, the East of England, compromising, Cambridgeshire, Norfolk, Suffolk, and Essex contributes a large proportion of cropped area towards the total English cropland in comparison to other regions (see Figure 4). This disproportionate contribution by the East of England is partly due to the location of large deposits of fertile peat where over 37% of all vegetables produced in England are grown (National Farmers Union, 2008).

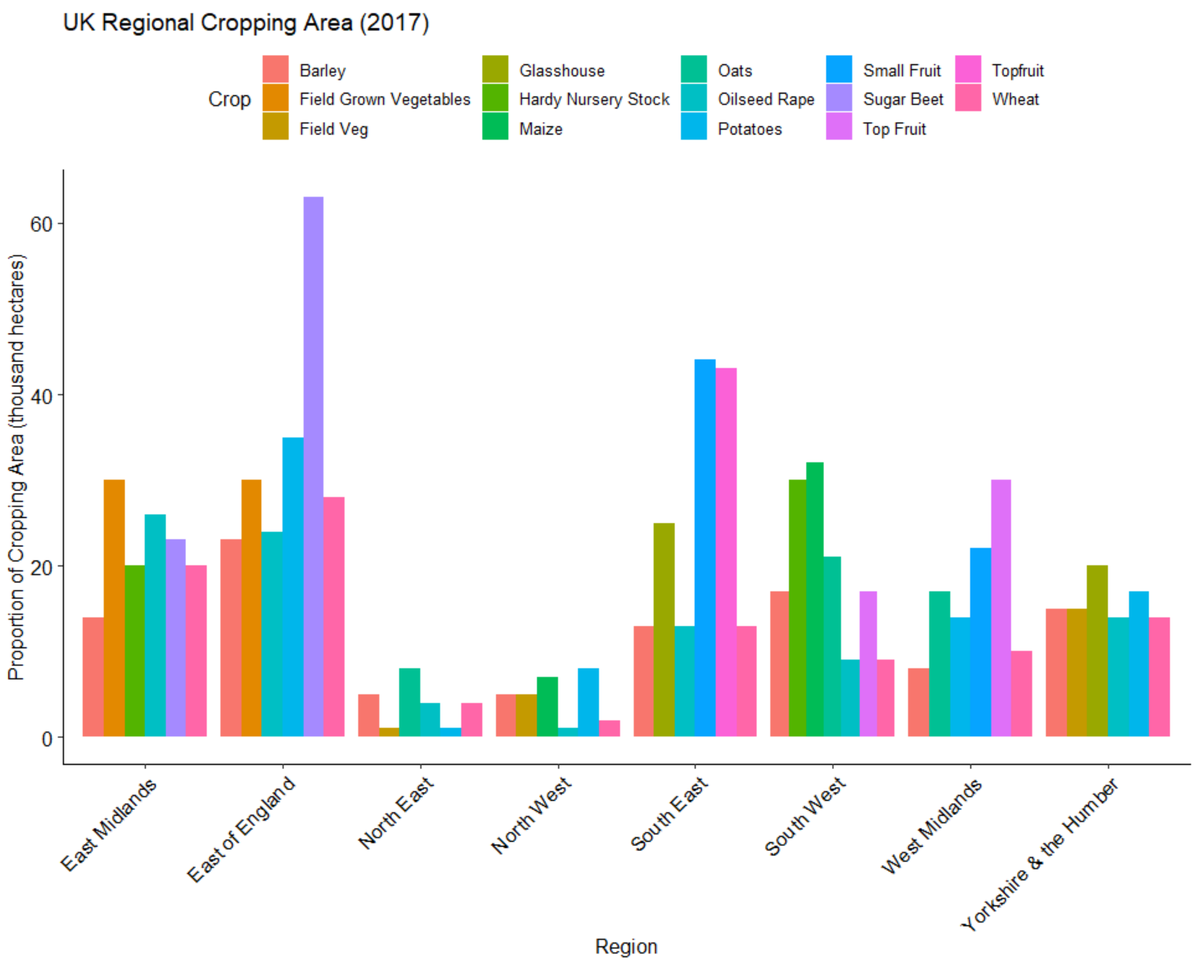

Figure 4: Data from DEFRA on the proportion each individual UK Region contributes towards English total crop area (Department for Environment Food and Rural Affairs, 2018b).

2.2.1 Conclusion

Imports are currently essential to UK food security. Reliance on importation displaces environmental impacts on other countries and exposes UK food security to future perturbations of global food production and supply. With the UK producing around half the food it requires, there is additional scope to expand production levels to meet demands. This expansion and intensification will need to be undertaken sustainably to prevent exasperating issues of soil degradation and environmental harm. A large percentage of crop output is produced within the East Anglian Fen area, particularly fruit and vegetables that are essential to a healthy diet. This high productivity can be attributed to the rich and fertile lowland peat that developed in the area. However, these areas are under anthropogenic threat of current and future degradation which will likely lead to a reduction in productivity if not managed sustainably.

2.3 Peatland Ecosystems

Recent modelling of global peatland distribution estimates total area to be 4.23 million km^2 (2.84% of the world land area), but indicating a current modelling overestimate the extent in the mid and high-latitude of the Northern Hemisphere (Xu *et al.*, 2018). From modelling, global peatland appears however to be dominant in the northern hemisphere, with other peaks in the mid hemisphere (see Figure 5).

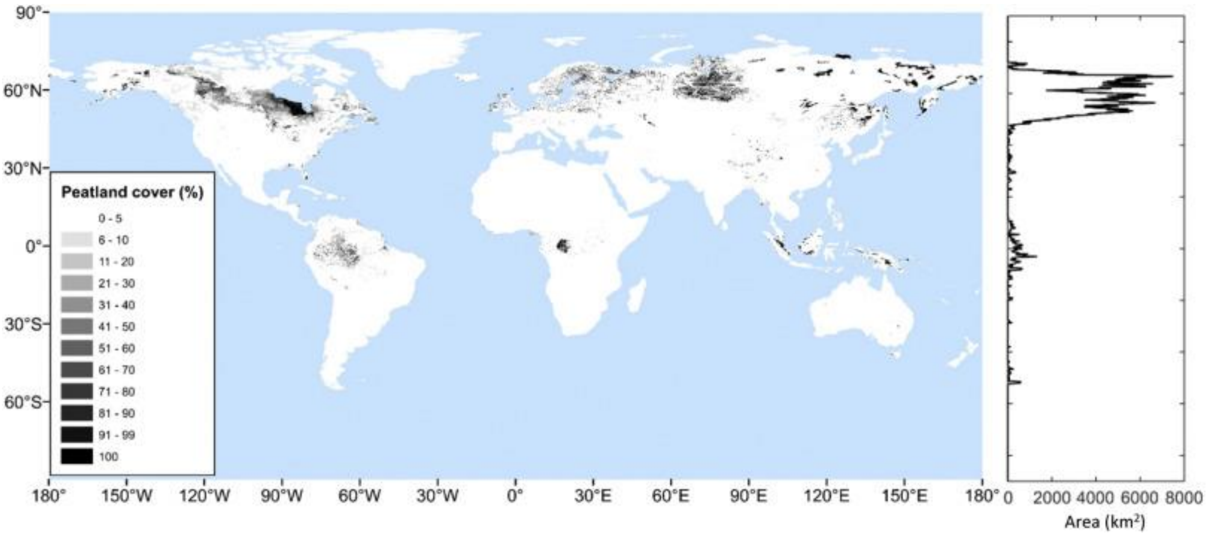

Figure 5: An amalgamated map of global estimate of peatland and its distribution along the latitude using a wide variety of data sources (Xu *et al.*, 2018).

Following is a brief introduction into the initial development of peatlands and the process of drainage and degradation that occurs. Peat is an organic sedentary material that is primarily formed from the remains of photosynthetically derived plant material accumulating under water-saturated conditions. These anoxic conditions, the low decomposability of plant material, and other complex causes leads to incomplete decomposition of the organic material (Moore and Basiliko, 2006). Natural Peatlands are complex eco-hydrological systems commonly conceptualised as consisting of two layers; the acrotelm (periodically saturated) and catotelm (permanently saturated). Although a well-accepted concept, the use of this diplotelmic model may be inherently inflexible, and a poor representation of natural peat systems (Morris *et al.*, 2011) but represents drained agricultural systems effectively. The hydrological regime is essential in peat formation and maintenance of the many ecosystem processes that occur. As described by Rydin and Jeglum (2013), peat systems differ based upon vegetation composition, moisture regimes, microtopography and nutrient regime (Table 1).

Table 1: Description of the characteristic of differing peat systems (based upon vegetation composition, moisture regimes, microtopography and nutrient regime) reproduced from Rydin and Jeglum, (2013)

Peatland Attribute	Marsh	Fen	Bog
Vegetation	Submergent, floating-leaved, reeds, tall sedges	Open or sparse cover of low trees, low shrubs, graminoids, herbs, bryophytes	Open or with low trees, dwarf shrubs, low cyperaceous plants, bryophytes
Soils/peats	Mineral, organic-rich mineral, or shallow peat	Usually >30cm peat; sedge and sedge-Sphagnum are common	Usually >30cm peat; Sphagnum peat
Moisture Regime	Permanently or seasonally flooded by lake or stream water	Groundwater fluctuates below to above surface in lawns, carpets, and mud-bottoms; hummocks mostly above water table	Groundwater fluctuates below to above surface in lawns, carpets, and mud-bottoms; hummocks well above water table
Microtopography	Level or tussocky	Level, or with scattered hummocks, or patterned with ridges alternating with depressions	Level, or patterned with hummocks or ridges alternating with hollows
Nutrient Regime	Minerotrophic; eu- to mesotrophic	Minerotrophic; eu- to oligotrophic	Ombrotrophic; oligotrophic

UK peatland distribution has been estimated to be almost 3 million hectares across England, Wales, Scotland and Northern Ireland, around 8.2% of total land area (Artz *et al.*, 2019). This figure may be an underestimate as figures are developed in consideration of national definitions of peat. For instance, England and Wales define peaty soils as >10cm depth and deep peat as >40cm, Scotland map peat as >50cm deep, Northern Ireland maps peat soils as >40cm and deep peat as being >50cm (JNCC, 2011a). The following work will use the definition of Peat using the England and Wales description noted above. Within the UK, a pocket of peat has developed across the lowlands of East Anglia, the fens have been accumulating carbon over the duration of the Holocene as the rising sea level flooded the fenland basin (Smith *et al.*, 2011). The Holocene was a major period of peatland growth around the world with highly productive fen peat forming in the West Siberian Lowland as well as in other high latitude locations around the world (Smith *et al.*, 2004). These sedentary peat layers overly a variety of geology in the East Anglian area including sulphate rich impermeable clays (Fen Clay and Oxford Clay) and Chalk groups from the Upper Cretaceous periods. These peatland ecosystems, where water is connected to or supplied over mineral parent materials, are called minerogenous and are nourished by mineral soil groundwater (i.e., minerotrophic). As a hydrological system, areas of lowland Fenland are minerogenous and topogenous in nature, with a dominant vertical flow of water (Maddock, 2008). Each individual lowland fen has differing characteristics, reflecting the source of their vegetation and the hydrological, chemical, and climatic regimes present (Rydin and Jeglum, 2013).

2.3.1 Process of peat drainage

Peatlands are drained to allow for agricultural and forestry practices. The process of drainage occurs when water is diverted from the region to remove the anoxic conditions through creation of ditches, drains and the inclusion of pumps to remove ground water (Page, Proby and Ladds, 1936). The most influential stage of drainage of the East Anglian fens took place in the 17th century when rivers were straightened by the creation of linear links and sluiced against tidal flows (Langslow, 1997). Following the initial reconstruction of waterways, shrinking and subsidence lead to the need to increase water removal to render drainage works useful (Holden, Chapman and Labadz, 2004). Artificial drainage of peatlands in the East of England lowers the water table to provide a deeper zone of aerated soil for agricultural exploitation. Lowering of the water table results in three distinct drainage processes that occur in peatland soils; (i) primary consolidation, (ii) secondary compression and (iii) oxidative wastage (Lindsay, Birnie and Clough, 2014). Primary consolidation occurs where loss of water leads to collapse and shrinkage of peat adjacent to the drain; Secondary compression follows the loss of water. The upper layers of peat are less buoyant and compress the lower layer. This effect extends outwards away from the drain. Oxidative wastage occurs as oxygen is allowed to penetrate the catotelm, fuelling decomposition of peat. Alongside these main processes, peat is also lost through wind erosion, removal of soil on crops, and accidental burning (Holman, 2009). As one of the most extensively drained areas in Europe (Baldock, 1984), drainage of British peatlands has played a fundamental role in the history of British farming. The UK has an extensive network of peatland, with different classes, that makes up around 11% of total land area in England (Figure 6) with lowland fens totalling 2880 km^2 (Natural England, 2010).

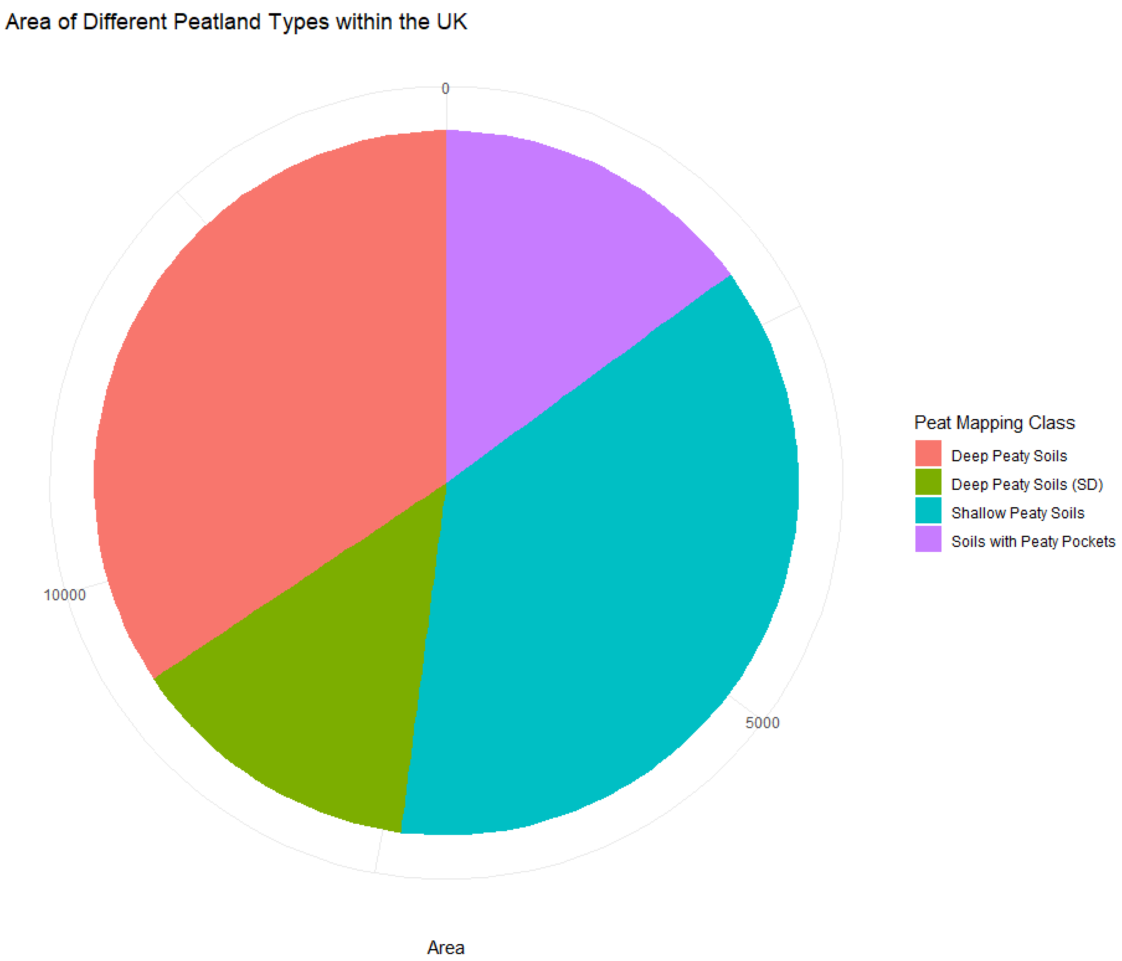

Figure 6: An indication of the area (km^2) of different peatland classess in England and the associated state following drainage. * SD stands for substantially degraded peatland due to drainage and cultivation. Data available from Natural England, 2010.

England's peatlands are fragile ecosystems that, following removal from their natural state, have been unavoidably degraded by anthropogenic activity. Natural England surveyed peatlands across England and noted that over 70% of peatlands show degradation and almost 40% of lowland fen peat is cultivated (Natural England, 2010). Given the importance of lowland peats to UK food security, their current state, and their fragility following drainage, it is essential that we sustainably manage these systems. The loss of ecosystem services and processes associated with this degradation is likely to impact future sustainability of agricultural production within the UK. To establish sustainable management practices, we must understand the ecosystem services and processes that occur in natural peatland systems and the evolution of these processes following drainage.

2.4. Peat Soils and Ecosystem Services

Peatlands are wetland ecosystems found globally, and deliver a range of environment, societal and financial benefits. These systems provide critical habitats for species and biodiversity, regulate water flow and pathways, provide clean drinking water, and store significant carbon content (Kimmel and Ü. Mander, 2010; Rydin and Jeglum, 2013). For example, up to 70% of UK drinking water is sourced from catchments dominated by peatland habitat, because these regions contain few pollutants and low levels of nutrients (International Union for the Conservation of Nature UK Peatland Programme, 2018). Despite their importance, problems associated with incomplete knowledge about these complex ecosystems processes exist and the establishment of disconnected policies and management strategies put these ecosystems at further risk (Whitfield *et al.*, 2011). Peatlands are therefore a large reserve of natural capital that provide a range of ecosystem services, with natural capital being the stock that provides the flow of these services. A further discussion of the important ecosystem services that peatlands provides is outlined below.

2.4.1 Ecosystem Services – What are they?

The Joint Nature Conservation Committee defines ecosystem services as the benefits people obtain from ecosystems. Dynamic and evolving, ecosystem processes (also known as functions) govern ecosystem services (and disservices). The concept of ecosystem services introduces an anthropogenic-value to the services and can be seen as a more meaningful way to convey the importance of the functioning of soils to decision makers (Robinson *et al.*, 2014). Soils provide a wide range of services which are critical to the functioning of the Earth's life support system, beyond food security (Costanza *et al.*, 1997). Several classification systems have been created including the Millennium Ecosystem Assessment, The Economics of Ecosystem and Biodiversity, and the Common Classification of Ecosystem Services. Fundamentally ecosystem services can be grouped into four overarching categories: provisioning services, regulating services, cultural services and supporting services (MEA 2005). This system can provide an adequate classification scheme for the discussion of soils and their related functioning. However, there are many different context specific frameworks that incorporate different ecosystem services and different definitions (Fisher, Turner and Morling, 2009). For example, Costanza et al. (1997) evaluated 17 soil ecosystem services and Haygarth and Ritz (2009) created a framework of 18 critical services for soils and land use (Haygarth and Ritz, 2009). The definition of ecosystem services varies since different stakeholders have different methods of assessment and classification (Abson *et al.*, 2014). The type, quantity, and quality of ecosystem services provided by a soil will also depend upon specific environmental characteristics that underpin soil properties and functions (Pereira *et al.*, 2018). The ecosystem services approach generally has great potential to quantify the immense value of soils. For example, services provided by soil biota are estimated to exceed 1.5 Trillion US dollars (Brussaard, de Ruiter and Brown, 2007). The ecosystem services and disservices that peatlands provide will differ based upon the geographical location, the type of peat, and the current management practices (Kimmel and U. Mander, 2010; Xu *et al.*, 2020). A summary of the provisioning, regulating, supporting, and cultural ecosystem services provided by peatlands is summarised below.

Provisioning

Peatlands provide a land space for the production of food, fibre and fuel used for; horticulture, agriculture, domestic heating, energy generation, medicine, wild or domesticated animals, and forestry (Schilstra and Gerding, 2004; Taskila, Särkelä and Tanskanen, 2016; Surahman, Soni and Shivakoti, 2018; Hatano, 2019; Mugerwa *et al.*, 2019; Buschmann *et al.*, 2020). Furthermore, fresh water provision is obtained from reservoirs draining across and through peatland areas throughout the world (Ireson *et al.*, 2015; Goodbrand, Westbrook and van der Kamp, 2019).

Regulating

Peatlands provide regulation of the climate through control of local climate and air quality by regulating greenhouse gases emissions, including carbon dioxide, methane, and nitrous oxide (Gorham, 1991; Roulet *et al.*, 1992; Segers, 1998; Belyea and Malmer, 2004; Frolking *et al.*, 2011; Joosten *et al.*, 2016). They also regulate carbon sequestration and storage (Roulet, 2000). Peatland ecosystem services also include the regulation of water, through storage discharge, the supply of water purification and waste treatment (Holden, 2006; Ritson *et al.*, 2016). Peatlands provide nutrient cycling services through the activities of the microbial community and their potential to transform nutrients into plant-available forms (Espenberg *et al.*, 2018), maintain balances and storage of nutrients (Salmon *et al.*, 2021).

Supporting

Peatlands provide unique habitats for a range of species and provide biodiversity preservation services (Parish *et al.*, 2008; Rydin and Jeglum, 2015; Grzybowski and Glińska-Lewczuk, 2020). Further, the process of peatland formation through organic carbon accumulation forms the peat/soil layer that supports habitat and growth of crops (Rydin and Jeglum, 2015).

Cultural

Peatlands provide cultural services through the access to space for recreation and appreciation of nature, religious significance, preservation of historical data, and opportunities for education, amongst other cultural services (Bonn and Joosten, 2016; Bonn *et al.*, 2016).

Drainage and the associated alteration of hydrological conditions inhibits the peat forming process (Charman *et al.*, 2013) and the subsequent management of peatland systems alters the range of ecosystem services that peatlands provide generally leading to a degradation of the system to provide the identified services (Swindles *et al.*, 2016). As previously noted, peatlands are drained to allow for intensive exploitation, resulting in increased provisioning services in the form of agricultural outputs. The focus of increasing the provisioning services leads to depletion of regulating and supporting services (Fell *et al.*, 2016). Ecosystem services and agriculture are inextricably linked. Agriculture has been shown to be a provider and beneficiary of a diverse range of ecosystem services that extend beyond the provision of food. Agriculture relies upon numerous ecosystem services, such as soil provision, pollination, pest regulation, and genetic diversity but leads to disservices including; water pollution, health risks, and biodiversity loss. Redressing the balance of trade-offs is imperative (Swinton *et al.*, 2007; Power, 2010). Through intensification and poor management practices, UK agriculture has had significant negative impacts on ecosystem services with annual external costs £2.3 billion in 1998 and soil degradation was calculated in 2010 to cost £1.2 billion every year, although these values are assumed to be an underestimate due to complexities in mapping ecosystems (Pretty *et al.*, 2000; Environment Agency, 2019). Given the vital role ecosystem services play in aiding food production and towards the critical functioning of earth systems it is imperative to quantify the relationships between management practices and the delivery of ecosystem services and investigate how farmed ecosystems can be managed more sustainably to preserve the future delivery of ecosystem services.

The supply of ecosystem services can be mapped at a local (Raudsepp-Hearne and Peterson, 2016), regional (Lautenbach *et al.*, 2011) or global (Naidoo *et al.*, 2008) scale depending upon the interests of the stakeholder or research group leading the project. To map the ecosystem services provided by soils, it is necessary to consider the underlying processes and functions occurring in these ecosystems. A service cascade concept can be used to summarise the ecosystem service paradigm (see Figure 7). This concept links the ecological and biophysical structures and processes with the benefits (and subjective value) we receive from the environment in the form of a production chain (Potschin and Haines-Young, 2011).

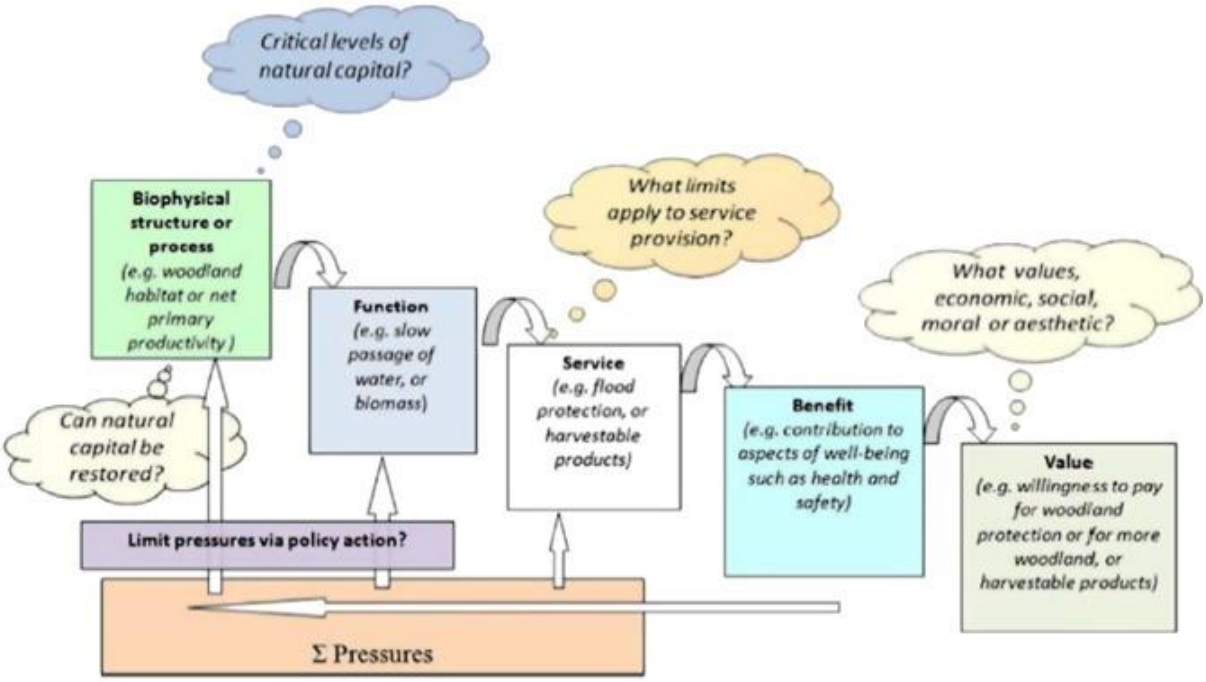

Figure 7: The Ecosystem service cascade model separating the benefits and values provided by the system *(Potschin and Haines-Young, 2011)*

The concept of ecosystem functions considers a subset of characteristics that are ecosystem specific and determines the provision of services identified as outputs. Therefore, the capacity of a soil to supply ecosystem services is determined by its ability to function, where each soil process or function can relate to either a single or multiple ecosystem service (Bouma, 2014). Soil functions can be seen as bundles of biophysical and chemical processes. Examples include decomposition cycles, biological population regulation, water cycling, organic matter decomposition and storage, and habitat provision (Bünemann *et al.*, 2018). As there are no single direct indicators to map all the ecosystem services or processes provided by soils, mapping approaches are varied. Ecosystem service metrics, used to establish the stock and flow of a soil's natural capital, are dominated in terms of quality and quantity by indicators for provisioning services, with indicators for other services deficient (Layke *et al.*, 2012). Furthermore, while many studies on soil and related ecosystem services exist, not all explore the direct relationship between ecosystem services and soil properties and instead focus on lower level concepts where soil properties can be directly incorporated (Adhikari and Hartemink, 2016). The provision of ecosystem services is therefore inferred through the assessment of the functioning of the soil system, which is often referred to as the 'health' of the soil.

2.4.2 Peatlands and Farming

Lowland peat systems are relatively accessible compared with their upland counterparts, which has led to large areas being drained and used for intensive agriculture. The use of peatlands for agriculture and associated drainage, alters the hydrology of the remaining natural habitat in the surrounding area (Lindsay, Birnie and Clough, 2014). Agricultural practices that occur on peatland soils can result in the loss of peat through wind erosion (mainly due to loss of vegetative cover), water erosion pathways (Li *et al.*, 2018), microbial decomposition, and future subsidence (Dawson *et al.*, 2010; Säurich *et al.*, 2019). Peats accumulate and store carbon through their formation. However, through drainage and intensified agriculture, this stored carbon becomes a large emission source of greenhouse gases.

Furthermore, the presence of agriculture on these systems increases the risk of flooding and increased costs with maintaining drainage (Allott *et al.*, 2019; Buschmann *et al.*, 2020). Cultivation of organic soils leads to the subsidence in peat layers, dropping the surface levels to below the flood water level and thus leading to an increase in flooding (Ikkala *et al.*, 2021) in addition to decreased infiltration and increased ponding of water (C. Kechavarzi, Dawson and Leeds-Harrison, 2010). Not only will this have long term impacts on flood and water management, but also directly affect farming through accessibility to fields, pests, and reduced yields. The degradation of peatlands associated with agriculture, and the transition to vascular plants, leads to an increase in dissolved organic carbon being emitted from these peat systems, creating peaty brown coloured water, and reducing the water quality (Ritson *et al.*, 2016; International Union for the Conservation of Nature UK Peatland Programme, 2018; Nieminen *et al.*, 2021). Considering plant diversity, farming reduces the natural abundance and diversity of vegetation (Zeng, Li and Ruiz-Menjivar, 2020), replacing natural vegetation with monocrops and cash crops. Natural and rewetted peatlands show an increased diversity of vegetation, indicating an increased biodiversity and habitats for flora and fauna (Henkin, Walczak and Kaplan, 2011; Gavazov *et al.*, 2018). Species diversity within a community and diversity of communities within a landscape are the most important levels of organisations for ecosystem service generation (Quijas *et al.*, 2012), and the loss of this diversity through implementation of farming, particularly on the complex mosaic found in natural peatlands (Minayeva, Bragg and Sirin, 2017), will directly affect ecosystem service provision.

Farming on peatlands additionally must contend with factors affecting all agricultural systems. Currently, safe operating spaces for humanity exists which allow us to meet the challenge of maintaining the Holocene state. However, these operating spaces are being transgressed, including climate change and nitrogen and phosphorous cycles (Rockström *et al.*, 2009). In particular, the process of farming peatland systems adds to these transgressions and increases the likelihood of crossing climate change thresholds due to increased organic matter loss to the environment and speeding up the cycling and associated loss of nitrogen (Prananto *et al.*, 2020). Agricultural production relies upon the non-renewable resource of phosphate rock. However, peak production is expected to occur around 2030 and the quantity of rock remaining is decreasing, while production costs increase (Cordell, Drangert and White, 2009). 70% of world phosphate supply is owned by four major countries, indicating both the possibility of market manipulation and a reduction in supply globally due to world events (Gilbert, 2009). Despite this, phosphorous loss pathways exist in agricultural systems on peatlands. It has been noted that the degradation of peat leads to the transformation of phosphorus compounds, resulting in an increase of labile and easily available forms, forms released in reduced conditions, and forms combines with metical oxides, apatite, capitate, carbonate and labile organic forms (Becher *et al.*, 2018). As such, farming on peat and the associated degradation can lead to loss of phosphorous from the system, further increasing the transgression of safe operating spaces and reducing use efficiency of the nutrient.

Drainage to allow for agricultural exploitation has different consequences across time scales. Drainage generally leads to the rapid loss of peat due to increased decomposition in the first 100 years after drainage, although water table dynamics alter over centuries (Young *et al.*, 2017). Despite the rapid increase in decomposition immediately following drainage, the decomposition of peat and release of CO_2 continues for centuries, albeit at a reduced rate (Urbanová and Bárta, 2016; Säurich *et al.*, 2019). Furthermore, the bacterial diversity following long term drainage decreases, with multiple distinct peatland ecosystems displaying similar community structure as long term drainage occurs (Urbanová and Bárta, 2016). This is further compounded by the introduction of modern agricultural practices which shift microbial population structure to a less diverse community (Gupta *et al.*, 2022). The introduction of agricultural practices also alters the cycle of carbon and nitrogen in the systems over time (MacBean and Peylin, 2014), including the dissolved organic components (Kalbitz and Geyer, 2002). Whilst the long term impacts of drainage and agriculture on peatlands is important, current peat health tools will need to focus on the short term changes (decadal) which farmers and land managers can monitor and alter.

2.5 Development of concepts for assessing soils

There has been a variety of approaches adopted to conceptualize the services and processes of soils and their assessment. It is important to discuss the history surrounding this development to allow us to fully understand the term 'soil health' and how it differs from previous concepts.

2.5.1 Soil Fertility

The concept of soil fertility has a range of definitions. The Soil Science Society of America defines soil fertility as *"the quality of a soil that enables it to provide nutrients in adequate amounts and in proper balance for the growth of specified plants or crops"* (Soil Science of America, 2021). Similarly, the Food and Agriculture Organization on the United Nations defines the concept as "*the capacity to receive, store and transmit energy to support plant growth*" (Food and Agriculture Organization of the United Nations, 2021). These definitions focus upon the concept of soil fertility on the soil's ability to produce crops. However, the concept has a boundless number of uses and definitions. The main features of the concept of soil fertility include; provisioning of yield, conceptualizing the term as the sum or resultant of something (i.e. its properties), an indicator of ecological processes, and its ability to serve plants (Patzel, Sticher and Karlen, 2000). Whilst the term soil fertility has been shown to incorporate a range of physical, chemical, and biological properties, the concept is primarily focused upon the provision of crop nutrients and water as demonstrated through its definition by major organisations.

2.5.2 Soil Quality

The complex interaction of physical, chemical and biological soil properties, in addition to the resulting levels of productivity of healthy and nutritious crops, is referred to as "soil quality" (Parr *et al.*, 1992). Soil quality is a complex concept looking at both the inherent (use-invariant) and dynamic (use-dependent) quality of soils, going beyond just its "fitness for use" (Carter *et al.*, 1997). Warkentin and Fletcher (1977) reasoned the concept of soil quality should recognize the range of uses of soil, the stakeholders concerned, the priorities of society, and that land-use and soil management are made within a human content. (Karlen, Ditzler and Andrews, 2003). In this form soil quality can be viewed as a soil's suitability for a particular use. Initially, the soil quality concept was critiqued due to fears of turning soil science into a value system, discontent with the ideas of universal soil quality index, the inclusion of bias for certain soil types, and for the emphasis and value placed on a limited number of crops (Letey *et al.*, 2003). The simple description of soil quality as the capacity of a soil to function was expanded upon to be defined as "*the capacity of a soil to function within ecosystem and land-use boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health*"(Doran and Parkin, 1994). There have been many attempts to define soil quality which stem from the author's point of view and to suit the particular research in question (Bastida *et al.*, 2008). Concerns are that assessments generally focus upon crop production and ecological functions as opposed to remediation and environmental remediation, despite a clear attempt to address multi-functionality of soil (Karlen, Andrews and Doran, 2001). Addressing the term from an environmental perspective, soil quality can be defined as "*the capacity of the soil to promote the growth of plants, protect watersheds by regulating the infiltration and partitioning of precipitation, and prevent water and air pollution by buffering potential pollutants such as agricultural chemicals, organic wastes, and industrial chemicals*"(Sims, Cunningham and Sumner, 1997). The difficulty associated with the development of concepts and definitions of soil quality reflects the complexity of the soil ecosystem both at a spatial and temporal scale. Quantifying soil quality is difficult due to the variety of land uses and the complexity of soil systems, including timeframes for dynamic properties of soil to alter (Nortcliff, 2002). Despite these difficulties, soil quality has been used in England and Wales to report upon the state of our soils (DEFRA, 2009) and for the basis of developing a set of indicators to measure soils quality (Merrington, 2006).

2.5.3 Soil Health

A broader, ecologically based, approach advancing on aspects of soil quality has introduced the definition of soil health as "*the continued capacity of soil to function as a vital living system, within ecosystem and land-use boundaries, to sustain biological productivity, maintain the quality of air and water environments, and promote plant, animal, and human health*"(Doran and Zeiss, 2000). The use of soil health over soil quality appears to indicate a move towards assessing the biological component as governance of the ecological services and processes of soils that differ it from weathered rock (Kibblewhite, Ritz and Swift, 2008). Use of the term 'soil health' instead of 'soil quality' can be seen as merely a preference and both soil quality and soil health have begun to take on similar meanings (Lehman *et al.*, 2015). As concepts and knowledge have develop, the divide between these two schools of thought has decreased and the two terms are used interchangeably, despite their differing definitions. Soil quality is generally directly related to specific soil functions whereas health presents the soil as a finite non-renewable and dynamic living resource.

2.5.4 Use of the term 'Soil Health' in this thesis

The use of the terms soil fertility, quality, and health results in substantial confusion and clarity is needed to create a clear conceptual approach (Patzel, Sticher and Karlen, 2000). It is therefore necessary to make clear the position on soil health this thesis takes going forward. Soil Health will be defined as the continued capacity of the system to function as a vital living ecosystem. This links soil health, to the functioning of the system, and sits within the ecosystem service paradigm described previously (Lehmann *et al.*, 2020).

The term soil health in this project focuses on drained lowland peatlands. As such it must be clarified that, in the context of this thesis, a peatland with good soil health will have properties and functions resembling its post drainage state, rather than pre-drainage state. Comparing the functioning of a drained peatland with natural vegetation, fluctuating groundwater and minerotrophic nutrient regimes would not be appropriate with a drained agricultural fenland system. This project will therefore consider a healthy lowland peat under agriculture to function similarly to its state immediately post drainage. As we introduced the concept of soil degradation earlier, degradation of peat health therefore considers the transition of the functioning of peat towards a reduction in the associated provision of ecosystem services and functions from the post drainage state. Therefore, degradation can be viewed as the trend in the reduction of the health status of a peatland site relative to its starting state immediately after drainage. That is, a deep peat will have a relatively higher health "status" immediately post drainage that a shallow peat but has a higher potential for degradation. This also frames the concept of sustainable agriculture on peatlands. In the traditional sense, sustainable agriculture aims to create farming systems that can meet society's food demands that are also resilient to climate change, protect biodiversity and protect future generations to meet their own needs (Janker, Mann and Rist, 2018). In terms of sustainability, draining peatland areas can be seen to directly compromise the protection of future generations to climate change and biodiversity declines. However, as noted, peatland areas are currently indispensable for food security in the UK agricultural system. As such, sustainable agriculture in terms of this project considers the long-term viability of farming of peatland areas. This intrinsically links into the concept of health, as the gap between the baseline post drainage state and current functioning of the system.

2.6 Soil Health Monitoring

Perceptions surrounding soil health have been viewed in two distinct manners; (i) a reductionist approach which is based upon estimation of conditions using a minimum set of soil properties, and (ii) an integrated approach, which assumes the health of a soil is more than the sum of its parts (Kibblewhite, Ritz and Swift, 2008). The health of soil systems is essential to the operation of agroecosystems and considerable effort has been applied to identify simple indicators to allow monitoring of ecosystem services and processes (Schwilch *et al.*, 2016; Griffiths, Faber and Bloem, 2018; Luján Soto, Cuéllar Padilla and de Vente, 2020). As demonstrated below, the reductionist approach dominates the field of soil health monitoring as it is an accessible and practical means of assessing and conveying soil health.

2.6.1 Soil Health and National Monitoring and Sampling

In the UK, nature has been taken for granted and undervalued across a range of ecosystems (Defra, 2011), and this remains true for UK soils (Parliamentary Office of Science and Technology, 2015). Whilst it is recognised that soil provides essential ecosystem services and functions, both on and off site, and market and non-market benefits (Environmental Audit Committee, 2016), there have been limited attempts to set up a nationwide soil health monitoring scheme. An initial approach to monitoring soil health within the UK was developed by the Environment Agency which led to the selection of a minimum dataset of indicators for assessing the role of soil functions in environmental interaction. This minimum dataset included soil organic carbon, total nitrogen, Olsen P, available and total Cu, Ni, and Zn, bulk density, and pH (Merrington, 2006). The Countryside Survey has studied and audited the natural resources of the UK countryside since 1978 (https://countrysidesurvey.org.uk). An Audit in 2007, under Work Package 4, assessed the status of key soil properties including pH, soil organic matter, soil organic carbon, bulk density, hand texture, total-N, soil C:N, Olsen-P, potential mineralisable nitrogen, invertebrate diversity by main taxa, and metals (https://countrysidesurvey.org.uk/content/soils) across a variety of differing systems and management practices. The Countryside Survey dataset allows the assessment of soil health, providing insight into how soils have changed across a decadal timescale. A national soil quality assessment was conducted by Cranfield University between the 1980's to mid-1990's as part of the National Soil Inventory (Cranfield University, 2021). Data collected ranged from over 20 topsoil indicators. While extensive, the dataset comprises a high quantity of chemical properties with little measurement of biological properties due to the unavailability of methods and a lack of recognition of the importance of soil biology at the time the surveys were undertaken. These schemes have provided a vast array of information to aide in monitoring soil health across the UK, however, many of these schemes have not been successfully in securing future funding (Emmett *et al.*, 2016).

The European Union attempts to address declining soil health through Common Agricultural Policy which encourages farmers to maintain good soil quality through financial incentives (Dedeurwaerdere, Polard and Melindi-Ghidi, 2015). Whilst the schemes discussed above have sampled across the breadth of the UK, the only soil monitoring programme active today is the European Union's Land Use/Cover Area frame Survey (LUCAS). LUCAS provides not only statistics on land use and cover across the whole of the EU, but in 2009 was extended to sample and analyse a suite of topsoil properties across the Member States of the EU. Soil properties include coarse fragments, soil texture, pH, organic carbon, carbonate content, nitrogen, phosphorus, cation exchange capacity, extractable potassium, and multispectral reflectance data. With the UK leaving the European Union, the continued operation and future datasets of the LUCAS programme may become unavailable or non-existent for British soils. Going into the future, the UK Government is keen to develop a soil health index, containing a variety of indicators, to aide farmers and land managers in monitoring their soil health (Department for Environment Food and Rural Affairs, 2018a). This has led to the development of multiple Environmental Land Management Schemes in the UK including; Sustainable Farming Incentive, Local Nature Recovery, and Landscape Recovery (Department for Environment Food and Rural Affairs, 2021b). These schemes are currently in development and whilst management indicators, such as the installation of hedgerows and wildflowers are identified, no single indicator set to monitor soil health has been developed. Therefore, the current list of soil properties to be assessed by the developing index is unclear. Recent development have attempted a logical sieve approach to identify indicators of soil health, identifying the following; pH, routinely sampled nutrients (P, K, Mg), organic matter, microbial activity, nematodes/earthworms, and visual assessment of soil structure (VESS) (Stockdale, Hargreaves and Bhogal, 2021). These indices have been established to monitor a diverse range of ecosystems. However, different ecosystems provide different quantities and qualities of ecosystem services and functions and as such require development of bespoke monitoring methodologies.

2.6.2 Soil Health Index Studies

Soil health indices aim to effectively combine a variety of available information to create decision tools enabling objective decision making on the health of soil systems (Karlen and Stott, 1994). There have been numerous attempts to develop soil health Indices using multivariate statistical analysis to select a minimum dataset. These minimum datasets are created to map soil functioning and health using the least number of soil properties as possible, while maintaining the maximum capability to distinguish health and unhealth soils. A huge variety of indicators to construct a minimum dataset, depending entirely upon objectives, target groups or stakeholders, spatial scales, and ecosystems in question (Bünemann *et al.*, 2018). Chemical and physical indicators are frequently used in soil health assessments with biological indicators starting to gain momentum (Andrews, Karlen and Mitchell, 2002a; Sparling and Schipper, 2002; Sparling *et al.*, 2004; Sangha *et al.*, 2005; Bastida *et al.*, 2006; Velasquez, Lavelle and Andrade, 2007a; Masto *et al.*, 2007; Armenise, Redmile-Gordon, *et al.*, 2013; Askari *et al.*, 2015; Congreves, Hayes, Verhallen and Van Eerd, 2015; Vasu, Singh, *et al.*, 2016; de Paul Obade and Lal, 2016a).

The study of biological life within soils has demonstrated that microorganisms provide a range ecosystem services and functions that we rely upon, including the improvement of soil structure and water regulation, the cycling of nutrients, the suppression of peats or pathogens, the promotion of plant growth through symbiotic relationships, and the degradation of pollutants (Coleman, 2001; Stirling *et al.*, 2016). Microbes within soil systems can have both a diverse and niche role to play in ecosystem processes. However, the idiosyncratic intra- and interaction between the soil food web, alongside high degrees of functional redundancy between species, indicates that a vast knowledge gap exists in understanding the outputs of soil biological indicators (Coleman, Crossley and Hendrix, 2004; Bardgett, 2005). The role of biology in soil systems is essential to understanding the provision of functions. However, incomplete knowledge of the diverse community roles, challenges with changing populations due to temperature, sampling date and drought conditions pose challenges to assessing soils conditions over spatial and temporal conditions. As such, what constitutes a diverse range of soil biology, and associated functioning of the system, is poorly understood at a species or functional group level (Bolger, 2001). Whilst levels of biological diversity and community composition are difficult to analyse, what is clear is that carbon substrates, both within and entering ecosystems, plays a key role in shaping the composition and activity of soil microbial communities through interaction pathways (See Figure 8) (Hooper *et al.*, 2000).

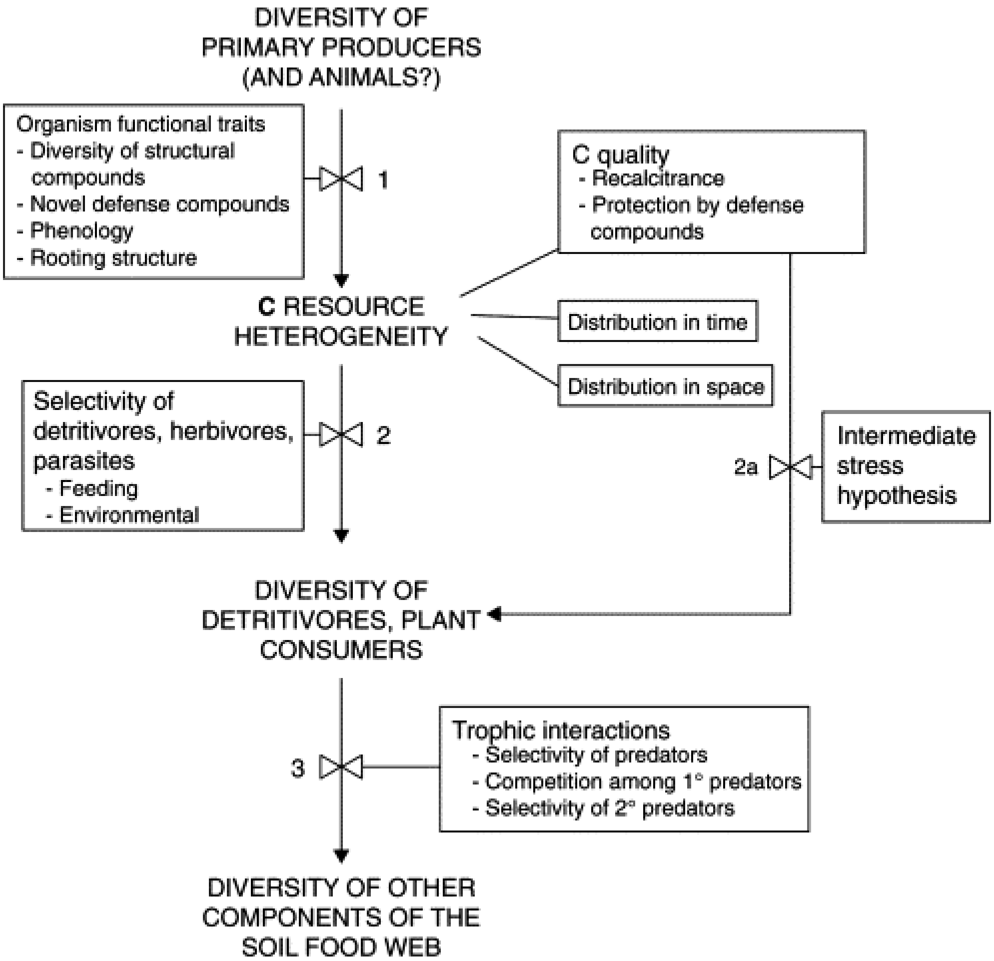

Figure 8: Reproduced from Coleman, Crossley and Hendrix 2004 – *"Step 1. Diversity of primary producers leads to diversity of C inputs belowground. Step 2. Carbon resource heterogeneity leads to diversity of herbivores and detritivores. (Alternative Step 2. Carbon resource quality, rather than heterogeneity, leads to diversity of detritivores.) Step 3. Diversity of detritivores or belowground herbivores leads to diversity of organisms at higher trophic levels in belowground food webs".*

The difficulties assessing and benchmarking soil biological community composition and diversity have led to the development of biological indicators that consider the functions provided by the biology in the system instead of the presence or absence of specific species (Liang *et al.*, 2009; Cong *et al.*, 2015; Hariharan *et al.*, 2017; Khan and Khan, 2020). However, despite these advances in biological analysis, soil remains a complex environment, where physiochemical properties affect microbial distribution, diversity and activity across the soil environment, and analysis techniques can be hampered through masking by dominant populations and associated costs (Lombard *et al.*, 2011; Bünemann *et al.*, 2018).

The constraints imposed by the chemical and physical components of soil include mediating access to water and nutrients and the creation of hospitable or inhospitable environments for the soil biota (Stirling *et al.*, 2016).

Investigating soil health indices further, the purpose of individual indices are varied and include includes indices designed to (i) compare organic and conventional agricultural systems (Andrews, Karlen and Mitchell, 2002a), quantify the effect of NPK additions, crop sequencing, and stubble management (Armenise, Redmile-Gordon, *et al.*, 2013), assess the influence of pasture systems (Sangha *et al.*, 2005), or represent the structure of soils (Askari *et al.*, 2015). A key finding that emerges from a review of existing soil health metrics is that current indices focus exclusively on mineral soil systems (Bastida *et al.*, 2006; Masto *et al.*, 2007; Velasquez, Lavelle and Andrade, 2007a; Congreves, Hayes, Verhallen and Van Eerd, 2015; de Paul Obade and Lal, 2016b; Vasu, Kumar, *et al.*, 2016). Where organic soils and peat are assessed for soil health, they are integrated with mineral soils rather than differentiated (Sparling and Schipper, 2002; Sparling *et al.*, 2004). Given that peat soils perform different functions and provide different quantities and qualities of different ecosystem services, the development of a specific health index is essential to quantify the health of lowland peat soils and identify land management practices that reduce the environmental impact of farming on soil health.

2.7 Summary

A healthy functioning soil is essential to agroecosystems, providing a range of ecosystem services and processes. The consequences associated with degradation is a reduction or plateau in yields, requirements for additional inputs to maintain soil fertility, and the overall loss of intrinsic physical, chemical, and biological soil quality (Nunes *et al.*, 2020). Major threats to the functioning of ecosystems exists through climate change, water scarcity and population increases. The process of anthropogenic degradation of soil ecosystems, through environmental practices and poor management, reduces the capacity of these systems to buffer against the aforementioned threats (Castellini *et al.*, 2021). This increased concern around the benefits we receive from soil systems, and the threats posed to it, has led to the increased discussion of soil system management within the policy sphere. The ecosystem service paradigm has been used to understand the functioning of soil systems to enable valuation of the benefits we receive. This paradigm focuses on identifying a healthy and functioning soil system and its continued capacity to provide services. Whilst previous work exists to identify and create soil health indicators to assess agroecosystems, the literature displays a bias towards designing these indices for evaluating mineral soils. However, given the economic and environmental importance of peatlands to UK agriculture and UK food security, it is imperative to create indices that allow farmers and land managers to benchmark lowland peat health, identify peat soils that are poorly functioning, and develop sustainable land management practices for lowland peat drained for agriculture.

Chapter 3: Development of an index for assessing the health of lowland drained agricultural peatland soils

Abstract

UK lowland peat performs a variety of ecosystem functions including the storage of carbon, regulation of water, and providing a habitat for biodiversity. Lowland peat has been drained to allow for intensive agricultural practices. However, this leads to degradation of peat soils, reducing productivity and leading to substantial environmental damage. This situation requires specific tools to enable sustainable management of lowland peat systems. Here we describe the development of two Peat Health Indexes (PHI) for lowland soils within the East Anglia Fen region by using Principal Component Analysis to derive a minimum suite of indicators, including biological, chemical, and physical soil properties, that adequately capture the variance across a peat health gradient. The PHI effectiveness was compared with farmer's perceptions of peat health and farm key performance indicators (KPIs). The indicators identified are cation exchange capacity, microbial activity, pH, and visual evaluation of soil structure. A Weighted PHI accounted for the relative contribution of each indicator to the variance in soil properties, whereas an Additive PHI summed the indicators and gave each equal weighting. Both indices correlated strongly with properties customarily associated with peat health. The Weighted PHI was best able to differentiate farmer identified subjective gradients of health. The Additive PHI developed was more efficient at identifying correlations with farm KPIs, identifying that healthier peats require fewer external inputs and are thus more capable of supporting sustainable crop production. The results demonstrate the applicability of the PHI to assess the health of peat soils using a minimum suite of indicators and provide a valuable tool for famers to inform management decisions that protect peat health.

3.1 Introduction

Fertile and healthy soils are essential for sustainable agriculture and achieving current food security. However, with increase in intensively cultivated land and the management practices associated with it, there has been a global increase in soil degradation and an associated loss of productivity (Horrigan, Lawrence and Walker, 2002; Tilman *et al.*, 2002). Soil degradation reduces the capacity of a soil to perform ecosystem functions and deliver ecosystem services, yet quantifying levels of degradation is challenging due to spatial heterogeneity. The antithesis of soil degradation is soil health. Soil health represents the continued capacity of the soil to function as a vital living ecosystem (Doran, 2002). The adoption of the term 'soil health' over 'soil quality' in the recent literature appears to indicate greater recognition of the role of the biological component in mediating the ecological functions and services that soils provide which differentiate it from weathered rock (Kibblewhite, Ritz and Swift, 2008). The degradation of a soil is therefore the transition of the health of a system away from the inherent potential to perform functions and deliver services (Maharjan, Das and Acharya, 2020). Approaches to monitoring soil health can be divided into two distinct manners; a reductionist approach which is an estimation of conditions based upon a minimum set of soil properties, and an integrated approach, which assumes the health of a soil is more than the sum of its parts (Kibblewhite, Ritz and Swift, 2008). The reductionist approach dominates the field of soil health monitoring as it is an accessible and practical means of assessing and conveying soil health to stakeholders (Bünemann *et al.*, 2018).

Approaches to measuring or assessing soil health have typically been developed with a focus on mineral soils. Peatlands (Histosols), whilst only covering 1.3% of the global land area, contain 22.7% of the organic carbon stored in soils (Eswaran, Van Den Berg and Reich, 1993) and differ fundamentally from mineral soils in terms of their formation and functioning. Therefore, soil health indices that are intended for use with mineral soils may not be appropriate for peatlands. Peat is an organic sedentary material that is primarily formed from the remains of photosynthetically derived plant material accumulating under water-saturated conditions. Under anoxic conditions, low decomposability of plant material leads to incomplete decomposition of the organic material (Moore and Basiliko, 2006). The hydrological regime is essential in peat formation and maintenance of the many ecosystem processes that occur (Rydin and Jeglum, 2006). Peatlands are often drained to allow for agricultural and forestry practices. The process of drainage occurs where water is diverted from the region to remove the anoxic conditions through creation of ditches, drains and the inclusion of pumps to remove ground water (Page, Proby and Ladds, 1936). Global peatland total area is estimated to be

4.23 million km^2 (2.84% of the world land area) (Xu *et al.*, 2018), with 7.5% of worldwide histosols (25 million hectares) is estimated to be drained for agriculture (Conchedda and Tubiello, 2020; Food and Agriculture Organization of the United Nations, 2020). As such, maintenance of peatland health and sustainable management of these systems is essential to global food security. Lowering of the water table leads to three distinct processes occur; primary consolidation, secondary compression and oxidative wastage (Lindsay, Birnie and Clough, 2014). Alongside these main processes, peat is also lost through wind erosion, removal of soil on crops and accidental burning (Holman, 2009). Wasted peat develops where a large part of the original peat layer has been lost or mixed with underlying mineral substrate. Within the UK, the most influential stage of lowland peat drainage took place in the 17th century where rivers were straightened through the creation of linear links and sluiced against tidal flows (Langslow, 1997). Within England, peatlands occupy 1.4185 million hectares, with 48% being Deep peat (>40cm depth), 37% Shallow peat (10cm – 40cm peat depth) and 15% soil with peaty pockets (Natural England, 2007). Much of England's lowland peatlands are now removed from their natural state and have been degraded by anthropogenic activity (Page and Baird, 2016). Lowland fens occupy 42% of Deep peats, yet over 65% of lowland peatlands are considered wasted (Natural England, 2007). Natural England further noted that over 70% of peatlands show signs of degradation and the majority of lowland peat is cultivated (Natural England, 2010). The loss of ecosystem functions and services associated with this degradation is likely to impact sustainability and future security of agricultural production within the UK. In the fens of Lincolnshire, Cambridgeshire and Norfolk, peat degradation has resulted in rates of peat loss in the order of 1-2 cm yr^{-1} (Richardson and Smith, 1977) and to the development of large areas of 'wasted' peat. Although lowland peatlands only occupy around 15% of the total UK peat area (Maddock, 2008), they may account for around 50% of total greenhouse gas emissions from all peat (Evans *et al.*, 2016). Lowland peat management strategies are urgently required to slow (and perhaps even reverse) the degradation of lowland peat. However, to benchmark, assess, and compare management strategies, a methodology for quantifying the soil health of lowland peat is needed.

An array of soil health tools exists to examine the functioning of the soil ecosystems. These can range from simple spade diagnosis (Guimarães *et al.*, 2013) to more complex Soil Life Suites (Fera, 2021) and organic matter balancing tools. The tools developed attempt to identify the sustainability of systems to continue to function based upon observable indicators. These indicators are evaluated in comparison to pre-defined values based upon expert opinion and sampling regimes. A large range of soil properties have been chosen to assess the health of soils (Bünemann *et al.*, 2018). In prior developed academic health/quality indexes, the indicators selected vary based upon the research aims of the index. For example, a minimum dataset for assessing soil degradation was developed being focused upon the microbiological and biogeochemical indicators (Bastida *et al.*, 2006). Further health indices have been developed based upon the use of normalized difference vegetation index (NDVI) data to assess the health of cropped systems (Li *et al.*, 2021). A range of indices containing a mixture of physical, chemical, and biological indicators have been developed by authors, and a sample is displayed below (Table 2). However, there is a distinct lack of indices to measure the health of agricultural (drained) peatlands since research on soil health indices has focused on developing indices for mineral soils or to assess restoration of upland peats to their natural state (Bonnett *et al.*, 2009).

Table 2: Examples of health/quality indicators developed to understand soil ecosystem functioning from a variety of different management systems, geographical locations and framework assessments derived from Clarivate Web of Science.

Author	**Title**	**Indicators Selected/ Suggested**	**Soil Type**
(Bai *et al.*, 2018)	Effects of agricultural management practices on soil quality: A review of long-term experiments for Europe and China	Soil Organic matter, pH, Aggregate Stability, water-holding capacity, earthworm count.	Range of soil types included in indices based upon use of existing datasets
(Andrews, Karlen and Mitchell, 2002a)	A comparison of soil quality indexing methods for vegetable production systems in Northern California	Total Nitrogen, Total Sodium, Exchangeable Calcium, pH, and Soluble Phosphorus.	Reiff loams (coarse-loamy, mixed, non-acid, thermic Mollic Xerofluvents) and Yolo silt loams (fine-silty, mixed, non-acid, thermic Typic Xerothents).
(Arshad and Martin, 2002)	Identifying critical limits for soil quality indicators in agroecosystems	organic matter, topsoil-depth, infiltration, aggregation, pH, electrical conductivity, suspected pollutants, and soil respiration	Soil types not mentioned, but states that indicators should be representative of ecological zone based upon similar soil types.
(Mukherjee and Lal, 2014)	Comparison of Soil Quality Index Using Three Methods - Statistically modelled SQI (SQI-3)	Soil Organic Carbon, Available Water Capacity, Water Stable Aggregates, pH	Samples collected from an organic and two mineral soils.

Another well-known example includes the Cornell Comprehensive Assessment of Soil Health (Moebius-Clune *et al.*, 2016) which focuses upon defining soils by the mineral fraction (Coarse, Medium and fine textured) and thus uses non liner curve to assign indicator scoring. These scoring functions underestimate the health of organic/peat soils since 4-6% organic matter content can provide a healthy score, whereas it is known that organic matter contents of peat soils generally exceed 20%. Furthermore, even those national assessments that identify peat as a separate soil type underestimate or over generalise the indicator scoring. The Environment Agency of England and Wales suggested a suite of indicators with associated "trigger values" to monitor soil quality and health (Merrington *et al.*, 2006). This project identified the need for alterative trigger values for peat soils in comparison to mineral soils. However, the projects focus was on monitoring the national soil inventory of the UK, rather than being developed specific to peat and so this focus influenced minimum dataset indicator selection. Moreover, trigger values for peat were set at a single value which, while useful to identify a degrading system, does not allow for identification of systems that are at different stages of degradation.

Soil health indices can effectively combine data from a variety of indicators to create decision tools (Karlen and Stott, 1994; Fine, van Es and Schindelbeck, 2017). Indices based upon a large number of indicators may be more informative, but analysis of multiple soil properties to understand the health of a soil is economically inefficient and unnecessary. Statistical analysis of large datasets can be used to identify properties which explain a large amount of the variance between samples. This identification of key soil properties has been performed using Principal Component Analysis (Andrews, Karlen and Mitchell, 2002a; Velasquez, Lavelle and Andrade, 2007b; Masto *et al.*, 2009; Armenise, Redmile-gordon, *et al.*, 2013; Askari and Holden, 2015; Congreves, Hayes, Verhallen and Eerd, 2015; Vasu, Kumar, *et al.*, 2016), Expert Opinion (Andrews, Karlen and Mitchell, 2002a; Vasu, Kumar, *et al.*, 2016), and Partial Least Square Regression (de Paul Obade and Lal, 2016a). The Principal Component Analysis (PCA) methodology obtains a minimum dataset that narrows down the suite of candidate indicators to a smaller, more manageable, and more affordable suite of soil properties (Andrews, Karlen and Mitchell, 2002a) to enable assessment of the health of drained peatlands. Prior work has established methods for either weighting Minimum Datasets by PCA outputs to create indexes (Edrisi, Tripathi and Abhilash, 2019; Bedolla-Rivera *et al.*, 2020) or incorporate an additive approach after PCA indictor selection instead of weighting (Andrews, Karlen and Mitchell, 2002a). Weighted approaches redefine the influence of each indicator selected, aiming to increase the influence of indicators explaining the most variance.

The objective of this study was to further develop and apply an existing statistical method to create a Peat Health Index (PHI) capable of evaluating the functioning of drained agricultural peatlands using a gradient of sites (ranging from Deep peat to Wasted peat). A selection of easily accessible and simple farmyard available indicators was measured on peat soils sampled across eight fields. Collected data was incorporated into an index to establish a minimum dataset and a linear scoring system implemented. Index results were evaluated through comparison with farm identified Key Performance Indicators (KPI) (including Yield, Inorganic Nutrient Inputs, Pest Management operations).

We hypothesised that the health scores from a Peat Health Index (PHI) created with simple indicators will display signification correlation with key farm performance indicators.

3.2 Methodology

3.2.1 The study area

The study area comprises fields under the management of G's Fresh Ltd in the East Anglian fens surrounding the village of Barway, near Ely, Cambridgeshire (52.3576° N, 0.2670° E). The soils in the study area were predominately classified as Histosols, where organic material accumulated in a thick organic horizon under anoxic conditions. Drainage of the area over the past two centuries to allow for agricultural exploitation has led to the development of a hortic (or anthropogenic) horizon. The superficial peat deposit across the study area sits on a variety of geological formations, including Kimmeridge Clay's and Gault Chalk formations and average elevation of 2 meters above sea level with vast swathes between 1-2 meters below sea levels (Natural England, 2015). The study area experiences average annual temperatures between 9.5°C and 10.5°C, although temperatures show both seasonal and diurnal variations. The East of England receives low, yet consistently distributed, annual rainfall of 700mm per year due to high ground to the west leading to a rain shadow effect and a high frequency of convective rainfall. The area managed by G's Fresh Ltd is intensively cultivated for agricultural and horticultural crop production. The major crops grown include Iceberg and Gem Lettuce, Wheat, Maize, Celery, Onion, Potatoes, and a Cover Crop mix. The application rates of organic and inorganic fertilisers to crops are advised by the AHDB Nutrient Management Guide (RB209) for each specific crop, soil nutrient testing, and farmer knowledge.

3.2.2 Sampling

Sample collection was conducted in summer 2018. Eight fields were selected across four farms (two fields per farm) to represent a gradient of degraded peats in the study area. The sampling regime selected fields that were planted with lettuce crops. This limitation led to an unequal variety of fields selected (four shallow, two deep, and two wasted). As such, it was established with the farmers that the four shallow fields selected were of differing quality based upon their opinion. Fields were selected after discussion with local farmers, using their extensive knowledge, to obtain a range of fields known to cover a wide range of peat depths and levels of degradation. Fields were classified by farmers into three categories; (i) Deep peat (>40cm in depth), (ii) Shallow peat (10 – 40 cm depth), and (iii) Wasted peat (<10cm depth where former peat soils that have OM content below 20% and are substantially mixed with mineral soils) (Table 3). Each field selected was planted with lettuce in 2018 and was sampled within the last two weeks before the harvest of the lettuce crop. Four sampling points for each field were selected using the Sampling Design Tool for ArcGIS using a stratified random procedure. 10 – 15 soil samples were taken using a soil corer in an 5m area surrounding the sampling point to a depth of 20cm and homogenised in-field using the cone and quarter method. At each sampling point, two intact cores were also collected to assess bulk density (5cm diameter by 5cm depth) and mesofauna abundance (10cm diameter by 10cm depth). A separate pit (20cm x 20cm x 20cm) at each location was excavated for analysis of earthworms and other soil invertebrates. Visual Evaluation of Soil Structure (VESS) was conducted on four undisturbed soil slices (25cm depth, 10cm thickness and 20cm width) extracted at the four sampling points in each field (Ball *et al.*, 2007). The extracted bloc underwent visual examination to observe any differing layers to assign scores separately, where scores would be relative to the depth of layer observed. The extracted bloc was gently manipulated by hand to reveal any cohesive slabs or clods and form natural aggregates. Results from this process were compared with a visual key attribute score which assigns scores to layers based upon a visual picture, size and strength of aggregates, porosity, root presence and soil colour (visual key accessible from Scotland's Rural College (Cloy, 2021)).

Table 3: Displaying the sites selected for the study ranging across a 300km^2 region of East Anglia. Classification of fields by farmers into (i) Deep peat (>100cm in depth), (ii) Shallow peat (<100cm depth), and (iii) Wasted peat (former peat soils that have OM content below 20% and are substantially mixed with mineral soils).

Farm Name	Field Name	Field Number	Classification

Redmere	P59	1	Wasted Peat
Redmere	P62	2	Wasted Peat
Plantation	Spooners 6	3	Shallow Peat
Plantation	Spooners 7	4	Shallow Peat
Engine	Creeks	5	Shallow Peat
Engine	Wills	6	Shallow Peat
Barway	Tilehouse	7	Deep Peat
Barway	Howes	8	Deep Peat

3.2.3 Laboratory Analyses

Upon return to the laboratory, the soil collected using the bulk density cores (98.17 cm^3) were removed from the corers, dried at 105 °C, and weighed to calculate bulk density (g/cm^3). Mesofauna cores (785.40 cm^3) were placed upside down above a Tullgren Funnel with a heat source (light bulb) suspended above the bottom of the core for 5 days. A sampling tube containing 70% alcohol was placed under the cores to collect mesofauna which were subsequently identified under a microscope and counted (George *et al.*, 2017). However, due to high temperatures during sampling, no mesofauna were identified. Earthworm sampling in-field failed to observe any to analyse within the laboratory.

Soil samples collected using the auger were divided into two sub-samples. One sub-sample was air dried at <30 °C and sieved with a 2 mm screen. The other was sieved moist to 4 mm, stored at 4 °C, and analysed within 48 hours. The moisture content of the moist samples was determined by weighing, drying in an oven at 105°C overnight, and reweighing. Water holding capacity was calculated as the difference in mass following saturation and gravimetric draining for 12 hours. Microbial activity was determined through Solvita Burst method by moistening a soil sample with deionised water to achieve 50% of the Water Holding Capacity, leading to a flush of CO_2 produced which was measured colorimetrically with a Solvita^{TM} digital colour reader (Woods End Labratories, 2013). Ammonium and Nitrate concentrations in the samples were determined on moist soil by extracting with 1M Potassium Chloride and analysing colorimetrically using a Skalar Continuous Flow Analyser. Ammonium and Nitrate concentrations were summed to determine available nitrogen.

The air-dried soils were subjected to a range of physical and chemical analyses. pH was determined potemtiometically after shaking samples with water at a 1:2.5 (w/v) ratio. Organic matter (OM) content was analysed on sub-samples dried at 105 ^{o}C by quantifying the mass lost after combustion at 430 ^{o}C. Extractable Phosphorus was determined by shaking 2.5 ml of soil with 50ml 0.5M Sodium Bicarbonate solution at pH 8.5 for 30 mins, reacting with Ammonium Molybdate and determining Phosphorus concentrations spectrophotometrically (Olsen, 1954). Extractable Potassium and Magnesium was determined by shaking 10.0 ml of soil with 50ml 1M Ammonium Nitrate at 20 °C for 30 minutes, filtering and determining the concentration of Potassium and Magnesium through atomic absorption spectrometry (Agricultural Development and Advisory Service, 1986). Particle size distribution was determined by laser diffraction and particle size classified using UK Classification values (Clay <0.002 mm, Silt 0.002 – 0.06 mm, Sand 0.06 – 2.0 mm)(Natural England, 2008). Particle density of samples was determined by the adjusted pycnometer method (Klute *et al.*, 1986). Cation exchange capacity was determined using the Compulsive Exchange method (Gillman and Sumpter, 1986) using differing molar strengths of Barium Chloride to displace cations. The extractants from the first Barium Chloride were analysed by ICP- OES analysis to examine Exchangeable Cations including; Calcium, Copper, Iron, Potassium, Magnesium, Nickle and Zinc (Thomas, 1983).

3.2.4 Peat Health Index (PHI) Development

A Peat Health Index (PHI) was developed through (1) selecting a variety of measurable biological, chemical and physical indicators through expert discussion, (2) identification of a minimum dataset, (3) scoring the minimum dataset, and (4) integrating the indictor scores into a relative health index (Andrews and Carroll, 2001). A multivariate data reduction technique, Principal Component Analysis (PCA), was used to select the minimum dataset for the index from the larger dataset of analysed soil properties. PCA reduces the dimensionality of a dataset while preserving the variability by finding new variables that are linear functions of the original dataset but are uncorrelated with each other (Jollife and Cadima, 2016). PCA was conducted using the Factoextra Package (Alboukadel and Mundt, 2020) in R where the prcomp() function was selected to examine the correlation between individuals and the matrix of soil properties were normalised to have zero mean and standard deviation of one. The following soil properties were included in the matrix; pH, extractable phosphorous, extractable potassium, organic matter content, microbial activity, sand, silt, clay, cation exchange capacity, bulk density, water holding capacity, available nitrogen, and VESS score. Exchangeable nutrients (Ca, Cu, Fe, K Mg, Ni, Zn) were excluded from the PCA analysis as Cu, Fe, Ni, and Zn observed multiple values below detection limits (high detection limits are noted as a disadvantage of ICP-OES (Wilschefski and

Baxter, 2019)). Further to this, Exchangeable K and Mg were excluded since Extractable K and Mg were already selected as indicators. Observed Exchangeable Ca was excluded as it was exceptionally abundant in all sites, indicating no limiting effect on critical enzymatic processes and microbial cell maintenance (Reicosky, 2018). The inclusion of available nitrogen, extractable phosphorous and potassium represented the biogeochemical cycling of nutrients in the peat system since these nutrients are usually the scarcest resource in agroecosystems. Further, porosity was not included in the PCA dataset because this was calculated using the bulk density values and thus perfectly correlated with bulk density.

Using the Kasier criterion (Kaiser, 1960) Principal Components with eigenvalues greater than 1 were selected to help identify soil properties for inclusion in a minimum dataset that represents the health of the system. For each selected Principal Component (PC), the eigenvectors (soil properties) within 10% absolute of the eigenvector with the largest magnitude were selected for inclusion in the minimum dataset (Mukherjee and Lal, 2014). The process of reducing properties within a principal component decreases the complexity of the final index, however, selecting properties with the highest influence retains the important component of each PC. Where two or more properties were retained under a single PC, correlation coefficients between the retained soil properties were determined and the property with the highest sum of correlation coefficients was selected as this was considered to best represent the group (Andrews, Karlen and Mitchell, 2002a).

After selecting the soil properties for inclusion in the minimum dataset, their values were transformed using linear scoring functions for inclusion into the PHI. Each property selected was sorted into one of three categories, based on our prior knowledge of how the soil property influences peat health, and transformed using the appropriate equation; (a) “more is better” (Equation 1), (b) “less is better” (Equation 2) or (c) “optimum” (Equation 1 where the measured value is below “optimum” and Equation 2 where the measured value is above “optimum”):

Equation 1: $S_{p,i} = \left(\frac{P^i}{P_{max}}\right)$

Equation 2:: $S_{p,i} = \left(\frac{P_{min}}{P^i}\right)$

Where $S_{p,i}$ is the score for soil property p in field i, P_i is the value of the soil property observed in that field, and P_{max} and P_{min} are the maximum and minimum values of these soil properties observed across the dataset. The sampling strategy of selecting fields along a degradation gradient allowed identification of an extensive range of values observed (i.e., from P_{min} to P_{max}). Once transformed, the scores ($S_{p,i}$) were incorporated into two indices: an Additive and a Weighted PHI. The Additive PHI was calculated by simply summing the transformed scores for each soil property (Equation 3). The Weighted PHI was calculated by multiplying the score by the percentage of the overall variance in the dataset (V) explained by the retained PCs that the property (*p*) was drawn from to calculate a Weighed PHI (Equation 4):

Equation 3: $Additive\ Peat\ Health\ Index\ (PHI) = \sum S_{p,i}$

Equation 4: $Weighted\ Peat\ Health\ Index\ (PHI) = \sum \left(S_{p,i} \times V_p\right)$

3.2.5 Statistical Analysis of soil properties and the Peat Health Index (PHI)

Soil data was statistically analysed using R (R Core Team, 2020) and figures produces using the ggplot2 package (Wickham, 2016). The complete soil dataset was compared with PHI outputs to identify correlations for each of the sites sampled using the Hmisc Package in R (Harrell Jr, 2021) allowing for exploration of reduction of indicators and information loss. Soil data and Peat Health Index outputs were assessed for potential outliers using the Inter Quartile Range criterion which determined an outlier existed where the value either exceeded or was below the values determined using Equation 5. If a potential outlier was identified, the datapoint was assessed for inclusion into the study based upon distance from other observations and context of the result.

Equation 5: $Outlier = (Quartile_{\ 0.25} - 1.5 \times IQR; Or;\ Quartile_{\ 0.75} + 1.5 \times IQR)$

3.2.6 Evaluation of the Peat Health Index (PHI)

To evaluate the performance of the PHI as a quantification of peat health that is useful for land managers, farm Key Performance Indicators (KPIs) were supplied by local famers, and analysed to identify correlations to the PHI values obtained for each of the 8 fields sampled using the Hmisc Package in R (Harrell Jr, 2021). Farm KPIs included the application rates of nitrogen, phosphorous potassium, and trace element fertilisers throughout the entire growing season (including the initial application during crop transplantation), the rates of herbicide, fungicide and insecticide applications, and the amount of irrigation applied during the growing season. Total Pesticide application was calculated by summing the herbicide, fungicide, insecticide alongside the use of adjuvants. Lettuce yield data was collected, including the number of harvested heads as a percentage of the number of heads transplanted. The average Additive and Weighted PHI values obtained for each field were compared with farm management operation data using Spearman's linear regressions to investigate relationships between PHI scores and the quantity of farm inputs required to produce lettuce crops.

3.3 Results

3.3.1 Peat Health Index

The first three PCs of the PCA (PC1, PC2, and PC3) had eigenvalues greater than 1 explaining, cumulatively, 78.58% of the variance in the dataset (Figure 9). The highly weighted variables under PC1 were organic matter content, sand, and silt content (%), cation exchange capacity, bulk density and water holding capacity. All variables were significantly correlated (r>0.7). The absolute sum of correlation coefficients between PC1 variables indicated that cation exchange capacity best represented the group and was retained for the minimum dataset. Under PC2 VESS and available nitrogen were identified as highly weighted. Available nitrogen is a transient soil property that is highly temporally dynamic (Powlson, 1993). A second consequent application experiment of the index (see chapter 4) identified that available nitrogen should be excluded from the PHI because it was not a temporally consistent property (i.e., it is heavily influenced by the timing of fertiliser applications and weather events, relative to soil sample collection). The PHI reported in the results section of this paper will be therefore based upon a PHI that excludes available nitrogen. Microbial activity and pH were highly weighted under PC3 and were not correlated with each other, so both retained.

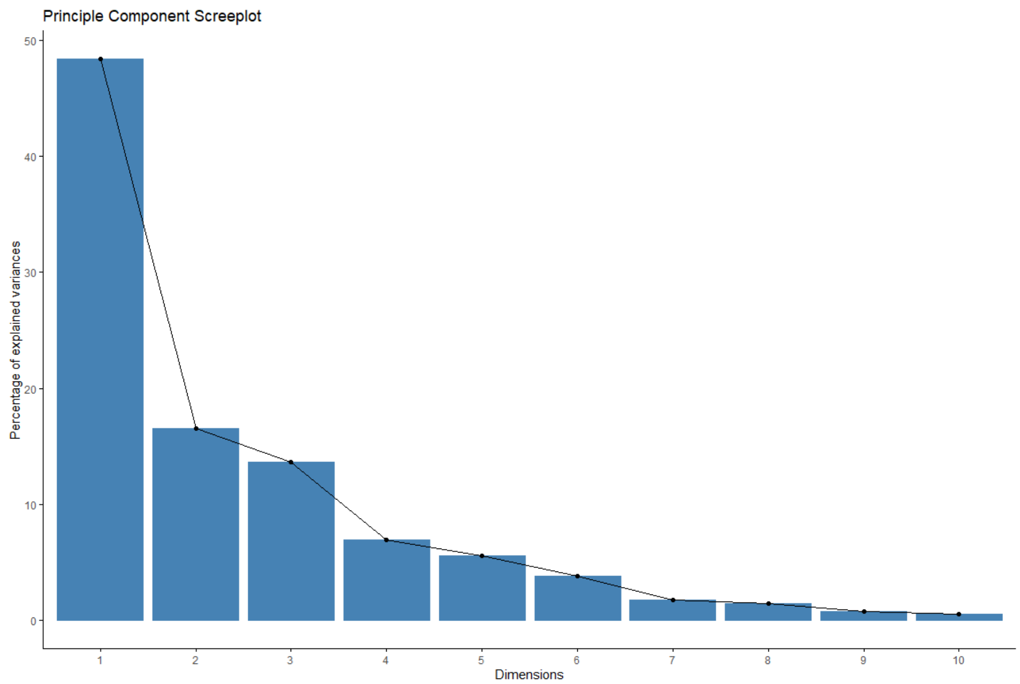

Figure 9: PCA Scree Plot identifying the first 3 dimensions which explain 78.58% of dataset variance thus retained for the Peat Health Index Minimum Dataset. Analysis of 13 indicators across 32 sites, showing the Principal Component dimensions against the percentage of variance explained by each.

The final minimum dataset (chosen using PCA) for peat soil health was cation exchange capacity, VESS, pH, and microbial activity. The resulting Additive and Weighted PHIs are shown in Equation 6 and Equation 7, respectively and used hereafter to infer peat health:

Equation 6: $PHI = \left(\frac{if\ pH > 6.5\ \left(\frac{6.5}{pH}\right)}{if\ pH < 6.5\ \left(\frac{pH}{6.5}\right)}\right) + \left(\frac{CEC}{58.6}\right) + \left(\frac{102}{SB}\right) + \left(\frac{1}{VESS}\right)$

Equation 7: $PHI = \left(\frac{if\ pH > 6.5\ \left(\frac{6.5}{pH}\right)}{if\ pH < 6.5\ \left(\frac{pH}{6.5}\right)} \times 0.174\right) + \left(\frac{CEC}{58.6} \times 0.616\right) + \left(\frac{102}{MA} \times 0.174\right) + \left(\frac{1}{VESS} \times 0.210\right)$

Where pH = pH (pH units), CEC = Cation Exchange Capacity (meq/100g), MA = Microbial Activity (CO_2-C ppm), and VESS = Visual Evaluation of Soil Structure score.

The linear scoring approach used in identifying health is highly dependent upon the variability of each original observation. The dataset was examined for skewness since skew can affect the scoring as each score is relative to the highest (or lowest) value observed during the index creation. Skewness was assessed through analysing the degree of asymmetry of the distribution through dividing the observation (minus the mean) by the standard deviation of the property. Furthermore, outliers were examined. Outliers were considered those values observed outside Quartile 1 - 1.5 times the Inter

Quartile Range or Quartile 3 +1.5 times the Inter-Quartile Range. This was achieved using the Minitab programme (Minitab LLC, 2021). pH, cation exchange capacity, and VESS displayed symmetrical skew (between -0.5 and 0.5 respectively) and microbial activity showed a moderate positive skew (0.82). No values within the dataset were considered outlier. As such, all datapoints were retained for combination into the health index.

The resulting Additive and Weighted PHIs for the eight fields (four sites within each field) are displayed in Figure 10. Scores from the Weighted and Additive system of scoring were highly correlated with one another ($r=0.85$, $p<0.05$). Figure 10 displays that the Weighted Index was able to identify between Shallow and Wasted sites (i.e. that the Shallow points scored higher outputs) in comparison to the Additive Index. Weighted PHI scores were linearly correlated with higher organic matter content, porosity, water holding capacity ($r = 0.86$ $p<0.01$, $r= 0.83$ $p<0.01$, $r= 0.89$ $p<0.01$) and lower bulk density ($r = -0.83$ $p<0.01$) with higher correlation coefficients than the Additive PHI.

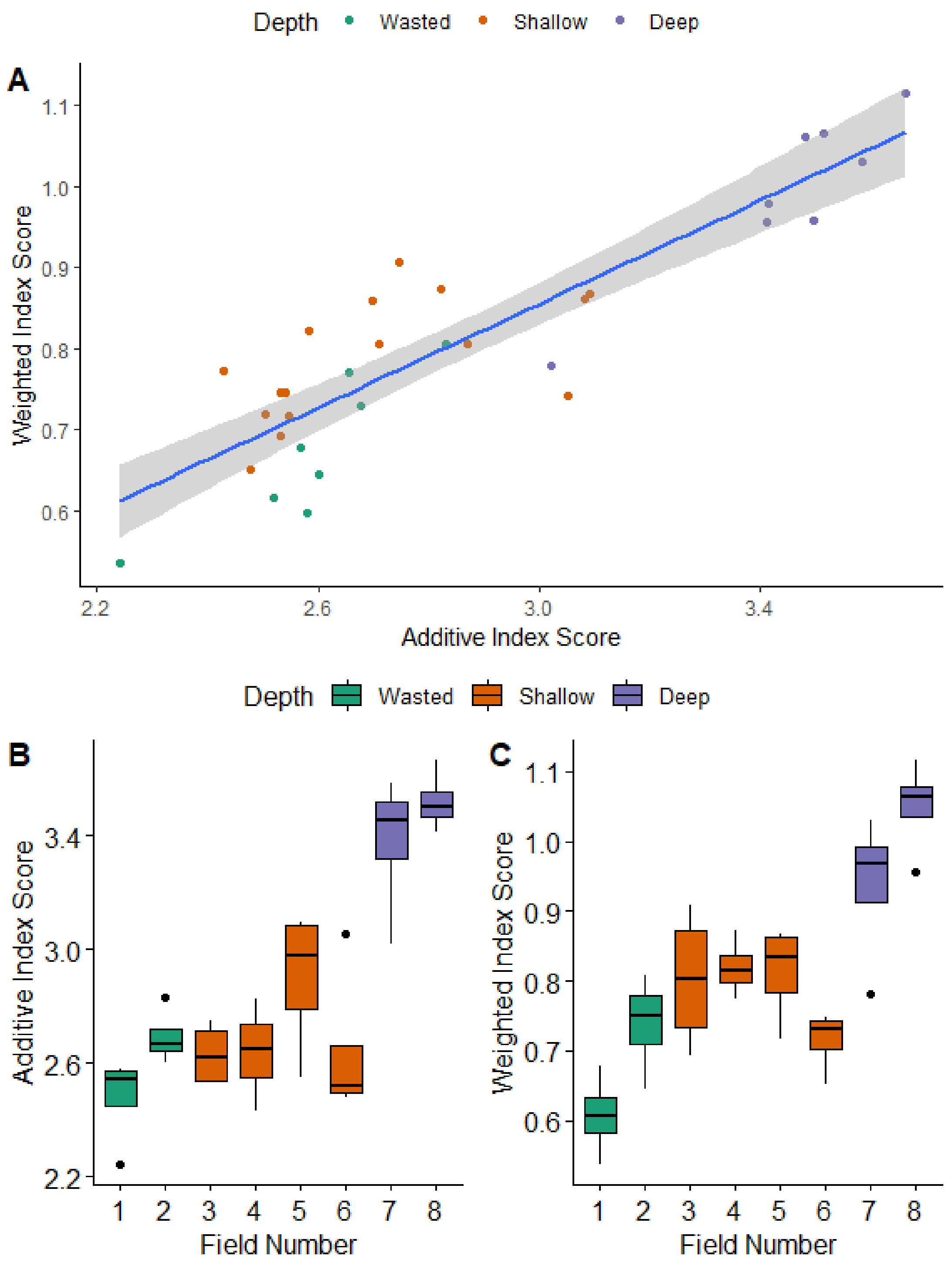

Figure 10: PHI scores increased with depth of peat, with the Weighted Index being more effective at distinguishing Shallow and Wasted sites. A) Scatterplot displaying the higher peat health scoring of Deep sites in comparison to Shallow and Wasted sites and the correlation between Weighted and Additive PHI scoring outputs with Regression line ($r=0.85$, $p<0.05$) and 95% confidence interval (grey shading), B-C) Boxplots of associated Index scores of Additive and Weighted PHI Scores identifying the differentiation of Wasted, Shallow and Deep sites for the Additive and Weighted indexes respectively.

Using the 25th, 50th and 75th percentile, the PHI scores can be assigned to “Poor”, “Below Average”, “Above Average” and “Good” descriptions of peat health, following Bastida et al., 2006. These numerical divisions are displayed in Table 4 and can be applied to other drained peat soils under agricultural land management beyond the fields included within the study dataset so that “Peat Health” classifications can be applied across other fields in the landscape (see chapter 4).

Table 4: Peat Health subjective classifications established using the 25th, 50th and 75th quartiles of the Additive and Weighted PHI scores, to allow farmers to establish and compare fields.

Health classification	Additive Score Range	Fields	Weighted Score Range	Fields
Poor	< 2.583	(P59, Wills)	< 0.715	(P59, Wills)
Below Average	2.584 - 2.638	(P62, Spooners 7)	0.716 - 0.801	(P62, Creeks)
Above Average	2.639 - 2.952	(Spooners 6, Creeks)	0.802 - 0.843	(Spooners 6, Spooners 7)
Good	> 2.953	(Tilehouse, Howes)	> 0.844	(Tilehouse, Howes)

The relative contribution to each indicator to the final index score can be seen in Table 5. On average the order of contribution of individual indicators for the Additive PHI score was pH (23.01%), microbial activity (17.48%), cation exchange capacity (16.51%) and VESS (13.29%). In comparison, the relative order of contribution of individual indicators to the Weighted PHI score was cation exchange capacity (34.65%), pH (13.64%), microbial activity (10.36%) and VESS (9.51%). Weighting the indicators by the percentage of variance significantly increased the influence of cation exchange capacity whilst reducing the contribution of all other MDS indicators towards the final index scores.

Table 5: Displaying the individual contribution (%) of each indicator selected for the index creation relative to the Additive and Weighted PHI final scoring. CEC was the dominant contributor for the Weighted Index, whereas each indicator contribution was uniform for the Additive Index.

	pH	**Cation exchange capacity**	**Microbial Activity**	**Visual Evaluation of Soil Structure**
Additive PHI	21.17 – 24.81%	9.16 – 22.71%	12.99 – 22.32%	6.76 – 25.00%
Weighted PHI	12.55 – 14.71%	19.29 – 47.67%	7.70 – 13.23%	4.83 – 17.89 %

We observed several significant correlations between the Weighted and Additive PHI scores and soil properties in the overall dataset (Table 6). Weighted PHI scores commonly observed stronger correlations with measured properties than the Additive PHI. Microbial activity and pH, which were both used in creation of the Index, showed weak linear correlations with both Index scores. Strong correlations were displayed between Index scores and organic matter content, bulk density, porosity, and water holding capacity. The method of selection of MDS indicators involved the reduction of chosen variables through correlation analysis. As such, the aforementioned properties were removed under PC1 and represented by cation exchange capacity which displayed strong correlation with them.

Table 6: Identifying Spearman rank correlation coefficients between soil properties measured and PHI scoring results. Stronger correlation values were observed with the Weighted index and measures soil properties including those traditionally associated with less degraded peat soils. Values in Bold represent a strong correlation. * indicates a p-value below 0.05

Soil Property	Additive PHI	Weighted PHI
pH	0.26	0.25
Extractable Phosphorus	-0.13	-0.34
Extractable Potassium	-0.17	-0.05
Extractable Magnesium	**-0.52***	-0.24
Soil Organic Matter	**0.57***	**0.86***
Microbial Activity	-0.04	0.20
Sand	0.05	-0.35
Silt	0.23	**0.60***
Clay	-0.02	0.28
Cation Exchange Capacity	**0.56***	**0.89***
Bulk Density	**-0.59***	**-0.83***
Porosity	**0.59***	**0.83***
Available Nitrogen	0.35*	0.25
Water Holding Capacity	**0.63***	**0.89***
Visual Evaluation of Soil Structure	**-0.83***	**-0.59***
Exchangeable Calcium	0.10	-0.05
Exchangeable Copper	0.25	0.19
Exchangeable Iron	**0.52***	**0.58***
Exchangeable Potassium	0.25	0.48
Exchangeable Magnesium	-0.14	0.27
Exchangeable Nickel	0.12	0.15
Exchangeable Zinc	0.13	0.02

Other measures soil properties measured were not linearly correlated with PHI scores. Exchangeable nutrients showed generally poor correlations with Index scores, yet as already noted, exchangeable nutrients were generally below detection limits of the ICP-OES. Texture content was uncorrelated (expect for Silt and the Weighted PHI) with the Index scores, although deeper soils contained similar texture composition (see Appendix: Supplementary information 1).

3.3.2 Evaluation of the Peat Health Index (PHI) using Farm KPIs

Scores created through the Additive and Weighted PHIs were compared with a range of farm KPIs including yields, inorganic nutrient applications, and pest management products. The spearman rank correlation coefficients between index scores and management operations are displayed below (Table 7).

Table 7: Table of Spearman rank correlation coefficient between Additive and Weighted PHI scores and management operations. Strong correlation indicates a functioning system that requires reduced inputs to produce a productive crop. * indicates a p-value below 0.05

	Percentage Heads (%)	**Total N (kg/ha)**	**Total P (kg/ha)**	**Total NPK (kg/ha)**
Additive PHI Score	0.71	-0.74*	-0.69	-0.74*
Weighted PHI Score	0.64	-0.48	-0.45	-0.48
	Trace Elements (kg/ha)	**Organic Manure (kg/ha)**	**Herbicides (kg/ha)**	**Fungicides (kg/ha)**
Additive PHI Score	-0.4	-0.57	-0.17	-0.55
Weighted PHI Score	-0.36	-0.3	0.17	-0.42
	Insecticides (kg/ha)	**Adjuvants (kg/ha)**	**Pesticides (kg/ha)**	
Additive PHI Score	0.49	-0.19	-0.31	
Weighted PHI Score	0.43	-0.13	-0.02	

Total Nitrogen, Total Phosphorus and Total NPK applied to the field throughout the entire growing season was strongly correlated with Additive PHI scores. The Weighted PHI scores had weaker correlations with Total Nitrogen, Total Phosphorus and Total NPK and these relationships were not significant. Furthermore, Additive PHI scores were strongly negatively (albeit not significantly) correlated with total Fungicide application through the entire growing season. The PHI scores were also compared with the lettuce yield of the crop in that growing season. Whilst all fields contained lettuce crop, two varieties were grown, Iceberg and Gem lettuce. During the growing season studied, one field (P62: Wasted site) was badly affected by lettuce head soft rot, reducing Iceberg heads harvested to 50% of those transplanted, as such, this field was removed from analysis. When observing the total percentage of heads harvested combining both Iceberg and Gem, a strong positive correlation was observed with both the Additive and Weighted PHI scores, although neither of these were statistically significant. In comparison, the percentage of heads harvested was negatively correlated with Total NPK ($r=-0.82$, $p > 0.05$), Trace Elements ($r=-0.61$, $p > 0.05$), and Organic Manure ($r = -0.78$, $p = 0.05$) additions.

3.4 Discussion

The Weighted PHI created in this study allows us to effectively distinguish between Deep peat and Wasted peat on commercially managed agricultural fields in the lowland fen region of East Anglia. The PHI created can be used to establish a scoring system for farmers and land managers to assess the health of their peat soils, identifying degraded sites where remediation is required. This study confirmed that use of the PCA index creation method (Andrews, Karlen and Mitchell, 2002b) could be successfully applied to peat soils to identify the health and functioning of the system given observable and interpretable soil properties. The development of quantitative divisions of peat health following the steps set out in Bastida et al., (2006) will permit the comparison of peats outside the selected study sites, and thus provide a useful management tool for farmers.

3.4.1 Peat Health Index (PHI)

As peatlands degrade, their properties begin to mimic those of mineral soils. This peatland degradation transition has been described as the "moorsh forming process" (Wallor, Rosskopf and Zeitz, 2018). The use of soil health indices non-specific to peat soils are inadequate to assess the health of drained peatlands (Environment Agency, 2019). Existing available soil health indicators are inadequate to map the health of lowland peats as many are designed for mineral soils, with peat sites achieving high soil health scores despite farm knowledge recognising the site as degraded. This study created two indexes, Additive and Weighted, that identify peat degradation gradient.

The Weighted PHI effectively distinguished a gradient of degradation across fields in the study site when viewed in the scope of all the properties assessed in the dataset. The Weighted PHI displayed stronger correlations with more properties indicative of a functioning peat system, compared to the Additive PHI. It is well established that the hydro-physiological profile of peats alters across a degradation gradient. Compaction and loss of organic matter following peat drainage alters pore geometry, water and air flow characteristics, accessibility of plant roots to nutrients and increases in Bulk Density (Gupta, Sharma and DeFranchi, 1989; Wells and Williams, 1996; Minkkinen and Laine, 2011; Mustamo *et al.*, 2016; Rezanezhad *et al.*, 2016). Sites with higher Weighted PHI scores were strongly positively correlated with organic matter, water holding capacity, and porosity, and negatively correlated with bulk density. These correlations were expected because weighting of the index increased the influence that cation exchange capacity had on the PHI and this was highly correlated with these indicators since they all contribute to the variance explained by PC1. In comparison the Additive PHI displayed correlation with management operations that farmers can use to understand the impact of a healthier peat on crop production.

3.4.2 Peat Health Index and KPIs

A healthy functioning soil is more likely to have a higher natural productivity, requiring fewer external inputs to maintain sustainable production. The Additive PHI created through this study displayed a strong negative relationship with external inorganic nutrient inputs (i.e., higher scored fields had lower inputs). However, these operations are influenced by environmental, societal, and economic factors, which must be kept in mind when using these to assess the performance of a PHI. The application of inorganic fertilisers aims to improve economic returns through optimising yields, yet over reliance can lead to lowering of pH, accumulation of NH_4^+, increased pollution and the loss of carbon (Ozlu and Kumar, 2018). Sites that require higher external input of nutrients may be an indication that the nutrient cycling function of a peat is not operating as desired. The Additive PHI indicates that healthier peat requires fewer nutrient inputs to grow a commercially viable crop, and thus, implies a better functioning soil. The indices use cation exchange capacity as part of the minimum dataset, and the main exchange sites for nutrients in peat soils are the acidic functional groups of organic matter (Huat *et al.*, 2011), as opposed to clay exchange sites which dominate in mineral soils (Parfitt, Giltrap and Whitton, 1995). The Additive PHI identifies that a site with higher cation exchange capacity (which was correlated organic matter) increases the ability of the peat to retain nutrients, reducing nutrient loss, and increasing nutrient use efficiency. Furthermore, the role of organic matter in catalysing crop resource capture through mineralisation and root development opportunities is well established (King *et al.*, 2020). It should be noted that peat health is not the only factor influencing the rate of fertiliser applications. External factors (e.g., commercial guidelines) also influence fertiliser application rates, regardless of peat health. These external factors can result in farmers and land managers inputting different quantities of foliar applications over the growing season to increase crop yield where necessary. Peatlands are large stores of mineralisable nutrients (due to the presence of high quantities of organic matter) with complex structures that allow for root developments, which is captured in the PHI scores.

The Additive PHI was negatively correlated with total fungicide applications and total pesticide applications and weakly positively correlated with insecticide applications (although no significance was observed). The function of fungicides is directed against the survival of parasitic fungi growths where natural controls have been exceeded. Biological suppression results from biotic and abiotic factors, such as increased total microbial biomass, which results in a low level protection against multiple pathogens due to competition for resources among other factors (Schlatter *et al.*, 2017; van Agtmaal *et al.*, 2018; Bongiorno *et al.*, 2019; Palojärvi *et al.*, 2020). Pathogen suppression is a natural functioning of peat systems where pathogens increase is related to disturbances in the balance between functional microbial groups in soils (Gil and Gil, 2011). A site which requires lower pesticide inputs indicates a soil biotic system which is more adept at controlling pathogens in the peat, therefore a system with increased capacity to continue to function. Despite this, the Additive PHI scores were not significantly correlated with microbial activity, which was observed to be lower in the Deep and Wasted peat than the Shallow sites. The method for assessing microbial activity is highly influenced by accumulated osmolytes (low molecular weight organic compounds) following drought conditions (Warren, 2014) in addition to disturbance of the microbial habitat. These conditions may limit the effectiveness of measured microbial activity to be related to pathogen suppression.

3.5 Conclusion

Current indices designed to assess the health of mineral soils are unsuitable to assess the health and degradation status of drained agricultural lowland peat soils. Therefore, new indices that are suited to specific soil types, that differ substantially in formation and functioning from mineral soils, are required to assess the health of lowland peat soils, such as those found on the East Anglian fenlands in the UK. We created a Weighted PHI scoring system that can effectively distinguish relatively healthy peat soils from wasted peat using a minimum dataset consisting of four soil properties (cation exchange capacity, pH, microbial activity, and VESS). Two indices were created, where one index weighted the influence of these properties (Weighted Index) and the other summed them (Additive PHI). Both PHIs correlated strongly with peat properties traditionally associated with peat health, such as organic matter content, bulk density, and water holding capacity. Whilst weighting affected the order in which fields were ranked, Additive PHI scores were more strongly correlated with farm key performance indicators. Both indices developed can be applied to peat fields in the East Anglia region and provide a protocol for assessing the health of drained peatlands. The use of a minimum dataset to observe the relative functioning of peat provides a valuable tool for famers and land managers to identify degraded sites and thus informing decision makers where interventions are best targeted.

Chapter 4: Evaluation and validation of a soil health index for assessing lowland drained agricultural peatland soils

Abstract:

Peatlands are complex ecosystems that provide a range of ecosystem services underpinned by various functions and processes. However, drainage of peatlands for intensive agricultural exploitation leads to the degradation of these ecosystems. Indices to quantify the health and functioning soils usually focus on mineral soils. In prior work (Chapter 3) we established a Peat Health Index (PHI) for lowland soils within the UK East Anglia Fen region by using Principal Component Analysis (PCA) to derive a minimum suite of indicators that included biological, chemical, and physical soil properties. Here we evaluate and validate this index by returning to the same fields where data was collected to create the index and visiting additional fields to quantify temporal and spatial variance and to compare index scores with farmer perceptions and key performance indicators (KPIs). The PHI required modification to improve the reproducibility of the index. Available nitrogen was removed from the minimum suite of indicators due to its fluctuating nature. Our final validated suite of indicators comprised cation exchange capacity, microbial activity, pH, and visual evaluation of soil structure. PHI scores were well correlated with farmer rankings of soil health and KPIs (fertiliser use and pesticide use), revealing that healthier peat soils require fewer external inputs and are thus more capable of supporting sustainable crop production. The results demonstrate the applicability of the PHI to distinguish fields and inform land management decisions.

4.1 Introduction

The continued degradation of agroecosystems is a major threat to food security and the sustainability of agricultural practices (Kibblewhite, Ritz and Swift, 2008). Peat soils are fertile, well structured, high organic matter ecosystems storing vast quantities of carbon. Globally, peatlands are estimated to contain 30% of all land-stored carbon whilst covering only 3% of land (Joosten, Tapio-Bistrom and Tol, 2012). Peatlands are, however, fragile to anthropogenic disturbances, particularly intensive agricultural practices where drainage leads to a net positive emission of greenhouse gases (Parish *et al.*, 2008; Buschmann *et al.*, 2020). Agricultural management operations including tillage, inorganic fertiliser additions, water table lowering, and increasing soil pH deplete the health of peatland ecosystems. This depletion results in the loss of stabilised carbon (Säurich *et al.*, 2019), a reduction in biodiversity (Littlewood *et al.*, 2010), and negative transformation of the peat structure through subsidence and compaction (Zeitz and Velty, 2002; C Kechavarzi, Dawson and Leeds-Harrison, 2010).

As peatlands are degraded, the delivery of ecosystem functions and services is downgraded (Westman and Laiho, 2003; Holden, Chapman and Labadz, 2004; Andersen, Chapman and Artz, 2013). Sustainable management of peatlands requires tools that allow famers and land managers to map functioning across the landscape and target interventions (Andrews and Carroll, 2001). Current soil health indices are ineffective at mapping the health of peatlands since they were developed for mineral soils. In prior work (see chapter 3) we created a Peat Health Index (PHI) that could map the health of the peat agroecosystem using a minimum suite of indicators that distinguished a deep healthy peat field from a wasted unhealthy peat field.

A good soil health index should be able to map peat health accurately across temporal and spatial variations. Indicators should be reliable, reproduceable, adequately sensitive to spatial and temporal variation, and sensitive to changes in management (Bünemann *et al.*, 2018). Previously developed indices of soil health have generally been developed by analysing samples collected at a single point in time. As such, the resulting indices do not assess temporal variations or the reliability and reproducibility of index scoring (Vasu, Singh, *et al.*, 2016; Biswas *et al.*, 2017; Raina and Das, 2017; Frost *et al.*, 2019). Our PHI was developed the analysis of samples collected across a single crop during one sampling season. The fields chosen to develop the PHI were carefully selected based on a gradient of “Healthy” to “Unhealthy” peat fields based on farmer perception. Farmers assessments of the health of their fields have been shown to be significantly correlated with measured soil health test scores (O'Neill, Sprunger and Robertson, 2021). However, to evaluate the temporal reproducibility of the PHI a second assessment of peat health on the same eight fields was undertaken. To validate the PHI this assessment was extended to an additional twelve fields not previously sampled and compared with farmer perceptions of soil health and key farm performance indicators. The aim was to determine the ability of the PHI to provide a practical and applicable management tool that was effective at identifying health peat soils across a wider spatial scale and with multiple crops. The objectives were to 1) evaluate the viability of the PHI to monitor peat health consistently over a temporal scale, 2) assess the applicability of the PHI to identify healthy fields in agreement with farmer opinion, and 3) validate the performance of the PHI to assess agricultural value by comparing scores with key farm performance indicators.

We hypothesised that the PHI scoring gradient developed in prior work would be reproduceable over time using the indicators developed in Chapter 3

We hypothesised that a significant correlation between PHI scores and farmer subjective opinion on health status of individual fields would exist

We hypothesised that the health scores from a Peat Health Index (PHI) created with simple indicators will display signification correlation with key farm performance indicators.

4.2 Method

4.2.1 The study area

The study area comprised fields under the management of G's Fresh Ltd in the East Anglian fens surrounding Ely, Cambridgeshire (52.3576° N, 0.2670° E). The area is intensively cultivated for agricultural and horticultural crop production including lettuce, wheat, maize, potatoes, celery, and a cover crop mixture. The soil receives applications of inorganic and organic fertilisers at rates recommended by the AHDB Nutrient Management Guide (RB209) in conjunction with farmer knowledge for each specific crop. The weather conditions at the study area, including maximum and minimum temperature and total rainfall, during the study period are displayed in Figure 11.

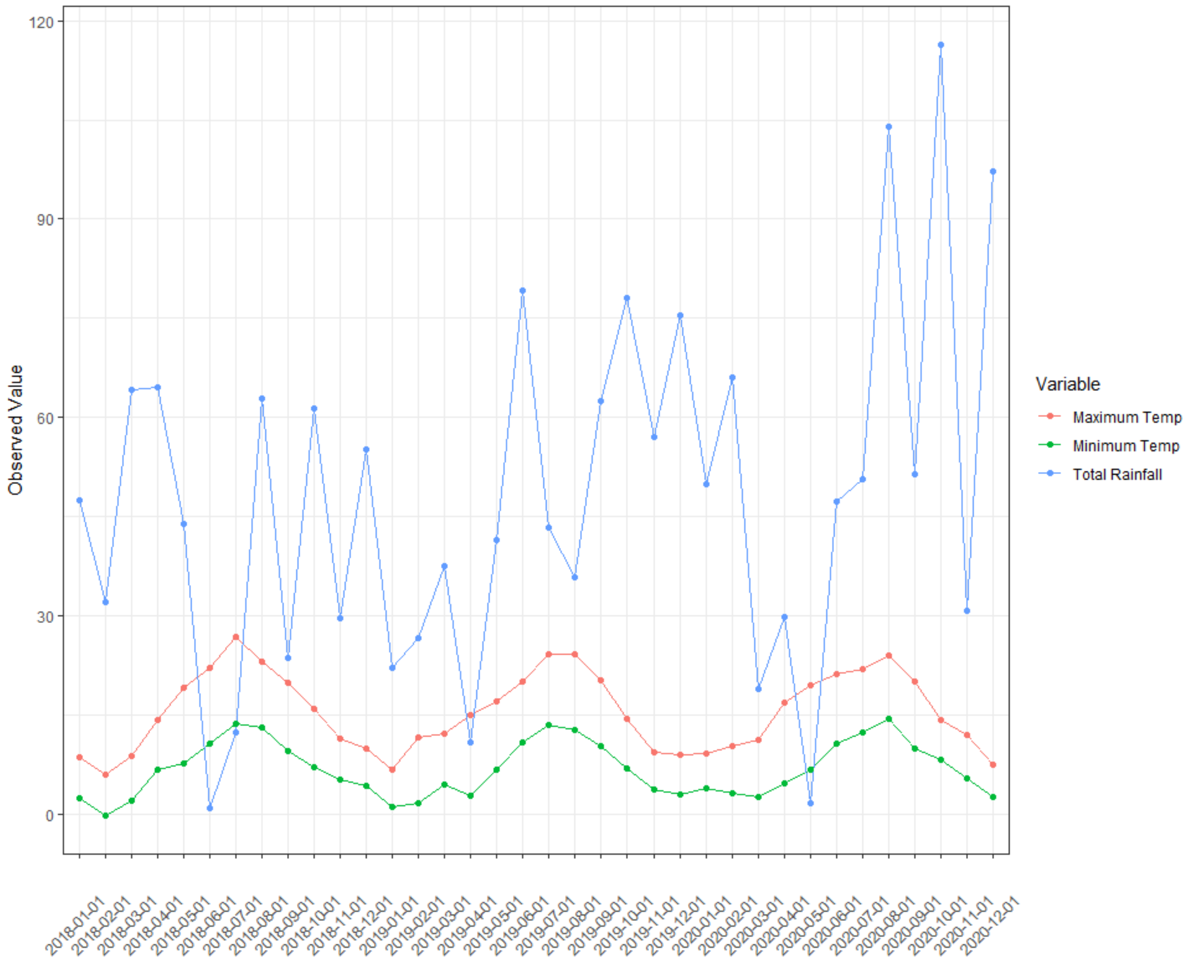

Figure 11: Time series of weather data between January 2018 and December 2020 taken from the local NIAB station. The red line is the monthly maximum temperature (°C), the green line is the monthly minimum temperature (°C), and the blue line is the monthly total rainfall (mm). Temperature remained relatively constant in the cyclic cycle, however, rainfall showed a slight spike just before Winter 2020 sampling.

4.2.2 Sampling

Sample collection was conducted in winter 2020 (January to February). Twenty fields were selected for sampling across four farms to represent a range of peat depths and a representative range of the crops grown across the study area (Table 8). These fields were spatially distributed over a 300km^2 area, at four randomly selected points in each of the field, a Visual Evaluation of Soil Structure (VESS) spade analysis was conducted on undisturbed soil slices (25cm depth, 10cm thickness and 20cm width) (Ball *et al.*, 2007). The extracted block underwent visual examination to observe any differing layers to assign scores separately, where scores would be relative to the depth of layer observed. The extracted block was gently manipulated by hand to reveal any cohesive slabs or clods and form natural aggregates. Results from this process were compared with a visual key attribute score which assigns scores to layers based upon a visual picture, size and strength of aggregates, porosity, root presence and soil colour (visual key accessible from Scotland's Rural College (Cloy, 2021)). The four VESS samples were averaged to create a single score for an entire field. An irregular sampling strategy (W-Shaped) across each field was implemented to obtain soil samples using an auger to a depth of 20cm, sampling at least 15 random points throughout the fields and using the cone and quarter method to create a composite sample. Samples were transported to and stored in a cold room at the University of Reading for analysis within 48 hours.

Table 8: Farm group name, current crop in the ground at time of sampling, and Field Name of study sites across the East Anglia farmed system

Farm	Crop	Field Name
Barway	Wheat	55 Acre
Engine	Iceberg	Bank Farm 2
Plantation	Maize	Creek
Barway	Potatoes	Howes Ground
Barway	Potatoes	Lakes Ground
Barway	Wheat	Nightingale
Redmere	Gem	P16
Redmere	Gem	P17
Redmere	Gem	P30
Redmere	Wheat	p32A
Redmere	Wheat	P32B
Redmere	Wheat	P33B
Redmere	Wheat	P34
Plantation	Maize	Piggery
Barway	Potatoes	Sheeps Ground
Engine	Iceberg	Spooners 1
Engine	Maize	Spooners 6
Engine	Maize	Spooners 7
Barway	Maize	Tilehouse
Plantation	Maize	Wills

4.2.3 Laboratory Analysis

Soil samples collected using an auger were divided into two sub-samples at University of Reading, whereupon half was air dried at <30 °C and sieved with a 2 mm screen and the other half was sieved moist to 4 mm, stored at 4 °C, and analysed within 48 hours. The moisture content of the moist samples was determined by weighing, drying in an oven at 105°C overnight, and reweighing. Microbial activity was determined using the Solvita Burst method by moistening a soil sample with deionised water to achieve 50% of the water holding capacity, leading to a flush of CO_2 produced which was measured colorimetrically with a Solvita^{TM} digital colour reader (Woods End Labratories, 2013). Ammonium and nitrate concentrations in the samples were determined on moist soil by extracting with 1M Potassium Chloride and analysing colorimetrically using a Skalar Continuous Flow Analyser. Ammonium and nitrate concentrations were summed to determine available nitrogen.

The air-dried soils were subjected to a range of physical and chemical analyses. pH was determined potemtiometically after shaking samples with water at a 1:2.5 (w/v) ratio. Organic Matter (OM) content was analysed on sub-samples dried at 105 ^{o}C by quantifying the mass lost after combustion at 430^{o}C. Cation exchange capacity (CEC) was determined using the compulsive exchange method (Gillman and Sumpter, 1986) using differing molar strengths of barium chloride to displace cations.

4.2.4 Peat Health Index (PHI) application

Soil properties were incorporated into two previously generated PHIs; an Additive and a Weighted PHI (see chapter 3). The Additive PHI was calculated by simply summing the transformed scores (S) for each soil property (p), following Equation 8. The Weighted PHI involved multiplying the transformed scores for each soil property by the overall variance explained by the principal component that the property was drawn from prior to summing for each property, following Equation 9:

Equation 8: $PHI = \left(\frac{if\ pH > 6.5\left(\frac{6.5}{pH}\right)}{if\ pH < 6.5\left(\frac{pH}{6.5}\right)}\right) + \left(\frac{CEC}{58.6}\right) + \left(\frac{102}{SB}\right) + \left(\frac{1}{VESS}\right)$

Equation 9: $PHI = \left(\frac{if\ pH > 6.5\left(\frac{6.5}{pH}\right)}{if\ pH < 6.5\left(\frac{pH}{6.5}\right)} \times 0.174\right) + \left(\frac{CEC}{58.6} \times 0.616\right) + \left(\frac{102}{MA} \times 0.174\right) + \left(\frac{1}{VESS} \times 0.210\right)$

PHI scores classified as 'Very Poor', 'Below Average', 'Above Average', and 'Good' (Table 9) using the 25th, 50th and 75th quartiles, as explained in Chapter 3. These were used to identify degraded fields and enable comparison of the PHIs with key performance indicators.

Table 9: Peat health classification for associated Additive and Weighted PHI scores, replicated from Chapter 3.

Peat health category	Additive PHI Score Range	Weighted PHI Score Range
Very Poor	< 2.583	< 0.715
Below Average	2.584 - 2.638	0.716 - 0.801
Above Average	2.639 - 2.952	0.802 - 0.843
Good	> 2.953	> 0.844

4.2.5 Evaluation of the Peat Health Index (PHI)

Because eight of the twenty fields sampled in winter 2020 had previously been sampled in summer 2018 to develop the indices, the scores obtained during these two sampling campaigns were compared to assess temporal reproducibility, since soil health is not expected to have considerably improved or deteriorated between the two sampling events. The PHI was evaluated by quantifying the reproducibility of the scores and comparing them with farmer's perception of soil health on the fields sampled. Farmers managing the twenty fields were asked to rank them in terms of perceived health and the farmer rankings were compared with the rankings derived from the Additive and Weighted PHIs.

4.2.6 Validation of the Peat Health Index (PHI)

To evaluate the performance of the PHIs as a quantification of peat health that is useful for farm managers making land management decisions, Key Performance Indicators (KPIs) for individual fields, identified by famers, were compared for each field with the Additive and Weighted PHI scores to see if the performance of the fields is predictive of the health of the soil. KPIs were fertiliser rates (N, P, K, and trace elements), pesticide rates (herbicides, fungicides, nematicides, and insecticide), and crop yields (either in tonnes per hectare, or percentage of heads harvested for lettuce crops). Because the units and typical ranges of each KPI is highly dependent on the type of crop being grown, Z scores were calculated for each KPI for each following Equation 10.

Equation 10: $Z = \left(\frac{x - \mu}{\sigma}\right)$

where x is the KPI for the field in question, μ is the average KPI for all the fields growing the same crop as the field in question, and σ is the standard deviation of the KPI for all the fields growing the crop. Positive Z scores indicate that the KPI value is higher than average, and negative Z scores indicate that the KPI value is lower than average. Heathier fields are expected to require lower fertiliser and pesticide rates and deliver higher crop yields.

4.2.7 Statistical Analysis

Datasets was statistically analysed using R 4.0.2 (R Core Team, 2020) and figures produces using the ggplot2 package (Wickham, 2016). The datasets consisted of (1) eight fields sampled across two differing years (Summer 2018 and Winter 2020) in a 300km^2 region of East Anglia and (2) a dataset consisting of 20 fields (including 8 from the prior mentioned dataset) in the 300km^2 region of East Anglia. Pearson correlation analysis between; (i) PHI scores determined on samples collected across the eight fields in summer 2018 and on samples collected in winter 2020 in order to assess the reproducibility of the index, (ii) Farmer subjective rankings and PHI rankings of the twenty fields sampled in Winter 2020 in order to assess the ability of the PHI to , and (iii) PHI scores and Z scores of KPIs from the twenty fields sampled in winter 2020 to identify the relationship between healthier fields and reduced inputs, were undertaken using the Hmisc Package in R (Harrell Jr, 2021).

4.3 Results

4.3.1 Evaluation of the Peat Health Index (PHI) temporal reproducibility

Scores created using the Additive and Weighted PHI from the analysis of samples collected in summer 2018 (to create the indices) were compared against scores created using the PHIs from the analysis of samples collected in same fields during winter 2020 (secondary sampling) (Figure 12). The PHI scores obtained from the two sampling events were substantially different from each other, with the magnitude and direction of change displayed in Table 10. On average, fields sampled during the second sampling recorded PHI scores that were 33.30% and 16.12% higher than initially observed for the Additive and Weighted methods respectively. Changes to scoring ranged from 50.69% to 14.74% for the Additive PHI and 31.72% to -3.81% for the Weighted PHI which demonstrated a poor reproducibility of the PHI method. Available nitrogen was identified as an indicator with poor reproducibility that contributed negatively to the reproducibility of the PHIs in these three fields. It accounted, on average, 3.79% towards the PHI scores obtained using the summer 2018 dataset, but 25.9% towards the PHI scores obtained using the winter 2020 dataset. The PHI reported in the results section of this paper will be therefore based upon an updated PHI that excludes available nitrogen.

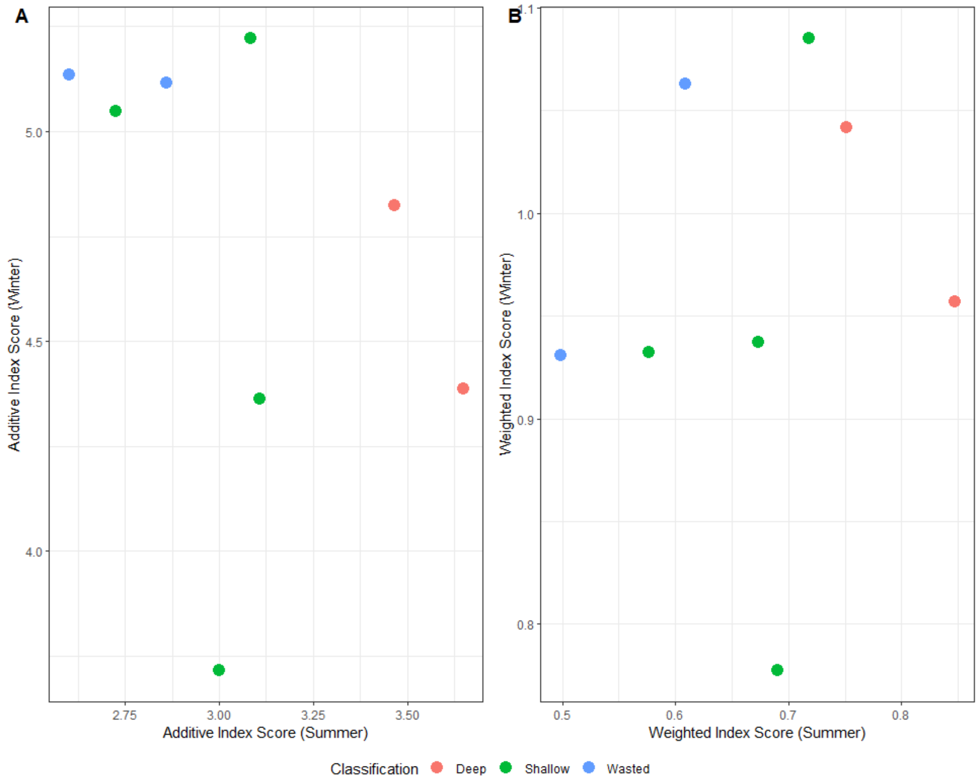

Figure 12: Scatterplot displaying the lack of consistency between Peat Health scoring of identical fields across the two sampling regimes. A) Additive PHI scores generated from analysis of samples collected in summer 2018 and winter 2020 and B) Weighted PHI scores generated from analysis of samples collected in summer 2018 and winter 2020.

Table 10: The magnitude and direction of change of indicators from winter to summer. A positive value would indicate an increase and a negative value a decrease. Microbial Activity and Available Nitrogen displayed the largest changes over the period.

Indicator	P59	P62	Spooners 6	Spooners 7	Creeks	Wills	Tilehouse	Howes
pH	0.71	0.48	0.89	0.22	0.60	-0.39	0.04	0.06
Microbial activity	-29.75	-4.00	-35.75	-51.75	-69.25	-44.00	22.75	0.75
CEC	3.62	14.81	-5.32	3.80	11.54	-3.46	11.50	-2.20
Available nitrogen	-11.88	-8.09	-4.16	-3.77	-6.40	-8.88	-16.44	-14.29
VESS	-0.38	-1.56	-1.00	0.05	2.32	0.18	0.08	0.00

4.3.1.2 The PHI after removal of available nitrogen as a peat health indicator

After the Weighted and Additive PHI scores were calculated without using available nitrogen as an indicator a strong correlation was observed between summer 2018 sampling and the winter 2020 sampling (r=0.70, p-value= 0.05 and r=0.76, p-value=0.02), respectively (Figure 13). The Additive and Weighted PHI scores obtained using the winter 2020 dataset were moderately well correlated with organic matter content (r =0.48 p-value=0.03 and r=0.57 p-value=0.01, respectively). Field P62 was identified as an outlier with scores increasing by 35% between the summer 2018 sampling and winter 2020. This can be explained by the observation of a substantial increase in organic matter content sampled as part of the sampling campaign. After removing P62 from the comparison, the correlation between the Weighted and Additive PHI scores obtained in summer 2018 and winter 2020 increased in strength (r=0.96, p-value= 0.0007 and r=0.94, p-value=0.001, respectively).

Individual indicators contributed varying amounts towards final index scores (Table 11). For both the summer 2018 and winter 2020 Additive PHIs, pH contributed the highest average percentage to scoring, followed by microbial activity, CEC, and then visual evaluation of soil structure. By contrast, for the Weighted PHIs CEC contributed the most towards index scores, followed by pH, microbial activity, and then visual evaluation of soil structure. Therefore, weighting the scores of indicators by the variance explained by the principal component that the property was drawn from increased the influence of CEC on the PHI score and decreased the influence of all other indicators.

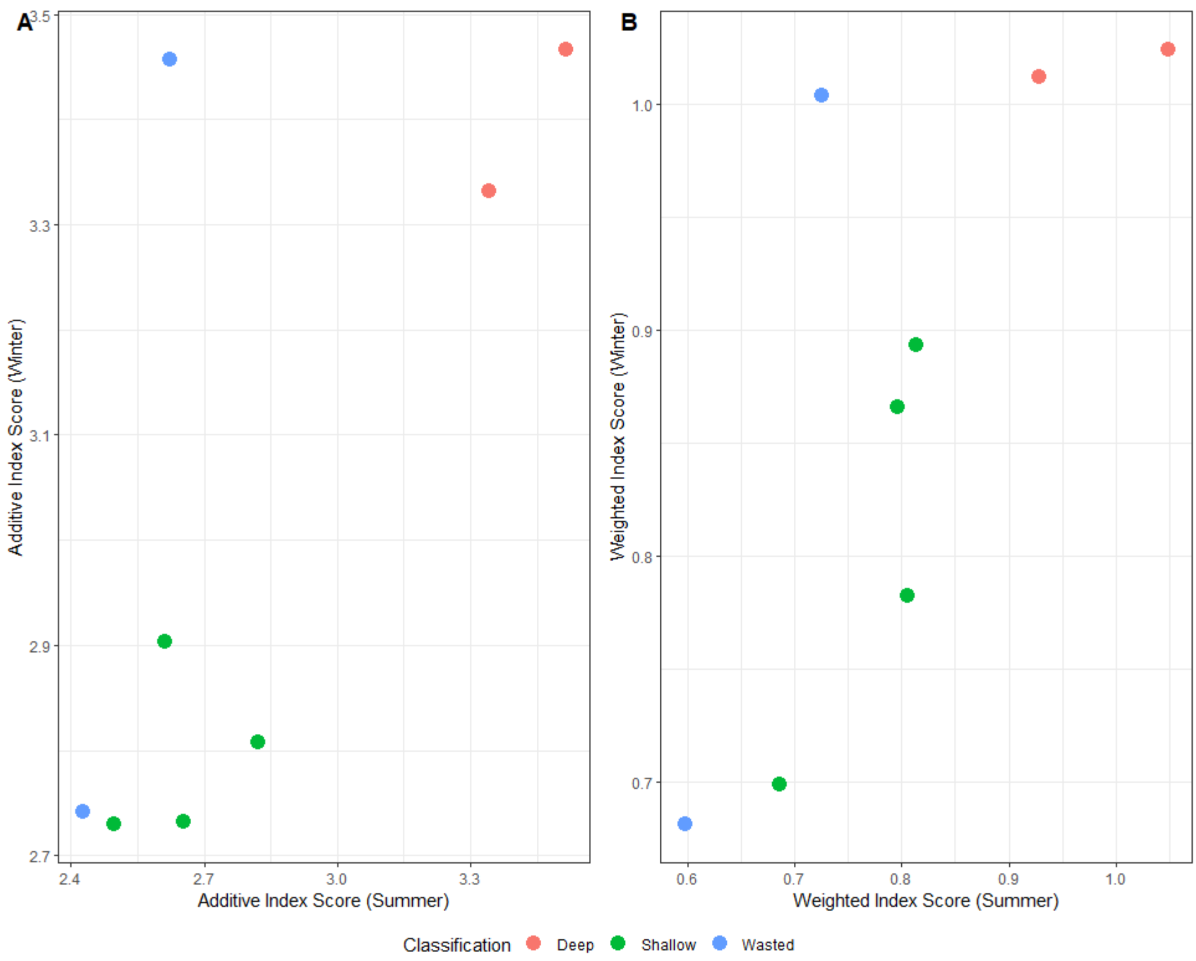

Figure 13: Removal of the AN indicator led to a more consistent output of the PHI. Scatterplot displaying the relationship between A) Additive PHI Scoring over the summer and winter sampling regimes (r=0.96, p-value= 0.0007) and B) Weighted PHI Scoring over the summer and winter sampling regime (r=0.94, p-value=0.001) with available nitrogen Indicator removed.

Table 11: Individual contribution of indicators to the Additive PHI score and Weighted PHI score calculated using datasets derived from the summer 2018 sampling and winter 2020 sampling.

		pH	**CEC**	**Microbial activity**	**Visual evaluation of soil structure**
Summer 2018	Additive PHI	21.17 – 24.81%	9.16 – 22.71%	12.99 – 22.32%	6.76 – 25.00%
	Weighted PHI	12.55 – 14.71%	19.29 – 47.67%	7.70 – 13.23%	4.83 – 17.89 %
Winter 2020	Additive PHI	20.62 – 24.39%	10.74 – 22.67%	18.16 – 24.29%	6.58 – 25.00%
	Weighted PHI	12.23 – 14.47%	22.53 – 47.78%	11.04 – 14.40%	4.71 – 17.89%

The PHI scores derived from the winter 2020 sampling were classed using the classification system provided in Table 4, and the results displayed in Table 12. When compared to the winter 2020 sampling, four of the eight fields previously sampled were classified differently by the Additive PHI, with all four fields classified as healthier in winter 2020 than in summer 2018. The Weighted PHI classification also resulted in a change in peat health classification over time for four fields as well, with three of the four fields classified as healthier and one field as less healthy.

Table 12: Classification of fields using predefined intervals was an unreliable method to assess Peat health. Number of fields classified in each peat health category using the Additive PHI and the Weighted PHI. n=20.

Health Classification	Additive PHI Score	Weighted PHI Score
Very Low	0	2
Below Average	0	2
Above Average	7	2
High	13	14

4.3.2 Evaluation of Peat Health Index (PHI) scores by comparison with farmer perception of soil health

Farmer's perceptions of soil health were used to select the fields sampled in summer 2018 to represent a gradient soil health and create a PHI that can distinguish a healthy peat soil from an unhealthy peat soil. This study looks at whether the developed PHI can be used to successfully identify the health of soils without the prior need for expert opinion. Fields were ranked using the Additive and Weighted PHI's scores from highest to lowest score (1-20) and compared to rankings provided separately by farmers, who ranked the 20 fields from 1 (healthiest) to 20 (least healthy). The PHI score rankings were strongly positively correlated with the farmer ranking of field (Figure 14) for both the Additive ($r=0.63$p-value = 0.002) and Weighted ($r=0.64$ p-value= 0.002) PHI, respectively.

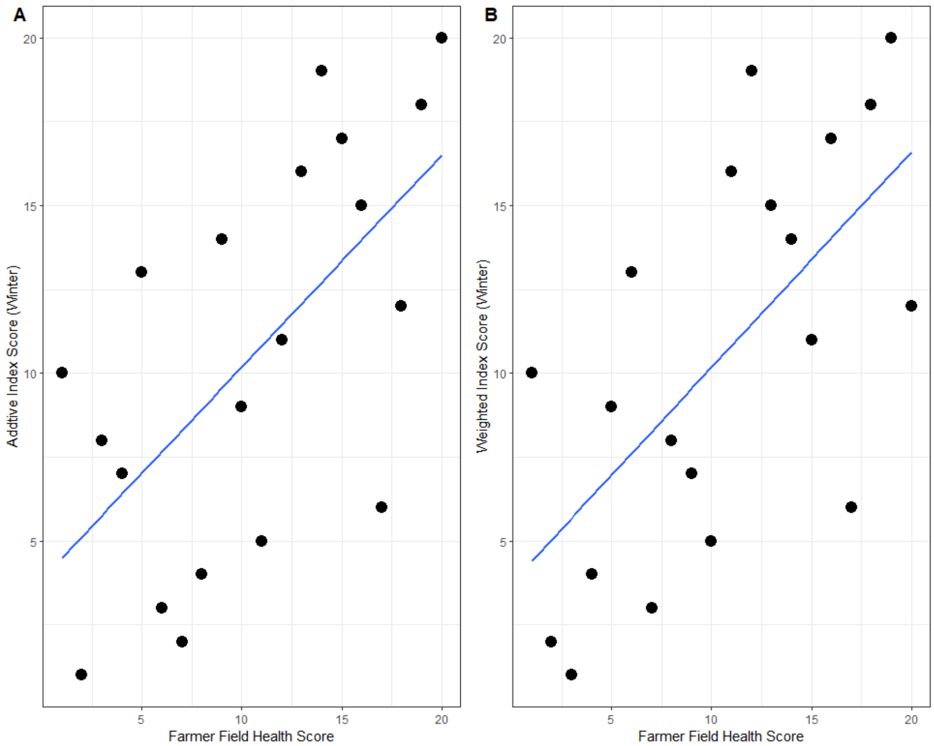

Figure 14: Scatterplot displaying field peat health rankings based on A) Additive PHI scores compared against farmer perception of peat health (r=0.63p-value = 0.002) and B) Weighted PHI scores compared against farmer perception of peat health (r=0.64 p-value= 0.002).

4.3.3 Validation of the PHI by comparing scores with Key farm Performance Indicators (KPIs)

The PHI scores generated with the Additive and Weighted PHI were compared against KPI's comprising fertiliser application rates, pesticide application rates, and crop yields (Figure 15). There were no correlations observed between pesticide application rates or crop yield and PHI scores. However, a negative correlation was found between the fertiliser Z score and both the Weighted and the Additive PHI (Figure 15A and 15B). Fields that have a higher PHI score (and there therefore considered healthier) require lower application rates of fertiliser than fields with a lower PHI score (that are considered less healthy). This correlation was statistically significant ($p < 0.05$) for the Additive PHI.

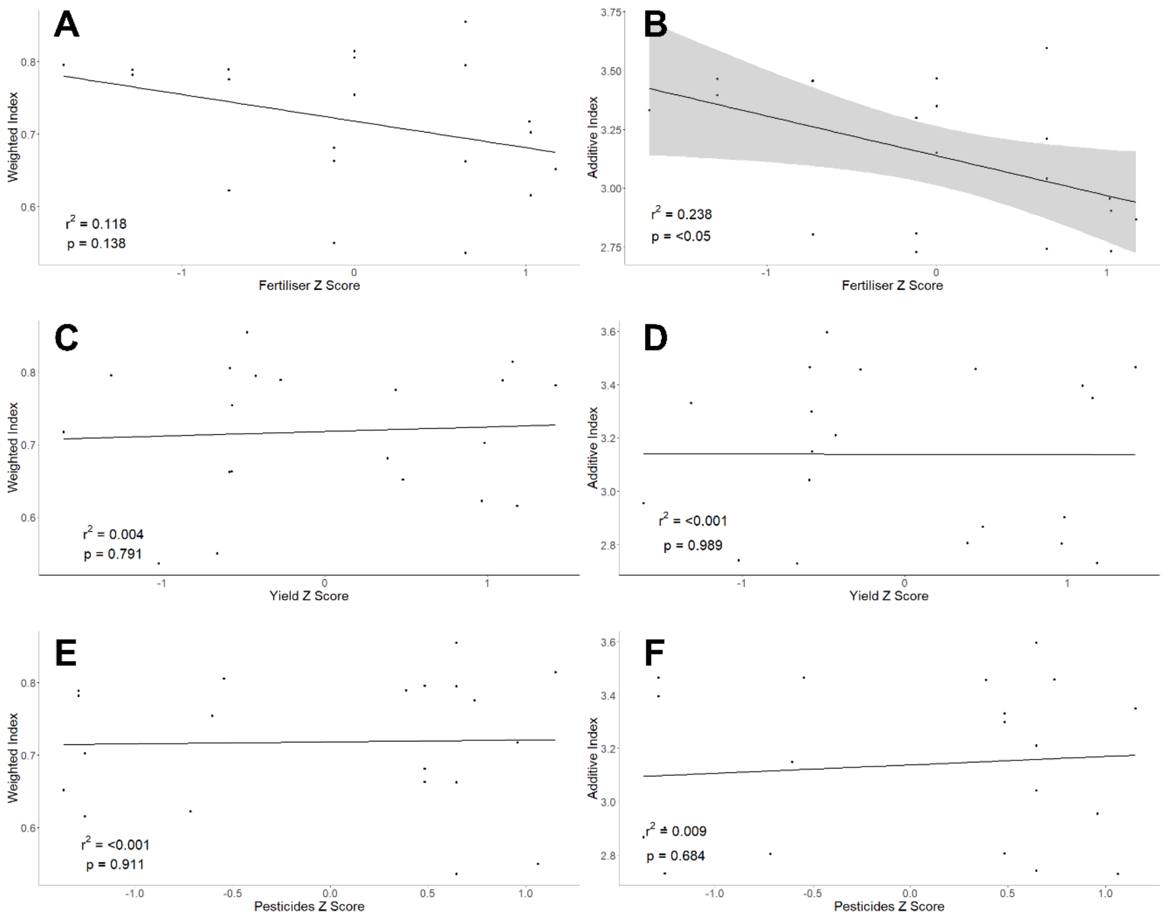

Figure 15: Fertliser applications were negativley correlated with Index scores indicating a healthier fields requires lower inorganic inputs. Scatterplots and regression models displaying relationships between the Weighted (A, C, E) and Additive (B, D, F) PHI and Key Performance Indicators (KPIs) represented by Z-scores for fertiliser rates, pesticide rates, and crop yields for 20 fields managed by G's Fresh growing lettuce (n = 5), maize (n = 6), potatoes (n = 3), and wheat (n = 6).

4.4 Discussion

Findings from this study support the use of a PHI comprising a minimum set of indicators to identify the soil health of peatlands. The reproducibility of the PHI was determined, and the index adjusted to improve reproducibility. The index was evaluated to confirm that it aligned with farmer perceptions of soil health, and the index was validated to confirm its relationship with farm KPIs. Current soil health indices focus upon the assessment of soil health on mineral soils (see Table 2) and are not easily applied to peatlands. This work sought to specifically validate a PHI that was found to be reliable and repeatable and captured the processes and functions that occur within peat soils drained for agriculture. This index has the potential to provide a practical tool for farmers and land managers to quickly and cost effectively identify degraded fields that require attention and to increase the sustainability of agriculture on peatlands.

4.4.1 Reproducibility of the PHI

To be effective, a PHI must contain a robust set of indicators that can differentiate between a healthy well-functioning peat and a wasted peat field. Indicators should be relevant to the system, sensitive to analysis, and reflect the functioning of the system (Cardoso *et al.*, 2013). While sensitivity to changes in land management practices is a pre-requisite for indicator selection, indicators that are too sensitive may lower the effectiveness of an index. Of the indicators used to build the PHI, available nitrogen, as an indicator of peat health, was observed to be too sensitive to temporal changes to be incorporated into the final PHI. Available nitrogen is a transient soil property affected biological, physical, chemical and climatic factors (Powlson, 1993). It was concluded that available nitrogen should be excluded from the PHI because it was not a temporally consistent soil property (i.e., it is heavily influenced by the timing of fertiliser applications, relative to soil sample collection and influenced by rainfall events). In comparison, the other indicators selected maintained relative consistency between the two sampling campaigns and each contributed a similar amount towards the final index scores for both the summer 2018 and winter 2020 sampling campaigns.

Small variations in the different values for individual PHI soil properties between the sampling campaigns may also have been due to the different locations sampled in the fields (i.e., there was no attempt to return to the same locations in the fields). Despite these small differences in individual PHI soil properties between the sampling campaigns, the PHI consistently distinguished the deep healthy peats from the wasted peats. A single field (P62) was identified as an outlier from this general trend. Examining the field location using GIS, multiple roddons (former silt and sand tidal creeks that have become positive topographical features following drainage (D. M. Smith *et al.*, 2010)) existed within this field. Sampling in summer 2018 may have inadvertently included a higher percentage of roddon areas, in comparison to winter 2020, which may have included more low-lying peat samples. This intra-field variability could explain the greater CEC and lower VESS scores observed in this field during winter 2020 (Table 10), which would be indicative of a deeper peat.

4.4.2 Evaluation of the PHI with farmer perceptions of soil health

The PHI was previously created by using farmer's prior perception of soil health across the farms to deliberately select deep, shallow, and wasted peat. Farmer knowledge and assessment of fields has been shown to align with soil health assays (O'Neill, Sprunger and Robertson, 2021). The PHI scored created using the Additive and Weighted PHI correlated well with the farmer's assessments of the health of the agricultural peat fields sampled (Figure 14). Weighting of the indicators used to create the PHI did not substantially alter the degree to which the PHI agreed with farmer perceptions of peat soil health. By confirming the ability of the model to predict farmer perceptions of soil health we have quantified a subjective opinion using accessible and simple suite of soil heath indicators which agree well with farmer knowledge. Farmer derived health rankings were based upon the prior knowledge of the functioning of the field in question. This inherent knowledge of soils is valuable. However, with a high average age of UK farmers and an increasing reliance on tenant farmers, tools that can represent this knowledge may aid land management decisions made by less experienced farmers, or farmers who are unfamiliar with the soils they are cultivating.

4.4.3 Validation of the PHI with farm Key Performance Indicators (KPIs)

A soil health index is only useful if it can effectively be used to guide land management practices. There are several ways in which a PHI index can be used by farmers. They could use it to identify which fields on a farm should receive restorative amendments, they could identify land management practices that have led to some fields being healthier than others, they could plan their crop rotations to ensure that the crops with the highest value are grown on the healthiest soils, or they could plan inputs (e.g., fertilisers and pesticides) based on the nutrient use efficiency of the soils. It is already the case that field-specific land management practices are adopted based on farmer's inherent knowledge of the soil health. For example, fields that are known to have a higher nutrient use efficiency typically receive less fertiliser. Here we validated the PHI by comparing the PHI scores with three farm KPIs: crop yield, fertiliser application rates, and pesticide application rates. We only found a significant correlation between fertiliser application rates and the Additive PHI. Significance is highly effected by sample size and the complexity of the relationship being observed (Thiese, Ronna and Ott, 2016) and due to the nature of the peat ecosystems, correlations observed, while not statistically significant, are also important to discuss.

Yield is a key performance indicator for farmers. Prior work established that the PHIs created were strongly correlated with percentage of lettuce heads harvested (see Chapter 3). The cause of this could not be explained by any individual property of the peat measured. However, the growth and harvest of crops is also influenced by economic drivers separately to peat health that may have led to a suboptimal harvest operation (Allen and Schuster, 2004). For lettuce in particular, different fields are harvested slightly differently to match the specifications of different customers. Furthermore, one field growing maize was severely affected by strong autumn winds which reduced the total yields. Farmers also compensate for poor soil health by applying more inputs (e.g., fertilisers and pesticides) which masks the direct effect of soil health on crop yield. These issues highlight that, while the PHI is capable of distinguishing healthy and unhealthy peat soils, other factors (such as extreme weather, commercial considerations, and field-specific land management decisions) can alter crop yields and mask the impact of soil health. These are likely reasons why no significant relationship was found between PHI scores and crop yields.

The ability of a peat soil to suppress harmful pathogens is governed by the microbial biomass and the diversity of the crop rotation through microbial antagonism, competition for resources, and the reduction in pathogen quantity (Expósito *et al.*, 2017; Schlatter *et al.*, 2017; Peralta *et al.*, 2018). Despite this, sites with higher PHI scores were not consistently displaying decreased requirements for pesticide applications. Fresh fruit and vegetables provide diverse niches for a range of organisms, both beneficial and harmful, which can differ based upon type of produce, agricultural practice or specific geographical area of production (Ramos *et al.*, 2013). This could explain the need for greater pesticide applications on lettuce crops, compared to other crops. Potato and maize crops grown in fields with a higher PHI score showed reduced need for pesticide inputs. This would indicate that under these fields, the suppression of pathogens and the beneficial relationship between soil biota and crops was functioning as intended (Bardgett, 2005). No field was noted to have suffered from any particular instances of pathogen attack or disease outbreak. Therefore, it is likely that much of the pesticide use is prophylactic and that reductions in pesticides application rates could be trialled on fields with higher PHI scores.

A well-functioning peat system supplies the essential macro and micronutrients required for adequate plant growth. The current nutrient management paradigm maintains agricultural ecosystems in a state of nutrient saturation in order to increase nutrient use by crops and increase yields at the expense of environmental degradation through nutrient loss (Drinkwater and Snapp, 2007). The general trend displayed within the work here is that the application of NPK based fertilisers and micronutrients were not positively correlated with higher crop yields. Instead, fields that achieved higher PHI scores showed a reduced requirement for nutrient inputs and achieved comparable yields. A prime example of this situation can be observed amongst the wheat growing fields, where identical management practices were employed following RB209 recommendations to create consistent yields. However, the fields that displayed higher yields were associated with a higher PHI score, thus identifying that nutrient application was not a solution to increasing yields sustainably this relationship was however not statically significant.

The significant negative correlation between fertiliser application rates and the Additive PHI score is an indication that farmers have reduced inputs on fields where the same yield can be obtained with lower inputs. The Additive PHI therefore represents a sensitive index that distinguishes healthy from unhealthy fields and adequately represents farmer's knowledge of peat health. The index could therefore be used to develop field-specific fertiliser application rates where farmer knowledge is lacking or provide an economic value (in terms of fertiliser savings) of peat health.

4.4.4 Use the PHI as a Decision Support Tool

The discretisation of the PHI scores using the subjective classification system (displayed in Table 9) did not reveal variations between subjective groupings and KPIs. The classification system was implemented to provide farmers and land managers an interpretable and comparable classification for each field. The process of discretisation has been found to lead to a loss of information (Jin, Breitbart and Muoh, 2008), despite the simplistically of subjective scoring being shown to be a useful tool (Purakayastha *et al.*, 2019; Chaudhary *et al.*, 2021). The use of continuous data in this context appears to provide a more relevant and interpretable scoring system for comparison with KPIs than the subjective classification. However, the subjective classification provides a simple and effective option for farmers and land managers to differentiate peat soils.

4.5. Conclusion

In this chapter, a previously created PHI was reproduced, evaluated, and validated. Locations previously sampled were returned to after two years and sampling was expanded to a larger number of fields across the study site to evaluate peat health on intensively managed agricultural lowland fens in East Anglia. The initial index contained an unsuitable indicator; the removal of available nitrogen as an indicator led to increased reproducibility of the PHI.

The ability of the PHI to distinguish health and unhealthy peat soils, as identified by farmers, was evaluated using a blind approach. The PHI derived ranking of twenty fields was in good agreement with how farmers ranked their fields, this allows for the quantification of subjective knowledge that has developed over decades of farming experience in the local area. The development of an index that coincides with farmer beliefs has the potential to increase uptake of such an index whilst promoting the sustainable management of lowland agricultural fens.

The correlation of the PHI scores with farm KPIs was used to validate the PHIs. The Additive PHI significantly correlated with fertiliser application rates. This confirms the ability of the index to represent farmer's knowledge of soils and the land management practices that are differently applied on soils with different peat health. The index could be used as a tool to quantify peat health on fields where farmer knowledge is lacking or derive an economic value for peat health.

Chapter 5: Creating the structure of a Bayesian network to evaluate peat health under intensively managed agricultural systems

Abstract

Soil degradation is decreasing the sustainability of agricultural practices on lowland peat systems within the UK. Attempts to model the functioning and health of soil systems has previously focused on mineral soils. Further, traditional frequentist modelling techniques fail to capture the uncertainty associated with ecosystem functions due to lack of empirical data or by failing to account for recent advances in knowledge. Bayesian networks offer promise for quantifying and mapping soil health and functions due to their combined use of expert and empirical data and explicit treatment of uncertainty. We elicited expert knowledge and undertook a literature review to define the structure of a Bayesian network to infer the health of a lowland fen system under intensive agriculture. The network structure created demonstrates that peat health can be inferred, in the most simplistic manner, through the combination of four soil functions: Carbon Respiration, Nitrogen Loss, Peat Structure and Pathogen Suppression. Our results demonstrate that specific indicators are required to understand the functioning and health of the peat system. The structure of the network can be incorporated into a Bayesian network with the introduction of conditional probability tables. We anticipate this network can be applied extensively across lowland peatlands in East Anglia, UK to provide a reliable tool for farmers and land managers to understand the health of their soils. Additionally, due to the ease with which Bayesian networks can be updated, our network is a starting point for the incorporation of more attributes and processes as our knowledge develops and datasets become available.

5.1 Introduction

5.1.1 Soil Ecosystem Modelling

Soil is a complex, variable, living medium which is essential to supporting life on earth, yet it is a non-renewable resource. There has been an increase in the awareness of the multifunctional role of soil systems, as shown by a number of key initiatives and studies, including the Millennial Ecosystem Assessment, The Economics of Ecosystems and Biodiversity, Sustainable Development Goals, and the 25-year Environment Plan (Department for Environment Food and Rural Affairs, 2018a; Wood *et al.*, 2018). Soil systems display both ecosystem multifunctionality and provide multiple services (Manning *et al.*, 2018) as shown in Figure 16. The need to sustain soil multifunctionality is well established (McBratney, Field and Koch, 2014) and is a beneficial lens in which to view soil systems.

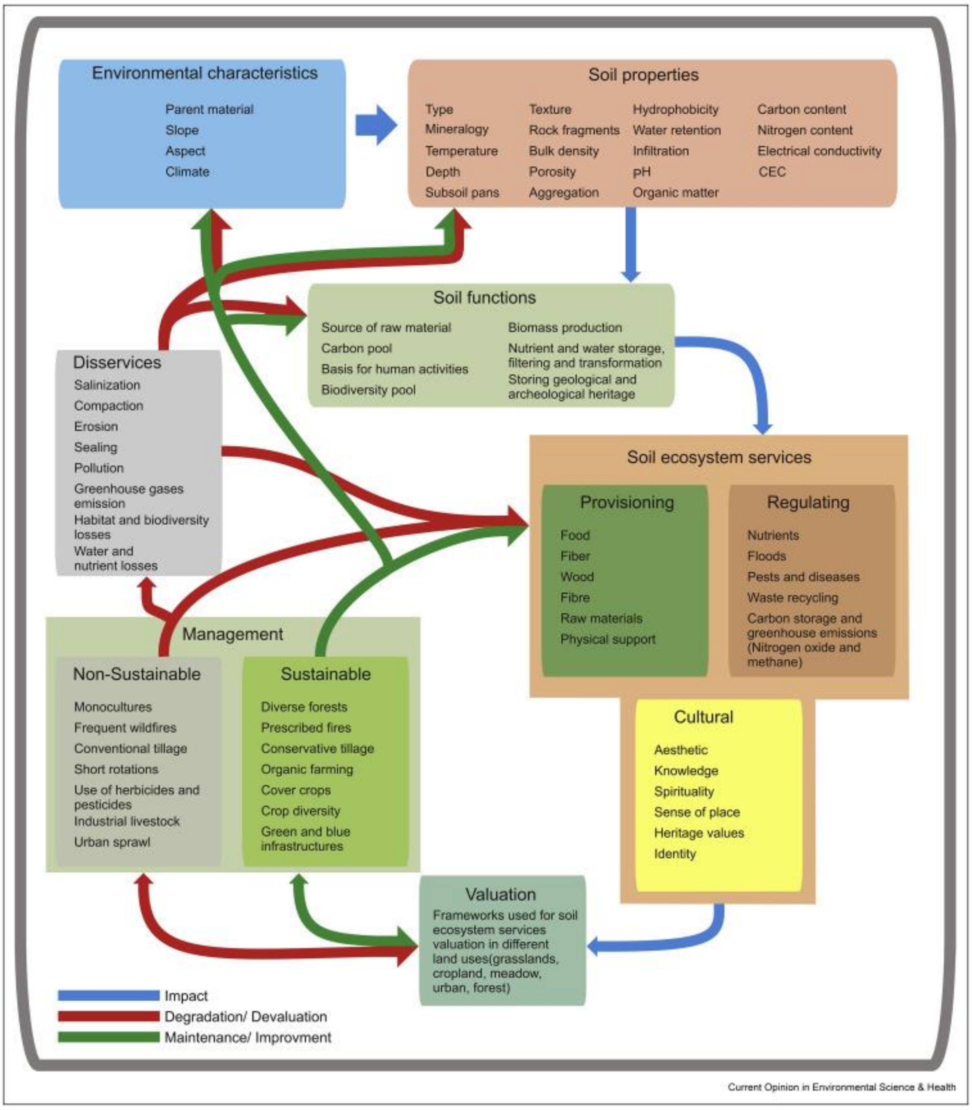

Figure 16: Soil Ecosystem Services and management framework. Reproduced from Pereira et al., 2018.

The ecosystem services paradigm is a conceptual innovation that attempts to categorise and quantify the goods and services that humans receive from ecosystems. This concept is a helpful communication tool, rendering conservation as economically attractive and extending conservation goals beyond protected areas (Hauck *et al.*, 2013). Like other general concepts, the paradigm suffers from limitations and inconsistencies, such as (i) simplifying that we only receive benefits from ecosystems (where in actual fact, disservices may be received or inflicted on systems), (ii) challenges associated with understanding anthropogenically modified systems, (iii) assessment of the ecosystem services themselves, and (iv) the trade-offs and synergies between ecosystem services and how these alter over time and space (Müller and Burkhard, 2012; Hauck *et al.*, 2013; Portman, 2013; Birkhofer *et al.*, 2015; Pereira *et al.*, 2018). However, these limitations can be prevented through careful and considerate planning at policy levels and developments through a transdisciplinary approach (Bouwma *et al.*, 2018; Carmen *et al.*, 2018). The provision of soil ecosystem services is, in part, controlled by the functionality of the soil that, in turn, is linked to the soil properties (Hatfield, Sauer and Cruse, 2017). This cascade is essential in understanding the soil as a dynamic medium, where the complex interaction of biological, chemical, and physical components across temporal and spatial scales controls the ecosystem services and functions delivered. It is apparent therefore that ecosystem functions, and their associated services, are spatially specific to each system in question (Troy and Wilson, 2006). However, ecosystem functioning can be degraded or devalued through anthropogenic activities. It is estimated that degradation of ecosystems has led to a loss of $6.3 trillion per year of ecosystem service value due to impaired ecosystem function (Sutton *et al.*, 2016). Soils are one component of ecosystems which are particularly susceptible to degradation. Soil health considers the capacity to function as a vital living ecosystem; it considers the actual functioning in relation to the potential functioning of the system (Lehmann *et al.*, 2020; Maharjan, Das and Acharya, 2020). The degradation of a system, and the subsequent reduction in the performance of its functions can be seen as a reduction in its health. Classifying and quantifying current soil health against potential soil health is essential to enable the protection and management of soil systems in a sustainable manner. However, soil health and functioning is a complex interaction of properties in non-linear fashion and, as such, requires the development of robust methods and models to facilitate classification and quantification (Adhikari and Hartemink, 2016).

The increased pressures placed upon the soil environment has led to the demand for tools to assess systems functioning (Vogel *et al.*, 2018). These tools attempt to estimate the delivery of functions or services indirectly by identifying key features or indicators; in essence, finding simplicity in complexity

(Wainwright and Mulligan, 2013). There have been multiple attempts to model the delivery of ecosystem functions and services of soil systems across different scales and scopes. Soil biodiversity and habitat provisions have been modelled using proxy-indicator systems across grasslands and cropland (van Leeuwen *et al.*, 2019). Multiple soil function potential versus actual states have been modelled using soil and site attributes in agricultural fields (Vogel *et al.*, 2019). Other modelling techniques have attempted to make use of current soil map and pedo-transfer functions to estimate soil functions and services (Lehmann and Stahr, 2010; Leh *et al.*, 2013). More complex models have additionally been developed. The Soil & Water Assessment Tool uses features of soils to model the impact of runoff, sediment loads, and loss of nutrients over large spatial scales in a systemic manner (Gassman *et al.*, 2007; Francesconi *et al.*, 2016). The Rothamsted carbon model (RothC) models the turnover of organic carbon in non-waterlogged soils, allowing for identification of organic matter decomposition and losses (Coleman and Jenkinson, 1996). Further models have been developed to model multiple functions of the soil system, including carbon and nitrogen dynamics in soils under agricultural and natural land management (Thomas, Bond and Hiscock, 2013; Li *et al.*, 2017; Smith *et al.*, 2019). These tools have generally been developed and applied on mineral soils and are therefore unsuitable for quantifying the health and functioning of organic soils.

Directly quantifying ecosystem functions has proven difficult and advances in our knowledge, such as recent developments in our understanding of carbon storage in soil (Rumpel and Kögel-Knabner, 2011) have caused redundancy where new information has come to light. Seemingly successful attempts to directly model ecosystem functions have, in reality, not taken into account directly measured values; thus invalidating model applicability (Crouzat *et al.*, 2015). In addition to difficulties in directly quantifying ecosystem functions, much research has been based on economic valuation of ecosystem services rather than quantifying their delivery (Logsdon and Chaubey, 2013; Horrocks *et al.*, 2014). Due to the complex nature of soil and our current imperfect understanding, models struggle to conclusively map ecosystem services at different spatial and temporal scales. For example, The Modelling Soil Ecosystem Services (MOSES) model (Aitkenhead *et al.*, 2011), was able to produce better matches with soil functions nearer the surface than at depth due some soil mechanisms and processes not being included in the model. Furthermore, the scale at which one models an ecosystem can affect the model's accuracy (Kuo *et al.*, 1999). Therefore, attempting to directly model ecosystem functioning and services is difficult due to the inherent complexity of environmental systems (Bonan, 2019), the poor measurability of indicators of services and functions, and the limited availability of empirical data (Pérez-Miñana, 2016a). Complex quantitative models have drawbacks including limited model transparency and excessive computation time (Landuyt *et al.*, 2013). Current research has identified that Bayesian networks can become an important framework tool to analyse complex systems and enable those involved in ecosystem management to make informed decisions.

5.1.2 Bayesian networks

It is beyond the scope of this chapter to provide a complete description of Bayesian statistics, but a brief overview is presented below after review of introductory texts (Koller and Friedman, 2009; Kruschke, 2015; Donovan and Mickey, 2019; Kurt, 2019). Bayesian statistics differs from frequentist statistics through the interpretation of probability as the "subjective degree of belief", rather than the frequentist view of the "relative frequency observed during many trials". Probabilities can be marginal, joint, or conditional. Marginal probabilities are unconditional on any other event, joint probabilities indicate the intersection of two or more events, and conditional probabilities indicate the probability of an event given that a second event had occurred. Probability distributions can be calculated through fundamental rules of probability:

$$Pr[A] = Pr[A \cap B_1] + Pr[A \cap B_2] + \cdots + Pr[A \cap B_n] \text{ or}$$

$$Pr[A] = Pr[A \mid B_1]Pr[B_1] + Pr[A \mid B_2]Pr[B_2] + \cdots + Pr[A \mid B_n]P[B_n] \text{ or}$$

$$Pr[A] = Pr[A \mid \mathrm{B}]Pr[B] + Pr[A \mid B^c]P[B^c]$$

$$Pr[A \mid \mathrm{B}] = \frac{Pr[A \cap B]}{\mathrm{Pr}[B]}$$

Equation 11:Laws of probability distributions

Bayes theorem allows us to describe the relationship between two conditional probabilities and, through modification, express how a degree of belief for a given hypothesis can be updated considering new evidence. Inclusion of subjectivity and adoption of Bayesian methods has been shown to allow for calculation of probabilities as the experiment processes and modification and adaption of the experimental plan, and may provide more realistic interpretations of hypotheses testing and analysis of data (Berger *et al.*, 1988). Science is typically required to be objective and devoid of bias and subjectivity has no place; yet concerns have arisen around objectivity obstructing the progress of research (Gelman *et al.*, 2015). Bayesian inference provides clear alternatives for estimating parameters and expressing degrees of confidence or uncertainty, although objectivity and subjectivity must be reconciled rather than divided (Ellison, 2004). The modified version of Bayes theorem frames probability problems within a scientific context, where a hypothesis is made, and then updated based upon data collection:

$$\Pr(A|\mathrm{B}) = \frac{\Pr(B|\mathrm{A}) \times \Pr\,(A)}{\Pr(B|\mathrm{A}) \times \Pr(A) + \Pr(B|{\sim}\mathrm{A}) \times \Pr\,({\sim}A)}$$

Equation 12: Bayes theorem used for inference.

The modified Bayes Theorem supposes that two hypotheses are being tested (A and B), however, this theorem can be generalised for *n* hypotheses:

$$\Pr(H_i|\mathrm{data}) = \frac{\Pr(H_i|\mathrm{data}) \;\times \Pr\,(H_i)}{\sum_{j=1}^{n} \Pr\big(data\big|H_j\big) \;\times \Pr\,(H_j)}$$

Equation 13: Generalised Bayes Theorem: Pr(H_i | data) notes the posterior probability of hypothesis *i* given the data observed. The numerator is the likelihood of observing the data under hypothesis *i* multiplied by the prior probability of the hypothesis. The denominator is the summation of all hypotheses given the observation of data.

The conditional relationships between variables can be implemented to create fully conditional models. However, these require enormous quantities of data and can lead to enormous quantities of calculations. The implementation of Bayesian networks allows for the development of conditional independencies between nodes within the network, providing an intermediary approach between fully conditional and fully conditional independent models. Bayesian networks further simplify the development of joint probability distributions through the application of the chain rule for probability (defined in Equation 14).

$$\Pr\,(\bigcap_{k=1}^{n} A_k) = \prod_{k=1}^{n} (A_k \,|\, \bigcap_{j=1}^{k-1} A_j\,)$$

Equation 14: The joint probability of n events called $A_1 \ldots A_n$ occurring is the product of n-1 conditional probability terms and one marginal probability term.

The laws and theorems described above lie at the heart of Bayesian networks and are used to estimate the probability of observing a state conditional on the state of liked variables, or it may be used to update the probabilities once a particular state has been observed. Bayesian networks are probabilistic graphical models that consist of three elements; system variables (referred to as nodes), causal relationships between the nodes visualised as arcs (combining arcs and nodes creates a Directed Acyclic Graph), and Conditional Probability Tables defining the nature of the relationships

(Pearl, 1988b). Nodes within a network represent a specific variable used to model the ecosystem in question. While these nodes may assume an infinite number of possible domains, they can be divided into two classes: continuous or discrete (i.e., continuous variables, such as age, discrete variables, such as True/False). Discretisation of continuous variables is usually implemented to divide nodes into **n** number of states (e.g., age 0-18, 19-30, 31-65, 66+). These states must encompass all possible conditions the node can take and be mutually exclusive from one another. Where a causal probabilistic dependence between two variables exists, the corresponding variables are connected by a directed edge, sometimes referred to as arc (Horný, 2014). The structure developed through linking nodes through connecting arcs creates a graphical illustration of interactions among the variables in the model and can mimic the causal structure of the real modelled world, although this is not a requirement. Where a node is connected via an arc, this indicates that one node is conditionally dependent upon another. Conditional Probability Tables are defined for these nodes in the network, where they express the probability for a state of the child given the states of its parent. Present in the Directed Acyclic Graph are root nodes that contain unconditional probability tables, these nodes have no parental arcs to them, and the Conditional Probability Table takes the form of a marginal probability distribution. The construction of a Bayesian network and connection of nodes through directed arcs dictates the flow of information through the network. These connections can be termed either Serial, Diverging or Converging (Taroni and Biedermann, 2015). Serial connections allow information to flow from the root node to the child node, provided no intermediate node is instantiated. Diverging connections allow transmission of information across child nodes, provided the parent is not instantiated. Converging connections can only allow transmission of information between parents of the same child when the child node has been made conditional on evidence.

5.1.2.1 Example Bayesian network

An example of a simple Bayesian network depicting the decision to take an umbrella out is displayed in Figure 17. The network is predicated on the knowledge that an individual is more likely to take an umbrella out when it is raining, but more likely to forget to take the umbrella out if they have not had breakfast. From this figure, we observe the nature of the dependence between variables and their parents through the Conditional Probability Tables. The diagram indicates that the decision to take an umbrella out (Umbrella node) is conditional on the presence of Rain (Rain node) and whether the individual has eaten breakfast that morning (Breakfast node). Further, the Rain node is conditional upon the Season and Cloud nodes. These relationships are indicated by the directed arcs between the nodes. Nodes with no parents (i.e., Season node) are defined as root nodes, and can represent observations, scenarios, or decisions, and contain a simple probability distribution. For child nodes, the strength of the causal relationships present in the network is displayed within the Conditional Probability Table. The probabilities displayed within the Umbrella node, as an example, are calculated using the equations displayed in Table 13.

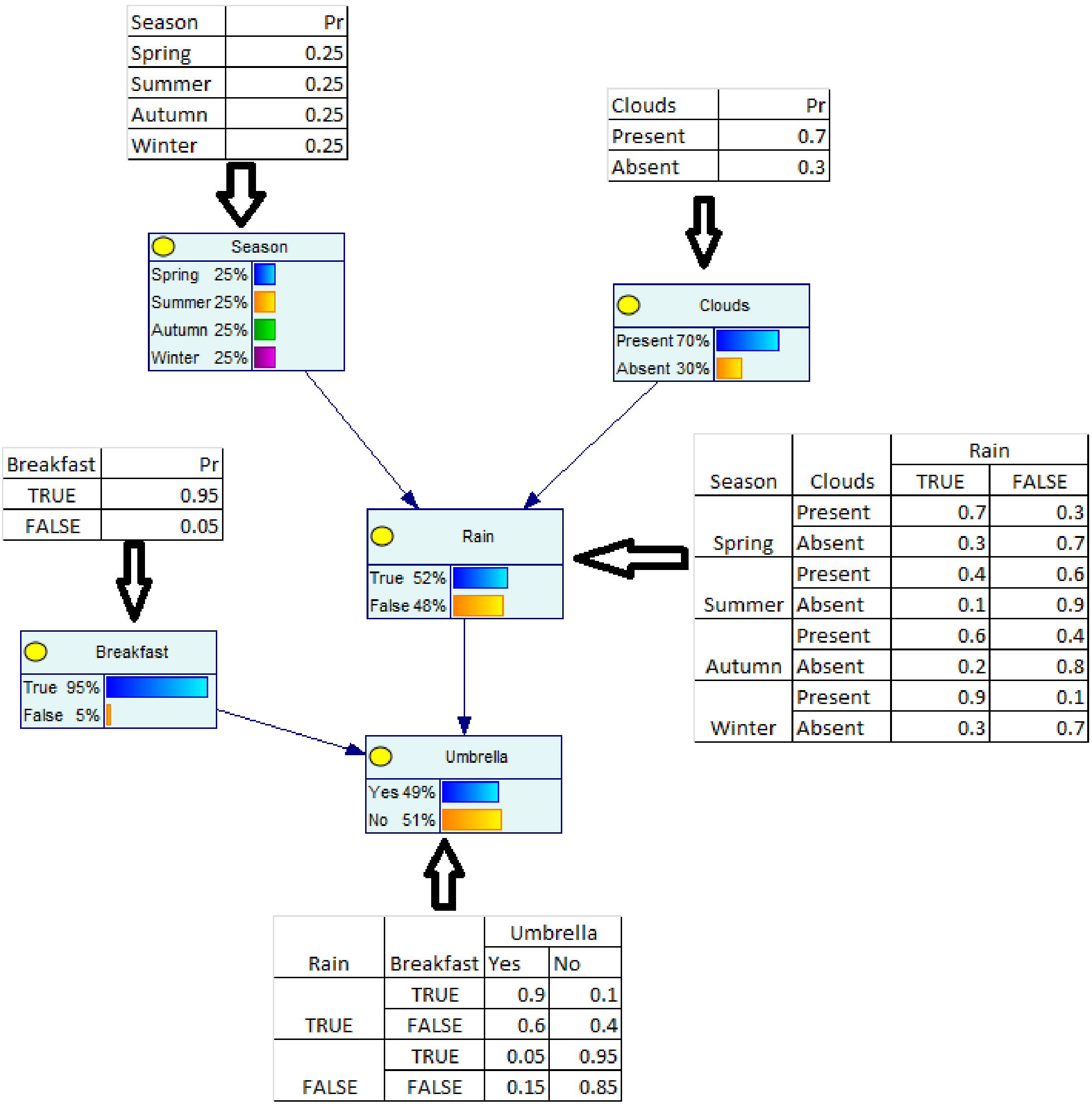

Figure 17: An example Bayesian network with associated Conditional Probability Tables.

Table 13:Joint Probability Table calculations for Umbrella Node

Rain	Rain(TRUE)		Rain(FALSE)		$\Pr(C) = \sum_{Rain,Breakfast} Pr(Rain, Breakfast, Umbrella)$
	Breakfast(TRUE)	**Breakfast(FALSE)**	**Breakfast(TRUE)**	**Breakfast(FALSE)**	
Yes	$\Pr(c^1\|a^1,b^1) \times \Pr(a^1) \times \Pr(b^1)$	$\Pr(c^1\|a^1,b^2) \times \Pr(a^1) \times \Pr(b^2)$	$\Pr(c^1\|a^2,b^1) \times \Pr(a^2) \times \Pr(b^1)$	$\Pr(c^1\|a^2,b^2) \times \Pr(a^2) \times \Pr(b^2)$	
	0.4446	**0.0156**	**0.0228**	**0.0036**	**0.4866**
No	$\Pr(c^2\|a^1,b^1) \times \Pr(a^1) \times \Pr(b^1)$	$\Pr(c^2\|a^1,b^2) \times \Pr(a^1) \times \Pr(b^2)$	$\Pr(c^2\|a^2,b^1) \times \Pr(a^2) \times \Pr(b^1)$	$\Pr(c^2\|a^2,b^2) \times \Pr(a^2) \times \Pr(b^2)$	
	0.0494	**0.0104**	**0.4332**	**0.0204**	**0.5134**

The chain rule can be used to calculate the probability of a particular state in the space. For example, the probability that in the season of spring (Season^{spring}), with clouds present (Clouds^{present}), rainfall does not occur (Rain^{False}), and the individual has eaten breakfast (Breakfast^{True}) but forgets their umbrella (Umbrella^{False}) can be calculated as follows:

$$P\left(season^{spring}, clouds^{present}, Rain^{False}, Breakfast^{True}, Umbrella^{False}\right) \\ = 0.25 \times 0.7 \times 0.3 \times 0.05 \times 0.95 = 0.013167$$

Equation 15: Example application of the chain rule

Bayesian networks can also be used for prediction and diagnosis of a system. This is achieved through instantiation of the root nodes (those without parents) or the child nodes. Predictive reasoning follows the joint probability described above (Table 13); however, the input parameters are altered. For instance, changing the state of Breakfast to 100% False (and therefore Breakfast being True = 0%) would alter the distribution of the network as displayed in Table 14.

Table 14: Joint Probability Table calculations for Umbrella Node where Breakfast has been instantiated to 100% False.

Rain	Rain(TRUE)		Rain(FALSE)		$\Pr(C) = \sum_{Rain,Breakfast} Pr(Rain, Breakfast, Umbrella)$
	Breakfast(TRUE)	**Breakfast(FALSE)**	**Breakfast(TRUE)**	**Breakfast(FALSE)**	
Yes	$\Pr(c^1\|a^1,b^1) \times \Pr(a^1) \times \Pr(b^1)$	$\Pr(c^1\|a^1,b^2) \times \Pr(a^1) \times \Pr(b^2)$	$\Pr(c^1\|a^2,b^1) \times \Pr(a^2) \times \Pr(b^1)$	$\Pr(c^1\|a^2,b^2) \times \Pr(a^2) \times \Pr(b^2)$	
	0	**0.312**	**0**	**0.072**	**0.384**
No	$\Pr(c^2\|a^1,b^1) \times \Pr(a^1) \times \Pr(b^1)$	$\Pr(c^2\|a^1,b^2) \times \Pr(a^1) \times \Pr(b^2)$	$\Pr(c^2\|a^2,b^1) \times \Pr(a^2) \times \Pr(b^1)$	$\Pr(c^2\|a^2,b^2) \times \Pr(a^2) \times \Pr(b^2)$	
	0	**0.208**	**0**	**0.408**	**0.616**

We can also perform diagnosis of the system to see how alterations in the child nodes, or the outputs, can change our beliefs in the most likely cause for this observation in the root nodes. This is achieved through application of Bayes theorem, as provided in Equation 14. For this example, we introduce a new network that contains two nodes: 1) the number of days in the month (with states X≤30 (A) and X>30 (B)) and 2) the Seasons (Figure 18).

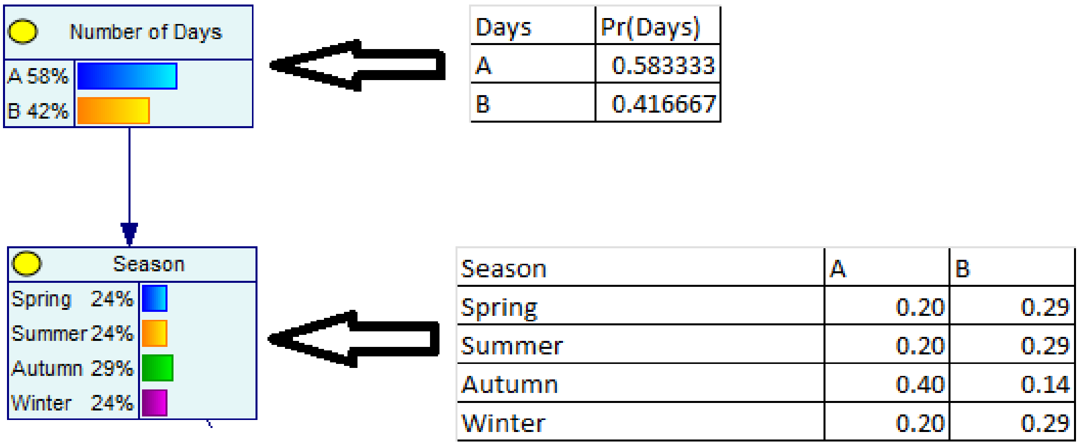

Figure 18: An example Bayesian network with Conditional Probability Tables.

If we observe that the current season is winter (thus instantiating the winter state in the Season node to 100% with all other seasons equalling 0% respectively), we can use Bayes theorem to update our belief of how many days are in the month. The change in distribution is shown in Table 15. As such, we can update our beliefs in how many days are in the month based upon which Season we have found ourselves to be in (i.e., we have increased our belief that the month contains more than 30 days within it).

Table 15: Probability distributions following evidence being found at a child node

Days in Month	**Season: Winter**
	$Pr(S^{Winter} \mid A^{\leq 30}) \times Pr(A^{\leq 30}) / Pr(S^{Winter})$
$A^{\leq 30}$	0.486110833
	$Pr(S^{Winter} \mid B^{>30}) \times Pr(B^{>30}) / Pr(S^{Winter})$
$B^{>30}$	0.503472625

Individually calculating the probability distributions of each node and state given an event occurring or a change in the probability distribution is time-consuming and computationally demanding. A range of Bayesian modelling programmes include Netica, Higun, Smile/GeNIe, and R-Packages, which have recently been compared in a review article (Pérez-Miñana, 2016b). The following work makes extensive use of the GeNIe programme (BayesFusion LLC, 2020). These user interfaces allow for application of multiple instances of the chain rule, joint probability calculations, and the application of Bayes theorem.

5.1.2.2 Bayesian network structure and parametrisation learning processes

The combinations of nodes and connecting arcs that create a structure can be combined into a network through a range of operations. The Bayesian network development process can be learned through complex methods including; Naïve and Tree Augment Naive algorithms (Taalab, Corstanje, Mayr, *et al.*, 2015), constraint-based algorithms (conditional independence tests to infer structures), score-based algorithms (using goodness of fit scores to infer structures) and hybrid algorithms (a combination of the prior approaches) (Marcot and Penman, 2019; Scutari, Graafland and Gutiérrez, 2019). However, these algorithms can result in greater model complexity than an expert elicited network structure (Pham *et al.*, 2021) and the learning process requires large quantities of data and displays high sensitivity to user input variables such as the number of states involved in discretisation (Alameddine, Cha and Reckhow, 2011). Expert opinion can either be combined with learning algorithms or applied on its own and thus implemented to define the structure of the network (Aguilera *et al.*, 2011). Generally, within ecosystem service modelling, the elicitation of stakeholder and expert knowledge has been the dominant process used to define the Directed Acyclic Graph (Landuyt *et al.*, 2013). Elicitation of knowledge from experts has been used in Bayesian modelling across a number of fields including but not limited too; Engineering (Li and Zhang, 2013), Mechanical Diagnosis (Chien, Chen and Lin, 2002), and Neuron Classification (López-Cruz *et al.*, 2014).

The Bayesian network structure creation and parametrisation process remains relatively similar regardless of the method chosen; the nodes of the network must be defined and identified, then the states associated with each node, and finally the connections between nodes. All nodes included in the network must either affect or be affected by the final output. Importantly, each node should be manageable, predictable, and observable at the relevant scale (M. Borsuk, Stow and Reckhow, 2004). Marcot et al., (2006) suggests that Bayesian networks should contain no more than five layers of nodes to avoid over complication and loss of information flow through the network. For large complex systems, it may be possible to split the model structure into modular sub-networks (or network fragments) that represent different components of the system (M. Borsuk, Stow and Reckhow, 2004; Laskey and Mahoney, 2013). The exact nature of each relationship between nodes in the network can be constructed using externally elicited expert opinions (Maskrey *et al.*, 2016), or the author's own expert opinion (Meynecke, Richards and Sahin, 2017).

The states of a node should represent the full distribution of values that the node may take and be mutually exclusive. A state should not be included if it is unlikely to be reached or is not relevant to the model objectives. Where a continuous data range is present, it may be discretised using either of two simple and commonly used discretisation techniques; the equal-width method and equal-frequency method, which divide the range of values (minimum to maximum) into a predefined number of intervals of equal-width or intervals containing the same number of data, respectively (Muhlenbach and Rakotomalala, 2005). If possible, the discretisation process should include some expert input to ensure the intervals are logical with respect to the model objectives. After the creation of the network structure, the Conditional Probability Tables for each node need to be parametrised. Initial input variables and states can be gathered by literature review (Franco *et al.*, 2016; Bakshan *et al.*, 2017; Mantyka-Pringle *et al.*, 2017), conversion from existing models (Landis *et al.*, 2017), individual scoping consultations (Katic and Morris, 2016), open list variable distributions (Gambelli *et al.*, 2017) exploratory expert workshops (Maskrey *et al.*, 2016), or a mixture of literature review and expert elicitation (Bakshan *et al.*, 2017). Identification of input variables is key, however, questions such as observability, predictive uncertainty from natural variation, and lack of knowledge mean choosing indicators is a balance of predictive precision and economic factors (M. E. Borsuk, Stow and Reckhow, 2004).

Model parameterisation can occur through a variety of actions including; prior determined equations and model simulations (Ames *et al.*, 2005; Vrebos *et al.*, 2021; Bao *et al.*, 2022), direct empirical measurements (Bressan *et al.*, 2009; Jorayev *et al.*, 2022), literature (Guisan and Zimmermann, 2000; Landis *et al.*, 2017), expert or stakeholder knowledge (Martin *et al.*, 2012; Gambelli *et al.*, 2017; Meynecke, Richards and Sahin, 2017), or a mixture (Nash *et al.*, 2010; Meynecke, Richards and Sahin, 2017; Forio *et al.*, 2020). In developing the structure and Conditional Probability Tables of the network, the use of qualitative information allows for integration of well-argued and informed interpretations of unquantifiable relationships. However, it lacks the explicitness and accountability of quantitative data (Busch *et al.*, 2012). Qualitative data should therefore be used as a proxy indicator or initial stage model development tool to be validated by quantitative data.

5.1.3 Bayesian networks use in Environmental Sciences

The application of Bayesian networks in environmental sciences has been systematically reviewed (Aguilera *et al.*, 2011; Landuyt *et al.*, 2013; Phan *et al.*, 2016; Kaikkonen *et al.*, 2021). A review of Bayesian networks in environment risk assessment identified that these have typically focused on freshwater and marine environments (71% of papers reviewed), rather than terrestrial and urban systems (29% of papers reviewed) (Kaikkonen *et al.*, 2021). Bayesian networks have been implemented to model a range of ecosystem services, including; wildfire prevention (2.13% of papers reviewed), water regulation (8.51% of papers reviewed), pest prevention (6.38% of papers reviewed), genetic resource provision (31.91% of papers reviewed), freshwater provision (10.64% of papers reviewed), climate regulation (4.26% of papers reviewed), food and fibre provision (4.26% of papers reviewed), or a mixture of services (31.91% of papers reviewed) (Landuyt *et al.*, 2013). The application of Bayesian networks in agriculture can be classified into five main themes; automated monitoring from sensor data, prediction from a base set of conditions, identification of primary causes of agricultural problems, classification problems (including land classification, disease identification etc), and decision support systems (Drury *et al.*, 2017). There are strengths and weaknesses that affect the ability for Bayesian networks to be useful tools to assess environmental systems, as discussed below.

5.1.3.1 Strengths of using Bayesian networks in Environmental Sciences

Bayesian networks have the potential to include of both expert knowledge and empirical data. This facet can be important where empirical data is of limited availability, which is especially present in environmental modelling (Constantinou, Fenton and Neil, 2016). It can be additionally beneficial due to the range of validation tools available apart from quantitative validation, including qualitative evaluation through expert analysis (Marcot, 2012). Furthermore, Bayesian networks are a suitable option for participatory modelling where the transparency associated with their structures and probability distributions encourages participation, enhances communication, and provides a tool to facilitate communication with non-experts (McCann, Marcot and Ellis, 2006). Bayesian networks are suitable for adaptive management; the ability to update relationships and nodes independently allows adaptation of model structure with relative ease (Bicking *et al.*, 2019), essential in the environmental modelling environment. Since Bayesian networks are modelled by means of probability distributions, risk and uncertainty can be estimated more accurately within the network, this makes Bayesian networks an appropriate tool for modelling environmental systems (Aguilera *et al.*, 2011).

5.1.3.2 Weaknesses of using Bayesian networks in Environmental Sciences

Despite the strengths of Bayesian networks for modelling environmental systems, these tools contain certain weaknesses as well. Bayesian networks have a limited capacity to model complex systems due to the absence of feedback loops and data discretisation. Feedback loops are a well-established concept in ecosystem modelling (Geary *et al.*, 2020). This weakness can be overcome by implementing dynamic Bayesian networks where necessary. However, this would substantially increase model complexity (Imoto, Miyano and Matsuno, 2006). Whilst data discretisation can lead to loss of information or over-complication of the network (Myllymäki *et al.*, 2002), preparatory data analysis can limit the impact of discretisation (Uusitalo, 2007a). A further weakness that stems from a prior strength is the role of expert knowledge in Directed Acyclic Graph and Conditional Probability Table construction. Experts can be inaccurate or encapsulate bias within probability distributions or this form of knowledge can be considered subjective and thus unscientific. The implementation of a structured approach to expert elicitation can limit the influence of these inaccuracies and biases and embed the same level of rigour provided by empirical data (Kuhnert, Martin and Griffiths, 2010).

5.1.4 Aims

Bayesian networks have previously been applied to a large variety of environmental ecosystems. However, they are yet to be applied for understanding the functioning and identifying the health of lowland peat soils that have been drained to allow for intensive agricultural exploitation. The importance of the functioning of these systems for ecosystem service delivery necessitates the development of tools to enable their sustainable management. Given the strengths of Bayesian networks in modelling environmental ecosystems, this work reported in this chapter aimed to define the nodes and connections that can be used to conceptualise the peat health in these systems. By combining a review of environmental science literature on peatlands and eliciting the expert knowledge of farmers and academics, we aimed to create the structure of a Bayesian network that identifies the essential indicators and functions required to infer peat health.

We hypothesised that the Bayesian network structure created through expert opinion would include a range of physical, chemical and biological Peat Health indicator nodes.

5.2 Methodology

Due to a lack of empirical datasets, creating the structure of Bayesian network for peat health was not possible using learning algorithms. Therefore, a mixture of expert knowledge elicitation and literature review was selected as the most appropriate approach for creating the network structure. Two expert groups were identified for knowledge elicitation: a Land Management Group and an Academic Group. Together, these groups represent a comprehensive knowledge base and include those that would use the output of the network to make management decisions. Members of the Academic Group were experts in the disciplines of Environmental Science or Agriculture at the University of Reading. The Land Management Group included agronomists and famers and were selected based on their regional and relevant local knowledge built over decades of farming on peat soils. Overall, around 20 members of the Academic Group and 10 members of the Land Management Group were consulted for the development of the Bayesian network structure. The expertise of an individual can be divided into four domains; (i) direct knowledge acquired directly from experience in the domain in question, (ii) indirect knowledge acquired through mentors or other experts (including literature), (iii) rules in which the domain operates (context-dependent heuristics) and (iv) the integration of the previous domains to generate an answer (Brooker, 2011). In the case of this work, group expertise was acquired through direct and indirect knowledge.

The initial development of the structure can be conceptualised as two stages, the expert structure development and structure modification in consideration of constraints and limitations. Certain constraints were agreed through the development of the Bayesian network. The model would be geographically explicit to the lowland fens of East Anglia and represent agriculturally managed systems where drainage had been implemented. Nodes within the network were required to be simple and observable. Additionally, nodes selected were required to either be in pre-existing datasets or be able to be predicted using existing soil models.

The iterative process of environmental model building has been well documented (Chen and Pollino, 2012). Jakeman et al. (2006) details ten general iterative steps to model development and evaluation (Jakeman, Letcher and Norton, 2006). Key components for good practice include; clearly defining model purpose and all underlying assumptions, comprehensive model evaluation process, and transparent reporting of the whole modelling process (Crout *et al.*, 2008). Therefore, before the expert knowledge elicitation process, the selected experts were contacted to confirm participation and provided with information regarding the aim, approach, and motive for developing the Bayesian network, as described below.

The Bayesian network was built with the aim of understanding the multi-functionality of a peat soil system. The purpose of the Bayesian network was to "map the continued capacity of the peat soil system to function as a vital living ecosystem". It was made clear to experts that this required them to define the specific functions provided by a drained fenland ecosystem, not the general functions provided by all soils. The scope of the model was to identify peat health at a field scale. The motive for developing the soil health model was to improve understanding of peat health, identify the key indicators to assess peat health, and provide land managers with a decision support tool. Although it was noted that feedback loops do exist in environmental systems, the purpose of the modelling exercise was not to map feedback loops within the model or incorporate temporal representations. As such, the use of Bayesian networks was considered a valid approach to achieve the aim.

Group elicitation exercises with each expert group were conducted online using MS Teams (Microsoft, 2021). The elicitation process was conducted over six separate meetings between June to December 2020, with each group in rotation (starting with the Academic group and then Land Management group), this would enable feedback in an alternative manner ensuring that model development remained relevant and applicable whilst capturing Peat Health. To conduct an effective meeting, the purpose of the exercise to develop a Bayesian Structure to establish Peat Health (as defined in the literature review) was introduced (or reintroduced) and the prior work established and revisited to keep experts up to date on model development at the start of each meeting. This enabled the setting of the assumption and ground rules in the expert's mind to maintain focus and clarity for the meeting. Meetings were limited to 2 hours to avoid fatigue of experts. To allow for experts to provide their opinion, a range of modes of communication were accepted, including private and public messages (both before, during and after the elicitation exercise) and group discussion during the elicitation exercise. During the first meeting, experts were asked to provide feedback to enable an evaluation and development of the approach for further elicitation exercises. For example, feedback highlighted the need for a clear and simple example of a Bayesian network that was unrelated to the soil system in question to be provided to help experts understand what they were aiming to create.

Group elicitation exercises are considered to create a more scientifically accurate outcome than individual elicitation (Salerno, Bottoms and Peter-Hagene, 2017), although groups are also affected by decision biases (Stettinger *et al.*, 2015). Due to the nature of the elicitation process, a modified Delphi approach to creating the Bayesian network structure was adopted. The Delphi process defining characteristics are anonymity, iterations, feedback, and aggregation of responses (Rowe, Wright and Bolger, 1991). Organisational limitations dictated that the anonymity usually associated with the Delphi method was not possible. Therefore, care was taken to avoid dominance or cues from supposed leaders of the group emerging. After a general introduction to the purpose of the study, participants were provided with pictures of sub-networks of a peat health network developed by the authors through a review of the literature. These sub-networks were based upon grouping of variables into functions that peatlands provide in the context of soil health and agriculture. To increase simplicity whilst maintaining the integrity of the model, an iterative process of literature reviews, focus group discussions, and interviews were conducted to eliminate variables that were deemed to not affect the final output node between June 2020 and December 2020. Experts were encouraged to review the model structure to reduce the number of nodes, and the number of connections between nodes. A large number of nodes, or connections between nodes, in a Bayesian network creates a scenario where the network becomes computationally problematic (Koller and Pfeffer, 1997). Furthermore, increasing the number of nodes between input variables and outputs can reduce the sensitivity of output nodes and increase its uncertainty. As such, simplicity can be seen as essential when constructing Bayesian networks (Marcot *et al.*, 2006). Guidance supplied by the facilitator was to keep node connections to a minimum (a maximum of 5 parent nodes connected to each child node) and, where this was exceeded, aggregating parent nodes or disaggregating child nodes was suggested. It is acknowledged that this can reduce the sensitivity of the network where excessive disaggregation is applied (Chen and Pollino, 2012). Model structure was confirmed when a quorum of 70% of experts agreed upon the final structure.

5.3 Results and Discussion

The peat health Bayesian network, derived from the elicitation of expert opinion combined with a review of the literature, contained four key functions that were each inferred by a sub-network (Carbon Respiration, Nitrogen Loss, Pathogen Suppression and Peat Structure), containing parent nodes (soil properties). The scientific basis for each sub-network is provided below.

5.3.1 Carbon Respiration Sub-Network

A key function of soils is the storage and mineralisation of organic materials that provides energy and nutrients to soil organisms and crops. Drainage of peatlands leads to an alteration of the ecosystem, creating an imbalance favouring decomposition over accumulation of organic matter (Holden, Chapman and Labadz, 2004). Microbial organisms within the peat ecosystem play a pivotal role in carbon cycling, controlling anabolic and catabolic pathways (Bender, Wagg and van der Heijden, 2016). Whilst the cycling of carbon is an important function in soils, for peatlands, it was identified that this function would be inferred using CO_2 Respiration. Managing decomposition rates is vital to allow for the continued capacity of peatlands to function, protecting the large quantities of carbon present within the soil.

The respiration of carbon dioxide results from the activity of microbes within the soil decomposing organic matter. Experts identified the quantity and quality of organic matter as an important node in assessing the functioning of carbon respiration within the peat systems. The fundamental function of organic matter is the provision of metabolic energy for biological processes, yet organic matter is a complex composition of materials derived from plant photosynthesis and modified by decomposition processes (Huang, Li and Sumner, 2011). Organic matter can be modelled by allocating carbon to different conceptual pools with different turnover rates due to their intrinsic decomposability (Coleman and Jenkinson, 1996; Smith *et al.*, 2019). Whilst organisms act upon pools of organic substrate in the peat, the decomposition process and microbial activity is modified by abiotic factors (Dondini *et al.*, 2017). The nodes specifically selected for the final BN were specifically chosen because they were pools modelled in the ECOSSE model used to generate the probability distributions and relationships. Experts and the literature identified important abiotic factors that mediate carbon respiration, including texture and bulk density. Texture within mineral soils has been shown to be related to porosity and the movement of water and gas diffusion (Yiqi *et al.*, 2006) and can therefore influence microbial access to substrates through the pore networks, altering respiration rates (Patel *et al.*, 2021). Texture in high organic matter soils has displayed that those with higher sand contents have better aggregation and a smoother feel, whereas increasing clay content display weaker clods and a fine tilth (Natural England, 2008). Whilst the impact of texture will increase as organic matter is lost from the system, its impact on microbial access is limited in comparison with bulk density. Within the ECOSSE model, texture is implemented to alter the partitioning between CO_2 evolved and the building of the Biomass and Humified pools, that is, it determines the efficiency of decomposition under non-N limiting conditions. Experts also identified Bulk Density to be an important factor in determining the respiration of carbon from the system. Like Texture, Bulk Density can be seen to control the movement of gas and water, mediate the accessibility of carbon, and indicate the availability of habitats for soil organisms (Huang, Li and Sumner, 2011). Furthermore, Bulk Density was deemed an important variable to infer the size of the carbon stock present within the peatland (Wang *et al.*, 2021). The elicitation of expert knowledge and literature review led to the creation of the Carbon Respiration sub-network following quorum agreement as displayed in Figure 19.

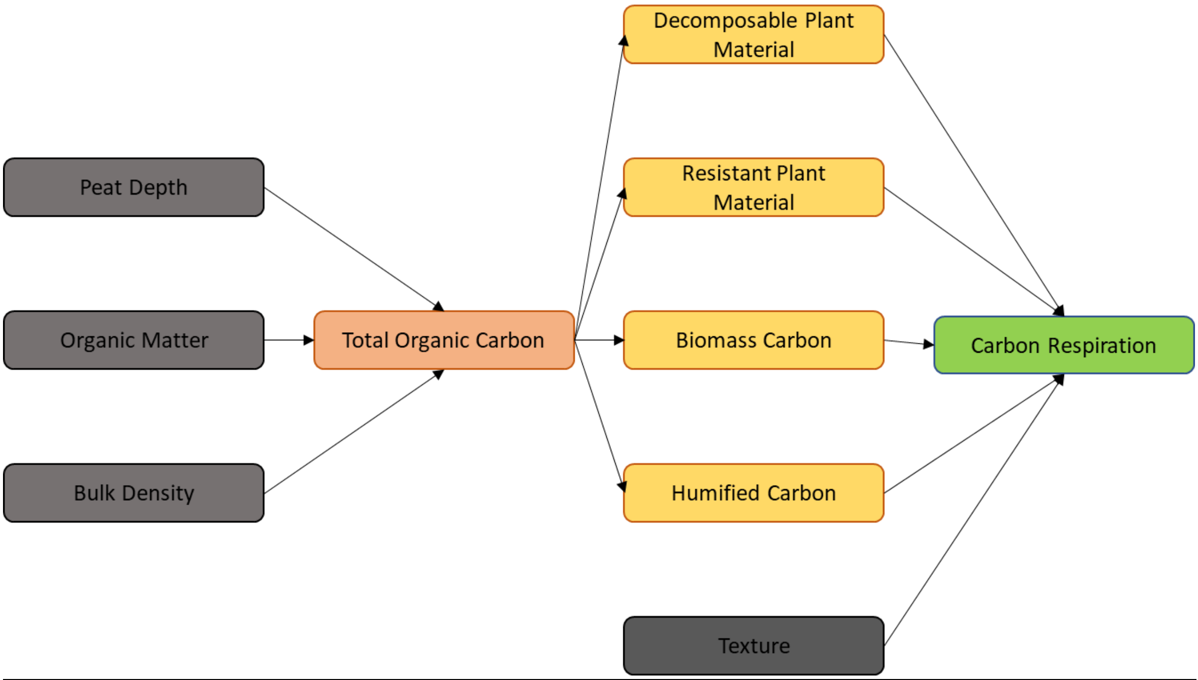

Figure 19: Carbon Respiration Sub-Network nodes and arcs as defined through multiple expert elicitation exercises as part of the larger Bayesian network structure.

5.3.2 Nitrogen Loss Sub-Network

The cycling of nutrients within a peat ecosystem is an essential function, defined as its ability to receive, store, make available and cycle macro and micro nutrients (Schröder *et al.*, 2016). It would be impractical to focus on every macro and micronutrient cycle within the ecosystem, so a focus is placed on nitrogen within the model. Nitrogen is an essential nutrient for promoting crop production (Kibblewhite, Ritz and Swift, 2008) and exhibits a wide range of transformations which can lead to synergies and trade-offs for other services provided by soils, such as water quality and carbon mineralisation (Tilman *et al.*, 2002). Nitrogen cycling has been shown to be important for drained peat, due to its lability and high potential to cause pollution (Vassiljev and Blinova, 2012; Vassiljev *et al.*, 2019). It is acknowledged that seasonal variations, soil conditions, and management practices can all limit the effectiveness of using available nitrogen as a soil health indicator (Gil-Sotres *et al.*, 2005).

Nutrient cycling therefore defines the relationship between mineralised nitrogen, stored nitrogen, and nitrogen lost from the system through leaching or denitrification. A large proportion of nitrogen is protected in organic forms (95-99%), but this is unavailable to plants (Weil and Brady, 2017). Microbially driven processes control the mineralisation of nitrogen which is additionally dependent upon the C:N ratio alongside the microbial activity (Colman and Schimel, 2013). Experts identified that the quantity of nitrogen was intrinsically modelled in the Organic Matter node, and that total mineralisation, and thus, total mobilisation of the nutrients was not a concerning issue (although timing of mobilisation was). Past literature supports this opinion, displaying positive net mineralisation rates for drained peatlands (Wells and Williams, 1996; Säurich *et al.*, 2019). Therefore, the most important component of nutrient cycling in peatlands, and thus the component retained for the peat health Bayesian network, was considered the loss of nitrogen from the system. Therefore, the nutrient cycling function was represented by the Nitrogen Loss node.

Nitrogen may be lost through a range of different pathways reducing crop yield, and causing environmental pollution (Cameron, Di and Moir, 2013). Loss pathways include leaching of Dissolved Organic Nitrogen, nitrification and leaching of nitrate, denitrification and gaseous emission of N_2O and N_2, and removal of nitrogen through harvesting operations (Bowles *et al.*, 2018). Nitrogen Leaching, Dissolved Organic Nitrogen and Nitrogen Denitrification were identified as important indicators of Nitrogen Loss. Leaching of nutrients is increasingly observed as an environmental and societal concern, and magnitude of loss is directly related to concentration of the nutrient within the soil porewater and the movement of the water (Rashmi *et al.*, 2017), which is of great concern to nutrient rich peatlands. Dissolved Organic Nitrogen release from drained peatlands is of particular importance, with losses remain constant despite increasing degradation of peatlands (i.e. loss of Organic Matter and decreasing C:N ratio), and appears to be preferential lost from decomposition of Organic Matter in the peat (Kalbitz and Geyer, 2002). Finally, the process of denitrification under agricultural peat soils is another important loss pathway of Nitrogen from peat systems, leading to the emission of harmful N_2O (Regina *et al.*, 2004; Butterbach-Bahl *et al.*, 2013; Espenberg *et al.*, 2018). The ECOSSE model was used to model the nitrogen loss within the peat system. ECOSSE uses a simple C:N ratio of 10:1 in agricultural systems to calculate the amount of nitrogen in the system, and like carbon, calculates the turnover of nitrogen in respect to pools of available nitrogen with different turnover times. Thus, Peat Depth, Bulk Density and Organic Matter content were used to calculate the Total Organic Nitrogen contained within the system. The elicitation of expert knowledge and literature review led to the creation of the Nitrogen Loss sub-network following quorum agreement as displayed in Figure 20.

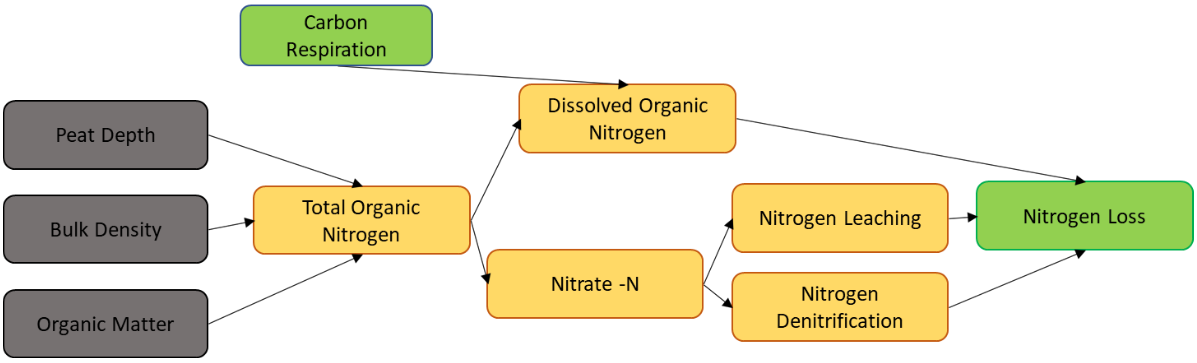

Figure 20: Nitrogen Loss Sub-Network nodes and arcs as defined through multiple expert elicitation exercises as part of the larger Bayesian network structure.

5.3.3 Peat Structure Index

The structure of soil influences a range of soil processes and functions including, but not limited to, biomass production, storage and filtering of water, storage and recycling of nutrients, carbon storage, habitat for biological activity, and physical stability and support for plants (Rabot *et al.*, 2018). To infer the peat structure function, expert knowledge and literature review conferred that organic matter and bulk density should be used as inference nodes. Peat soils are highly complex porous media with distinct characteristic physical and hydraulic properties, but as the peat layer is oxidized and further compressed, the structure of the peat layer becomes degraded (Holden *et al.*, 2006; Mustamo *et al.*, 2016; Rezanezhad *et al.*, 2016). The oxidisation of peat leads to a reduction in the macropore structure, which facilitates water movement and solute transport, reducing saturated hydraulic conductivity, increasing bulk density and lowering porosity (Liu and Lennartz, 2019). The peat structure node therefore defines the current predicted structure of the peat to provide a habitat for organisms/biomass and to facilitate the flow and storage of water. The elicitation of expert knowledge and literature review led to the creation of the Peat Structure sub-network following quorum agreement as displayed in Figure 21.

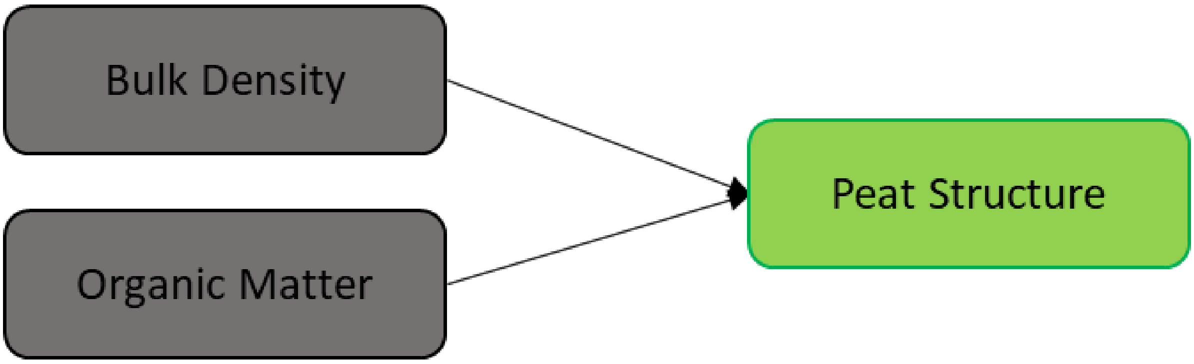

Figure 21: Peat Structure Sub-Network nodes and arcs as defined through multiple expert elicitation exercises as part of the larger Bayesian network structure.

5.3.4 Pathogen Suppression Index

The Pathogen Suppression node considers the functioning of the peat to reduce the amount of disease through antagonistic relationships with pathogens. A healthy and functioning microbiome defends against soil-borne pathogens through direct methods, such as antibiosis or parasitism, or indirectly by enhancing plant immune responses (Peralta *et al.*, 2018). Experts identified Microbial Biomass and Rotation Diversity as important indicators to infer Pathogen Suppression function. General suppression in soil is considered a function of the aggregate capacity of diverse soil microbes to antagonize pathogen populations. Differences in microbiome composition, structure, and diversity dictate general and specific suppressive capacities yet remain poorly understood (Expósito *et al.*, 2017; Schlatter *et al.*, 2017). However, increased total Microbial Biomass within soil systems has been shown to correlate with general soil suppressiveness (Schlatter *et al.*, 2017; van Agtmaal *et al.*, 2018; Bongiorno *et al.*, 2019; Palojärvi *et al.*, 2020). As such, increased biomass levels are inferred to increase general pathogen suppression of the peat. A diverse crop rotation and inputs significantly improves disease and pest management (He *et al.*, 2019), influencing bacterial community composition (Peralta *et al.*, 2018), and decreasing the incidences of disease on crops (Termorshuizen *et al.*, 2006; Hiddink, Termorshuizen and van Bruggen, 2010; Fan *et al.*, 2020). Crop rotations can directly reduce inoculum density of pathogens, and alter the physical, chemical and biological environment in the soil, promoting changes to community composition (Peralta *et al.*, 2018; Badial *et al.*, 2020; Moura *et al.*, 2020). The elicitation of expert knowledge and literature review led to the creation of the Pathogen Suppression sub-network following quorum agreement as displayed in Figure 22.

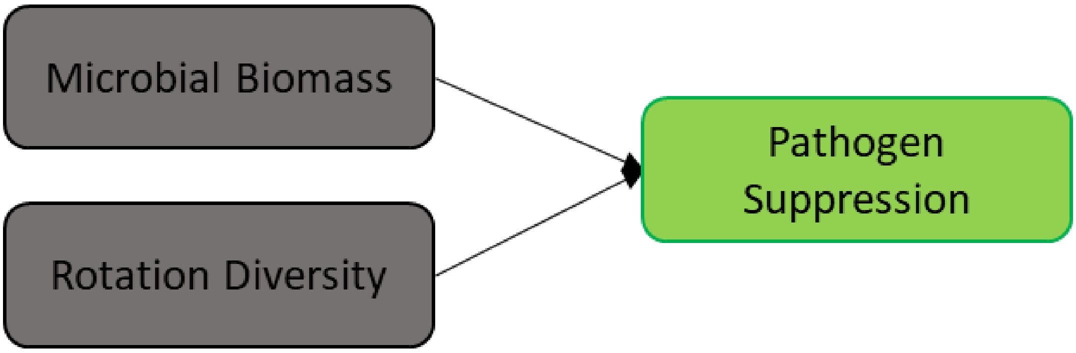

Figure 22: Pathogen Suppression Sub-Network nodes and arcs as defined through multiple expert elicitation exercises as part of the larger Bayesian network structure.

5.3.5 Complete peat health Bayesian network

Peat health was defined as the continued capacity of the peat system to function as a vital living ecosystem. The capacity of the soil to provide these function stem from outputs of a range of biological processes within the living soil system, operating in complex interactions within abiotic conditions (Kibblewhite, Ritz and Swift, 2008). The above functions attempt to infer the functioning of the peat system using easily accessible and simple on-farm indicators/properties. Each of these functions can both be seen to improve or degrade the health status of a peat and their combination can influence a systems resilience (Lehmann *et al.*, 2020). To establish whether a function was considered to be beneficial or detrimental to peat health, a modified version of the soil health gap concept was applied (Maharjan, Das and Acharya, 2020). A healthy functioning peat was considered to be one where the respiration of carbon is lower, the nutrient loss is low, the peat structure is good, and the pathogen suppression is present. The reverse will be true for an unhealthy system. The functioning of each component noted above will infer the health of the peat ecosystem, and the overall structure for inferring the health of a drained peat system is displayed in Figure 23.

5.3.6 Future Structure Development

Literature reviews and discussions with experts while creating the structure of the peat health Bayesian network revealed areas where improvements could be implemented if limitations and constraints were not present. Experts expressed concerns about the simplicity of the modelled variables. The aim of the modelling techniques was to identify a suite of variables that could infer each function and thus the health of the peat system. Developing simplistic models of processes should be preferred to more complex solutions (Wainwright and Mulligan, 2013). However, future iterations of the Bayesian network could incorporate a more complex structure to allow an understanding of peat health with greater depth. This could include the inclusion of utility or decision nodes, such as the likelihood or satisfaction with a crop yield potential based upon the health of the system, or the decision to conduct a certain practice, such as tillage, and how this will affect the nodes within the network. Experts attempted to increase the complexity of the network by incorporating soil biological community indicators into the structure. Discussions focussed on what indicators were possible to reliably measure and how these should be incorporated into the network. Such biological indicators, indicative of soil health, include soil enzyme activity (Alkorta *et al.*, 2003), mesofauna and arbuscular mycorrhizal fungi (Mahdi *et al.*, 2017), and phospholipid analysis or bacteria/fungi diversity indexes (van Bruggen and Semenov, 2000). However, due to high spatial variability of these indicators, the presence of substantial functional redundancy, and the current limited understanding of which organisms perform certain soil functions (Reicosky, 2018), it was deemed inappropriate to include these biological indicators to infer peat health. As knowledge concerning the role of soil biology in peatland ecosystems develops and measurement becomes more routine, biological indicators could be incorporated into the Bayesian network. The current network represents processes that are biologically mediated (e.g. carbon and nitrogen cycling) without explicitly modelling the contribution of specific groups of organisms.

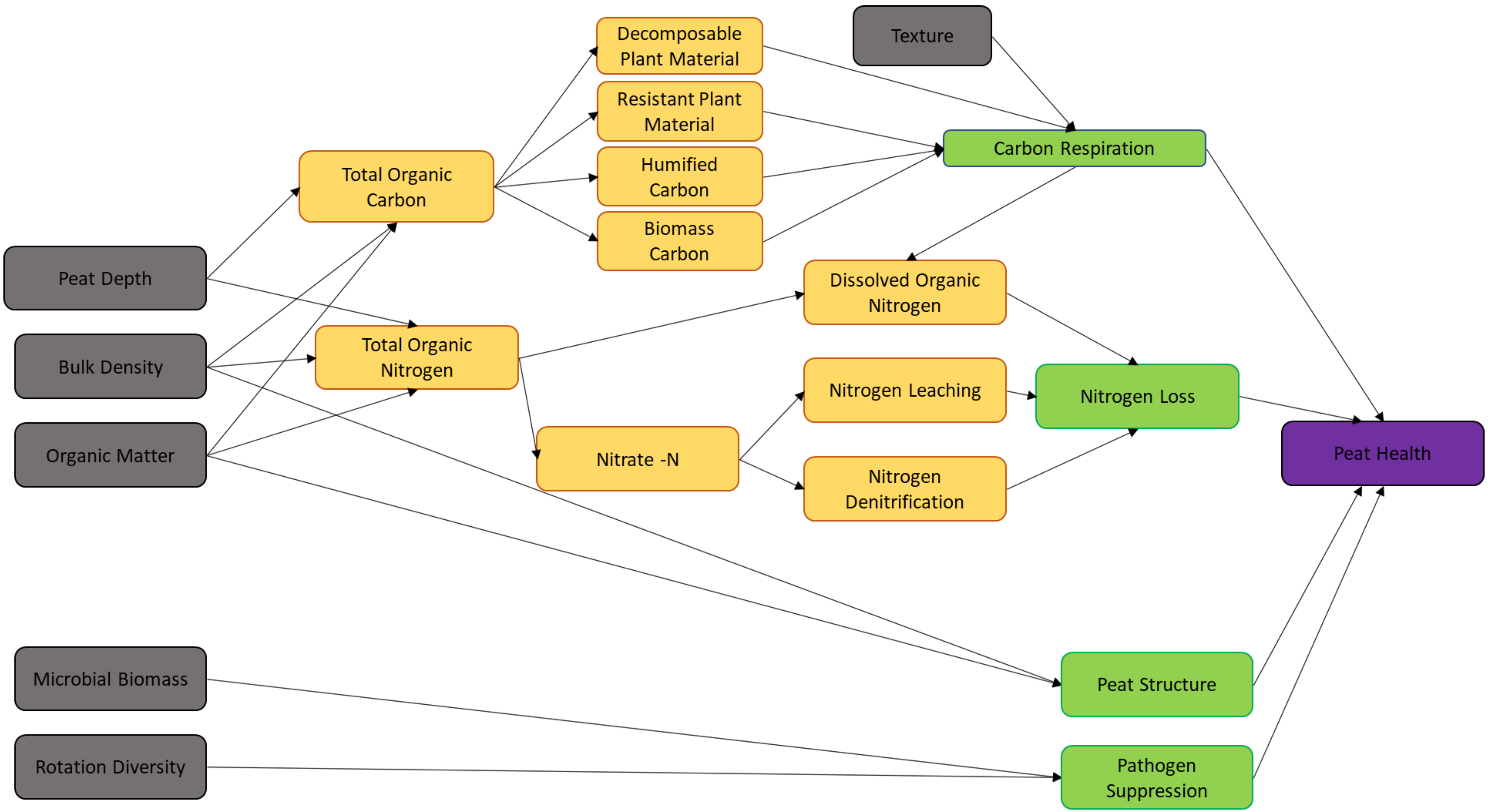

Figure 23: Complete peat health Bayesian network structure with nodes and arcs used to infer the flow of information as defined through multiple expert elicitation exercises with the Academic and Land Management group after agreement by quorum. The network identifies the simplest combination of indicators to infer the health status of a lowland peat under agriculture.

The elicitation of expert knowledge highlighted the role of organic matter chemical composition in mediating the rate of organic matter decomposition and consequent release of CO_2 from drained peat ecosystems. The increased degradation of peat after drainage, inferred by lower C:N ratio and reduced organic matter content, correlates with a higher specific basal respiration (Säurich *et al.*, 2019). However, because we selected the ECOSSE model to parameterise the Conditional Probability Tables within the Carbon respiration sub-network (see Chapter 6) we were constrained by the design of the model, which does not have the utility to alter the C:N ratio (which was kept constant at 10:1). Future development of the Bayesian network could lead to the inclusion of C:N ratio as a node, thus altering the network structure to include the degradation status of the peat system. Experts commented that microbial activity (and thus CO_2 respiration) can be altered by soil temperature, moisture content alteration of the groundwater table or displacement of CO_2. These physical mechanisms drive mass flow of CO_2 loss from soil systems (Kutsch, Bahn and Heinemeyer, 2010). A limitation of the network was that it aimed to provide a snapshot of the health of the system, meaning that the implementation of these factors was considered as a longer-term average over a single point in time. If the model were to be applied at a location different to where the meteorological data was obtained to run the ECOSSE model and parameterise the Conditional Probability Tables was collected, or if the model was used to project peat health for future climate change scenarios, then the network would need to be re-parametrised. Future updates of the network may include further drivers of microbial decomposition, which could be incorporated into the network, especially if a different soil carbon and nitrogen model were used that accounts for these processes.

It was noted that recent advances in our understanding of the mechanisms by which organic matter is chemically and physically protected from decomposition could be explicitly considered in future development of the model. Microbial community composition controls the fate of carbon compounds, yet, the protection mechanisms afforded by the abiotic environment control the decomposition rate of carbon in soils (Schimel and Schaeffer, 2012). Research has shown that the protection mechanisms of organic carbon present in mineral soils (occlusion and binding to minerals) are of little importance in peatlands (Han *et al.*, 2016). Furthermore, intrinsic decomposability of organic matter, considered to be a cause of variation in carbon decomposition, has not been shown to correlate with CO_2 emissions (Reiche, Gleixner and Küsel, 2010; Bader, Müller, Schulin, *et al.*, 2018; Leifeld, Klein and Wüst-Galley, 2020). Protection of carbon within the drained peat ecosystem rather occurs through the addition of fresh organic matter, which provides a preferential carbon source for biological communities (Bader, Müller, Szidat, *et al.*, 2018). However, peat decomposition is not completely negated by the addition of fresh organic matter since older carbon still mineralised, depending upon the degradation status of the peat (Bader, Müller, Szidat, *et al.*, 2018).

Experts identified pH as another important abiotic factor controlling respiration. pH regulates both chemical and biological reactions within the soil system, and can limit the production of CO_2 in acidic conditions due to retarding effects on decomposition (Laiho, 2006). Organisms within the peat, and crops grown on it, can have different sensitivities to pH. However, an optimum pH for microbial activity and crop production typically ranges between 5.0 and 7.5 (Stirling *et al.*, 2016). Natural peatlands contain a variety of organisms that have developed tolerances to the low oxygen availability and high acidity environment. However, soil biological community structure changes after drainage, indicating a change in the tolerance to abiotic conditions (Espenberg *et al.*, 2018). Peatlands used for agricultural practices are regularly maintained at neutral pH (or within a reasonable range) and so it was not deemed necessary to include pH as a node in the Bayesian network. If the network were used for semi-natural peatlands or restored peatlands in the future, then this may necessitate including soil pH within the network.

5.4 Conclusion

Bayesian networks are an important tool for ecosystem modelling due to their ability to combine expert opinion with empirical data, engage stakeholders during the model construction process, and explicitly consider uncertainties. We used literature review and elicited expert opinion to define the structure of a Bayesian network which identified four key functions that infer the health of a peat soil. Using this approach, a simple and effective structure was developed that could then be further implemented into a Bayesian network by defining Conditional Probability Tables. Future improvements to the network structure were identified which could be implemented when constraints and limitations are eliminated or overcome.

Chapter 6: Evaluation of peat health under intensively managed agricultural systems using a Bayesian network approach.

Abstract

The concept of soil health has gained attention due to the understanding that soils deliver multiple ecosystem services in agricultural systems but are susceptible to degradation. As a result, several 'soil health tools' have been developed that allow farmers and stakeholders to benchmark and compare soils within agro-ecosystems. These tools are however typically designed for use on mineral soils, despite the environmental and economic importance of lowland drained peatlands for agriculture and food security, particularly in the UK. Tools to assess soil health are often reductionist; generating scores based on the combination of soil property measurements without considering how the attributes of a soil interact to deliver the ecosystem functions and services that underpin soil health. Bayesian networks display simplified causal structures using mutually exclusive nodes and states, which are connected through arcs representing the flow of information with regards to the state of the system given observations made. Here we describe a Bayesian network to define the interactions, graphically and statically, between key soil properties that underpin soil processes that influence soil functions, which can be combined to infer the health of peatlands under intensive agriculture in a data poor environment. The Bayesian network was parameterised using a combination of expert opinion elicitation and biogeochemical modelling to predict the likelihood that a lowland drained agricultural peatland is healthy or unhealthy based upon measurable attributes (peat depth, organic matter content, soil texture, bulk density, microbial biomass, and crop rotation diversity). We validated the Bayesian network using published datasets and expert knowledge and conducted retrospective propagation scenario testing and sensitivity analysis. We demonstrate that the Bayesian network successfully distinguishes a deep well-structured peat, a deep compacted peat, a shallow well-structured peat, and a shallow compacted peat. The Bayesian network we created is a multi-functional tool to assess the peatland system in a holistic manner rather than focusing on a single function or arbitrary combination of measured properties. It is a sensitive metric that can be used by farmers to compare and benchmark fields and investigate the influence of land management on the degradation or restoration of ecosystem functions. We discuss the strengths and weaknesses of the Bayesian network and how it could be developed further in future iterations.

6.1 Introduction

Soils are vital for the food security since they are responsible for 99% of the world's food production (Hatfield, Sauer and Cruse, 2017). This reliance stems from the ability of soils to deliver multiple functions and ecosystem services that we benefit from (Power, 2010). However, not all soil types contribute equally to food security. Peatlands are disproportionally used for high-value agricultural crops due their inherent fertility and high value in terms of ecosystem service delivery, despite their susceptibility to degradation through intensive agricultural management (Parent and Illnicki, 2003; Dawson *et al.*, 2010; Whitfield *et al.*, 2011; Bonn *et al.*, 2014; Evans *et al.*, 2016).

Recent developments have established the multi-functionality of soil systems by identifying and quantifying the physical, chemical, and biological properties that underpin the soil processes that deliver functions (Kibblewhite, Ritz and Swift, 2008; Bünemann *et al.*, 2018; Tahat *et al.*, 2020). As a result, an increased awareness on the effects of human intervention on the degradation of soil systems has become increasingly recognised (Jie *et al.*, 2002; Montanarella, 2012; Stephens, Jones and Parsons, 2017). The development of sustainability goals within the UK has cumulated into the adoption of the soil health concept, the establishment of a Soil Health Action Plan (Department for Environment Food and Rural Affairs, 2018a), and the creation of a Lowland Peat Task Force, tasked with improving the condition of England's farmed lowland peat (Department for Environment Food and Rural Affairs, 2020, 2021d). A key step towards improving peatland condition is the development of a method to measure the soil health of peatlands to compare and benchmark fields and investigate the influence of land management on the degradation or restoration of ecosystem functions.

Current approaches to soil health assessment comprise three stages (Figure 24); (i) the selection of relevant soil properties or attributes through qualitative or quantitative methods, (ii) the scoring of selected attributes, and (iii), integration of scores into indices (Rinot *et al.*, 2019). This approach emphasises simple and applicable methods that allow farmers and land managers to understand the current state of their land (Mukherjee and Lal, 2014; Askari and Holden, 2015; Igalavithana *et al.*, 2017; Purakayastha *et al.*, 2019). However, the development of indices to map soil health often focus on single ecosystem functions or services the soil provides (e.g. agricultural productivity), rather than considering a holistic view of the entire multi-functionality of soil systems to provide a range of soil ecosystem functions and services (Reicosky, 2018; Rinot *et al.*, 2019; Lehmann *et al.*, 2020;

Friedrichsen *et al.*, 2021). However, the relationship between soil properties, soil processes, soil functions, and ecosystem services are complex and non-linear, and 'black-box' (where underlying mechanisms are hidden) modelling techniques can be seen as inappropriate to assess the capacity of soil systems to function given their multi-functional nature (Taalab, Corstanje, Zawadzka, *et al.*, 2015). Due to the complexity of these relationships, there is often insufficient data to adequately model them. However, expert knowledge can be used to provide understanding in a data poor environment. Therefore, the development of models to establish the health of soil systems, particularly peatlands under intensive agriculture, must incorporate expert-derived opinion alongside quantitative dataset measurements to represent soil health. One approach capable of combining expert opinion and experimental or modelled data is Bayesian networks.

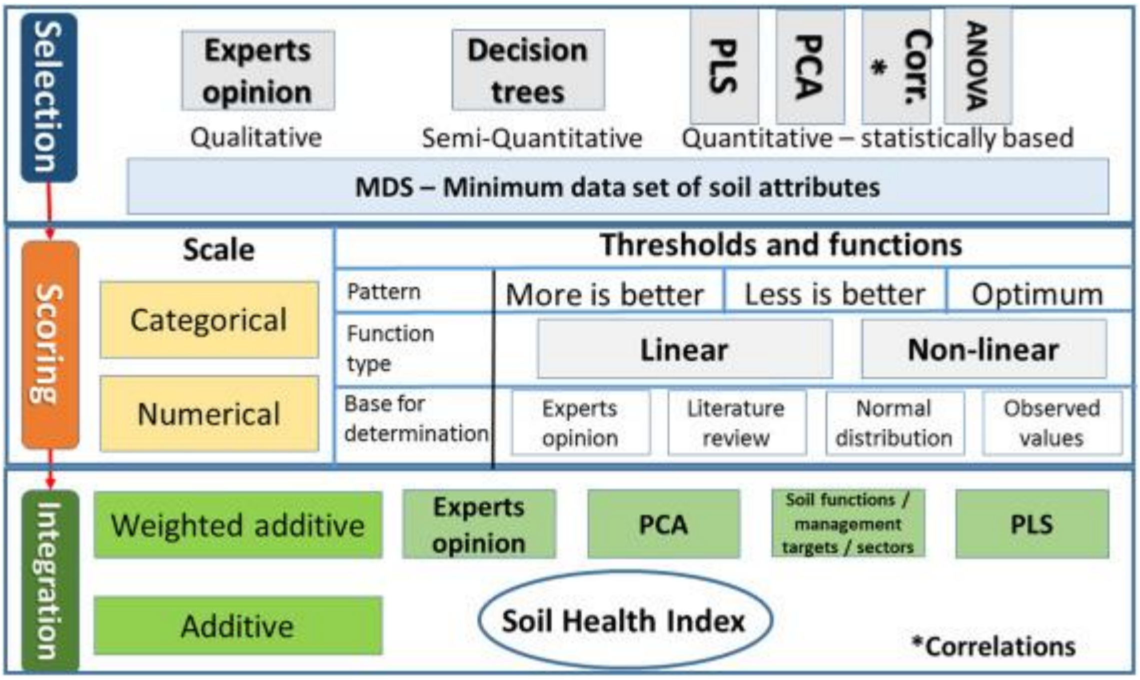

Figure 24: Approaches to Soil Health Index creation and assessment. Reproduced from Rinot et al., 2019.

6.1.2 Bayesian networks

Bayesian networks are probabilistic graphical models that are formed of two components; a qualitative directed acyclic graph (DAG), and quantitative conditional probability tables (CPTs) (Landuyt *et al.*, 2015). The DAG is formed of a set of variables (termed as nodes) which represent the system being modelled and the arcs that connect nodes represent direct causal influence (Jensen and Nielsen, 2007). Each node represents a specific variable and is divided into a finite discrete and mutually exclusive number of states of which the observed node value must belong (Landuyt *et al.*, 2013). These nodes and connecting arcs can be constructed into a network based upon expert elicitations or learned through complex algorithms. However, use of algorithms to construct the network can increase model complexity in comparison to expert elicited network structure, and require further refinement and validation by experts (Pham *et al.*, 2021). Whilst the DAG defines the structure of the modelled system, the CPTs define the relationships between a child node and its parents (Jensen and Nielsen, 2007). A CPT is required whenever two nodes are connected through an arc, indicating a causal relationship between the parent and child node. CPTs are parameterised using a range of methods including expert elicitation, pre-existing datasets, or the use of model simulations (Bowden, 2004; Barton *et al.*, 2008; Zorrilla *et al.*, 2010). The conditional probability of a child node exhibiting a specific state is determined by the probability that each of the parent nodes is in each possible state. Where a node has no parents, a simple probability distribution exists (Pearl, 1988a).

A Bayesian network applies Bayes Theorem which describes the probability of an event, based upon prior knowledge of the conditions that are related to the event using Equation 16:

Equation 16: $$P(A/B) = \frac{P(B/A) \times P(A)}{P(B)}$$

where P(A/B), the posterior, is the probability of A given B is observed, P(B/A) is the probability of B given A is observed, P(A), the Prior (or prior knowledge), is the probability of A, and P(B), the marginalization, is the probability of B being observed.

Bayesian networks use Bayes' Theorem to update beliefs of the probabilities associated with the states of each node within the systems in relation to observed new evidence. Bayes theorem can be used for both the downward and upward propagation of evidence (i.e. finds at a parent or child node) (Ames *et al.*, 2005). This makes Bayesian networks a useful tool for analysing complex ecosystem services where observed data is not readily available (Landuyt *et al.*, 2013).

Bayesian networks are increasingly used to analyse environmental systems, including grassland degradation risks (Zhou and Peng, 2021), ecosystem service provision (Landuyt *et al.*, 2014; Poppenborg and Koellner, 2014; Landuyt, Broekx and Goethals, 2016; Bicking *et al.*, 2019; Tang *et al.*, 2019), water quality management (Fox *et al.*, 2017), wetland conservation (MacPherson *et al.*, 2018), and digital soil mapping (Taalab, Corstanje, Zawadzka, *et al.*, 2015). The usefulness of Bayesian networks within the ecosystem services paradigm is therefore well established. The strengths of using Bayesian network to monitor environmental systems includes the potential to include both expert knowledge and empirical data, the suitability for participatory modelling, the explicit treatment of uncertainties and the ability to validate the models through statistical and expert methodologies (Landuyt *et al.*, 2013).

For this study, we parametrised a Bayesian network to allow for the understanding and exploration of soil health on lowland peat. To achieve this, we examined four previously identified key functions of soil to provide a holistic overview of the processes underpinning the functioning of a peatland system that deliver ecosystem services. These four functions were Peat Structure, Carbon Respiration, Nitrogen Loss, and Pathogen Suppression. The Bayesian network development integrated data from a range of sources. Probability distributions created from hypothetical scenario runs of the ECOSSE model (Smith *et al.*, 2019) and the elicitation of knowledge from experts to identify distributions where data was not present/available. ECOSSE outputs were validated against published datasets and expert elicited distributions validated against expert knowledge. The resulting network tests the ability to infer the subjective health of a peat ecosystem under intensive agriculture. The network can be used to examine the influence of key site-specific soil properties on the state of peat health, and vice versa.

We hypothesised that the parametrised Bayesian network could distinguished between a (1) deep well structured peat, (2) a deep compacted peat, (3) A Shallow well-structured Peat, and (4) a Shallow compacted Peat

6.2. Methodology

6.2.1 Study Location

The Bayesian network was designed to be used to infer Peat Health across the lowland fenlands located in the East of England (Figure 1). This area is a low-lying flat landscape which drains into the Wash (a tidal estuary), much of the land lies below sea level, thus relying upon pumping stations and sluices to control water tables (Richardson and Smith, 1977). The land use of the area is predominately agricultural in nature (Karra *et al.*, 2021). The drained peatland provides excellent conditions for arable and horticultural crop production, which has led to the area becoming vitally important to national crop production (Natural England, 2015). However, due to degrading conditions associated with drainage, exacerbated by intensive agricultural practices, the peatland area is reducing in size and depth (Natural England, 2010). Over the period of 2000 to 2020, the average annual rainfall in the area was around 550 mm, with mean annual maximum and minimum temperature equating to 15°C and 6.7°C respectively.

6.2.2.1 Directed Acyclic Graph (DAG) Development

A DAG framework was previously developed with an interdisciplinary group of experts and by reviewing literature. The group of experts consisted of experts ranging from academic fields (including Earth Science, Agriculture and Geography) alongside those within the industrial domain (including peatland farmers, agronomists, and farm advisers). The objective of the model was to build an understanding of the continued functioning of the peat ecosystem (termed peat health) which had been drained and is currently under agricultural land use. The DAG framework identified key functions associated with inferring the health of the system, and the measurable soil properties that can be used to assess functioning. The preliminary DAG underwent validation by returning to experts for feedback, further discussion, and modification. Modifications were also made to fit the structure of the soil biogeochemical model ECOSSE and to ensure that the parentless soil property nodes were attributes that could relatively easily be measured by land managers. The final DAG developed consisted of 21 nodes and 31 arcs connecting nodes (Figure 25) and was created using the GeNIe modelling software (BayesFusion LLC, 2020).

The discretisation of states was determined after exploration of available datasets and through expert opinion. Where the elicitation of expert knowledge was used to identify CPTs, nodes were discretised into a maximum of three states to minimise the required number of permutations of parent node states that each required the expert to define probabilities of the child node being in each possible state. This restriction reduces issues associated with going beyond an experts knowledge base or incorporating bias (Pollino *et al.*, 2007; Hart and Pollino, 2008; Aguilera *et al.*, 2011). Discretisation of nodes representing continuous variables can lead to information loss and statistical inaccuracy if too few states are selected, whereas too many states can over-complicate a network (Myllymäki *et al.*, 2002). The challenges associated with discretisation of continuous variables were avoided, where possible, by analysis of an entire dataset for the variable in question, inferring the number of appropriate intervals, the significance of the breakpoints, and ensuring that intervals contain a reasonable number of observations (Uusitalo, 2007b). To achieve this, the Discretise function within the GeNIe Modeler software (BayesFusion LLC, 2020) was applied to the dataset produced by biogeochemical modelling (described in Section 6.2.3.2). This process allowed for analysis of node histograms, assessment of percentiles, and exploration of the range of values contained within each state following discretisation. The nodes and states are presented in Table 17. In several cases, including the Peat Health node, a traffic light system was used to label states whereby 'Green' represents a higher value or healthier peat, and 'Red' represents a lower value or unhealthier peat.

6.2.3 Bayesian network Parametrisation

The CPTs were created for the Bayesian network through a combination of expert knowledge and the use of the soil biogeochemical model ECOSSE (J. Smith *et al.*, 2010). The ECOSSE model was used to populate the carbon respiration and nitrogen loss sub-networks in the Bayesian network. Where no datasets were available, CPTs were defined through the elicitation of expert knowledge. Expert knowledge was used to populate the peat structure and pathogen suppression sub-networks and to define how the four functions (carbon respiration, nitrogen loss, peat structure, and pathogen suppression) influence peat health.

6.2.3.1 Expert Elicitation

The elicitation of expert opinion has associated challenges due to the quantity of information required and the ability of experts to quantify subjective beliefs (Kuhnert, Martin and Griffiths, 2010). A method and programme has been developed entitled the Application for Conditional Probability Elicitation (ACE), to extract probability distributions from experts using simple questions to capture the overall shape of probability distributions (Hassall *et al.*, 2019). The ACE approach was implemented in this project to extract probability distributions from experts. The elicitation of expert knowledge was conducted following Kuhnert, Martin and Griffiths, (2010).

Seven experts were carefully chosen for CPT probability elicitation, with three industrial experts and four academic experts. Experts were interviewed online using a modification to the ACE programme. Following the Delphi method (Ling and Bruckmayer, 2021), experts were asked to define their beliefs on the state of soil functions given the observed parent values (the conditional probability distributions). These conditional probability distributions were then aggregated to create the CPTs and shared with the experts to elicit further feedback. Aggregation and incorporation of the Delphi approach allowed us to incorporate the beliefs of experts that spanned multiple fields while reducing the undue influence of a single expert. Bias was minimised by developing a document that clearly explained the states, values, and descriptions of nodes and arcs defined within the network. This document was circulated to all experts before knowledge elicitation. During the elicitation sessions, each expert was provided with a verbal summary of the document, explained the purpose of the exercise, and asked the same questions as each other.

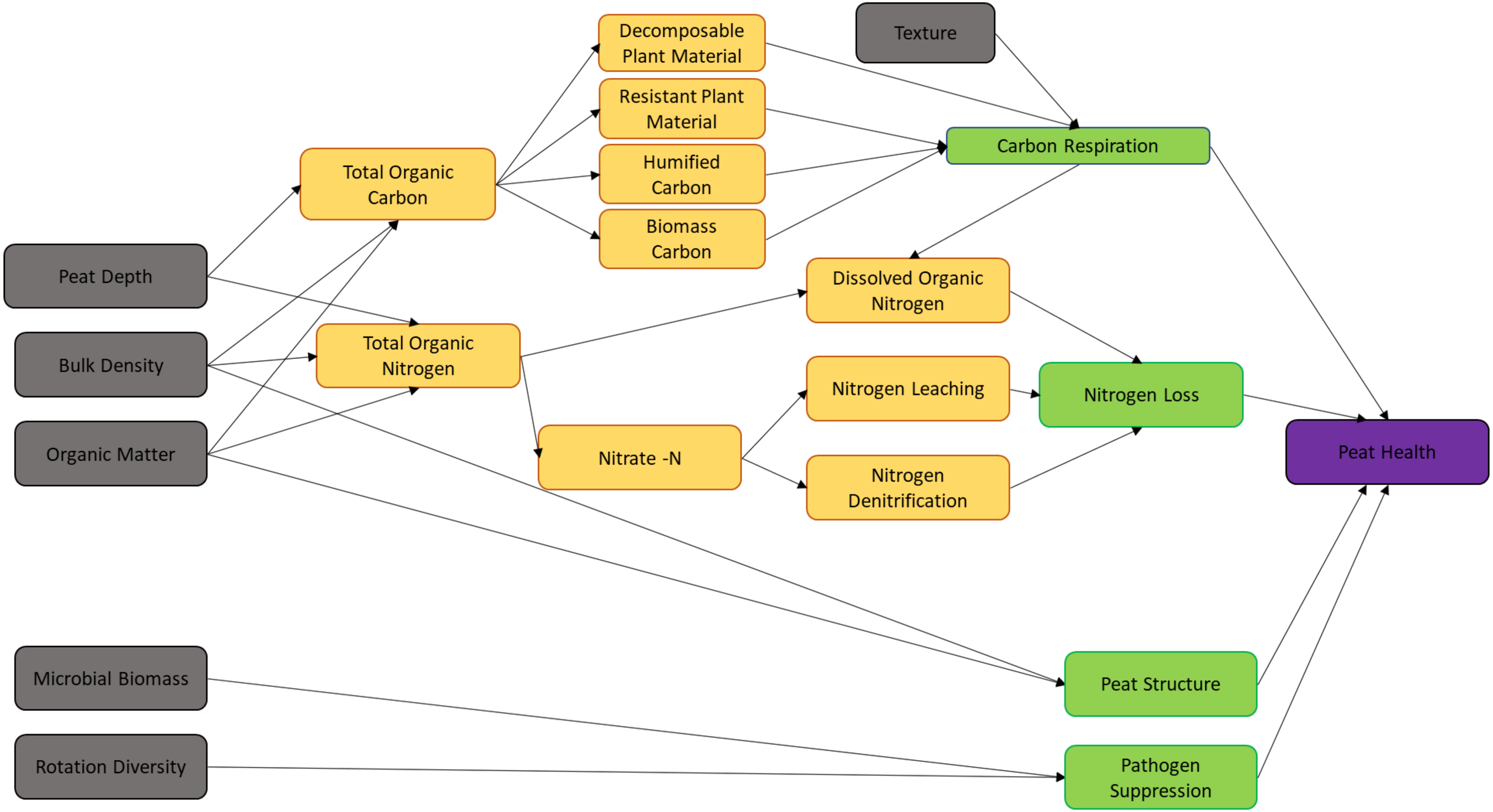

Figure 25: Bayesian network structure. Grey indicates parentless soil properties nodes. Green indicates soil function nodes. Purple indicates the Peat Health output node. Carbon pools, developed through the ECOSSE model, are decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), and humus HUM)

6.2.3.2 ECOSSE Model

The ECOSSE model was created to simulate carbon and nitrogen dynamics in highly organic soils from concepts derived for mineral soils in the RothC and SUNDIAL models (J. Smith *et al.*, 2010). The ECOSSE model was selected as it was designed for use in highly organic Soils, and the required input features of the model were readily available and identifiable. The model could also be simulated across a range of sites and thus allowed for future development where necessary. The model uses a pool approach describing soil organic matter as pools of inert organic matter, humus, biomass, resistant plant material, and decomposable plant material. The ECOSSE model captures to major processes associated with C and N turnover (described in depth in the ECOSSE user manual (Smith *et al.*, 2019)), but each is simulated using only simple equations driven by readily available data. This allows the model to be scaled from a field-based model to a national scale tool without losing accuracy or requiring complex data sets. In summary, as described in Smith et al 2019, plant C and N inputs, alongside inorganic and organic nutrient or manure applications are added in monthly timesteps to the decomposable plant material (DPM) and resistant plant material (RPM) pools. The inputs from vegetation are estimated by use of a plant input equation (Bradbury *et al.*, 1993). During decomposition processes, material is exchanged between the organic matter pools according to first order rate equations, characterised by specific rate constant for each pool (the rate constants used are DPM k_{DPM} = 10 yr^{-1}, for RPM k_{RPM}= 0.3 yr^{-1}, for BIO k_{BIO} = 0.66 yr^{-1}, and for HUM k_{HUM} = 0.02 yr^{-1}) and modified according to rate modifiers depending on the temperature, moisture, crop cover, and pH of the soil. The model assumes that the enzymes within the soil profile responsible for organic matter turnover are in excess and, as such, aerobic decomposition is only dependent on the concentration of C in the decomposing pool. The N content of the soil follows the decomposition of the organic matter, with a stable C:N ratio defined for each pool at a given pH and N being either mineralised or immobilised to maintain this ratio. Nitrogen released from decomposing soil organic matter as ammonium (NH_4^+) or added to the soil may be nitrified to nitrate (NO_3^-). Carbon and N may be lost from the soil by the processes of leaching (NO_3^-, dissolved organic C (DOC), and dissolved organic N (DON)), denitrification, volatilisation or crop offtake, or C and N may be returned to the soil by plant inputs, inorganic fertilizers, atmospheric deposition, or organic amendments. The soil is divided into 5cm layers to facilitate the accurate simulation of these processes down the soil profile to a depth of 3meters.

The ECOSSE model was used to quantify caron respiration and nitrogen loss for several site-specific scenarios that were systematically tested based on soil, environmental, and management input data described in Table 16. The combination of these scenarios was implemented through creating multiple input files for the ECOSSE model using MatLab (MATLAB, 2021) leading to over 15550 runs of the model. These combinations were compiled as they incorporated a full range of possible permutations which real-world values could take. The ECOSSE model initialisation to determine the initial sizes of the organic matter pools was simulated by an equilibrium run of the RothC model which runs under the assumption that the system is at a steady state. This method uses a spin-up approach that adjusts the decomposition rates using both plant inputs from measured net primary productivity and measured total organic carbon content. The initialisation processes are detailed in Smith et al 2010. After spin-up, the model was run over 2 years given known management operations (including tillage, fertiliser applications, crop type etc). The outputs of the last year of the modelling ECOSSE model were selected for development of the CPTs and averaged over an annual period to smooth out the influence of seasonal climatic variables. CPTs for the BN were created through the data learning function in GeNIe, where data was discretised and then a joint probability distribution created.

Validation of the ECOSSE model could not be conducted through analysis of both pre-existing carbon respiration and nitrogen loss datasets specific to lowland fen regions in the UK. Rather, measurements exists for CO_2 respiration from eddy covariance and static gas chamber measurements (Evans *et al.*, 2016) within the region. This study contains similar background soil data (Bulk Density, Depth and Organic Matter content) to allow for a comparison of CO_2 respiration with BN classification. This will be principally achieved by classifying the CO_2 measured respiration within the state, and observing whether inputting similar background soil data leads to the same state being observed in the BN.

Table 16:The ECOSSE input data (including sources, where necessary) used to simulate the carbon and nitrogen cycling in soils under a range of different conditions to generate a dataset used to parameterise the Bayesian network

Input data	Notes
30-year average monthly rainfall (mm), temperature (ºC) and potential evapotranspiration (mm).	The ECOSSE model was run using 30-year average and monthly rainfall and temperature accessed through one of the Met Office long running historic weather stations located at NIAB Cambridge (Location: 543500E 260600N, Lat 52.245 Lon 0.102). (https://www.metoffice.gov.uk/pub/data/weather/uk/climate/stationdata/cambridgedata.txt) Average Potential Evapotranspiration was calculated using CropWat version 8.0 (Smith, 1992). The programme calculates potential evapotranspiration using the Penman Montieth equation (Allen *et al.*, 1994).
Initial soil C content (kg/ ha)	The ECOSSE model was run with soil organic carbon content ranging between 20% organic matter to 65% organic matter in 5% intervals. Organic matter percentage was converted to organic carbon using a conversion factor of 0.5 (Pribyl, 2010; Klingenfuß *et al.*, 2014). This was then multiplied by bulk density, depth, and volume to calculate carbon content in kg/ha.
Soil Depth at which soil properties have been measured (cm)	The ECOSSE model was run with peat depths of 20cm, 50cm and 100cm.
Soil Sand, Silt, and Clay content (%)	The ECOSSE model was run for each of the 12 textural classes identified in Natural England Technical Information Note 037 (2008) http://publications.naturalengland.org.uk/publication/32016
Soil Bulk Density (g/cm^3)	The ECOSSE model was run with bulk density values between 0.2 and 1.0 g/cm^3 at 0.1 g/cm^3 intervals.
Soil pH	The ECOSSE model was run with pH values between 5 and 9, at 1-unit intervals.
Crop Type, tillage operations, inorganic and organic manure applications for each simulation year	The ECOSSE model was run with crop type and management operations established through conversations with local farmers and land managers. The crop rotation was a winter maize followed by either a single lettuce or double lettuce.
Water Table depth (cm)	The ECOSSE model was run with a water table depth set to either 100cm or 50cm

6.2.4 Scenario testing

The Bayesian network was tested using example scenarios to identify information flow through the network by predictive and retrospective propagation (Vrebos *et al.*, 2021). This was achieved by instantiating either an input node or the Peat Health node and observing how this propagates through the Bayesian network and alters the probability distribution of the states of the other nodes.

6.2.4.1 Predictive Propagation Scenario Testing

Predictive propagation involves instantiating a parentless input node in the network to 100% probability distribution for one state and observing how this alters the probability distribution of child variables flowing down the network to the final output. There are a total of 69,984 parent state combinations available to assess. However, we examined four strategic scenarios to display the predictive power of the network for assessing Peat Health node. These four scenarios are broadly representative of the input node states expected for a deep well-structured peat, a deep compacted peat, a shallow well-structured peat, and a shallow compacted peat. Where no parent states were instantiated and the model was setup with each parent node having an equal probability of being in any of the available states, the probability distribution of the Peat Health node had a 26.4% probability of being in the Green state, 30.8% probability of being in the Amber state and 42.8% probability of being in the Red state.

6.2.4.1 Retrospective Propagation Scenario Testing

Propagation through instantiation of the end outcome allows observation of how information flows upwards through the network. By instancing the Peat Health node state, we can observe how changes to the measurable properties in the Bayesian network most likely contribute towards increasing or decreasing peat health. To do this, the Peat Health node states were instantiated to either 100% Green, 100% Amber, or 100% Red, and the changes to the parent probability distributions were measured.

6.2.5 Bayesian network Validation

Marcot, 2012 presented a range of metrics to gauge Bayesian network performance and uncertainty (Marcot, 2012). Validation of Bayesian network outputs generally include stakeholder validation or sensitivity analysis but in some cases, validation is not discussed (Landuyt *et al.*, 2013)**.** We validated the Bayesian network using (i) expert opinion through face validity, (ii) K-fold cross validation, and (iii) sensitivity analysis.

6.2.5.1 Expert Opinion Validation using the Face Validity Method

Because the Bayesian network contains connections and nodes that represent subjective descriptors, expert opinion through face validity was used to validate the probability distributions of the network (Pitchforth and Mengersen, 2013). To avoid criterion contamination, the experts were individually asked to complete CPTs for the pathogen suppression node, the peat structure node, and the Peat Health node. Following this, all elicitation results were aggregated into a single CPT, and referred to the experts individually to assess the validity of the network. The network CPTs were considered valid if over 75% of experts agreed with the final aggregated CPT. This protocol provides greater robustness than face validity using a modified version of a control group and validation group (Pitchforth and Mengersen, 2013).

6.2.5.2 K-Fold cross-validation of the ECOSSE dataset

K-fold cross-validation can be used where a model is built and evaluated with the same dataset. This process, as stated in the GeNIe manual (BayesFusion LLC, 2020), sequentially divides the dataset into K parts of equal size, trains the network on K-1 parts, and tests it on the last, K^{th} part. This process is repeated K times, with different part of the data being selected for testing, until all subsets have been used. The value of K is a subjective choice, however, k=10 is a common selection to enable thorough analysis (Marcot, 2012) and was chosen here for this reason. Following this, Receiver Operating Characteristic (ROC) Curves were assessed using the GeNIe function. ROC curves are graphical plots that show the diagnostic ability of the model given the discrete classifiers set. They plot the true positive rate (sensitivity) in function of the false positive rate (Specificity) for different cut off points of a parameter. The Area Under the ROC (AUC) is calculated and can be viewed as equivalent to the probability that a randomly chosen data point is correctly identified in a classifier rather than incorrectly y identified. As such, the ROC curve and AUC value indicate the diagnostic accuracy of the k-fold cross validation.

6.2.5.3: Sensitivity Analysis

Sensitivity analysis in Bayesian network modelling relates to determining the degree to which a new finding in a target node is explained by other variables (termed finding nodes), and essentially depicts the underlying probability structure of a model given prior probability distributions (Li and Mahadevan, 2017). Model sensitivity can be calculated as variance reduction for continuous variables or entropy reduction for categorical variables (Marcot 2012). We used the GeNIe software, which implements an algorithm developed by Kjaerulff and van der Gaag (2000), to calculate efficiently a complete set of derivatives of the posterior probability distributions for each target node over each of the numerical parameters of the network (BayesFusion LLC, 2020). The output from this process indicates how a change in a parameter changes the posteriors of a target node.

6.3 Results

The final developed and populated Bayesian network can be seen in Figure 26. The network includes 21 nodes and 31 arcs connecting parent and child nodes. The six parentless nodes (peat depth, organic matter content, soil texture, bulk density, microbial biomass, and crop rotation diversity) are all measurable attributes that can be defined for individual peatland fields. Nodes had between two and twelve states that defined the condition of the node. The quantitative boundaries of states are provided in Table 17.

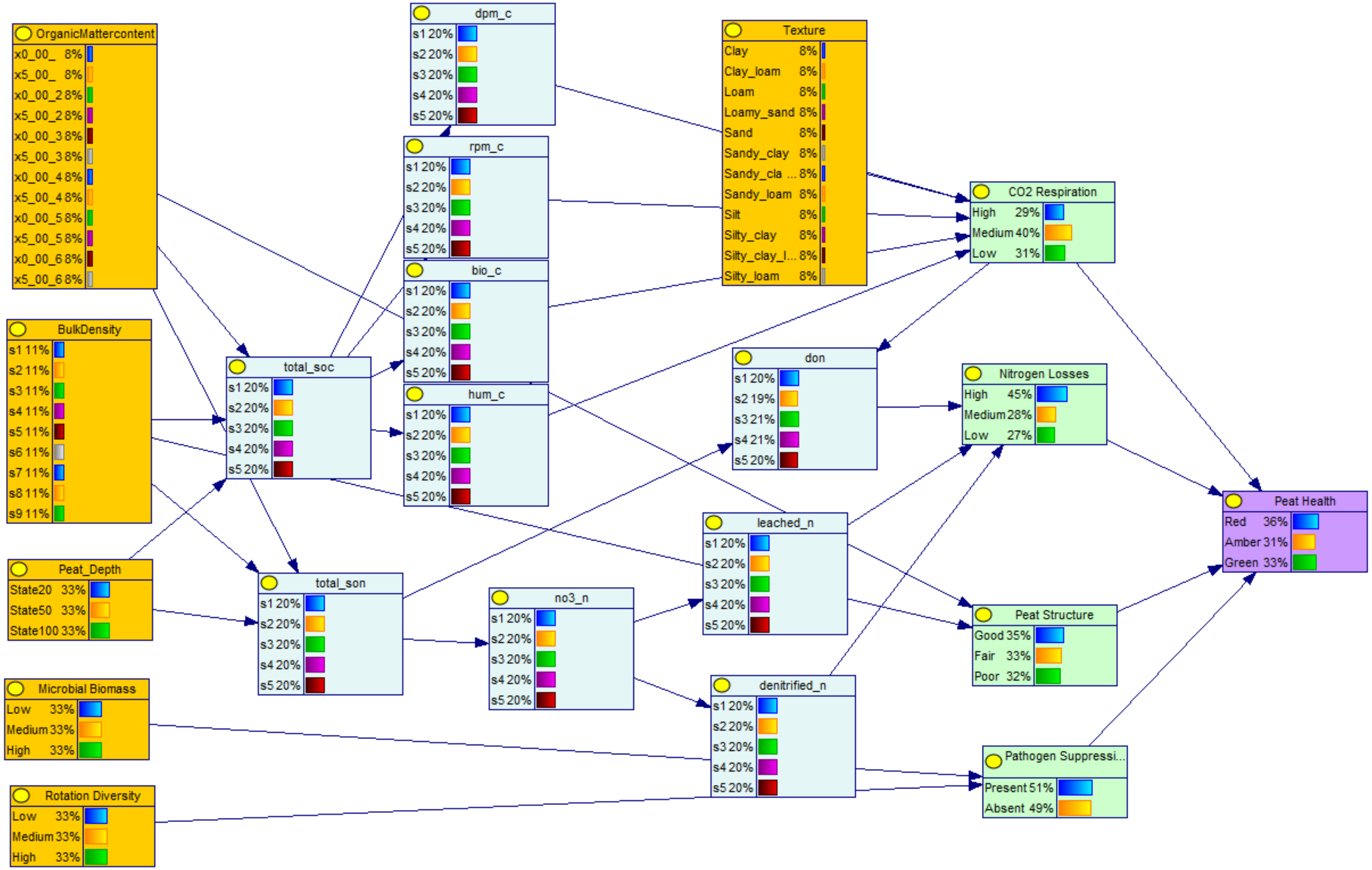

Figure 26: The Bayesian network with populated CPT's developed through expert opinion and outputs from the ECOSSE model. Yellow nodes indicate parentless soil properties. Green nodes indicate soil functions. The purple node is the Peat Health output. States are listed underneath the name of each node and the probability distribution given for the child nodes when there is an equal probability of parent nodes being in any of the given states. See Table 14 for a breakdown of the states.

Table 17: Node titles and associated states and reference to be read in conjunction with Figure 26. Nodes with A, B, C,D,E state divisions are created through Discretisation of ECOSSE dataset into 5 equal width states.

Node	States	Reference
Organic Matter (%)	10% to 65% in 5% intervals	Peatlands in the UK are classified by depth and organic matter content, and generally over the UK requires at least 20% organic matter content (Lindsay, 2010); however, degradation leads to values falling below this level. The range of values was decided through literature review and expert knowledge (Holman, 2009; JNCC, 2011b; Bader, Müller, Schulin, *et al.*, 2018; Säurich *et al.*, 2019; Leifeld, Klein and Wüst-Galley, 2020) to incorporate a range of degraded peat systems.
Peat Depth (cm)	20 50 100	Peat depths were modelled at 20, 50 and 100cm. These values were chosen to represent wasted, shallow and deep peats respectively (Holman, 2009; JNCC, 2011b; Department for Environment Food and Rural Affairs, 2021a)
Bulk Density (g/cm^3)	0.2 to 1.0 g/cm^3 in 0.1 intervals	Analysis of literature and expert knowledge observed that bulk densities were modelled from 0.2 g/cm^3 to 1.0 g/cm^3 since this encompassed values that can be observed through a transition of peat functioning towards mineral soil functioning (Holden *et al.*, 2006; Mustamo *et al.*, 2016; Rezanezhad *et al.*, 2016; Liu and Lennartz, 2019).
Total Soil Organic Carbon (kg C / Ha)	A = <169246.2 B = 169246.2 - 312120 C = 312120 - 539399.9 D = 539399.9 - 997172.9 E = >997172.9	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Total Soil Organic Nitrogen (kg N / Ha)	A = <15266.58 B = 15266.58 - 28546.08 C = 28546.08 - 49415.5 D = 49415.5 - 93738.42 E= >93738.42	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Texture	Sand, Loamy sand, Sandy loam, Loam, Silty loam, Silt, Clay loam, Sandy clay loam, Silty clay loam, Sandy clay, Silty clay, Clay	As defined by Natural England Soil Texture Guide (Natural England, 2008)
Decomposable Plant Material (Carbon) (kg C / Ha)	A = <20874.03 B = 20874.03 - 39792.8 C = 39792.8 - 67090.16 D = 67090.16 - 106998.2 E = >106998.2	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis

Resistant Plant Material (Carbon) (kg C / Ha)	A = <55004.54 B = 55004.54 - 92719.7 C = 92719.7 - 142865.6 D = 142865.6 - 225561.9 E = > 225561.9	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Biomass Carbon (kg C / Ha)	A = <5089.25 B = 5089.25 - 8314.9 C = 8314.9 - 12779.78 D = 12779.78 - 22425.61 E = >22425.61	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Humified Carbon (kg C / Ha)	A = <41976.96 B = 41976.96 - 115178.5 C = 115178.5 - 297929 D = 297929 - 586247.1 E = > 586247.1	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
CO2 Respiration (kg C / Ha)	High Medium Low	Based upon Säurich et al., (2019) and Evans et al., (2016) datasets. CO_2 respiration data (converted to kg Carbon/ per ha) was normalised to 1cm depth. High: Values greater than the median (> 58.697 Kg Carbon respired per Hectare per month) were noted to fall into the High state of CO_2 Respiration. Medium: Values in between 22.589 - 58.697 Kg Carbon respired per Hectare per month were identified to fall into the Medium state. Low: Values below Quartile 1 were noted to fall into the Low state (< 22.589 Kg Carbon respired per Hectare per month).
N_2O (kg N / Ha)	A = < 4.257575 B = 4.257575 - 4.771425 C = 4.771425 - 5.402425 D = 5.402425 - 6.106492 E = > 6.106492	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Dissolved Organic Nitrogen (kg N / Ha)	A = < 0.18975 B = 0.18975 - 0.547525 C = 0.547525 - 1.41135 D = 1.41135 - 3.444833 E = > 3.444833	Dataset analysis and use of expert knowledge: Division of ECOSSE outputs through Equal Count analysis
Nitrogen Loss (%)	High Medium Low	States defined by expert opinion and Dataset analysis. The method for calculating Nitrogen loss was to sum the nitrogen lost through Dissolved Organic Nitrogen, Leaching and Denitrification, following this, the summed value was divided by the Total Organic Nitrogen and normalised to 1cm depth. High: High Nitrogen losses occurred where values exceeded the median (> 50% (0.00014%)

		Medium: Nitrogen losses that occurred between the median and 1st quartile fall into this state (between 0.000048% – 0.00014%). Low: Lower than the 1st quartile indicate low nitrogen loss from the system (< 25% (0.000048%)
Peat Structure	Good Fair Poor	States based upon literature review (Holden *et al.*, 2006; Mustamo *et al.*, 2016; Rezanezhad *et al.*, 2016; Rabot *et al.*, 2018) and expert assessment. Good: indicates a peat system that maintains a good structure despite drainage, with a high degree of porosity and high saturated hydraulic conductivity. Fair: indicative of a transitioning peat systems towards a mineral soil whose structure is degrading, with lower porosity, increasing bulk density, and reduced hydraulic conductivity. Poor: indicates a system with reduced hydraulic conductivity, poor drainage, low porosity and indicating poor structure for roots and habitat for biodiversity. This system mimics that towards a mineral soil in comparison to a peat.
Microbial Biomass	High Medium Low	States based upon literature review (van Os and van Ginkel, 2001; Pankhurst *et al.*, 2002; Kowalchuk *et al.*, 2003; van Bruggen *et al.*, 2015) and expert assessment. High: Associated with a high total microbial biomass, indicating higher potential for pathogen suppression through competition (> 175 mg/kg Microbial Biomass) Medium: Microbial Biomass is between (65 – 175 mg/kg) indicating a system with Low: Associated with low total microbial biomass in the peat ecosystem and thus low underlying primary defence against pathogens (< 65 mg/kg Microbial Biomass)
Rotational Diversity	High Medium Low	States defined through a review of the literature (Termorshuizen *et al.*, 2006; Hiddink, Termorshuizen and van Bruggen, 2010; Peralta *et al.*, 2018; He *et al.*, 2019; Fan *et al.*, 2020) and conceptualised by Expert Opinion.

		High: Associated where crop rotation involves not growing the same family crops for over 5 years. This would be associated with wider range of carbon inputs to the system, the development of a diverse microbial community, and the interrupts the life cycle of pathogens. Medium: Associated to crop rotation which involves not growing crops of the same family within 2-5 years of each other. Low: Where crop rotation involves growing crops of the same family within 2 years of each other. This reduces influx of a range of plant debris and reduces the probability bacteria diversity increases.
Pathogen Suppression	Present Absent	States divided into whether the function of the peat in providing pathogen suppression with either present, leading to a reduction in pathogen incidences during the growing season, or, absent, which indicates pathogens suppression is incorrectly occurring and incidences of
Peat Health	Green Amber Red	Expert Opinion: Green: The system is functioning to a high capacity and has the continued capacity to function. No further action required. Amber: The system is beginning to decline in functioning, further monitoring is essential. Red: Associated with the poor functioning of the peat ecosystem. This would be correlated with a highly degraded system that requires immediate attention.

6.3.1 Scenario Testing

6.3.1.1 Predictive Propagation Scenario Testing

Scenarios were run that are broadly representative of the input node states expected for a deep well-structured peat, a deep compacted peat, a shallow well-structured peat, and a shallow compacted peat and compared to the control scenario and it was observed how these altered the probability distribution of the Peat Health node in an expected manner (Table 18). The deep well-structured peat simulation increased the probability that the Peat Health node was 'Green' by 8.42% and the shallow compacted peat increased the probability that the Peat Health node was 'Red' by 7.13%. The predictive propagation scenario testing clearly indicates that the Bayesian network can distinguish a deep well-structured peat, a deep compacted peat, a shallow well-structured peat, and a shallow compacted peat.

Table 18: Displaying the states of the model instantiated to predefined examples of healthy systems and the associated change to the probability distribution of the Peat Health node for the four predictive propagation scenarios examined, compared to a default simulation with an equal probability of parentless nodes being in any of the given states.

Scenario	State instantiation	% Probability Change of Peat Health State
1 – Deep well-structured Peat	Bulk Density: 0.4 Organic Matter Content: 40% Peat Depth: 100cm Rotation Diversity: High	Green: +7.79 Amber: -0.06 Red: -7.73
2 – Deep compacted Peat	Bulk Density: 0.9 Organic Matter Content: 40% Peat Depth: 100cm Rotation Diversity: Low	Green: -1.48 Amber: 0.02 Red: +1.46
3 – Shallow well-structured Peat	Bulk Density: 0.4 Organic Matter Content: 20% Peat Depth: 20cm Rotation Diversity: Low	Green: -5.76 Amber: -0.26 Red: +6.01
4- Shallow compacted Peat	Bulk Density: 0.9 Organic Matter Content: 20% Peat Depth: 20cm Rotation Diversity: High	Green: -6.91 Amber: -0.29 Red: +7.20

6.3.1.2 Retrospective Propagation Scenario Testing

The instantiation of the Peat Health node to 100% ‘Amber’ state created no observable alterations to the probability distributions of the parent nodes examined, with results showing <1% change in probability distributions compared to the control scenario where no parent states were instantiated. The instantiation of the Peat Health node to 100% ‘Green’ state resulted in changes to the probability distributions reflecting an increase in the probability of, higher organic matter content, lower bulk density, increased peat depth, higher microbial biomass, and greater rotational diversity. Instantiation of the Peat Health node to 100% ‘Red’ state altered probability distributions in a reverse manner to that of ‘Green’ state instantiation with similar magnitude of changes (albeit in the opposite direction).

6.3.2 ECOSSE model evaluation: CO_2 Respiration

The probability distributions of the BN in comparison to measured soil properties can be seen in Table 19. Sites were instantiated on properties which matched nearest to the measured values. The BN outputs, as developed through the ECOSSE model, showed a moderate ability to predict State Classification given through measured soil values. For shallow sites, averaging the probability distributions, the model correctly assessed the probability that the site would be in the low state 35.5%. In comparison, it predicted the probability of the state being in either the Medium or High category 40% and 23.5% respectively. For the deeper sites, the model predicted that the probability of the low state was on average 55.5%, the Medium state 34.5% and the high state 10.5%. Peat sites within the region studied were relatively deep (all above 50cm), whereas in comparison, the ECOSSE model was run on depths of 20cm, 50cm and 100cm.

Table 19: Results from instantiating the states of the ECOSSE model component of the Bayesian Network in comparison to examples from prior research. ECOSSE modelling showed an ability to identify the correct states based upon this instantiation. Site: EF-SA means East Anglia Fenlands – Shallow depth of peat (Agricultural land) and EF-DA means East Anglia Fenlands – Deep depth of peat (Agricultural land). Measured Soil Properties and selected parent node soil property state are in the order (Organic Matter (%), Peat Depth (cm), Bulk Density (g/cm^3))

Measured Soil Values				BN: ECOSSE modelled state	
Site	Measured Soil Properties	Kg C per hectare per cm	State Classification	Selected Parent Node States	BN Distribution
EF-SA	30.8, 75, 0.62	21.707	Low	30, 50, 0.6	High: 0.31 Medium: 0.38 Low: 0.31

EF-SA	30.8, 75, 0.62	17.656	Low	30, 100,0.6	High: 0.16 Medium: 0.42 Low: 0.42
EF-DA	43.6, 200, 0.5	6.564	Low	40, 100, 0.5	High: 0.14 Medium: 0.39 Low: 0.47
EF-DA	43.6, 200, 0.5	5.413	Low	45, 100, 0.5	High: 0.07 Medium: 0.30 Low: 0.64

6.3.3 Bayesian network Validation

6.3.3.1 Expert Opinion Validation using the Face Validity Method

6.3.3.1.1 Pathogen Suppression

The probability distributions elicited by individual academic and industry experts gathered through use of the ACE package had minor differences with the aggregated scores for the Pathogen Suppression node. Industry experts' probability distributions were within ±1.38% of the aggregated scores for both the presence and absence of pathogen suppression given its parents. One industrial experts' opinion differed substantially from the aggregated scores, with five of the nine probability distributions having a variation of over ±10%. The expert was questioned on their probability distributions but was confident in the distributions that they defined and so these were not altered. The academic experts' probability distributions were within ±0.63% of aggregated scores. The final expert elicited aggregated probability distributions for the Pathogen Suppression node are provided in Appendix: Supplementary Information 2 (Table 20).

6.3.3.1.2 Peat Structure

The average difference between industry experts' elicited probability distributions and aggregated distributions for the Peat Structure node was small. However, there were differences between the probability distributions elicited from academic experts and industry experts. On average, industry experts' distributions were lower for 'Poor' Peat Structure given its parent's states (-1.41%), similar for 'Fair' and 'Good' Peat Structure given its parent's states (0.49% and 0.92% respectively). One industry expert defined 30% of their probability distributions as ±10% different from the aggregated scores. This difference manifested itself as a greater confidence that the state of the Peat Structure node being in the ‘Good’ category given the combination of parent’s states. The expert self-declared a high degree of confidence in their elicited structure and a high degree of expertise in the subject. The average difference between academic experts’ elicited probability distributions and aggregated distributions was also small. On average, academic expert distributions displayed slight variations for ‘Poor’ and ‘Good’ Peat Structure given its parent’s states (1.82% and -1.67% respectively), and limited differences for ‘Fair’ Peat Structure given its parent’s states (-0.15%). A single academic expert defined 41% of their probability distributions as ±10% different from aggregated scores. However, unlike the industry expert, the academic expert did not consistently define the Peat Structure node state as either better or worse than the aggregated scores, given its parent’s states. The expert self-declared their confidence as ‘medium’ indicating they were reasonably confident in their final probability distributions. The final expert elicited probability distributions for the Peat Structure node are provided in Appendix: Supplementary Information (Table 21).

6.3.3.1.3 Peat Health

Expert elicited probability distributions for the Peat Health node resulted in a greater difference between experts than the Pathogen Suppression and Peat Structure nodes. The average difference between industry expert aggregated probability distributions and the overall aggregated probability distribution was relatively small for the ‘Red’ state (-0.99%), ‘Amber’ state (-0.63%), and ‘Green’ state (1.62%). Two industry experts defined probability distributions with over ±20% difference from the aggregated probability distribution (30.25% and 30.86% respectively). One of the industry experts showed a consistently higher degree of confidence that the Peat Health node is in the ‘Green’ State, given its parent’s states, in comparison to the aggregated probability distributions. The other industry expert who generated probability distributions substantially different to the aggregated distributions consistently defined the Peat Health node as less likely to be in the ‘Green’ state, given its parent’s states, compared to the aggregated probability distributions. The average difference between academic experts’ aggregated probability distributions and overall aggregated probability distribution was relatively small, with minor differences observed for the ‘Red’ state (1.5%), ‘Amber’ state (0.01%), and ‘Green’ state (-1.51%). However, two academic experts elicited probability distributions that were over ±20% different than the aggregated probability distribution (50.00% and 53.09% respectively). One academic expert considered the probability of the ‘Green’ state occurring over 10% lower than the aggregated probability distribution, indicating a decreased belief in Peat Health being in a ‘Green’ state given its parent's states. The other academic expert also predicted a lower probability of the 'Green' state occurring, given its parent's states, except where lower CO_2 Respiration was observed, when the expert predicted a higher probability of the 'Green' state occurring. The final expert elicited probability distributions for the Peat Health node are presented in Appendix: Supplementary Information (Table 22).

6.3.3.2 K-Fold Cross validation

K-Fold cross validation was performed for all the CPTs generated with the ECOSSE biogeochemical model. This included the CO_2 Respiration and Nitrogen Loss nodes and their respective parents. The overall accuracy the Bayesian network found during validation was 72.24%, correctly identifying 22507 out of the total 31104 records building the sections of the network. CO_2 Respiration showed a high degree of accuracy at predicting states through validation, correctly identifying 71.69% of observations (11149 out of the 15552 observations). Validation correctly predicted the 'High' state with 72.82% accuracy (3481 out of 4780 observations), the 'Medium' state with 66.85% accuracy (4077 out of 6099 observations), and the 'Low' state with 76.85% accuracy (3591 out of 4673observations). For all states, Receiver Operating Characteristics (ROC) Curves were assessed, which express the quality of a model, independent of the classification decision. The ROC curves developed showed curves above the hypothetical classifier, indicating that the classifiers (i.e., 'High', 'Medium' or 'Low') maintain high sensitivity to observations. An example ROC curve is provided in Figure 27. High and Low States for the CO_2 Respiration node returned Area Under the Curve (AUC) scores of over 0.9 indicting they are excellent at accurately classifying observations, whereas the Medium state displayed a weaker AUC of 0.8.

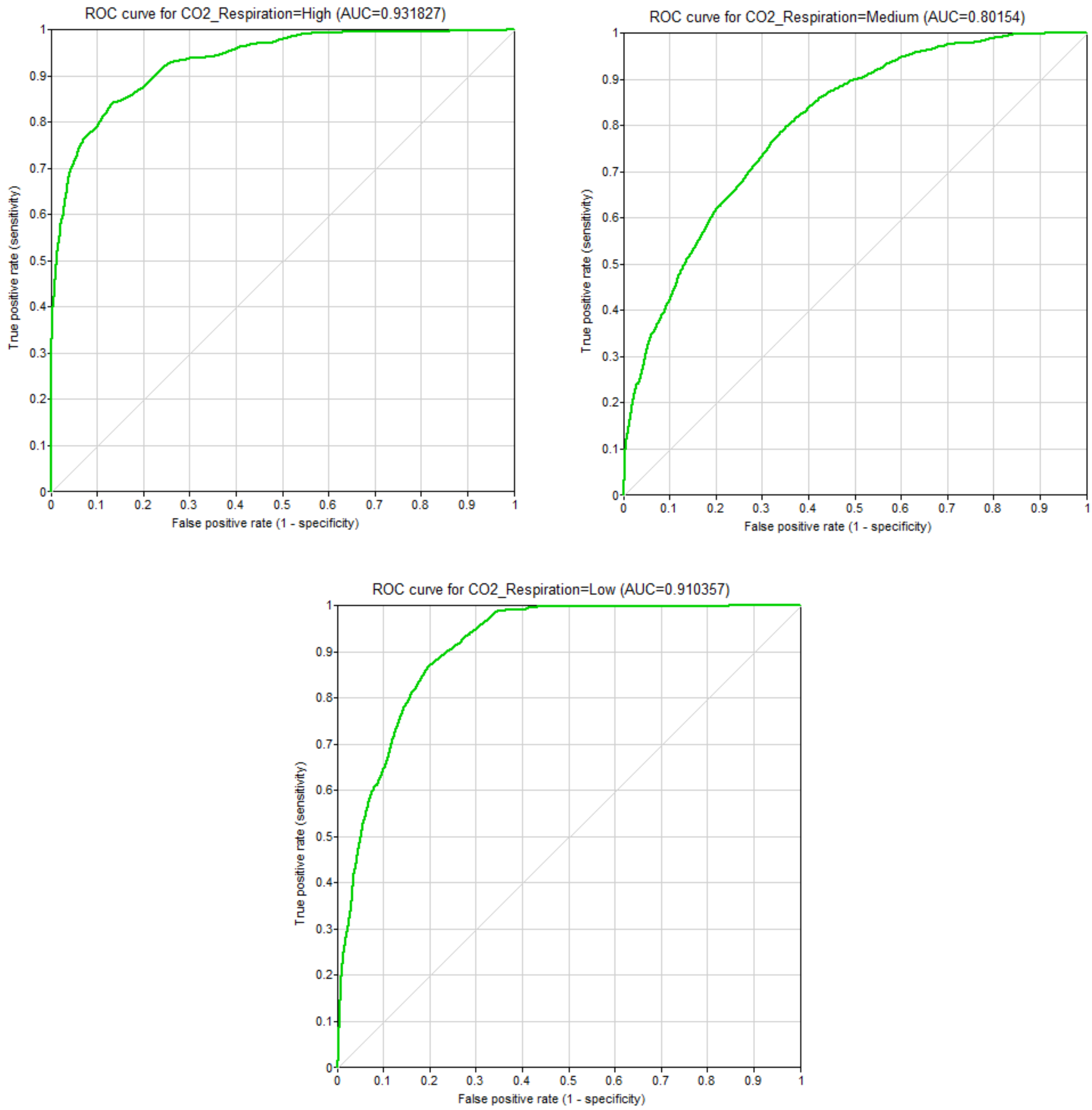

Figure 27: Results indicate a strong ability of the Bayesian Network to correctly identify the state of the CO_2 Respiration node. Displaying Receiver Operating Characteristics (ROC) curve for the CO_2 Respiration node. The green Line is the ROC curve, indicating the sensitivity (i.e., the number of true positives as a percentage) against the specificity (i.e., the percentage of false positives). The grey line indicates a hypothetical curve that displays an inadequate level of accuracy.

K-Fold cross validation of the Nitrogen losses node also a revealed a high degree of accuracy at predicting states through validation, correctly identifying 73.03% (11358 out of 15552) of observations. Validation correctly predicted the 'High' state for 88.17% of observations (6857 out of 7777), however, the 'Medium' state, with a lower accuracy, for 42.06% (1635 out of 3887) of observations, and the 'Low' state for 73.71% (2866 out of 3888) of observations. For all states except one, ROC curves were above the hypothetical classifier class, and AUC scores above 0.9, indicating an excellent ability to accurately classify observations. The Nitrogen Losses nodes 'Medium' state had a shallower ROC curve than the other states, indicating a weaker sensitivity and accuracy (AUC score 0.80).

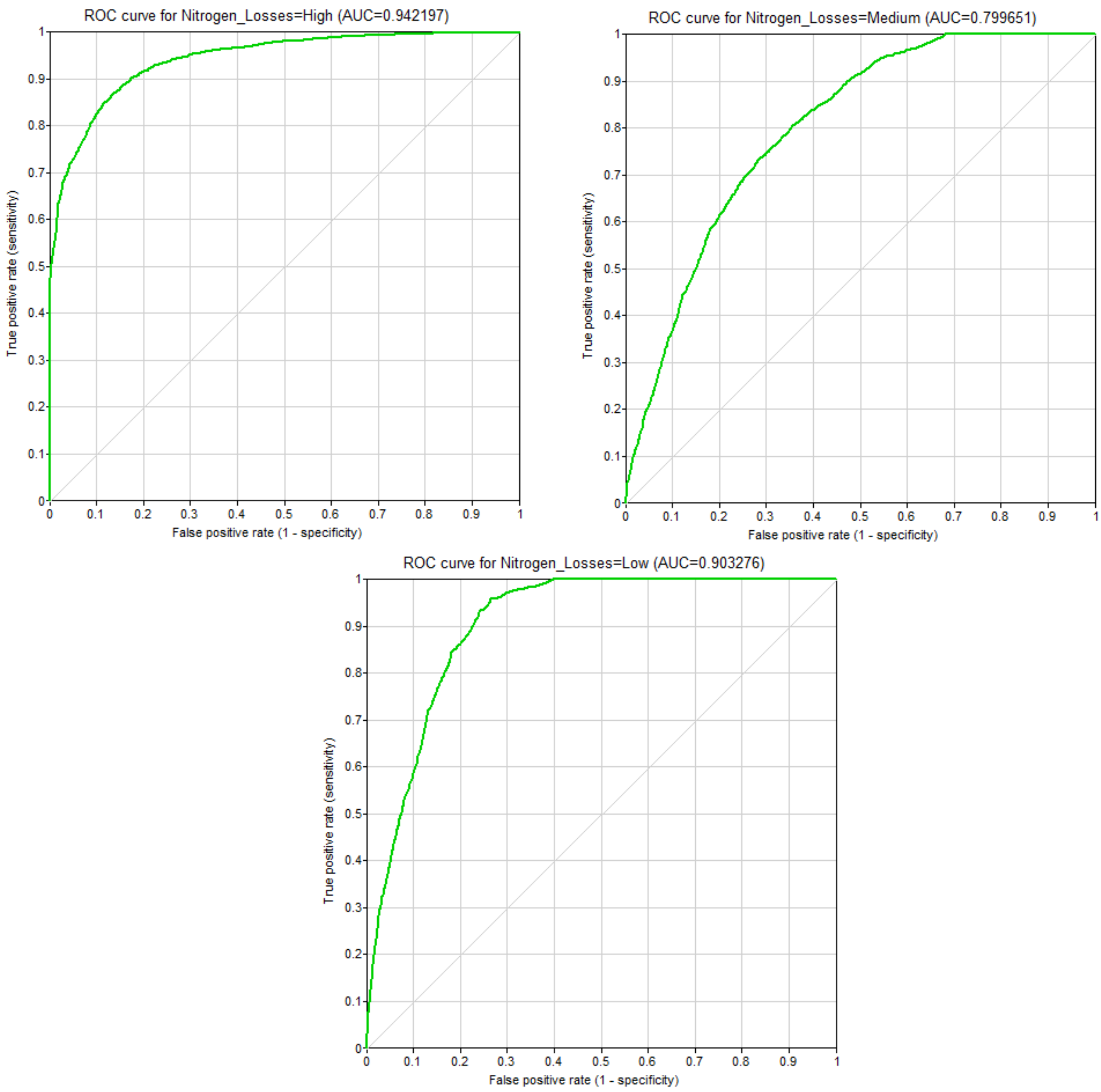

Figure 28: Results indicate a strong ability of the Bayesian Network to correctly identify the state of the Nitrogen Loss node. Displaying Receiver Operating Characteristics (ROC) curve for the Nitrogen Loss node. The green Line is the ROC curve, indicating the sensitivity (i.e., the number of true positives as a percentage) against the specificity (i.e., the percentage of false positives). The grey line indicates a hypothetical curve that displays an inadequate level of accuracy.

6.3.3.3 Sensitivity Analysis

The sensitivity analysis of the Bayesian network using GeNIe revealed that all nodes within the network display a level of influence upon the Peat Health output node (Figure 29). Apart from the Texture node, it is the parentless input nodes that the Peat Health node is most sensitive to. The Peat

Depth and Organic Matter Content are the nodes that influence Peat Health more than the other nodes. This finding indicates that a shift in the probability distribution of the Peat Depth or Organic Matter Content is more likely to alter the probability distribution of the Peat Health node than any of the other nodes.

6.4 Discussion

The Bayesian network presented here is successfully distinguishes a deep well-structured peat, a deep compacted peat, a shallow well-structured peat, and a shallow compacted peat. Peat health is more likely to be in a 'Green' state (i.e., healthy) when deep and/or well structured (low bulk density, high organic matter content, deep depth, and high rotation diversity). Therefore, the model is a sensitive tool that represents current understanding of peatland processes in drained agricultural peat soils (Oleszczuk *et al.*, 2008; C Kechavarzi, Dawson and Leeds-Harrison, 2010; Dawson *et al.*, 2010). Peatlands are key resources for both food security and the provision of a range of beneficial functions that support multiple of ecosystem services. Peats, like all soil systems, are complex multi-functional systems that are influenced by the management practices applied to them. Unlike previous attempts to create soil health indices, the peat health Bayesian network includes multiple key functions peatlands provide, as elicited by experts (CO_2 Respiration, Nitrogen Losses, Peat Structure, and Pathogen Suppression). Because the network was designed and parametrised using a combination of both expert knowledge and datasets generated by a soil biogeochemical model it goes further than previous models of individual peatland processes (Arah and Stephen, 1998; Yu *et al.*, 2001; Ballard *et al.*, 2011; Baird, Morris and Belyea, 2012) that rely on causal relationships that can be quantified by measurements.

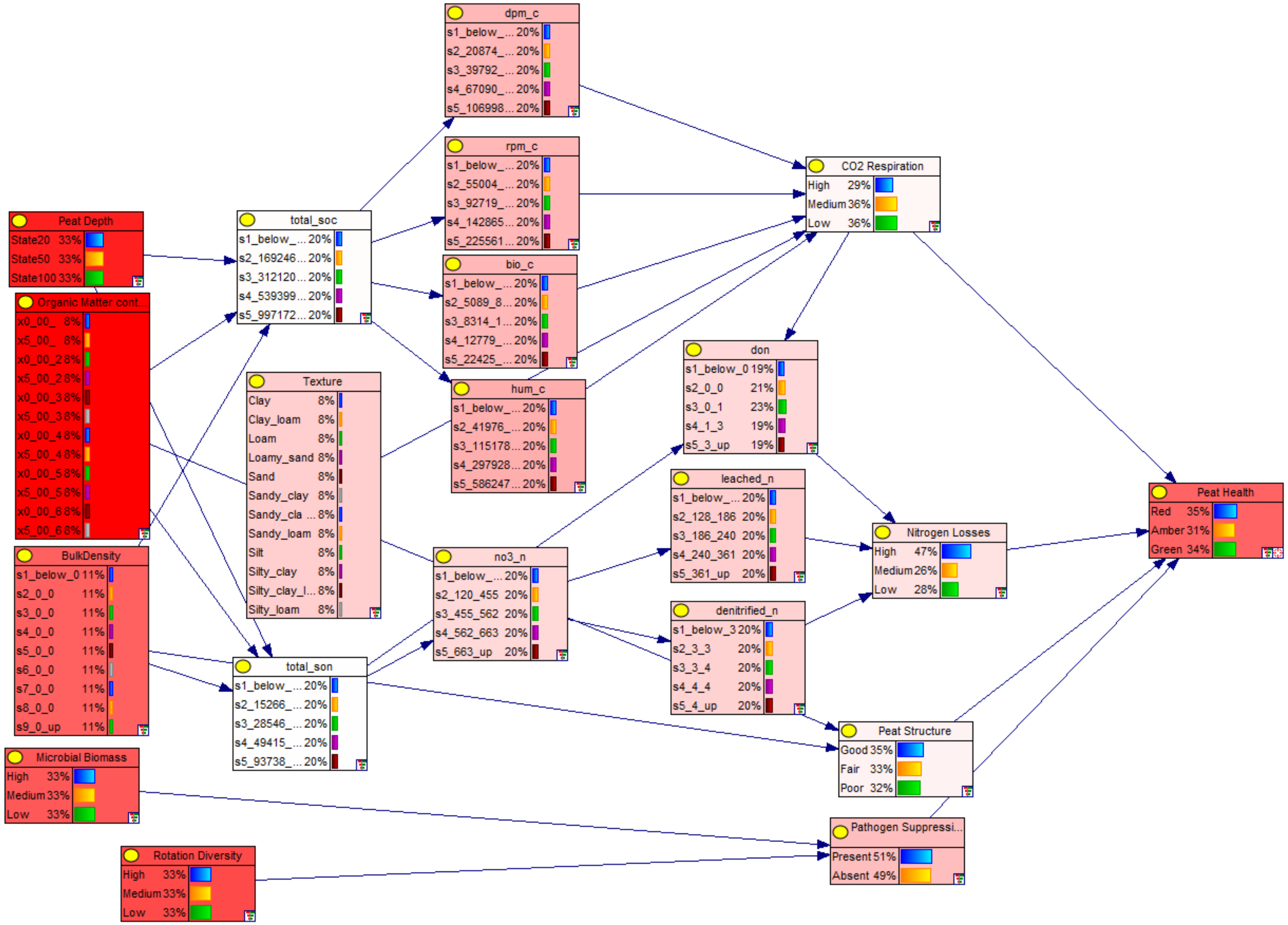

Figure 29: Sensitivity analysis indicating the strength of the relationship present between the Peat Health node and the other nodes in the Bayesian network. The intensity of the colour indicates the strength of the relationship.

A key constraint imposed during the development and parameterisation of the model was to select nodes for which large datasets were available or obtainable and to avoid the requirement for sophisticated measurements to be made for the end user to run the model. The input data (parentless nodes) required to run the model and generate a probability distribution for peat health at a particular site or field includes Peat Depth, Organic Matter Content, Soil Texture, Bulk Density, Microbial Biomass, and Rotation Diversity. This contrasts with soil health indices that require time consuming or expensive measurements that are generally not available to farmers (Bruyn and Abbey, 2003; Idowu *et al.*, 2009; Ritz *et al.*, 2009; Morrow *et al.*, 2016). Because the parentless nodes in our Bayesian network are all simple measurable attributes, the model is an accessible tool that allows farmers to assess the health of their peat fields in a data poor environment. If data associated with a particular parentless node is unknown then the model can still be run by parameterising that node either with the expert knowledge of the user (Troldborg *et al.*, 2013), or by leaving that node with an equal probability of being in each state.

Developing a bespoke tool to assess the health of drained lowland agricultural peatlands was essential because current tools are designed commonly for use on mineral soils and not appropriate for peatlands. For instance, a key property that is often used as an indicator of soil health is soil organic matter content (Weil and Magdoff, 2004; Obalum *et al.*, 2017). Yet, because peat soils generally have a much higher organic matter content than mineral soils (Cannell *et al.*, 1999; Reijneveld, van Wensem and Oenema, 2009), arbitrary use of a soil health index on peat soils would lead to the classification of peatlands as very healthy, even if expert intuition dictates that they are not in a healthy state. Soil microbial activity (represented in our Bayesian network as CO_2 Respiration) is often considered a positive soil health indicator in mineral soils because the degradation of organic inputs (e.g. crop residues, manures, or root exudates) mineralises nutrients and makes them available to plants (Ferris and Tuomisto, 2015; Sahu *et al.*, 2017). However, much of the CO_2 respired from drained agricultural peatlands emanates from the peat itself (Kechavarzi *et al.*, 2007; Bader, Müller, Schulin, *et al.*, 2018; Taft, Cross and Jones, 2018), depleting the carbon stock of the peat, reducing its quality as a growing media, and contributing to the flux of greenhouse gases to the atmosphere (Musarika *et al.*, 2017; Matysek *et al.*, 2019; Peacock *et al.*, 2019). Therefore, peatlands with high CO_2 Respiration are considered, in our Bayesian network, less likely to be healthy than peatlands with low CO_2 Respiration. Modelling this process presented challenges because deep peat contains more carbon down the soil profile and therefore respires more CO_2, after drainage, than a shallow or wasted peat (as noted in Abdalla et al., (2014) where ecosystem respiration, simulated by the ECOSSE model, was observed to increase with increasing peat depth). However, we know that deeper peats are inherently more "healthy" than degraded shallow or wasted peat in terms of their functioning and service provision (Natural England, 2010; Evans *et al.*, 2016; Gewin, 2020). We addressed this dilemma in the design of the model by defining the units of the CO_2 Respiration node as kg of C per ha per cm of peat. The result is a model that accounts for the negative influence of CO_2 Respiration on peat health, but also accounts for the positive influence of Peat Depth on Peat Health (Säurich *et al.*, 2019).

6.4.1 Evaluation of use of the ECOSSE outputs

The ability of ECOSSE to model both carbon and nitrogen cycling has been reviewed by previous authors. Heterotrophic respiration through ECOSSE simulations has correlated with total observed carbon (Dondini *et al.*, 2016) and measured fluxes of CO_2 from gas chamber and eddy covariance experiments in arable fields (Khalil *et al.*, 2013), near natural peatlands (Abdalla *et al.*, 2014), and short rotation forestry (Dondini *et al.*, 2017). Evaluation of the ECOSSE model showed that outputs were in some instances over-estimating the quantity of CO_2 respired from the peat. We reviewed the CO_2 outputs from the simulated ECOSSE runs in this study with eddy covariance respiration data from deep and shallow agricultural systems within the study area, the ECOSSE model showed a moderate ability to predict observed data, although not conclusive. This may indicate that the discretisation of the carbon respiration node into three states may have led to information loss within the network. Future development may increase the number of states to improve predictive ability of the network to assess CO_2 loss from the drained peat ecosystem.

Furthermore, the ECOSSE model has successfully simulated nitrogen dynamics in European croplands at monthly intervals (Bell *et al.*, 2012). The ECOSSE model has also been used by national governments to estimate the effects of nitrogen fertilisers on greenhouse gas balances (Abdalla *et al.*, 2016) and reviewed for predicting the environmental impacts of land use change on water, carbon and nitrogen cycling (Thomas, Bond and Hiscock, 2013). However, in the accuracy of the ECOSSE model outputs developed for the current Bayesian network are questionable. No datasets specific to East Anglian drained fenlands were available to assess the loss of nitrogen through denitrification, dissolved organic nitrogen or leaching of nitrogen pathways. We reviewed the ECOSSE outputs of nitrogen losses with results from a variety of studies, albeit from different climatic conditions, management practices and use of peat. Whilst we were not aiming to predict or evaluate the nitrogen losses to validate the ECOSSE model, we were looking to observe whether nitrogen losses were within appropriate ranges. ECOSSE outputs were generally inconsistent when compared with a range of peat soils across Europe for nitrogen losses. For instance, denitrification losses from Peat soils across Europe observed significantly lower values than ECOSSE outputs (De Klein and Van Logtestijn, 1994, 1996; Zwart *et al.*, 2004; Vermaat and Hellmann, 2010). Studies that do exist for lowland fen agricultural sites displayed annual nitrogen losses through nitrous oxide release pathway displayed higher than expected values. However, these values were compared against a mixture of studies with either low organic matter soils (9% organic matter) or under varying management regimes across Europe (Regina *et al.*, 2004; Bell *et al.*, 2012). Tiemyer and Kahle (2014) noted that there are relatively few studies providing Nitrogen leaching values for drained peatlands. Given the excess of Nitrogen stored in peat ecosystems, the use of irrigation, and the drainage systems in place, excessive leaching of Nitrogen is likely present in these agricultural systems (Kløve *et al.*, 2017). Leaching has been shown to be an increasing issue in drained peatlands, with excessive quantities of applied fertiliser leaching (Razzaque and Hanafi, 2005). It has been noted that the ECOSSE model may struggle to model leaching correctly due to water table and water movement descriptions (Bell *et al.*, 2012). To improve the nitrogen cycling node, it is recommended that further sampling is conducted. The use of Nitrogen balances to observe inputs and outputs of Nitrogen from the system will allow examination on the sustainability of peat agroecosystems (Sainju, 2017; He *et al.*, 2018). The required data for these balances matches the node structure of the peat health network and as such can easily be implemented in updating the network probability distributions to increase accuracy of the Network in identifying Nutrient Cycling function.

6.4.2 Evaluation of the Bayesian network CPT's

It has been noted that Bayesian networks used in environmental modelling are not routinely validated, with over 37.7% receiving no validation (Aguilera *et al.*, 2011). Evaluation of the model CPTs in the current work involved a mixture of quantitative and subjective review to allow for complete model validation. Experts who took part in the individual creation of CPT's validated the aggregated distributions through face validity. It has been established that expert probability elicitation for Bayesian networks contains issues related to human capabilities (Renooij, 2001), where evaluation is based upon personal knowledge, commercial pressures, and attitude to the elicitation exercise, amongst other factors (Taalab, Corstanje, Mayr, *et al.*, 2015). Overall, despite there being variation between an individual expert and the final aggregated distribution, a consensus was formed. The inclusion of a range of experts allowed for the development of a robust distribution, considering a wide range of viewpoints and concerns. However, the number of experts involved was limited and may have contributed towards the aggregated agreement due to a lack of diverse opinions. Experts stated they were unlikely to disagree with the aggregated consensus of the probability distributions as they could not value their opinion on the distribution ahead of other experts. However, they noted that the aggregation method provided a safety net to allow them to express probability distributions with an increased degree of confidence. Given the data-poor and subjective nature of peat health, it was necessary to move forward with expert knowledge as an acceptable substitute for empirical data.

Despite the problems associated with the overestimation of Nitrogen losses stemming from the ECOSSE model use, the networks developed and validated through K-fold cross validation showed a prediction of states with a high degree of accuracy. The challenges facing modelling of soil processes, including ecosystem respiration and nitrogen cycling, derive from their inherent complexity and lead to considerable uncertainty (Vereecken *et al.*, 2016). As such, whilst the modelled outputs showed variations from actual observed values, the use of the ECOSSE model is a valid approach to understanding the carbon and nitrogen cycle across large scales using limited and easily accessible data inputs to create CPT's.

Further, the ECOSSE modelling predicted CO_2 Respiration rates would be more probable to be classified in the higher state for lower bulk densities. Physical and chemical properties, including bulk density, of drained and cultivated peats have not shown clear correlations with CO_2 emissions although a positive trend was observed (Norberg, Berglund and Berglund, 2018). This trend observed in our dataset may have resulted from the process of normalising the CO_2 release over the depth of peat. If CO_2 production was left unnormalized, the network would suggest that a deeper peat would be less healthy due to increased carbon content available for respiration. Prior work noted that as organic matter content decreases, bulk density increases (Mustamo *et al.*, 2016; Rezanezhad *et al.*, 2016; Säurich *et al.*, 2019), indicating that it would be unlikely to observe a situation in the real world where this would affect the network.

6.4.3 Future Model Development

The Bayesian network developed here can be successfully implemented to value the health of a drained peatland field given the input of easily measurable attributes. However, model development is an iterative process and, as such, areas for future improvement can be identified. For example, populating the CPT's through direct sampling strategies may increase the validity and applicability of the network, improving its ability to predict the functioning and health of the system.

The current network required substantial modification from the original expert defined network structure elicited. This was due to limitations on sampling and dataset availability. As such, the structure of the network was altered to allow for the incorporation of nodes relevant to ECOSSE outputs. Future work to develop the model could revert the model structure towards the more complex structure identified in the initial elicitation before it was simplified. The benefit of the modular format of Bayesian networks allows for this type of modification (Landuyt *et al.*, 2013).

The software used to create the Bayesian network required the discretisation of the continuous ECOSSE data. The discretisation of the other nodes in the network was conducted through expert review. Discretisation has the potential to result in a loss of information. However, whilst multiple methods exist, the selection of one method over another cannot be justified, and it is instead recommended that caution is applied whenever discretising a state (Nojavan A., Qian and Stow, 2017). Within the work, a uniform count method was selected to discretise the nodes, dividing the variables into ten bins. This created equal probability of an event given an un-instantiated parent. Discretisation through uniform widths of states (i.e., dividing the range into equal parts) would have increased the influence of outlier or extreme variables and, as such, was deemed an inadequate method of discretisation. The discretisation of the data would have benefited from field sampling to provide a real-world division of states rather than a theoretical division.

6.5 Conclusion

The model developed and validated within this chapter highlights the power and capabilities of Bayesian networks for inferring the health of a drained peat ecosystem. The network allows for the development of a holistic view of the system, incorporating the multi-functionality of peatlands. The inclusion of both expert opinion and a biogeochemical model to parameterise the conditional probability tables allows for the assessment of these functionalities despite limited data present. Furthermore, the development of sub-functions of peat health is a powerful tool for including multidisciplinary approaches to understanding peat health. The development of this Bayesian network is a useful tool for understanding peat health and functioning of peatland ecosystems.

Chapter 7: General Discussion and Conclusion

Healthy soils are fundamental for the development of sustainable production systems, increasing resilience to climate change, and providing the ecosystem services we benefit from. This PhD set out to develop effective and implementable tools to measure soil health on lowland peat, allowing farmers and land managers to identify sustainable management options. Literature reviewed in Chapter 2 outlined the threats which limit our capability to achieve food security. Of particular importance to this project was the degradation of soils and the declining productivity of agricultural land. The food production capabilities of the UK were reviewed, identifying East Anglia within the UK as a vital area for UK food security due, in part, to the extensive lowland peat that existed in the region. The formation and management of peatlands was discussed, and drainage for agricultural exploration was identified as a leading cause of soil degradation and the loss of ecosystem service provision. Methods to assess soil fertility and quality have been routinely used for many years. However, the current plateau in yields and the environmental degradation of agricultural systems has led to the emergence of soil health as a concept. A variety of soil monitoring techniques have been developed to assess soil health. However, these methods were typically developed for mineral soils. Soil organic matter is often used as a key soil health indicator, and this can lead to an overestimation of soil health when these assessment methods are applied to peat soils. Even very degraded peat soils have organic matter contents that are higher than very healthy mineral soils. This problem in assessing the soil health of peatlands points to a fundamental difference in the formation of these soils and the processes that lead to their degradation. Given the environmental and commercial importance of lowland peat to UK food security, creating methods to assess peat health is a vital step to enable sustainable management of these systems.

This thesis outlines the creation of two statistical tools to assess soil health for lowland peat systems under intensive agriculture: a Principal Component Analysis (PCA) derived Peat Health Index (containing two indices), and a Bayesian network. These tools represent the first soil health indices specifically designed for lowland peat. The creation of these tools represents important progress towards assessing peat health, as recommended in the 25-year Environment Plan and the Lowland Agricultural Peat Taskforce.

Soil health indices have previously been created using principal component analysis to identify suitable properties that serve as soil health indicators. In Chapter 3, this method was applied to lowland peat systems to identify indictors specific to lowland peat soils. Two indices were developed that capture the variation in soil properties between Wasted, Shallow, and Deep peat soils: a Weighted and an Additive PHI. The results revealed that the Weighted PHI could fully distinguish a gradient of health at contrasting sites across drained peat ecosystems using a minimum dataset of four variables (cation exchange capacity, pH, Visual Evaluation of Soil Structure, and microbial activity). By comparison, the Additive PHI displayed a stronger correlation with farm key performance indicators such as crop yield and fertiliser use. These indices provide insights into the functioning of the peat, allowing farmers to identify degraded sites or areas requiring interventions. Both indices were reproduced, evaluated, and validated in Chapter 4. The process allowed reproducibility of the indices to be assessed across a larger spatial scale and identified key weaknesses that distorted results due to the inclusion of an unsuitable indicator (available nitrogen), which was subsequently removed from the indices. The indices successfully reinforced farmer's subjective beliefs concerning the health of their fields. This study therefore developed indices which could be applied to quantitatively assess peat health and functioning, allowing fields to be quantitatively valued, benchmarked, and compared.

A second approach to assess health of a peat soil under agricultural land management is described in Chapters 5 and 6 using Bayesian networks. A Bayesian network is based on probability distributions and allows exploration of uncertainty and risk within the network. Chapter 5 defines the structure of a Bayesian network to evaluate peatlands, identifying four key functions to infer peat health: carbon respiration, nitrogen loss, peat structure and pathogen suppression. The network represents the most simplistic combination of indicators and functions to infer peat health and can be viewed as a starting point for the development of a more complex (both in terms of structure and type of indicators used) network. The network structure was parameterised and evaluated in Chapter 6. This process used a combination of expert opinion (both academic and industry experts) and a biogeochemical model. The Bayesian network enables farmers to predict the health status of a lowland peat based upon measurable attributes. The network was validated using a combination of k-fold cross validation, propagation testing, and sensitivity analysis. The validation process demonstrated that the network could be used to distinguish between deep well-structured peat soils and shallow compacted peat soils. The modelling process allowed for a holistic assessment and insight of the multi-functioning nature of peat soils, blending the use of expert opinion and empirical data.

The PCA derived Peat Health Indices described in Chapters 3 and 4 produces a simple soil health score, enabling quick assessment and comparison between sites. There are strengths and weaknesses of the Additive and Weighted PHI depend on the method of model validation used. Weighting of the index strengthened its ability to predict degradation status and coincided better with farmer's opinions of soil health. Use of the Additive PHI, without weighting, resulted in scores that had a stronger correlation with farm key performance indicators. However, these key farm performance indicators are heavily weighted towards the commercial interests of the farm rather than the holistic suite of ecosystem services provided by peatland soils. The specific indicators chosen to create the minimum dataset required to generate the index were dominated by physical and chemical soil properties. The selection was based upon the need for indicators to be measurable by farmers and easily interpretable. Biological techniques to assess population diversity and community distribution were deemed too complicated and uninterpretable to assess peat health and functioning. Despite this, the physical and chemical indicators were interpreted in context of how these abiotic factors influence biological process within the soil using literature review. In identifying the variables used in the minimum dataset, the PCA approach assumes that the dataset to be analysed contains a wide range of properties and observed values. The soils used to develop the index represented a gradient soil health on fields that farmers identified to incorporate the greatest possible variation in peat properties. This approach was deemed an adequate for our purposes. However, a more extensive sampling network could have increased the probability that a full range of measurable values was observed.

Instead of a simple peat health score, the Bayesian network produces a probability distribution for each node, allowing the user to explore the uncertainty associated with environmental systems. In comparison to the Peat Health Index approach, the Bayesian network results in greater complexity when benchmarking and comparing between sites (i.e., one output versus a distribution). The use of probability distributions can provide more information on the current state of a soil function as it incorporates the uncertainty that a state is achieved. This can provide farmers with a more nuanced understanding that enables land management decisions to be better informed. The development of the network required identifying key nodes and arcs to infer peat health through expert discussion. To maintain network simplicity and its ability to be used by farmers, an iterative process of node reduction was undertaken. The reduction may have led to a loss of information as nodes and arcs were either divorced or incorporated into one another. A parallel data reduction technique was implemented using PCA to identify the minimum dataset for the Peat Health Index. However, both approaches resulted in the selection of relatively similar indicators to identify peat health, indicating the strength of expert knowledge in this area. The use of expert opinion in creating and parameterising the Bayesian network allowed more opportunities to incorporate biological process. Although chemical and physical soil properties dominated the nodes the ECOSSE model was used to incorporate the effect of these physical factors on biological processes through underlying equations. Further research is required to identify specific biological indicators of peat health. However, the approach of incorporating the processes that stem from biological interactions within the model rather than measuring them directly is an effective alternative to allow farmers to monitor the health of their systems.

As discussed at the beginning of the thesis, peat health in this case considers the degradation of a peat system from its immediate post drainage state. Peatland degradation is a process that occurs over various timescales as noted in the review of the literature and is also influenced through agricultural practices. The tools developed through this thesis attempt to capture the short term, recognizable changes that a farm can measure and observe. The concept driving the development of these tools considered that these would be employed by farmers and land managers in tandem with current sampling strategies. That is, there would be an annual measurement of peat health and this resulting output would allow the indication of the trend which the health of the peat is travelling. The selection of indicators was required to be accessible and understandable by farmers, while also providing valuable commercial and environmental information. Useful indicators of the health status of peat will show an observable change to anthropogenic actions, allowing the implementation and adoption of sustainable management techniques. The selected indicators for both tools provided a range of biological, chemical and physical indicators that had altering response timescales, providing a clear and comprehensive indicator of health status transitioning. We should reinforce that the tools were developed for lowland peat systems under intensive agriculture. Further tools would be required to restore the health status of peat systems towards their natural functioning.

As stated, the application of these tools to identify the health status of peat is focused upon lowland fen peats in East Anglia. This currently provides a limit on the applicability of the tools in the thesis to that location. For instance, the use of the ECOSSE model required parameterization through inputting local weather conditions that would influence the cycling of nutrients in the system and the management regime the current farm is employing. The application of the tool to other locations would require further parameterization. However, the concept behind the development of peat specific tools could be expanded to include tropical peat systems converted to plantations. Future work could explore how the implementation of these tools across tropical or other boreal systems alters the structure (i.e. the choice of indicators) and whether the current indicator selection is appropriate. It is highly likely that, with changes to the ECOSSE modelling, both tools in this thesis could be applied to boreal and temperate parts of the northern hemisphere where peat has formed under high precipitation and low temperature climatic regions. Furthermore, the tools developed here could indicate sites where the health of the peat systems has degraded and thus would benefit from peatland restoration. This could be seen from the perspective of a farm group, where restoration and the incentives offered, outweigh the current profit from farming the area. Alternatively, this tool could be used by environmental advisers to identify sites which could benefit from restoration due to degradation and the possible ecosystem services and functions they could supply.

As two different approaches to assessing soil health have been used here to develop different methods, the choice between which assessment method of soil health to use, PCA derived index or Bayesian network, is subjective in nature. The PCA derived index may be seen as a more 'farmer friendly' method to measure soil health. This is due to the assessment of key soil properties that are regularly sampled within current farm monitoring regimes. Furthermore, the simple equation used to derive the index can be easily understood, quickly interpreted, and benchmarked against other fields within the same farm or region. The Bayesian network analysis may be more appropriate for organisations providing information to key stakeholders. Groups with additional funding and time would be more appropriate to develop the Bayesian network. An example could be the IUCN (National Committee United Kingdom) Peatland Programme, which has launched a PeatDataHub aiming to communicate peatland science and managing peatland monitoring data (IUCN, 2021). Currently the information includes water table data, photographs, and ancillary data. The Bayesian network could be incorporated within the data provision provided by the group, enabling sustainable management of peat systems. This would not only encourage the development of further Bayesian networks for different management systems, but also the continuous updating of the model given the advancement of our current knowledge.

7.1 Suggestions for Future Work

The development of the Bayesian network was impacted by the COVID-19 pandemic which delayed expert knowledge elicitation, prevented face-to-face meetings to facilitate expert knowledge elicitation, and eliminated the opportunity to gather data from field sampling during the 2020-2021 season. As such, field data was not available to construct the Conditional Probability Tables of the Bayesian network. Therefore, an obvious next step would be to parametrise the Conditional Probability Tables through an extensive sampling campaign across lowland fen regions. The process of sampling can improve the nature of the relationships between nodes in addition to reducing information loss through discretisation. Additionally, this process would identify whether any of the states in the model were unnecessary or missing, increasing the validity of the model. The use of the Bayesian network modelling process has highlighted a useful and practical tool to assess soil health and due to the nature of the approach, the network can be easily updated as new information or data becomes available through direct soil sampling.

During this thesis, tools to assess peat health were developed exclusively on fields cultivated by a single farming cooperative who farm within a particular geographical area of the East Anglian fen region. This was because they were CASE partners on the PhD project, contributing funds and will likely be the primary beneficiary. Whilst the sampling strategies and determination of soil property distribution enabled examination of a wide range of peat states, further validation of these tools, could involve trials of the Peat Health Index and the Bayesian network across the region to allow for widespread validation. This process would enable identification of challenges and opportunities for each tool, enabling a more thorough evaluation of their applicability and informing further development. This would be a necessary step prior to integration within a national soil health monitoring scheme. Expanding the application of the network would require a re-parametrisation of the Conditional Probability Tables generated using the ECOSSE model since these require local climatic information alongside management practices, both of which are likely to vary across the country. The Bayesian network modelling process has been shown to be a novel but suitable tool to monitor the health of a peat soil. As such, this modelling process could be applied to other soil types (including mineral soils) and land management types (including forestry, paludiculture, grassland etc.) to enable a comprehensive context-specific approach to modelling soil health on a national scale.

8. Reference

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9. Appendix

Supporting Information 1 (Chapter 3)

Some soil properties clearly recorded higher values in the Deep (healthy) peat and lower values in the Wasted peat (e.g., Organic Matter content, % Silt, % Clay, and Water Holding Capacity). Other soil properties recorded higher values in the wasted peat (e.g., % Sand and Bulk Density), whereas Microbial Activity and VESS recorded the highest values in the Shallow peat. Figure 30 displays the measured properties across the degradation gradient of drained peatlands.

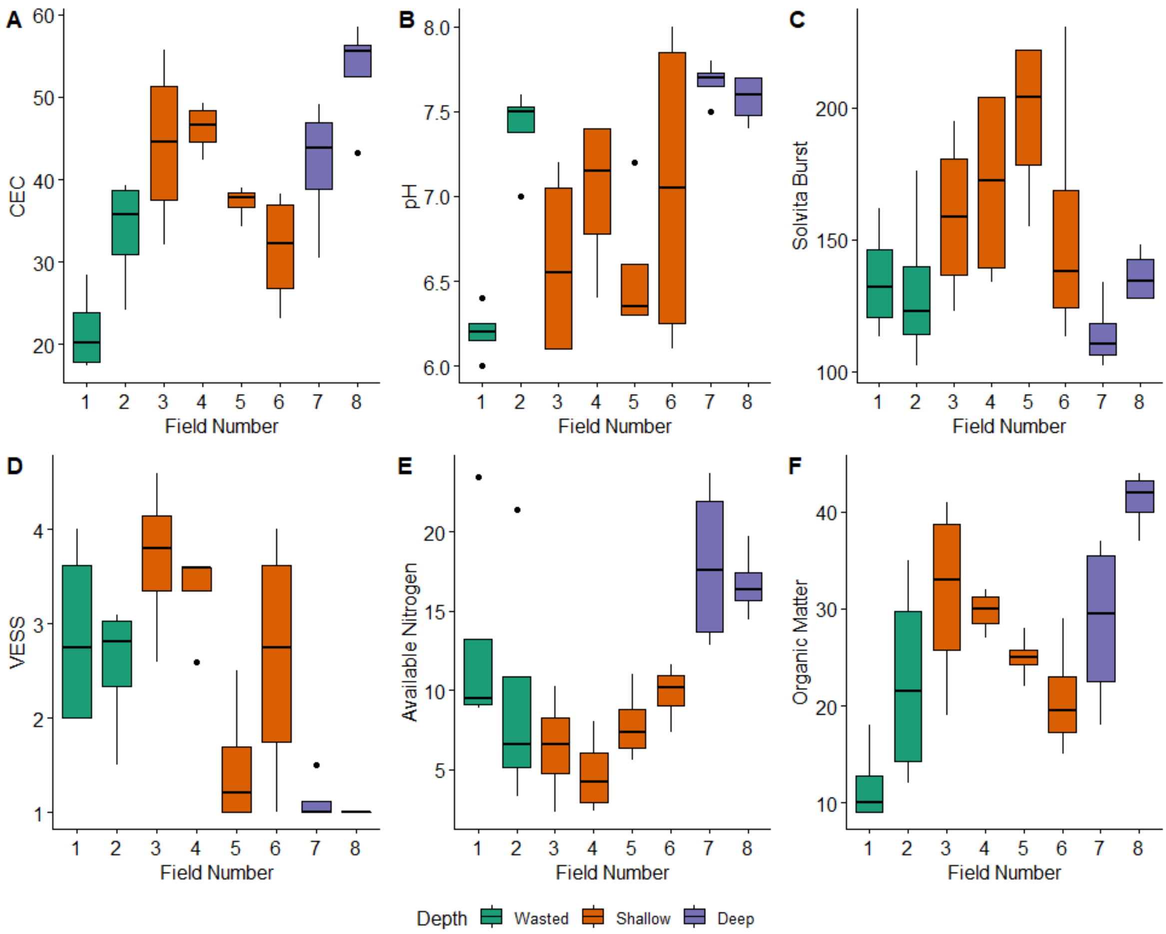

Figure 30: Boxplots of soil properties measured across a gradient of peat depths and initially retained for the Minimum dataset: A) cation exchange capacity (meq/100g), B) pH (pH Units), C) Solvita Burst (ppm CO_2-C), D) Visual Evaluation of Soil Structure, E) available Nitrogen (mg/l), F) Organic Matter Content (%).

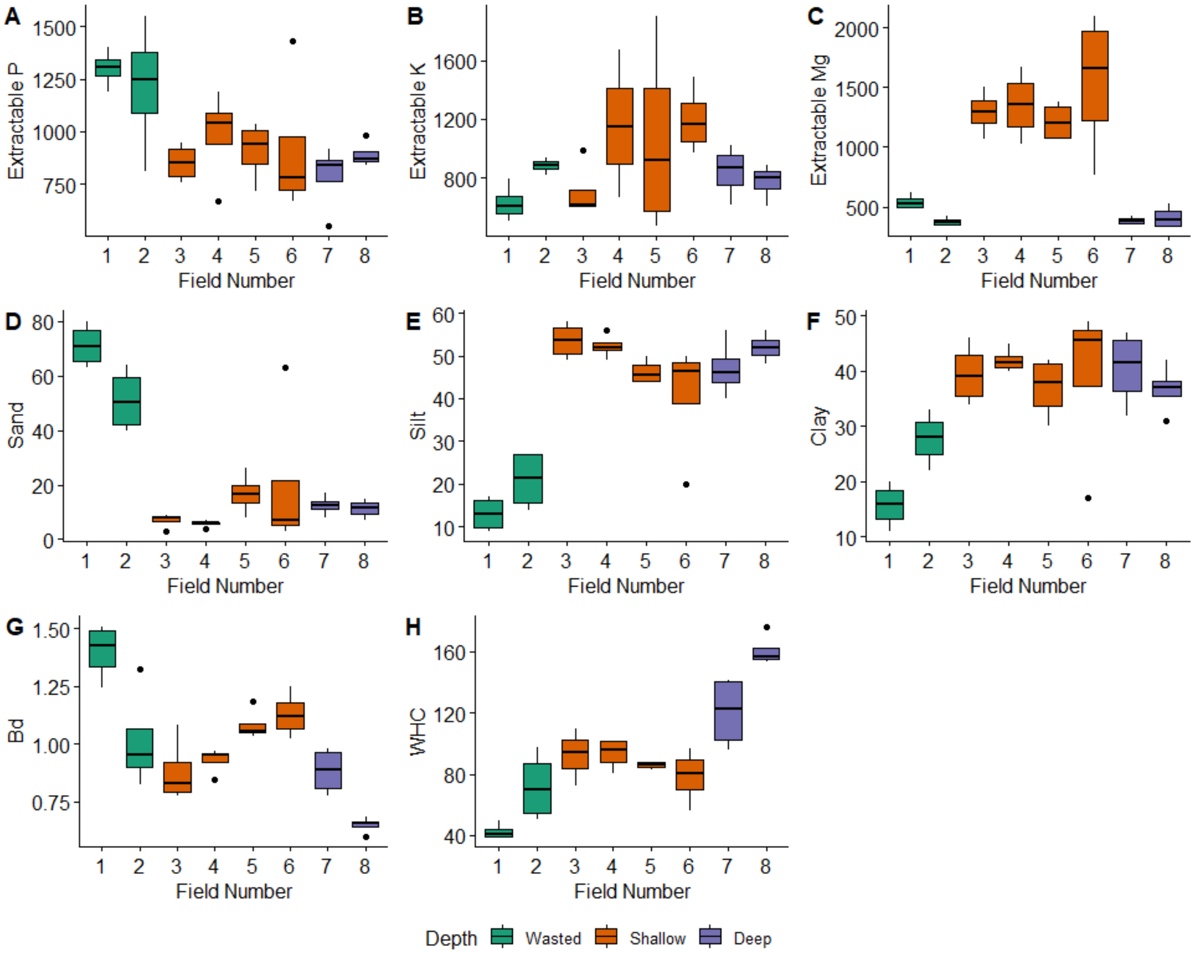

Figure 31: Boxplots of soil properties measured across a gradient of peat depths: A) Extractable Phosphorous (mg/kg), B) Extractable Potassium (mg/kg), C) Extractable Magnesium (mg/kg), D-F) Soil Texture (%), G) Bulk Density (g/cm^3), H) Water Holding Capacity (%)

Supporting Information 2 (Chapter 6)

Table 20: Conditional Probability Table (CPT) for the Pathogen Suppression node

States of parent nodes		Child node probability distribution given the states of the parent nodes	
Microbial Biomass	Rotation Diversity	Pathogen Suppression: Present	Pathogen Suppression: Absent
Low	Low	5.00%	95.00%
Low	Medium	28.57%	71.43%
Low	High	51.43%	48.57%
Medium	Low	25.71%	74.29%
Medium	Medium	52.86%	47.14%
Medium	High	75.71%	24.29%
High	Low	46.43%	53.57%
High	Medium	75.71%	24.29%
High	High	94.29%	5.71%

Table 21: Conditional Probability Table (CPT) for the Peat Structure node

States of parent nodes		Child node probability distribution given the states of the parent nodes		
Organic Matter Content	Bulk Density	Peat Structure: Poor	Peat Structure: Fair	Peat Structure: Good
Low	Low	28.67%	33.80%	37.53%
Low	Medium	45.15%	32.27%	22.59%
Low	High	61.33%	29.00%	9.67%
Medium	Low	17.11%	35.53%	47.36%
Medium	Medium	32.53%	34.93%	32.53%
Medium	High	45.76%	34.93%	19.31%
High	Low	7.44%	30.73%	61.82%
High	Medium	23.07%	32.93%	44.00%
High	High	40.89%	31.53%	27.58%

Table 22: Conditional Probability Table (CPT) for the Peat Health Node

States of parent nodes				Child node probability distribution given the states of the parent nodes		
Pathogen Suppression	Peat Structure	Specific Carbon Respiration	Nutrient Use Efficiency	Peat Health: Red	Peat Health: Amber	Peat Health: Green
Present	Good	Medium	High	23.04%	32.00%	44.96%
Present	Good	Low	High	13.53%	27.95%	58.51%
Present	Good	High	Medium	5.44%	13.62%	80.94%
Present	Good	Medium	Medium	25.68%	33.62%	40.70%
Present	Good	Low	Medium	16.86%	30.95%	52.19%
Present	Good	High	Low	10.50%	25.24%	64.26%
Present	Good	Medium	Low	32.95%	34.57%	32.48%
Present	Good	Low	Low	21.81%	34.43%	43.76%
Present	Fair	High	High	16.39%	29.14%	54.47%
Present	Fair	Medium	High	33.07%	34.24%	32.69%
Present	Fair	Low	High	22.00%	35.38%	42.62%
Present	Fair	High	Medium	14.93%	30.38%	54.69%
Present	Fair	Medium	Medium	38.44%	36.14%	25.41%
Present	Fair	Low	Medium	28.31%	35.57%	36.12%
Present	Fair	High	Low	21.25%	30.95%	47.80%
Present	Fair	Medium	Low	46.01%	31.67%	22.33%
Present	Fair	Low	Low	34.07%	34.81%	31.12%
Present	Poor	High	High	24.33%	34.43%	41.24%
Present	Poor	Medium	High	45.68%	32.38%	21.94%
Present	Poor	Low	High	34.47%	35.24%	30.30%
Present	Poor	High	Medium	27.68%	32.10%	40.23%
Present	Poor	Medium	Medium	51.29%	30.24%	18.47%
Present	Poor	Low	Medium	41.22%	34.81%	23.97%
Present	Poor	High	Low	31.83%	32.71%	35.46%
Present	Poor	Medium	Low	59.11%	27.67%	13.23%
Present	Poor	Low	Low	46.83%	33.10%	20.08%
Absent	Good	High	High	37.04%	33.81%	29.15%
Absent	Good	Medium	High	30.30%	35.95%	33.75%

Absent	Good	Low	High	18.08%	34.24%	47.68%
Absent	Good	High	Medium	11.03%	27.90%	61.06%
Absent	Good	Medium	Medium	32.48%	35.10%	32.43%
Absent	Good	Low	Medium	25.12%	33.24%	41.65%
Absent	Good	High	Low	17.90%	32.81%	49.29%
Absent	Good	Medium	Low	42.08%	34.24%	23.68%
Absent	Good	Low	Low	31.58%	34.24%	34.18%
Absent	Fair	High	High	24.79%	34.52%	40.68%
Absent	Fair	Medium	High	45.30%	31.71%	22.98%
Absent	Fair	Low	High	34.26%	34.67%	31.07%
Absent	Fair	High	Medium	25.61%	33.95%	40.43%
Absent	Fair	Medium	Medium	49.08%	30.95%	19.96%
Absent	Fair	Low	Medium	38.44%	33.52%	28.04%
Absent	Fair	High	Low	30.51%	34.10%	35.40%
Absent	Fair	Medium	Low	56.41%	27.67%	15.93%
Absent	Fair	Low	Low	45.90%	30.95%	23.14%
Absent	Poor	High	High	36.69%	31.10%	32.22%
Absent	Poor	Medium	High	57.23%	27.81%	14.96%
Absent	Poor	Low	High	48.44%	30.38%	21.18%
Absent	Poor	High	Medium	38.65%	31.52%	29.83%
Absent	Poor	Medium	Medium	62.26%	25.81%	11.93%
Absent	Poor	Low	Medium	52.19%	29.95%	17.86%
Absent	Poor	High	Low	42.70%	31.90%	25.40%
Absent	Poor	Medium	Low	75.22%	17.90%	6.87%
Absent	Poor	Low	Low	58.23%	27.38%	14.39%