A Wetland Vulnerability Assessment: consequences for the avian communities of saltmarshes

Daniel Alexander

Ecosystems and Environment Research Centre

School of Science, Engineering and Environment

University of Salford

Salford

United Kingdom

Submitted in Partial Fulfilment of the Requirement of the Degree of Doctor of Philosophy

December 2020

Contents

Chapter 6 – Characterising Site Ecology – Avian Biodiversity……………………………….….….…104

Chapter 8 – Discussion

List of Figures

List of Tables

Formulae

Acknowledgements

First, I would like to express special thanks and gratitude to my supervisor Professor Philip James for his unerring and continuous support during the past three and a half years, without which, I might never have been able to say that I finished writing my thesis.

I would also like to express a deep thank you to Paul Oldfield at the Mersey Gateway Environmental Trust who facilitated every aspect of the practical work, and gave me solid advice, professional guidance, and opportunity for growth throughout my time with the Trust.

Numerous university staff have played a large role in assisting me during the course of this project. My co-supervisor, Dr Richard Armitage helped shape my project. Marie, and the team at KTP are second to none in terms of project support. Jeff Clarke, Rob Smith, and Tony Parker for the assistance during the field work. Dr Andrea Drewitt for the many hours out in the field, and for a much-needed ear to my problems. Elaine Newall for her passion and dedication to people and their projects.

I would like to express a deep gratitude to, my Mum, Dad, my brother Ryan, my partner Hannah, and my ‘extended family’ the Brocks, all for their continuous love and support. Finally, my close friends, our camping trips and walks in the hills allowed me to take a step back when I needed to. For that I am truly thankful.

Abstract

Understanding better the consequences of anthropogenic pressure and environmental change is a substantial area of research for modern conservation ecology. This aim of this research is to investigate these consequences for the avian communities of saltmarshes and associated reed beds. The research has four objectives: to classify saltmarsh and reed bed vegetation distribution; to assess the vulnerability of these habitats to sea level rise; to determine the impacts of sea level rise on nesting avifauna; and to derive recommendations for conservation practice.

Vegetation classification methods using data from satellites and Unmanned Aerial Vehicles (UAV) for the Upper Mersey Estuary were explored. Satellite data failed to provide adequate classification due to a large spatial resolution. Object-based methods carried out on UAV data produced an accurate vegetation classification. The implications for adopting this method in a vegetation monitoring system are discussed.

In 2016 a series of habitat interventions (grazing by cattle, scrape creation, and establishing a reed bed cutting 20-year cycle) on saltmarsh and reedbeds within the Upper Mersey Estuary were commenced. These interventions were maintained during the three years of this study. Changes in the ecology resulting from these interventions were monitored using the Common Bird Census technique between March and July 2015 - 2018, Wetland Bird Survey counts, and wintering bird surveys. These habitat management interventions were associated with increased diversity of wetland species (both feeding and breeding) and therefore, increased habitat connectivity with the Mersey Estuary SPA.

Modelling highlighted the moderate sensitivity of saltmarsh habitats in the Upper Mersey Estuary to sea level rise. With lower sea level rise, nesting sites for all avian species were found to be restricted by periodic tidal flooding and under the top-end estimate of tidal increase (between 1.1 – 1.9 metres) the species studied would not be able to breed successfully.

The findings reported here have implications for global estuarine saltmarsh management.

Chapter 1 – Introduction

1.1 – Research Context

During the twentieth century the human population has increased from 1.5 to 6.1 billion (Roser and Ortiz-Ospina, 2017). To sustain this growth landscapes have been greatly altered to maximise the provision of food, fresh water, timber, and fuel (MA, 2005). This population growth, particularly within the last 50 years, has led to grave impacts on the natural environment. Ecosystems and species have been lost as extinction rates have increased between 100 – 1000 times more than in the early 20th century (MA, 2005). Since the 1970s, 56 % of species have declined in the United Kingdom because of land transformation, urbanisation, and agricultural intensification (Hayhow et al., 2016). These processes have led to the disruption of ecosystems, the natural links between ecosystems, and their populations (Zipperer, 2011). We now understand that the negative impacts derived from these processes are non-linear, non-reversible, and unsustainable (MA, 2005; Lawton et al., 2010; Zipperer, 2011). Eventually, with this understanding came an acknowledgement of our responsibility. Manifest as the field of ecological restoration, we are now seeking to reverse the damages done to these systems by assisting in their recovery (SER, 2004). The field of ecological restoration, however, has been defined as a process that restores an ecosystem from a degraded state back toward an historical trajectory (SER, 2004). This framing assumes that the ecosystems of the future will be as sustainable as those of the past. It assumes that the environment, and the world in which we currently live, is a static system (Collof et al., 2017).

During the past few decades, it has become clearer that we are entering an era of pervasive change. The period between 1984 – 2012 is likely the warmest three-decade period in 1,400 years and by the end of the 21st century, global mean temperature will have increased by between 1.7°C and 4.8°C (IPCC, 2014). A key driver of this process of climate change has been the release of large amounts of atmospheric carbon, through anthropogenic processes including industrial processes, agricultural intensification, and land conversion (Heller and Zavaleta, 2009; IPCC, 2014). It is predicted that a change such as this will be associated with a multitude of derived impacts on environmental and ecological processes. These impacts will include phenological mismatches, species range shifts, and secondary effects such as climate change derived sea level rise (IPCC, 2014). Impacts such as these will further exacerbate the challenges that ecological restoration currently faces by incorporating a factor of uncertainty.

Only recently was climate change considered an integral constituent of conservation planning with papers as late as 2006 stating that ecological restoration had no clear approach to incorporating this challenge into practice (Clewell and Arsonson, 2006; Heller and Zavaleta, 2009). It can be argued that we still have no clear approach to incorporating the impacts of climate change into practice as the systems through which to integrate the science of uncertainty into conservation planning are not yet in place (Dickinson et al., 2015; Collof et al., 2017). The frameworks of the past, those based on the traditional approaches towards managing ecological restoration, may not be appropriate within the context environmental change and uncertainty (Collof et al., 2017). This is a concern when many extant ecosystems are already in an unfavourable state or are threatened by human encroachment (Lawton, 2010).

Coastal habitats have suffered similar declines to those of terrestrial ecosystems. Human population density is generally higher around coastal and estuarine areas, exacerbating habitat loss (Davies et al., 2016). Coastal wetlands and saltmarshes are valuable habitats for a multitude of reasons: they are highly productive habitats, they represent a key ecosystem for often threatened avian species and act as natural flood barriers for human habitation (Wolters et al., 2005; Chen et al., 2013). Saltmarshes, especially those situated in heavily urbanised estuaries, could be sensitive to the secondary impacts of climate change such as sea level rise. The increase in sea level rise has been forecast between 0.3 – 1.9 metres by the end of the century (Jevrejeva et al., 2014). In the UK, threats to coastal habitats varies with geographic area (Nicholls et al., 2013), however, with sea level rise representing a very real challenge in the future the impacts need to be assessed on a site by site basis (Doody, 2008).

Coastal conservation and restoration managers, in the UK and globally, must face the prospect of these environmental changes under the implicit uncertainty of climate change projections (Dickinson et al., 2016). Clearly, we need to ask the question: how can we monitor, map, and evaluate uncertain environmental impacts and incorporate them into management objectives? This is the challenge that we must face to reduce the compounded impacts of present habitat loss with future environmental change (Collof et al., 2017). Adaptive management and scenario testing are likely integral to the transformative approach we must adopt in order to mitigate for future risks (Dickinson et al., 2016; Wyborn et al., 2016, Collof et al., 2017). We need to accept uncertainty and incorporate it within future management scenarios (Dickinson et al., 2016). Conservation and restoration need to incorporate systems to monitor and report ecosystem condition to determine the relative impacts of change on specific ecosystems more widely. This process is the emergent science of vulnerability assessment and requires inclusion of all stakeholders across disciplines (Dickinson et al., 2016; Collof et al., 2017).

To address the gaps related to the management of ecosystems under environmental uncertainty this study has the broad aim to evaluate relevant methods for the consistent monitoring and reporting of future environmental impacts on a managed restoration project in the context of wetland vulnerability assessment, and within the context of the literature, falls within the paradigm of ecosystem vulnerability assessment (Collof et al., 2017). The recommendations within the literature are combined into three objectives pertinent to the study of a constrained saltmarsh under future environmental uncertainty. This research uses a multidisciplinary approach utilising the Upper Mersey Estuary in the northwest of England as a case study. A practical application and final contribution of this research will be to assist the Mersey Gateway Environmental Trust – the body responsible for ecological restoration within the Upper Mersey Estuary – with future scenarios for conservation and management under projections of sea level rise.

1.2 – Thesis Structure

The structure of the thesis is summarised in Figure 1.1. In Chapter 2 the literature relating to ecological restoration within a dynamic world, saltmarsh ecology, wetland monitoring, and the overarching themes of ecological vulnerability are critically evaluated. Gaps and opportunities for research are identified and translated into the aims and objectives, which are presented at the end of Chapter 2.

In Chapter 3 the research area and the justification for the selection of this location were described, the Upper Mersey Estuary saltmarshes under the supervision of the Mersey

Gateway Environmental Trust. Following this, the methods of analysis and data collection that are appropriate to address the research objectives are described.

Chapter 4 consists of an exploration of data derived from the European Space Agencies' Sentinel-2 satellite system as a platform from which to monitor saltmarsh vegetation. In the first part of the chapter the ability of this system to differentiate saltmarsh cover types, including saltmarsh grasses and reed bed, utilising vegetation indices and spectral plots is explored. The second half of this chapter compares three classification approaches and their performance in mapping the saltmarsh cover of Upper Moss Side saltmarsh.

The data presented Chapter 5 were used to explore the application of an Unmanned Aerial Vehicle mounted with consumer-grade cameras for mapping the distribution of saltmarsh cover classes. This was first initiated as a technique to mitigate the risks that may affect the collection of satellite data, namely cloud cover. However, as is presented in the chapter, an exploration of this technique allowed for further gaps within the research literature to be addressed. The same three classification procedures that were applied in Chapter 4 were applied to the data collected for Chapter 5.

In Chapter 6, the main objective was to characterise the avian ecology of the study area to inform the vulnerability analysis that follows in Chapter 7. In total, four species were identified as potentially vulnerable to climate change effects, these were all ground nesting birds: meadow pipit (*Anthus pratensis*), skylark (*Alauda arvensis*), northern lapwing (*Vanellus vanellus*), and redshank (*Tringa totanus*), among others. The collection of these data allowed for a comparison of diversity pre/post habitat management. Diversity profiles derived from Hill numbers were identified as a possible means to reflect biotic changes between sites and dates, when supported by statistical methods of change.

In Chapter 7 an analysis of the vulnerability of ground nesting avifauna, identified in Chapter 6, to the impacts of sea level rise was explored. The analysis included elevation data, tide gauge data, sea level rise scenarios, avian territory distribution, and avian breeding ecology statistics to determine under which scenarios might the breeding season of the selected species be interrupted. The data analysis undertaken here represents the first case study of ecosystem vulnerability for saltmarshes in the northwest of England, and the first vulnerability analysis of this kind. The implications for future management are discussed in Chapter 8.

In Chapter 8 the outcomes of the research presented in this thesis are brought together and interpreted within the context of vulnerability assessment. The contributions that the current research has made are made explicit and opportunities for further research are explored. Management practices that may need to be implemented considering the findings presented in this research are also discussed.

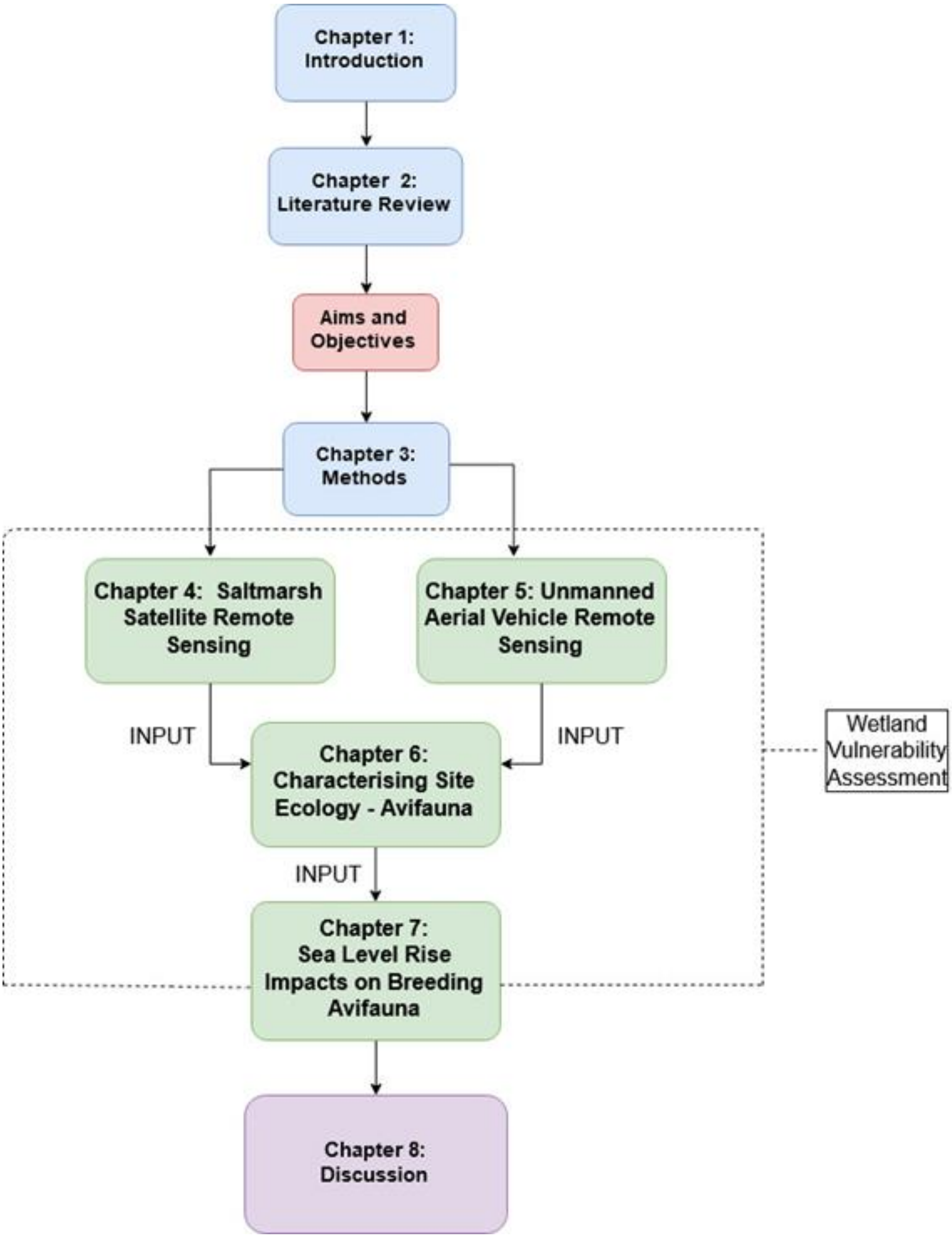


Figure 1.1 – Thesis Structure representing the links between chapters. Data outputs from each chapter serves as an input data set for the subsequent chapters.

Chapter 2 – Literature Review

2.1 – Ecological Restoration and Humankind

The human relationship with the natural world has a dynamic and value-driven history (Wilson, 1984; Berkes, 1998; Berkes et al., 2008; Egan, 2011; Lubick and Jordan, 2011). The development of this association is inextricably linked to our understanding of modern ecological restoration and the issues encapsulated by its practice (Egan et al., 2011). As an integral part of nature, humankind plays a substantial role in shaping the condition of the environment based on their perception of place within it – either consciously or otherwise (Egan, 2011; Lubick and Jordon, 2011). The relationship can be represented as a continuum between two opposing ideals: nature as itself and its manipulation by humanity (Wilson, 1984). A period in human development during the Epipaleolithic (20,000 BP – 10,000 BP) known as the Natufian (14,500 BP – 11,500 BP) represents a shift in this history with the dawn of both agriculture, through the selective breeding of wild grains, and fruticulture (Mithen, 2004). This shift placed mankind on a course towards the latter of the two ideals that would lead to the settling of landscapes and the emergence of civilisations (Wilson, 1984). In many ways, the intensification of this development led to a disconnect between people and the natural world, and to the perception that nature exists solely for our provision. Perhaps this is best represented as a frontier mentality (Wilson, 1984; Farina et al., 2003).

The dispersal of humanity across the globe has generally resulted in the degradation of ecosystems and a loss of species, and even though there have been periods of stability and equilibrium, the relationship has not been sustainable (Berkes, 2000; Egan, 2011). In contrast the culture of indigenous populations, and those documented in the history of our past, represent humans as an inherent part of their landscape. The persistence of such cultures – often for millennia – relies on the individuals and groups developing a stake in the sustainable use and conservation of their environment, living and hunting within the capacity of their habitat (Berkes, 1998; Lubick and Jordan, 2011). This way of living represents an aspect of values that are more ecocentric, but this is perhaps more a consideration of social livelihood, rather than nature as a sole beneficiary (Lubick and Jordan, 2011).

Berkes (1998) describes a more ecosystem focussed model of this relationship which incorporates the consideration of culture and spirituality. The idea and existence of the sacred grove is common in cultures across the world. These groves represent areas protected from formal land management, and often honour a deity or God or are set aside to preserve the wild area for its own intrinsic value. Indeed, the Hindi word *"auron"*, which is used to describe sacred groves, can be interpreted as "for others" and represents the idea of the preservation of nature and all its parts for its own sake (Jha, 1991, cited in Lubick and Jordan, 2011). In this context, the significance of the sacred grove concept — while a manifestation of a protected area — also relates to the values cultures place in nature: the grove exists as a symbol, illustrating the importance of fostering the relationship between people and the natural world (Lubick and Jordan, 2011). The implication can be applied to the modern movement of ecological restoration; it is, in some ways, less to do with acts of preservation or maintenance of the human habitat, but more related to the upkeep and maintenance of the moral, ethical, and behavioural structures on which the preservation depends (Berkes et al., 2008, Egan, 2011, Jordan and Lubick, 2011). In this way, understanding the human place within the context of ecological restoration is vital to the success of long-term projects that include multiple interests and stakeholders outside of the secular or scientific communities (Egan et al., 2011; Mace 2014). This is particularly relevant as ecological restoration moves towards a multi-disciplinary manner of study (Hannah et al., 2002; Mace, 2015). Viewing ecology outside the strictly scientific perspective might enable us to capture a more complete view of the issues, specifically relating to the creation of values through restoration. Perhaps, within the dynamic and challenging world biodiversity conservation faces today, the ability to reshape our values will provide the adaptability on which the modern human-nature relationship might depend (Egan et al*.,* 2011; Jordan and Lubick, 2011). The history of this relationship runs deep but what is clear is that our perception of the environment – the model in which we perceive our place within, and the context for our impact on nature – has evolved with our society, culture, and science (Jackson et al., 1995; Lubick and Jordan, 2011).

2.2 – Framings of Ecological Restoration

Restoration science in the 21st century has grown and adapted to shifts in perspective. Traditionally, ecological restoration can be defined as: "… the process of assisting the recovery of an ecosystem that has been degraded, damaged, or destroyed" (SER, 2004, p. 3). This is a recognition of the acceleration of human impacts on natural areas since the 19th century and an acknowledgement of our responsibility (Dickinson et al., 2015). Landscapes and ecosystems have been altered greatly, surpassing the threshold of socio-economic sustainability to support an ever-growing human population (Aronson et al., 2006; Dickinson et al., 2015). The root of the modern wave of anthropogenically driven biodiversity loss is the result of the rapid expansion of modern society, within which social-economic processes are operating at a spatio-temporal scale finer than the adaptive capacity of ecosystems (Krebs, 2001; Elqvist et al., 2003; Lawton et al., 2010).

Ecological restoration aims to restore ecosystems to their historical trajectory (SER, 2004). It is considered successful when the ecosystem has recovered sufficient biotic and abiotic resources to sustain itself structurally and functionally without assistance (SER, 2004). Aronson et al., (2006 p.136) take the 'bare-bones' definition further, that: "… ecosystem restoration is a process that recovers and improves the functionality of ecosystems within landscapes consisting of lands in agricultural production as well as set-aside nature reserves", concerning land where people, live, work, and produce food, i.e., within cultural habitats (Hurford, 2006). Incorporating landscapes outside traditional protected areas, where most conservation is focussed, promotes the sustainable use of biodiversity and ecosystem services and integrates humans into the restoration framing (Aronson et al., 2006; UNESCO 2017). Traditional human practices outside reserves have shaped ecosystems for thousands of years, through practices such as grazing, burning, and agriculture (Jackson et al., 1996). For this reason, in Europe and the United Kingdom, most habitats are termed 'semi-natural', as there are few that have not seen some form of modification, and many of these – heathland, saltmarsh, grassland – require ongoing intervention to maintain maximum biodiversity by limiting succession (Lawton et al., 2010; Hayhow et al., 2016). In the inclusive view of humans and nature, the process of ecological restoration must include these activities. The inclusion of human cultural relationships with landscape is a key part in the overall process of restoration, where management programmes are viewed as necessary ongoing interactions between people and nature, rather than intervention, and it is as such that these systems are described cultural ecosystems (Jackson et al., 1996; Hurford, 2006). However, as a result of this relationship, systems can be left to degrade if intervention is not continued (Hurford, 2006). In the UK, the loss of biodiversity since the 1950s has been attributed to two main drivers: habitat loss and habitat deterioration (Lawton et al., 2010; Hayhow et al., 2016). Habitat loss has led to a fragmented landscape of patchy habitat, replacing a continuous mosaic of diverse, semi-natural habitats that existed before. Species will become threatened if a minimum viable population size is not maintained (Foreman, 2014). The UK has, however, seen large-scale agricultural and urban development as the driver of this transformation which interrupts natural processes and the natural succession of a landscape (Zipperer, 2011). Natural succession within urban areas is limited: native species are homogenised favouring generalists, edge dwellers and non-native species, and the effective links between habitat parcels are cut off impacting the resilience of species and ecosystems (Douglas, 2010; Zipperer, 2011). A recent report “State of Nature 2016” which compiled data from over fifty UK conservation charities and NGOs reports how 56 per cent of species have declined since the 1970s (Hayhow et al, 2016). The drivers of decline can be attributed to the intensification and expansion of agriculture in the late 20th century, which consequently left little room for wildlife. As a product of this development, semi-natural habitat became increasingly fragmented and fast growing ‘weed’ plant species spread in favour of more sensitive vascular plants. This process is ongoing, 73% of the loss of Biodiversity Action Plan (BAP) habitats in 2008 was a direct result of agricultural practice (JNCC, 2015, Lawton, 2010; Hayhow et al., 2016). The “State of Nature 2016” report also highlights how another key impact, the deterioration of habitats through changing management, also negatively impacts biodiversity in the UK, this is also identified in the Lawton report, and is again linked to fundamental changes in our relationship with the land (Lawton, 2010). In lowland Britain, four per cent of grasslands remained in a biodiverse, unimproved state with the majority being degraded by agricultural pollution and deterioration through a withdrawal of traditional management practices (Colston, 2003).

In response to declining species population trends and habitat deterioration, conservation has shifted towards large-scale restoration projects in the UK. This has influenced the uptake of larger scale conservation projects, looking beyond single site work, towards the values outlined in the Lawton report (Lawton et al, 2010). In recent years there have been several landscape scale projects stemming from the conservation NGOs, chiefly, the RSPB's Futurscapes in 2001 and 2010, and the Wildlife Trusts' Living Landscapes since 2005 (Adams et al., 2014).

The implementation of conservation restoration and ecological knowledge into national policy is known by many commentators as a significant source of frustration (Waylen and Young, 2014). Ecosystems continue to degrade, despite advances in scientific understanding and the knowledge that these systems support human wellbeing through a multitude of ways (Diaz et al., 2006; Waylen and Young, 2014). International and national initiatives have been undertaken to synthesise and disseminate ecological knowledge particularly by raising awareness within the context of national policy. The 2005 UN Millennium Ecosystem Assessment (MEA) and subsequently the UK National Ecosystem Assessment (UKNEA) both brought to the forefront the concepts of natural capital and ecosystem services, and the links between humans and ecosystems, with the overarching objective to directly impact national policy (MA, 2005, NEA, 2011). Ecosystems are known to contribute to all aspects of human health and wellbeing, and people derive benefits to both their physical and mental health by interacting with nature and green spaces (MA, 2005). Both the MEA and the UKNEA assessments contributed to a widespread adoption of ideas within conservation practice and policy, with the broad reception of ecosystem services as an inclusive model in which to view, conserve, and benefit from nature (MA, 2005; Tallis, 2008; Mace, 2014). In the past decade, ecosystem services became a main area of focus for biodiversity policy and conservation representing, what some have identified, as a shift in the objectives of ecological restoration (Bullock et al., 2011). The development of global conservation objectives within the last century has seen several distinct phases. The monetisation and valuation through ecosystem services being one of the most recent (Mace, 2014). This has largely been due to a realisation that nature provides goods and services vital to humanity. These goods had been somewhat taken for granted, and the result of this has been continued degradation and negative impacts to people due to the degradation of these services. In recent years, this realisation has prompted conservation toward an integrative mode of management, with an aim to sustain the global human population as well as the biotic resource (MA, 2005; NEA, 2011; Mace, 2014). As part of this integrated approach to conservation and restoration, the dissemination of knowledge is a key challenge. The challenge facing the scientific community is how best to present findings, and communicate pressures facing ecosystems to stakeholders within the public domain (Krolik-Root et al., 2015; Collof et al., 2017). This is a key framework through which this thesis will be presented and represents a significant theme within the extant literature.

There are numerous frameworks and justifications for the restoration of ecosystems (Jackson et al., 1995; Aronson et al., 2006; Clewell and Aronson, 2006; Harris et al., 2006). These are determined by project specific conditions, and whether these are conducive to successful restoration, through social commitment, ecological circumstance, quality of judgement and values (Jackson et al., 1995; Clewell and Aronson, 2006). According to Clewell and Aronson (2006), the pragmatic motivation for restoration would one day be cited as the key argument for ecological restoration. While, in their interpretation, they somewhat segregate the 'pragmatic' theme from the holistic, value-driven restoration process mentioned previously, they acknowledge two key elements: restoration for natural capital, and restoration for the amelioration of climate effects (Clewell and Aronson, 2006). These two categories now pertain to some of the greatest challenges in modern conservation science and practice (Mawdsley et al., 2009; Lawton et al., 2010; Mace, 2014; Dickinson et al., 2015; Collof et al., 2017). In Clewell and Aronson's (2006) paper the second recommendation for development within the pragmatic approach was the amelioration of climate change impacts through restoration. Despite the recognition that the development of restoration for natural capital and climate change effects would have the most impact on human welfare, the authors comment that within the 2006 literature, this approach towards restoration was one of the least developed (Clewell and Aronson, 2006). More recently, climate change is regarded as integral to conservation planning (Heller and Zavaleta, 2009, Dickinson et al., 2015). The rate of climate warming is now regarded as unprecedented when compared to changes in past centuries, it is likely that the period between 1983 – 2012 was the warmest three-decade period in 1400 years, with an approximate increase of 0.2°C (IPCC, 2014). Global mean temperature by the end of the

21st century is predicted to increase between 1.7°C to 4.8°C, depending upon the carbon emission scenario (IPCC, 2014). The implications of these changes — other than direct biotic impacts of temperature change — are an increasing likelihood of variations in global weather patterns characterised by increasing sea level and incidence of extreme weather events (Harris et al., 2006). Changes at such scale present implications to the sustainability of natural systems (Heller and Zavaleta, 2009; IPCC, 2014).

2.3 – Climate Change and Ecology

Along with continuing land-use change and population growth, it is widely recognised that climate change and it's impacts on biodiversity are a major threat to the integrity and resilience of ecosystems, amplifying the range of non-climatic threats already present (Erwin, 2009; Heller and Zavaleta, 2009; Dickinson et al., 2015). Ongoing land conversion, when combined with climate change, is predicted to be a key threat to the exacerbation of the carbon cycle and its trickle-down effects on biodiversity (Schroter, 2005). The productivity of ecosystems is impacted as the balance of productivity is altered, the fixation of carbon by photosynthesis in comparison to its remineralisation through respiration ultimately determines whether an ecosystem acts as a carbon source, or a sink (Houghton et al., 1998; Yvon-Durocher et al., 2010). As these mechanisms contribute to a positive feedback mechanism it is predicted that the release of atmospheric carbon will be elevated under continuous climate change (Houghton et al., 1998; Knorr et al., 2005). A carbon-climate model constructed by Cox et al., (2000) indicated that under a 'business as usual scenario', the global biosphere will switch to a carbon source by 2050, and the oceans capacity for carbon uptake will be balanced by the terrestrial carbon source at 2100 (Cox et al., 2000).

Biological responses to climate change are numerous and may already be driving species extinctions (McLaughlin et al., 2002 cited in Heller and Zavaleta, 2009). The alteration of species ranges will introduce new interactions, not previously encountered, due to spatial and climatic exclusion (Van der Putten et al., 2010; Walther, 2010). This has been reported across latitudinal as well as altitudinal gradients (Parmesan et al., 1999; Holzinger et al., 2008 cited in Walther, 2010; Hodgson et al., 2015). This will potentiate the likelihood of invasive species becoming naturalised in new ecosystems (Walther, 2010, Travis et al., 2013). Changes in community composition are predicted, destabilising ecosystems when interspecific interactions are disrupted (Elmqvist, 2003; Walther, 2010). In addition to the physical changes in community composition, alterations of species' phenology and behaviour impact the wider ecology through a decoupling of interactions (Post and Forchahammer, 2008; Van der Putten et al., 2010). Asynchronicity in the range of responses to phenological triggers is a source of uncertainty when trying to predict these shifts; species will respond individualistically and not as communities (Post and Forchahammer, 2008; Van der Putten et al., 2010; Dickinson et al., 2015). The biotic responses to environmental change are likely to be exacerbated by abiotic limits. The fragmentation of habitats as a product of human development, in addition to natural barriers to dispersion, will limit the ability of some species to track climate change potentially leading to extinctions and degradation of ecosystem resilience (Fahrig, 2003; Huntley et al., 2008; Laliberte et al., 2010; Doerr et al., 2011; Dickinson et al., 2015).

Processes derived from climate change, through a manifestation secondary effects, will further contribute to the stressors that ecosystems will be subjected to. Within the context of coastal ecosystems this is manifest particularly by sea level rise (SLR), as a result of glacial/ ice cap melt water and the thermal expansion of sea water (Jevrejeva et al., 2014). This process will threaten coastal systems to varying degrees based on local constraints and conditions and will impose further risk to those systems that may be physically constrained through urban encroachment or lack of habitat connectivity (Kirwan et al., 2010). Intertidal habitats across the globe are likely to be impacted, however this is likely to be more severe in the mid to high latitudes (Chust et al., 2008). The International Panel on Climate Change (IPCC), in their fifth assessment report, predicted continued sea-level rise, with 'medium' confidence as a global increase of 44 – 74 cm (IPCC, 2013). The IPCC projections, however, may still be conservative (Kirwan et al., 2010). Recent work suggests that the melting ice sheets may have an increased contribution to sea-level rise (Jevrejeva et al., 2014). While the confidence that can be assigned to these predictions may be lower than those from the IPCC, the prospect of a 1.9 m rise in sea level before the end of the twenty-first century that comes from these predictions provides a stark scenario for the future of biodiversity in the intertidal zone and is a reality that those involved in coastal conservation and urban planning will have to recognise (Kirwan et al., 2010; Jevrejeva, 2012). In the UK, the value for global annual sea-level rise closely matches that of the IPCC fifth assessment predictions (IPCC, 2007; Woodworth et al., 2009). Relative sea-level rise varies from north to south as a product post-glacial isostatic adjustment, uplift and subsidence. Between the southeast and northwest of England the difference in relative sea-level rise is around 1.5 mm/yr with an increase to 2 mm/yr after 2055, based on current projections (Nicholls et al., 2013). The northwest experiences positive land movement (i.e., it is rising) of 0.8 mm/y in contrast to a negative (i.e. sinking) 0.8 mm/yr in the southeast (Defra, 2009). As a result, in the variance of relative sea-level rise, threats to coastal habitats vary across the UK. Studies indicate an approximate loss of <100ha of saltmarsh per year in the east-midlands and southeast, but the impacts of relative sea level rise will need to be assessed on a site by site basis, as conditions around the UK differ (Doody, 2008). Therefore, there is an opportunity to expand on the published literature by exploring relative sea-level rise impacts on individual sites and novel systems, and as such, this is an aim of the current research.

2.4 – Threats to Coastal Habitats – Saltmarsh Ecology

The continuous loss and degradation of coastal habitats are concerns for coastal management and nature conservation, particularly within the context of projected SLR (Chust et al., 2008; Davies et al., 2016). Saltmarshes are a relatively common habitat within estuaries, particularly in the mid to high latitudes, and globally saltmarshes and wetlands are some of the most productive habitats, producing up to 3000g C/m^2/y (Chen et al., 2013; Giuliani and Belluci, 2019). There are significant commercial and recreational attributes associated with these habitats, particularly through the abundance of fish stocks and a high diversity of breeding and wintering avifauna which exist as the highest trophic level in these systems, and subsequently attract bird watchers throughout the year (chiefly waders, gulls, terns and passerines) (Chen et al., 2013; Klemas 2013; Greenberg et al., 2014; Giulliani and Belluci, 2019). Many of the bird species found within coastal/ estuarine habitat are of conservation concern, and many estuaries in Europe hold populations of international importance.

The morphology of saltmarshes varies regionally and is dictated by a multitude of biotic and abiotic processes. Saltmarshes often show clear zonation between the vegetative communities present. Typically, this has been linked to elevation and the length of inundation and salinity ranges between the mudflats and the mean high-water level (Giuliani and Belluci, 2019). The establishment of vegetation on the estuarine or coastal mudflats occurs when sediment has accreted to a level at which they are covered by the tide for less than six hours a day, and therefore can support vegetation (Van Duin et al., 1996). This is known as the pioneer zone and is typically characterised by the presence of *Salicornia* and *Suada* species, both salt tolerant succulent plants that are found within the lower zones in a saltmarsh system (Giuliani and Belluci, 2019). The density and height of vegetation determines the effectiveness of the saltmarsh in trapping sediment. A direct relationship has been demonstrated between the height of vegetation, its density, and its ability to slow water (Boorman et al., 1998, Giuliani and Belluci, 2019). Taller vegetation is flattened easily by the movement of water, shorter stiffer species associated with the pioneer zone are more effective at slowing flow and, when combined with the greater period of tidal inundation, increases sediment deposition at the lower expanse of the marsh (Dale et al., 2017). As a result of this process, and as elevation increases with wave direction, the duration of inundation decreases, and a wider range of plant species then colonise the mid to higher marsh elevation (Giulliani and Belluci, 2019). Then, the rhizomes and root profile of the colonising grass species further stabilises the marsh sediment (Giuliani and Belluci, 2019). Therefore, saltmarsh habitats act as natural dissipaters of tidal energy and, therefore, protect landward sea defences, private land, and businesses from damage and erosion (Wolters et al., 2005; Doody, 2008). The primary mechanisms for this are through wave attenuation, floodwater attenuation, and shoreline stabilisation (Gedan., 2011; Shepard et al., 2011; Rupprecht et al., 2017). By these mechanisms, saltmarshes reduce the impact and duration of storm surges, the depth of saltmarsh sediment and the creek network further alleviates this draining and absorbing flood waters, reducing flood risk and damage in the coastal zone (Gedan et al., 2011, Shepard et al., 2011). However, with the prevalence of these risks projected to increase in the future, the persistence and protection of these habitats is paramount within the context of coastal protection (Giuliani and Belluci, 2019).

Differences in sediment load within the water source, soil properties and sub-surface water flow further influences the distribution of vegetation, marsh structure, elevation and the resilience of the habitat between different locations (Silvestri et al., 2005). Long term monitoring has revealed, in some cases, that the dynamics of saltmarsh vegetation does not always follow the established model of succession, and further, that paleo-ecological analysis has shown that at some sites, the species present represent a stable community that has existed for many thousands of years (Adam, 1990; Silvestri et al., 2005). While it is often appropriate to view the general mechanism of marsh development through the traditional definitions of succession, when management is being undertaken it is still important to consider that these habitats are dynamic, and responsive to local conditions, leading to the potential establishment of novel systems (Silvestri et al., 2005; Gedan and Bertness, 2009; Stagg et al., 2016).

Coastal wetlands respond through a complex feedback process between surface elevation, sediment accretion, and plant growth (Stagg et al., 2016). The resilience of wetland ecosystems may be attributed to this emergent ecosystem response and, depending on estuarine sediment supply, enable marshes to keep pace with relative sea-level rise (Stagg et al., 2016). The outcome of this feedback process is an example of an ecosystem in which a response to climate change may be controlled by eco-geomorphic processes (Kirwan et al, 2010). Many studies have failed to consider the dynamic nature of saltmarsh processes. Numerous forecasts of ecosystem change have relied on the supposition that sea-level rise will occur across a static landscape: known generally as the ‘bathtub’ model (Kirwan et al., 2010; Kirwan et al., 2016; Davies et al., 2016). In saltmarshes, vegetation growth is generally increased at lower elevations. During times of increasing sea level and high-water events, sediment trapping may be enhanced due to increased deposition rates (Morris, 2002; Kirwan et al., 2002). Consequently, vertical erosion may be suppressed. This may explain the presence and persistence of wetlands in the intertidal zone after their development by rapid sea level rise during the post-glacial period (Davies et al., 2016).

As seasonal tidal flooding is the main mechanism of sediment supply to the saltmarsh platform and, as such, these habitats are inextricably linked to variations in the tidal limit and sea level rise (Fagherazzi et al., 2012). Several studies quantify the variability across UK saltmarshes. Work conducted in the Thames Estuary and the Solent suggest that vertical sediment accretion has exceeded the rate of sea level rise in the past two decades and that these tidal marshes are currently able to maintain their tidal elevation (Cundy & Croudace 1996; Hughes 2004; van der Wal & Pye 2004; Foster et al., 2013). Hughes and Paramor (2004), suggest that a loss of saltmarsh pioneer plant communities does not necessarily result in a corresponding loss of upper marsh communities; *Puccinellia maritima* and similar species are effective in sediment trapping (Langlois et al., 2003). Accelerated global sea level rise, however, and increasing projected values cause this issue to remain problematic as these values may exceed vertical sediment accretion in the future (Foster et al., 2013).

While there have been wide-spread observations and projections of saltmarsh submergence, complete saltmarsh loss is rare, and generally a result of human involvement leading to either a reduction of the sediment supply or increasing subsidence rates (Kirwan et al., 2010; Kirwan et al., 2016). River estuaries in Europe are highly urbanised and contribute to these processes. These changes include port development, dredging, tidal barrages, and training wall construction (Halcrow, 2010). It might also be considered that post-glacial fluvial and coastal sediment resource has decreased (Redfield, 1972; Robins et al., 2016). As a result of these processes, eco-geomorphic processes, i.e., sediment supply, may be altered, reducing the resilience of the saltmarsh ecosystem to sea level rise and environmental change (Kirwan et al., 2010). Kirwan et al., (2010) compare five dynamic models used to assess saltmarsh response to sea level rise. They found that sediment availability is a strong influence on a saltmarsh's ability to survive high sea level rise, and a positive relationship was found between this threshold and the estuary tidal range. These macro-tidal estuaries were found to be more sensitive to a reduction of sediment supply, however, a high tidal range and a concentration of sediment greater than 20 mg/L was found to support their resilience (Kirwan et al., 2010). The authors demonstrate a range of scenarios that – under their dynamic models – intertidal marshes in northwest Europe could survive sea level rise, and comment that the prediction of saltmarsh loss made under static scenarios and past trends would be difficult to defend. However, under rapid sea level rise based on the projections in Jevrejeva et al., (2014), we would see a large-scale submergence of saltmarshes before 2100 (Kirwan et al., 2010; Kirwan et al., 2016; Jevrejeva et al., 2012). This implications of this disparity in predictions is an area requiring further investigation and will be explored within this thesis.

The presence of urban areas or constraining land use further the survival of the saltmarshes long term (Giulliani and Belluci, 2019). Saltmarshes have lost fifty percent of their global coverage over the past two centuries, and most of these losses are ascribable to human involvement, either directly or indirectly (Barbier et al., 2011). Historically, land reclamation for port development, and draining and ditching for agricultural use has led to the direct loss of saltmarshes (Giulliani and Belluci, 2019). More recently, an indirect mechanism of saltmarsh loss has been defined in the literature by a process known as "coastal squeeze" (Doody, 2004).

There have been numerous discussions within the literature as to the definition, and impact of coastal squeeze on saltmarshes. Doody (2004) describes it as:

> " … where rising sea levels and other factors such as increased storminess push the coastal habitats landward. At the same time in areas where land claim or coastal defences has created a static, artificial margin between land and sea or where the land rises relative to the coastal plain, habitats become squeezed into a narrowing zone. Manifestation of this process is most obvious along the seaward margins of coastal habitats, especially salt marshes, when erosion takes place." – Doody (2004).

These fixed defences, walls or built to protect the adjacent urban areas prevent the natural migration of the marsh to a higher elevation when the seaward edge is eroded by storm surges and rising sea levels (Giulliani and Belluci, 2019). As the total area of the saltmarsh is reduced, this begins to endanger the man-made physical barriers as the existence of saltmarsh protects the integrity of these structure through wave and water attenuation (Dale et al., 2017).

Coastal squeeze as a mechanism has been criticised. Pontee (2016) reports that coastal narrowing has been observed on both undefended and defended coastal profiles, and that wind wave climate and sediment profile are factors that can influence a greater loss of habitat than the traditional definition of coastal squeeze. While this sentiment is true and has been echoed within the literature, changes to the sediment regime, and an increase in storm surges when combined with a fixed sea wall or boundary will only exacerbate habitat loss in the intertidal zone. Despite the critique of Pontee (2016), the term “coastal squeeze” is now well established and well used within the literature (Crosby et al., 2016; Davies et al., 2016; Dale et al., 2017; Borchert et al., 2018; Giuliani and Bellucci, 2019; Leo et al., 2019). Since the use of this terminology is associated with an emerging area of research, the definitions and approaches related to coastal squeeze are not standardised, however, the impact of the mechanism known as ‘coastal squeeze’ can no longer be denied (Leo et al., 2019). The conclusions drawn from the current body of research suggests that habitat connectivity, and promoting the ease of saltmarsh landwards migration are critical factors for the long term sustainability of saltmarshes in the face of sea level rise, and that coastal squeeze remains one of the greatest threats to ecosystems of this kind (Kirwan et al., 2016). Indeed, this issue is controllable, as the impacts of coastal squeeze are linked to policy decisions such as shoreline management plans (Davies et al., 2016). In combination with the impacts of weather pattern changes and sea level rise, loss of intertidal habitats can be expected to increase as the use of sea walls and hard flood defences continues (Leo et al., 2019). Without a shift in paradigm this is unlikely to change, this approach of coastal defence is societies current preference, and with urban infrastructure and development bordering these structures in many areas there is little option (Calder, 2015; Leo et al., 2019). Human population density, and subsequently urbanisation, is generally higher around coastal areas such that in some systems it could be said that it is the town and cities themselves that are constraining the saltmarsh ecosystems (Davies et al., 2016). With many coasts already heavily armoured, the extinction and fragmentation of intertidal saltmarsh habitats will continue to occur and increase in prevalence unless active recovery and positive management occurs (Leo et al., 2019).

2.5 – Global Change-ready Approach

A pervading theme throughout the literature is that conservation and restoration must be ready to respond to and communicate future environmental change, however, it must also incorporate implicit uncertainty across a range of scales, this is manifest within the range of SLR scenarios currently published (Jevrejeva et al., 2014; IPCC, 2014). Such uncertainty can represent a barrier to decisions being made (Harris et al., 2006). Conservation managers, under these circumstances, must have a means to assess a range of future climate change effects and appropriate management options. They require techniques to be able to do this. These techniques might include sensitivity analyses conducted for a system under specific scenarios, the spatial impacts would then be mapped to communicate future impacts for incorporation into management plans (Hannah et al, 2002). The emerging practice of 'integrated vulnerability assessment' which utilises multiples sources of information to understand better and predict the impacts of climate change serves as a mean to assess the sensitivity of a system (Dickinson et al., 2015). The practice is built into a model incorporating adaptive management and facilitates the identification of the most appropriate strategy and the urgency of intervention required (Ausden, 2014; Dickinson, et al., 2015). The iterative process involves consistent monitoring and re-evaluation of actions that are then fed back into the decision-making process. These actions are considered crucial as a tactic for restoration when understanding climate change impacts (Hannah et al., 2002; Dickinson et al., 2016; Wyborn et al., 2016). However, adaptation based on the framing of localised and marginal change could prove ineffective. This system, based on a multidisciplinary mode of study, allows the incorporation of all stakeholders and as such, the communication of the problem is central to the process (Collof et al., 2017) Uptake and implementation within restoration projects has been slow and a transformative adaptation approach is likely to be needed (Haggerman and Satterfield, 2014; Wyborn et al., 2016; Collof et al., 2017).

Climate change vulnerability is described by the International Panel on Climate Change (IPCC) as the susceptibility of a resource, species or system to the negative effects of climate change, and other stressors (Gitay et al., 2011; Glick et al., 2011; IPCC, 2014). The term vulnerability here is defined by three components: exposure, sensitivity and adaptive capacity (Glick et al., 2011). These are defined thusly:

- Exposure: the amount and rate of change that a species or system experiences from the either direct or indirect impacts of climate change,
- Sensitivity: the characteristics of a species or system that are dependent on specific environmental conditions, and to the degree to which this will be altered by climate change,

- Adaptive capacity: the ability of a species to cope and persist under changing conditions through acclimation, dispersal, migration evolution or phenotypic plasticity.

The emergent science of climate change vulnerability assessment (CCVA), is a set of tools that can be used as an initial step in the process of climate adaptation or mitigation by identifying the greatest risks facing a species, habitat or system (Glick et al., 2011). These risks can either be direct or indirect effects, as well as non-climate related factors, for example, land-use change and habitat fragmentation (Glick et al., 2011). The process of conducting a CCVA includes the synthesis of existing species, or system data, and the identification of knowledge gaps (MCAP, 2015). This information will then be incorporated with projections of climate change to identify the elements comprising the systems vulnerability, i.e., the exposure, sensitivity and adaptive capacity of the system (Glick et al., 2011; MCAP, 2015).

As yet, there is no standard approach or framework through which to conduct a CCVA, and a variety of methods are being implemented across various governments and institutions (Glick et al., 2011). Much of the published work around this topic is within the grey literature, specifically that produced by various governmental institutions across the United States of America, where there has been a broad uptake towards CCVA as an operational management tool across a range of ecosystems (MCAP, 2015). However, due to the lack of a centralised set of guidelines it is important to consider how each of the three components set out by the IPCC describing climate vulnerability are evaluated within the context of an assessment, and how these inform the overall objectives set out by the project management (Glick et al., 2011; MCAP, 2015).

The European Union White Paper on a European adaptation framework stated that the research on climate change and ecosystem vulnerability studies was fragmented, with information not being shared between the decision-making levels (EC, 2009). The outputs published by the research community were generally in relation to predefined scenarios and thus hindered knowledge integration, limiting the applicability of this knowledge to stakeholders of other systems (Harrison et al., 2015). More recently, the European Environment Agency published a report in 2016 assessing the projected climate change impacts on ecosystems and society. This report is the fourth published report of a four-year cycle reviewing the trends and development of adaptation policy within the member states (Castalleri and Kurnik, 2017). Several knowledge gaps were highlighted within this document relating to the broad scale advancements and application of climate planning across the continent. The presence of robust vulnerability assessments, the tools to support adaptation policy, and an integrated knowledge regarding effective adaptation case studies were all reported as gaps in knowledge across the member regions (Castalleri and Kurnik, 2017). Between 2007-2013 the EU's FP7 scheme covered climate-relevant research, the project 'Climate change integrated assessment methodology for cross-sectoral adaptation and vulnerability in Europe' (CLIMSAVE) being the most appropriate within the context of CCVAs (Castalleri and Kurnik, 2017). This project identified the need for a user driven, participatory tool for integrated vulnerability assessment in Europe (Harrison et al., 2015). The output of this project was an interactive web-based tool to allow stakeholders to quantitatively assess climate change impacts for a range of sectors, including agriculture, forestry, biodiversity, coasts, water resources and urban environments (Harrison et al., 2015). Following the advent of the FP7 scheme, Horizon 2020 has covered a diverse range of disciplines and research initiatives, with climate science accounting for 35% of the budget Castalleri and Kurnik, 2017). As such, the contribution of these advances will be published within the fifth edition of the European Environment Agency report cycle. Within these studies, there is a lack of detailed research relating to the vulnerability of key breeding bird species within the context of climate change derived vulnerability. While this has been well studies in the USA (Glick et al., 2011; Raposa et al., 2017), studies in the UK are general and do not focus on wetlands or saltmarshes or specific associated species, such as the redshank (*Tringa totanus*) (Greenwood et al., 2016; Martay et al., 2017). This is despite the recognition by Eaton et al., (2015) that climate change will exacerbate population trends in the future for already threatened UK species. This assessment however only acknowledges broad 'climate envelope' assessments and does not acknowledge secondary effects, such as sea level rise, and the implications for wetland birds. The lack of published research relating to ecosystem vulnerability assessment in Europe provides an opportunity to address the gaps highlighted by the European Environment Agency (Castalleri and Kurnik, 2017), i.e., through the provision of a case study relating to a vulnerability assessment undertaken to a specific system, and further that an integrated knowledge approach is used in order to effectively communicate vulnerability or resilience. Further to this, addressing the vulnerability of specific species and groups to the secondary effects of climate change is an area of research that is lacking within the UK. This theme will be addressed within the current thesis with the focus on key saltmarsh bird species.

2.6 – Monitoring Changes in Biodiversity

Implicit to the success of long-term conservation projects, particularly within the context of environmental change and ecosystem vulnerability assessment, is the ability to determine when an ecosystem itself changes, and if so, at what rate (Buckland et al., 2005). This relates to observing the exposure and sensitivity of a system within the framework of CCVA (IPCC, 2014). This is an important consideration within the context of the 2020 Convention on Biological Diversity Target to halt overall biodiversity loss (CBD, 2010). Ultimately, to address the matter appropriately, managers need to ask three questions: Why monitor? What should be monitored? How should monitoring be carried out? (Yoccoz et al., 2001; Buckland et al., 2005).The first two questions should be informed by local targets with relation to national/ international objectives, for example in the UK this could be the BAP target species for a specific region, key species within an Special Protection Area (SPA) citation or by historic records of species of conservation concern (JNCC, 2018). It is important that the species or habitat that is the subject of monitoring is made clear from the offset and that baseline conditions are established (Maturo and Battista, 2018). Benchmarks can be derived through a variety of methods, generally these might include empirically derived reference conditions, the first point of a time series or identification of a desired goal by an expert (Taft et al., 2006; Maturo and Battista, 2018). Through an appropriately designed monitoring system, the three components of ecosystem vulnerability can then be addressed adequately, i.e., the sensitivity, exposure and finally the adaptive capacity of the species or habitat to which the management objectives are related (IPCC, 2014). Without this clear vision, the work will fall closer to the definition of ecosystem surveillance, where the detection of trends in habitats or populations is the aim, rather than the extent of variation from an expected baseline, or target, as monitoring is defined (Hurford, 2006). Though surveillance may represent a portion of the pre-monitoring work at the outset of a project (Maturo and Battista, 2018). While similar, both are methods which are important to distinguish, particularly in cultural habitats (Hurford, 2006). The pressures facing these cultural systems i.e., those derived from human activity or management intervention, are sensitive to environmental change as many exist within a fragmented landscape (Hurford 2006; Lawton, 2010). Therefore, it is a key benefit of monitoring that it promotes responsible conservation by encouraging practitioners to consider why sites are important, that the most important habitats and species are prioritised, that sufficient data is gathered to recognise when conservation value is under threat, and that this can be identified and an appropriate management response is taken before the conservation value is lost (Hurford, 2006). Within the context of long-term projects seeking to plan for climate change, particularly within the framework of climate change vulnerability analysis, a stringent and well-defined monitoring system will overcome issues relating to changes in management (Hurford, 2006; IPCC, 2014).

In practice, there are a multitude of considerations when determining the data required and the methods to utilise for ecological monitoring. These will be intimately linked to the management objectives and the species or system under scrutiny, however, setting a threshold at which the system switches from unfavourable to favourable condition is central to this process. This could be defined by the presence (or lack of) of target species, or the quality/ diversity of a habitat (Hurford, 2006). Within the context of the research presented in this thesis, the ecological processes linked to saltmarshes, and the techniques through which they are monitored, are broad. The management objectives set for a specific site will dictate which techniques are most appropriate. Within the framework of ecosystem vulnerability assessment, the impact of future environmental change on tidal regime, saltmarsh habitat area, saltmarsh morphology, and species ecology are central challenges facing management, and subsequently, monitoring (EA, 2007; McCowen et al., 2017).

Recently, quantifying species diversity has seen a resurgence within the literature, with studies seeking to address the best way in which to depict the biodiversity of a system (Cox et al., 2017). The simplest, and most common measure of biodiversity is species richness, which is the absolute number of species within a community. Despite this metric’s strong foundation within the literature and within models of community ecology (MacArthur and Wilson, 1967), an issue with this measure relates to its biased underestimation of a community due to its sensitivity to sample size, and that it does not incorporate relative abundance as all species carry equal weight (Chao et al, 2014). There are numerous compound indices that have been created to combine measures of species richness and species abundance, Shannon and Simpson's diversity being the most commonly used (Morris et al., 2014). However, the use of these traditional indices has been criticised as they tend to be highly correlated, are not expressed in sensible units, and do not allow for true comparisons (Cox et al., 2017). Recently, the use of Hill numbers has seen a resurgence within the scientific literature. Hill numbers are a unified group of diversity indices which incorporate species richness and relative abundance (Jost, 2007; Chao et al., 2014). The use of the Hill numbers offers several advantages over the other diversity indices. They obey the doubling property, i.e., if two completely distinct species groups are combined (with identical relative abundance) then the Hill number doubles (Chiu et al, 2013), different assemblages can be directly compared and provides unambiguous differences within the diversity values (Chao et al., 2014; Cox et al., 2017). In tandem with traditional statistical means, such as the Kruskall-Wallis, and the Mann Whitney-Wilcoxon tests, this provides restoration practitioners with a usable metric that summarises the broad diversity of a site, is sensitive to community change, and is within a format that is easily communicable (Cox et al., 2017). This line of enquiry will be pursued within this thesis.

If the management purpose is to increase the diversity of another biotic group, invertebrates, or plants for example, then vegetation surveys are undertaken using established techniques. The National Vegetation Classification (NVC) is a standardised system which sought to produce a comprehensive classification and description of plant communities within the UK (Rodwell et al., 2000). This technique acts as the key terrestrial habitat classification system for guidance on SSSI site selection, UK common standards monitoring guidance, and numerous conservation organisations/ consultancies methodology for detailed site assessment. NVC provides a highly detailed picture of community structure, when compared to more general classification schemes, such as Phase 1 habitat survey, a generally less labour-intensive technique. The use of these techniques is closely related to the management objectives of a site, though both are commonly used for baseline habitat description and the vegetative classes are interlinked

(JNCC, 2010). Following the characterisation of habitat, the monitoring program might then follow a set of predefined condition indicators to determine habitat change against the benchmark (Hurford, 2006). In general, this approach will require unambiguous definition as to the both the favourable extent and favourable condition of a habitat (Hurford, 2006). The application of traditional field-based techniques (NVC and Phase 1) has seen integration with wetland-based impact assessments and in the UK. In 2009, the Environment Agency undertook a large-scale review of wetland habitats and identified condition thresholds that may be sensitive to future change (EA, 2009). Within the context of saltmarsh management, optimum habitat might relate to sward height in addition to floristic diversity if encouraging breeding waders is an objective, as redshank and lapwing both prefer to breed on grazed grass swards (Sharps et al., 2016). Monitoring regimes utilising these traditional methods, while providing very high detailed libraries of biotic change, are limited by their time and resource expense, particularly when large scale, regional to national assessments are required (JNCC, 2007). Remote sensing is a discipline that can provide an opportunity for more frequent observations of these systems, and data collection at hard to access sites. The systems are particularly suited to providing regular assessments of habitat extent, which may be supported by field-based methods. Recent advances within the technology are leading to an increase in uptake (Adam et al., 2010). The ability to regularly acquire detailed images provides an opportunity for site managers to tie together systems and species information visually, aiding communication trends, and to identify sources of future threat (Harris et al., 2006; Collof et al., 2016; Wyborn et al., 2016).

2.7 – Monitoring Wetland Habitats – Remote Sensing

The sustainable management of wetlands and their associated habitats requires the effective and timely mapping and monitoring of vegetation distribution particularly under mounting anthropogenic and climatic pressures (Adam et al., 2010). Traditional methods for assessing vegetation characteristics involves field work that, depending on the area of study and the methods utilised, may be hindered by site size and accessibility, and safety (Anderson et al., 2014). Remote sensing is the process of gathering information about a feature, object or area using a sensor to record the data, and a platform to which the sensor is mounted is flown or orbits over this object of interest (Cordell et al., 2016). The sensor itself detects electromagnetic energy that is emitted or reflected by the features on the Earth's surface. The platform itself can be anything that can be reliably flown. Historically, the first aerial photography was taken from balloons, however, in the early 20th century, imagery was taken from aircraft as the original application was that of military surveillance (Colomina and Molina, 2014). The discipline offers a set of analytically powerful techniques for the discrimination of wetland vegetation and biophysical properties that can complement ground-based measurements and can be used to improve the efficiency of field sampling and monitoring (Adam et al., 2010). Remote sensing data, due to the repeat coverage of orbiting satellite sensors, or aerial photography flights, can be acquired at regular intervals without the researcher being in contact with a site and is easily integrated into Geographic Information Systems (GIS) for analysis (Adam and Mutanga, 2009). This provides ecologists and conservationists with a potential tool to include within long term habitat monitoring programmes, either by way of supporting existing vegetation survey techniques, or providing an alternative source of data collection.

Key platforms from which remote sensing data are collected are satellites, aircraft and more recently, unmanned aerial vehicles (UAVs). In general, the decision as to which platform is appropriate for the system of study is to consider a set of trade-offs which will be dictated by project objectives and revenue. Historically, aerial photography has been a primary source for the mapping and monitoring of change in habitats and landscapes (Morgan et al., 2010). The use of aerial photography far pre-dates the emergence of satellite remote sensing, with the launch of the first space borne sensors in the 1970s and in some cases provides data for long term change detection studies, where the data has been collected (Campbell, 2011). The advent of satellite remote sensing saw a broad uptake within academic institutions, and through its practical application, quantitative image analysis and classification techniques were developed as the discipline progressed (Morgan et al., 2010). Through the use of satellite borne multispectral sensors, multispectral relating to the acquisition of data across a large number of wavelengths, entire landscapes could be monitored across a time series, enabling researchers to quantify large-scale ecological shifts such as deforestation trends (Song et al., 2014), monitoring woodland burn scars (Cao et al., 2009), assessing forest fire risk (Jaiswal et al., 2002), and monitoring long-term habitat change in wetlands (Niu et al., 2012). However, long satellite revisit times, obscuring cloud cover, and coarse spatial resolution of some datasets can limit the applicability of satellite sensors when being utilised to meet local or regional objectives, as the data are often too general (Wulder et al., 2004; Anderson, 2013). The spatial resolution of a satellite sensor relates the ‘on the ground’ representation of a pixel. Landsat-8, one of the most widely utilised within research because of its long service time, has a spatial resolution of 30m, and although some low spatial resolution satellite data (e.g., European Space Agency Sentinel-2, Landsat series, MODIS) are freely available, high resolution data, which are critical for accurate vegetation monitoring (e.g., IKONOS 3.2 m resolution, Quickbird 2.44 m resolution) often comes at a prohibitively high financial cost, thus limiting the potential for uptake within smaller conservation or research bodies around the world (Koh and Wich, 2012). The twin-satellite Sentinel-2 mission developed by the European Space Agency (ESA) has been providing data of high spatial, spectral and temporal resolution since mid-2016. The sensor pair contains a Multi-Spectral Imager that records spectral bands across the visible spectrum, near infra-red (NIR), and shortwave infrared including three bands in the red-edge region. In remote sensing, this portion of the electromagnetic spectrum (red-edge to near infra-red) is reflected strongly by healthy vegetation, and as such is a useful parameter for detecting change based on plant based attributes. The NIR and visible bands are recorded at a spatial resolution of 10m, while the ‘red-edge’ bands (bands 5 – 7) record at 20m (Delegido et al., 2011; Stratoulias et al., 2015). While providing continuity to the SPOT and Landsat missions, these attributes and the short revisit time and large swath width may be advantageous when considering Sentinel-2 for vegetation monitoring in estuarine environments in the United Kingdom (Martimort et al., 2007; Stratoulias et al., 2015). While these platforms are in no way redundant, utilising remote sensing for the assessment of local sites and land parcels that sit within a broader landscape require techniques that are cost-effective, timely, and at a scale appropriate to ecological processes and management objectives (Anderson, 2013; Angus, 2017).

Aerial photography is a platform suited to mapping small scale ecosystems, and fine landscape features due to the high spatial resolution of the mounted camera/sensor. The technique, as with other remote sensing methods, is subject to numerous challenges within its application, however these differ from those of satellite data. In general, imagery collected from an aerial platform has a limited spatial coverage, also known as swath width, which is a function of the altitude at which the sensor is collecting the data. Morgan et al., (2010) describe that until recently, the practical application of aerial photography relied on image interpreters, through which land cover was delineated through a subjective procedure relying on interpreter experience. Within the last two decades, aerial photography has benefited from the advancements in remote sensing image analysis originally developed within the context of satellite digital data sets (Campbell, 2011). The earlier subjective interpretation of aerial photography data did not require radiometric standardisation – or calibration –, however, utilising quantitative classification methods requires normalisation of images throughout the flight path and between dates for analyses to be valid (Dronova, 2015). This poses a challenge for data derived from aerial photography, as the imagery taken as part of one flight, or the constituents of a larger mosaic of images, might have significant variations in illumination, either due to atmospheric conditions or in the angle of solar illumination (Dronova, 2015; Anderson et ., 2018). Techniques developed for very high-resolution data sets, specifically object-based approaches, have been successfully applied to aerial image analysis (Morgan, et al., 2010; Dronova, 2015). Object-based approaches provide an alternative to the traditional pixel-based analyses and offers a key set of advantages when using data that is of very high resolution, particularly in wetlands due to narrow successional gradients. The variability of adjacent pixels, variable soil moisture, and the similarity of spectral characteristics between cover types can lead to inferior, speckled image products, characterised by the term “salt-and-pepper” (Dronova, 2015). Within an object-based approach, the collected image is segmented into objects (groups of pixels) based on specific elements, habitats or features, which than then be classified (Dronova, 2015).

The emerging technology of Unmanned Aerial Systems offers new possibilities within the application of remote sensing (Rosnell et al., 2011). The platform is a branch of the field of aerial photography, and like the former, allows remote imagery to be collected under cloudy conditions that would obscure the satellite platform. In some applications, including time series mapping, data must be collected under highly variable illumination conditions (Rosnell et al., 2011). While this has been a limitation to the platform, it also provides opportunities within remote sensing research to develop and refine data collection methods through image normalisation and calibration.

Unmanned Aerial Vehicles (UAVs) have been the focus of a new swath of ecological research focussed on addressing the limitations of the satellite-based methods, indeed, there are those who claim that the application of UAV systems has revolutionised spatial ecology (Anderson, 2013). The basis for the prediction is that UAVs will prove to be ground-breaking within ecology is that eventually the cost effectiveness and accuracy of this platform will exceed that of traditional methods in field ecology (Hodgson et al., 2016). Until this claim can be truly tested, continuous research is being undertaken focusing on refining techniques used in data collection in various habitats and ecosystems. In coastal environments, UAVs have been utilised to assess sea-grass meadows (Duffy et al, 2018), assess viable fish nurseries (Ventura et al., 2016) and monitor beach and sand-dune structure (Goncalves and Henriques, 2015) and coral reefs (Chirayath and Earle, 2016). Beyond the traditional uses for mapping purposes, the application of UAVs has potential for use in species surveying in difficult to access area, for example, Orangutan (*Pongo borneo*) in Indonesia, and breeding bird colonies in Australia (Koh and Wich, 2012; Hodgson et al., 2016).

While the area of study offers the potential for great advances within the fields of ecology, the successful deployment of the platform needs to be considered along with the potential limitations, and indeed, it's translation from the scientific literature into professional practice (Duffy et al., 2017). Within the context of practical conservation projects within the UK, the viability of this technology and the development of a UAV system will have to be considered within a set of trade-offs. One particular limitation within the application of a UAV system is the lack of standardisation between studies. As with most technological advancement, the cost ceiling within the field of UAVs is high, and as such there are a multitude of classes to consider. Originally developed from military grade technology, early unmanned applications were undertaken by NASA's *Ikhana* vehicle, a modified MQ-9 Predator drone. This system was utilised in environments that were unsafe for a manned mission, such as real-time wildfire monitoring (Ambrosia et al., 2010). The large systems, such as *Ikhana*, involve prohibitive costs in ground-based operation and deployment and are, as such, unsuitable for ecological research needs (Duffy et al., 2017). A medium sized fixed wing UAV system with hyperspectral array can be purchased for upwards of £12,000 (www.mapir.camera) and the Parrot Sequoia multispectral sensor for approximately £3000 (www.parrot.com) – prices correct in September 2018. These costs can be considered as a limitation to application within ecological research and conservation when considering the potential of inherent environmental risks and ease of deployment (Koh and Wich, 2012; Duffy et al., 2017). Duffy et al., (2017) provide an in-depth review of the range of UAV platforms available for environmental research, including operational constraints, and applicability of use. In general, light weight, multi-rotor platforms are the most used platform for environmental research (Anderson and Garston; 2013, Hodgson et al., 2015, Duffy at al. 2017; Duffy et al., 2018). Low cost (£500-1000), ease of deployment and the ability to take stationary footage allows this platform to contribute most to the field of ecology (Duffy et al, 2017).

2.8 – Remote Sensing Analysis

Determining habitat cover types with high accuracy is a challenge when monitoring wetland ecosystems with remote sensing data (Ouyang et al., 2011; Dronova, 2015). The properties of wetland plants are less easily detectable than terrestrial communities because of high spatial and spectral similarities within these ecosystems (Adam et al., 2010). For wholly aquatic vegetation ecosystems, either emergent or floating vegetation, the signal detected by a sensor is heavily influenced by the presence of water. The strong absorption of infrared and near-infrared electromagnetic radiation attenuates the performance of these bands that are used for vegetation classification (Silva et al., 2008; Adam et al., 2010). While the spectral response of the terrestrial and freshwater vegetation itself may be similar, the presence of water of various depths and cover can considerably alter the radiometric response derived from the vegetation image, which, in combination with background soil reflectance and atmospheric water vapour, can further complicate vegetation classification (Silva et al., 2008; Wolf et al., 2013; Villa et al., 2014). This is a factor of consideration pertinent to saltmarsh ecosystems. Inundation by spring tides is seasonal and, hence, the background of the vegetation throughout the study area will fluctuate between water, intermediate zones, and bare mud.

Zonation and detectability of saltmarsh communities, *Phragmites australis* reed beds, and wetland macrophyte communities, poses another challenge for remote sensing in the form of spatial resolution and detectability; these habitats are successional due to steep environmental gradients (Adam et al., 2010). The complex spatial heterogeneity of fine scale wetland habitats poses a problem for monitoring using multispectral sensors such as Landsat-8. A 30m pixel resolution, the resolution of Landsat-8 images, is too coarse to reliably identify and classify vegetation communities due to the mixed pixel problem (Stratoulias et al., 2015). Poor temporal resolution in some sensors, for example Worldview-3, can be of limited application for monitoring as a narrow swath width reduces the frequency that an image can be acquired at a consistent viewing angle (Stratoulias et al., 2015(a); Stratoulias et al., 2015(b)). Variation in image viewing angles reduces comparability due to differing atmospheric effects owing to off-nadir image acquisition and angular variability in reflected radiation due to the fact Earth surfaces are not Lambertian in nature (Milton et al., 2006). The application of space borne optical sensors, utilising visible and NIR bands, must also assume a cloud-free environment. Partially scattered cloud can obscure areas of interest and preclude study areas from observation (Armitage et al., 2012). This represents an implicit problem when utilising remote sensing for applications within the UK. After analysing a 15-year archive of Landsat imagery, Konteos and Stakenborg (1990) found that only 50% of the imagery was cloud-free during the summer months. Armitage et al., (2012) revised this with an updated study utilising MODIS cloud mask. The results estimated the yearly cloud-free probability as 21.3%, with a monthly mean probability varying between 12.9% and 33.3% (Armitage et al., 2013).

2.8.1 – Vegetation Classification Techniques

While the finer resolution from very high spatial resolution platforms are advantageous to discriminate the steep successional zones of some saltmarsh ecosystems, the heterogeneity between local pixel values, spectral similarity among cover types, and variations in soil moisture limit the use of a sole pixel-based approach to inform the classification procedure (Ouyang et al., 2011; Dronova, 2015). Classification procedures are usually described as supervised, or unsupervised. Within the supervised approach, the user will identify key areas within the site that characterise specific cover types. A sample of the spectral data will be collected from each (with replicates) for use as a training area. A classification algorithm (e.g., maximum likelihood) is then selected which assigns every pixel within the image to one of the identified groups (Campbell, 2008). Within unsupervised classification, the selected algorithm automatically groups all pixels to a number of predefined classes.

Utilising a supervised classification scheme, a sample of pixels, representing a spectrally pure sample of each class would be collected as a training set. A classification algorithm would then be used to compare the image pixels to the reference library and assign each to a class (Lillesand et al., 2008; Campbell and Wynne, 2011). The maximum likelihood classifier, a statistics-based approach, assumes a Gaussian distribution of classes across feature space (Pal and Mather, 2003). More recently techniques such as artificial neural networks were designed as pattern recognition and analysis tools that simulate human neural storage and analytical processes (Yuan et al., 2009). These algorithms require extensive training and parameterisation by the user, and changes to the values at each stage can impact the accuracy and performance of the classifier (Pal and Mather, 2003). However, the neural approach can estimate non-linear relationships between the inputs and output classes (Yuan et al., 2009). Decision trees are based on logical tests or decisions that split the input at a node into a series of subclasses, or 'leaves' (Pal and Mather, 2003). Advantages of the decision tree approach to pixel-based analysis lie in the ability to incorporate data from different measurement scales and the lack of statistical assumptions on the frequency distribution of the data sets (Pal and Mather, 2003). When comparing all three methods on a Landsat ETM+ data sets, Pal and Mather (2003) found that the decision tree method resulted in a higher classification accuracy than the statistical maximum likelihood approach. Historically, the maximum likelihood approach is the preferred method, but this is dependent on project objectives and input data (Pall and Mather, 2003). More recently, studies have been comparing the commonly used parametric procedures – such as maximum likelihood – to the machine learning techniques such as support vector machines and random forest classifiers (Noi and Kappas, 2018). These non-parametric techniques have gained the most attention in recent years for implementation in classification studies (Breiman, 2001; Adam et al., 2014). Support vector machines and random forest classifiers are insensitive to overtraining and data related noise, and generally perform similarly, exceeding the accuracy of the maximum likelihood technique (Adam et al., 2014; Noi and Kappas, 2018). However, determining the most appropriate classification technique for optimal accuracy assessment has generally been inconclusive, with different techniques performing better under different applications. There is only limited published research comparing these within the context of Sentinel-2 data, and none for the UAV platforms (Noi and Kappas, 2018). Random forest is reported to perform better with high noise data sets, such as wetlands or drylands, however this has not been widely explored, and the application of this algorithm is valid research area for exploration within the context of a saltmarsh ecosystem (Tian et al., 2016). It is then an opportunity within this field to compare these three classifiers with data derived Sentinel-2 satellite data and UAV collected data. The classifiers, the commonly used maximum likelihood parametric classifier, and the two non-parametric machine learning classifiers that are currently prominent within the literature: support vector machine and random forests (Noi and Kappas, 2018) enables a further contribution to be made by applying these to a saltmarsh ecosystem.

While the traditional methods of image classification were originally developed for pixel-based approaches, these techniques have seen uptake within studies utilising the aforementioned object-based classification procedure (Dronova, 2015). In many cases, information important for the understanding of an image is not represented in the individual pixels, but rather the derived image objects and their associated relationships (Blaschke et al., 2000). This coincides with human perception and provides ecological meaning through spatial context (Blaschke et al., 2000; Dronova, 2015). Object-based image analysis (OBIA) might be a framework through which the issues with traditional, pixel-based approaches may be addressed. In this method, texture, shape, and spectral information are utilised for classification, allowing the identification of single objects, as opposed to pixels (Wan et al., 2014). Image pixels will be accumulated into objects through a segmentation process, in which these objects will be homogenous depending on the base characteristic used for their delineation – spatial or spectral properties (Wan et al., 2014; Dronova, 2015). The benefits of the object-based method, relative to pixel-based approaches include: the incorporation of contextual information into the classification, smoothing of variation and noise between objects which can increase accuracy, and the ability to account for hierarchy and ecostructure (Dronova, 2015). Addressing the use of OBIA utilising a high-resolution data set applied to a saltmarsh system is therefore a gap within the literature that will be addressed within the current literature.

2.8.2 – Vegetation Indices

Principal techniques in assessing vegetation characteristics and phenology can be derived from Vegetation Indices (VIs). VIs can be used as tools to determine biophysical properties of vegetation such as Leaf Area Index (LAI), which equates to the development of a canopy at a given time, and productivity; several VIs are related to LAI for specific crops and communities (Villa et al., 2014). A VI is used to enhance the sensitivity to the biophysical attributes of the plant, to regulate the impact of external distortion effects such as the atmosphere, and to reduce the contamination of the response due to differences in canopy background radiation (Huete et al., 1994; Villa et al., 2014). The normalised difference vegetation index (NDVI) is an early example of an index utilised for vegetation monitoring. Many subsequent indices have been derived from this, for example the normalised difference water index (NDWI) based on water as a background for correction rather than soil (Gao, 1996; Villa et al., 2014). A VI is principally a ratio between two or more inversely related spectral bands associated with the same biophysical property. The value of the ratio itself expressing the contrast between these; for the NDVI, it is the absorption of red light by chlorophyll and reflection at the near infrared portion of the spectrum, controlled by leaf structure in the spongy mesophyll from which this information is derived in the index (Campbell et al., 2011).

Vegetation indices (VIs) are a useful approach when utilising remote sensing applications; they are easier to implement than other techniques and remain consistent across a variety of platforms (Villa et al., 2013). In macrophyte communities they have been utilised to monitor the conservation status of *Phragmites australis* reed bed in Lake Garda (Italy) and Lake Balaton (Hungary) utilising remote sensing methods. Principally, four VIs were tested by Villa et al., (2013) to ascertain the morphological complexity of the *Phragmites australis* stand as well as the competency of the vegetation indices for conservation monitoring. The enhanced vegetation index (EVI), normalized difference vegetation index (NDVI), normalized difference aquatic vegetation index (NDAVI), and red green ratio index (RGRI) were examined and, in a further study, the water adjusted vegetation index (WAVI) (Villa et al., 2013; Villa, Bresciani et al., 2014). The work demonstrates the value of vegetation indices for reed bed monitoring and the NDAVI indices ability to distinguish the distorting effects of water in low density vegetation and WAVI in medium high-density vegetation. The authors comment on the transferability and further testing of the NDAVI and WAVI indices for future monitoring across a general geographical setting and range of habitats (Villa et al., 2013; Villa et al., 2014; Villa et al., 2015). These indices are relevant for utilisation in the current study as these have not been tested in a mixed saltmarsh ecosystem using multispectral sensors. Vegetation indices derived from narrow band hyperspectral sensors are often regarded as the most appropriate choice for discriminating spectrally similar vegetation. This is due to the greater range of narrow bands derived from the sensor and the inherent problems with the diverse spatial scale of wetland habitats (Artigas and Yang 2005; Hestir et al., 2015). Hyperspectral data are generally more expensive, more difficult to acquire than broadband multi-spectral imagery, and more difficult to process. For the utilisation of VIs such as NDVI and WAVI that focus on vegetation greenness and the associated background effects, narrow band hyperspectral data has been shown to only slightly outperform the multiband versions, for which reasons multispectral sensors are considered in many ways a better option for vegetation monitoring using remote sensing (Elvidge and Chen, 1995; Villa et al., 2014). This provides an opportunity to determine the applicability of these VIs in distinguishing the vegetation cover of mixed saltmarsh habitat. As a further application in the study of vegetation indices, several published works document the utilisation of the VI data as an input for classification, both on single data and time series data, as opposed to unprocessed satellite bands (Tien et al, 2016; Lie et al, 2020). This has yielded high classification accuracies within time series data and utilises machine learning classifiers such as support vector machine and random forests. The application of random forests has been undertaken in wetland sites, however this has been limited to Landsat data, and provides an opportunity for research within the current study, particularly when utilising VIs as an input source for a machine learning algorithm (Liu et al., 2020).

The effective management of saltmarsh habitats requires consistent and repeatable monitoring, with derived data relating to habitat extent, composition and phenology; the demanding physiological nature of the system means that even moderate changes in nutrient input and environmental conditions can lead to changes in plant vigour and resilience (Dörnhöfer and Oppelt, 2016). While the traditional ecological approaches provide in depth assessments of such habitats, these methods are time consuming, may be constrained through limited site access and subject to bias through variations in site assessor (Rodwell, 2000; Adam et al., 2010; Villa et al., 2014). Remote sensing offers a range of repeatable, quantitative procedures that can be applied to vegetation studies and can complement the efficiency of traditional field work (Villa et al., 2014). As such, the literature cited within the previous section highlight several opportunities for research which will be explored within this thesis.

2.9 – Recommendations Derived from the Literature

The current literature indicates that a holistic approach to landscape management is required, one driven by the relationship between humans and nature across reserves and developed land in order to address climate change (Heller and Zavaleta, 2009).The application of orthodox conservation and restoration methods – the maintenance and establishment of protected areas – will remain key but that a transformative approach is required in the way projects are governed and policy created (Hannah et al., 2002; Harris et al., 2006; Collof et al., 2016; Wyborn et al., 2016). Society needs new systems better suited to monitoring and reporting ecosystem condition, and examples of application across novel ecosystems. This needs to be extended regionally and incorporated into reserve management (Harris et al., 2006; Heller and Zavaleta, 2009). Without adaptation within practice and policy this might result in the interpretation that wildlife and humans have conflicting needs if global climate change leads to crises (Harris et al., 2006). It is, therefore, an essential part of the challenge in adapting ecological restoration and conservation that the consequences of different land-use and climate scenarios are made as explicit as possible (Krolik-Root et al., 2015; Tolvanen and Aronsen, 2016).

2.10 – Aim and Objectives

The future of biodiversity under climate change is intimately linked with the sensitivity of an ecosystem to specific future scenarios. Conservation and restoration management needs to determine the potential impacts of climate change on various aspects of the systems function so that this can be incorporated into long term management plans. Furthermore, these changes within a system, and projected scenarios of future change, need to be communicated explicitly to all stakeholders, across disciplines. This view, when aligned with research questions prevalent within the literature leads to the current study’s aim:

To evaluate relevant methods for the consistent monitoring and communicating of future environmental impacts on a managed restoration project in the context of coastal vulnerability assessment.

The research presented within this thesis addresses the above aim by first testing the use of remote sensing techniques in the habitat mapping of saltmarshes. This relates to two of the key knowledge generating chapters of this Thesis, Chapter 4 and Chapter 5. These data then fed into a vulnerability analysis, using ecological field data (Chapter 6) to provide context to a climate change derived sea level rise model as a vulnerability analysis. Through the linking of these data the final contribution of this research was derived - incorporating this ecological information within a vulnerability analysis (Chapter 7), with a focus on communication to non-scientists, the public and key stakeholders

To achieve this, the following objectives were devised:

1.) What remote sensing system is best suited to collecting spatial and temporal data of wetlands?
2.) What pressures face wetland ecosystems within a cultural landscape?
3.) Can these issues be communicated in a format suitable for a multi-stakeholder environment?

These questions have been addressed through the following null hypotheses which were derived from the literature review:

1.) Fine scale UAV systems do not produce greater accuracy maps of saltmarsh habitats than satellite derived techniques,
2.) Remote sensing does not provide saltmarsh habitat maps sufficient for a vulnerability analysis,
3.) Habitat management does not impact on bird populations using saltmarsh and reedbed estuarine vegetation,
4.) Sea level rise poses no risk to breeding birds in the Upper Mersey Estuary.

Chapter 3 – Methods

In this chapter, the broad methods identified to address the aims and objectives, and the subsequent null-hypotheses presented within the Literature Review (Chapter 2), are described. Details related to data collection are presented within chapters 4, 5, 6 and 7. The broad scope of these methods is in the holistic, multi-disciplinary approach to habitat assessment that reflects the wetland vulnerability assessment framework, a key framework identified in the literature (Dickinson et al., 2015; Collof et al., 2017). This research to address the objectives in a holistic manner, as such the outputs from each chapter will serve as the input for the subsequent chapters, this is conceptualised within Figure 1.1, with the objective to build an assessment of the habitats, species and subsequent pressures within the UME fulfilling recommendations for wetland vulnerability assessment (Gitay et al., 2011). The methods associated with Chapters 4 and 5 were used to investigate repeatable and reliable techniques used to determine habitat extent, and as a basis for the detection of change within wetland habitats. In Chapter 6, data representing the avian ecology, their community changes and representation with diversity profiles is presented. The focus of Chapter 7 in the assessment of changes in relative sea level rise under climate change scenarios and the potential derived impacts on avian breeding communities, and their subsequent vulnerability. A commentary of the implications of these findings, and the subsequent recommendations for the future management and study of this ecosystem are presented in the final chapter of the thesis, Chapter 8.

3.1 – Research Area

The Mersey Estuary occupies a glacially over deepened, permo-triassic rock basin that since the late Pleistocene and the retreat of the Devensian ice sheet has been subject to an influx and partial filling of alluvial and fluvial sediments (Gresswell, 1964; HBC, 2008; (CH2M Halcow, 2013). The increase in post-glacial temperate climates during the Holocene led to a rise in sea level, and the subsequent formation of the estuary by tidal waters around 5000 BP. The change of temperate climate led to a stabilisation of the land around the Mersey by deciduous forest, though this has been developed further through anthropogenic intervention into agricultural and industrial land (McDowell and O'Conner, 1977; HBC, 2008; (CH2M Halcow, 2013).

The estuary has undergone a gradual reduction in capacity since its establishment due to an influx of sediment, however anthropogenic land claim, port development, the construction of training walls, and the dumping of dredged soil has accelerated this process since the turn of the 20th century (O'Conner, 1987; HBC, 2008; (CH2M Halcow, 2013). During the 19th century the estuary was considered to be in dynamic equilibrium with limited net changes in the Inner Mersey Estuary, characterised by channel migration (O'Conner, 1987).

The Mersey Estuary is an example of an unusual bottle shape morphology with a narrow mouth at the 'Narrows' restricted by the underlying geology, widening to a broad shallow channel at the main Estuary course, narrowing again to a typical upper river estuary course past Runcorn and Widnes to Howley Weir in Warrington (HBC, 2008). This morphology limits wave propagation in the estuary, though locally generated waves can be stimulated by south-westerly and north-westerly winds (CH2M Halcow, 2013). The sediment structure of the Mersey Estuary is influenced in a greater proportion by marine tidal flooding, in comparison to fluvial sources, due to a comparably low fresh water input (25 – 200 m^3/s) compared to a much higher tidal influx (1200 – 2000 m^3/s) (O'Conner, 1987; HBC, 2008). The erosion of Ince Bank and the soft cliffs at Speke may supply a minimal source of sediment. The Manchester Ship Canal acts as a sediment trap to incoming fluvial deposits through this route (CH2M Halcow, 2013).

Most the river's course through the Lower Mersey Estuary is characterised by mudflats, sandbanks, and saltmarshes at Frodsham. The estuary is subject to a range of national and international wildlife designations including RAMSAR, SPA and SSSI for avian communities at Dungeon Banks and Ince Banks within the SSSI mudflat zone (JNCC, 2017). The Upper Mersey Estuary is situated between the new towns of Runcorn, Widnes, and Warrington, where the estuary reaches its tidal limit at Howley, Warrington (CH2M Halcow, 2013). Throughout this stretch the estuary narrows to a channel 1.5 km to 0.5 km in approximate width and is bordered by saltmarsh throughout much of its extent (Figure. 3.1).

In 2008 Halton Borough Council commissioned a series of vegetation surveys across the saltmarshes, to establish baseline condition (HBC, 2008). The saltmarsh habitats present in the Upper Mersey Estuary are similar in morphology and vegetation community structure throughout, these include Widnes Warth, and Cuerdley Marsh on the north bank, and

Astmoor, and Upper Moss Side on the south bank (Figure 3.1). The habitats typify upper saltmarsh communities. Much of the saltmarsh exists at the extreme tidal limit and, thus, are only inundated during the seasonal high tides. As a result of this phenomenon – a common feature at the landward extent of estuaries – the habitats themselves are generally species poor, other than at edges and within creeks (HBC, 2008). Key vegetation cover comprises *Elymus* species: common couch (*Elymus repens*), sea couch (*Elymus athericus*), or the hybrid *Elymus x drucei* (HBC, 2008; EVR, 2011).

Figure. 3.1 – Upper Mersey Estuary, Mersey Gateway Environment Trust ecological boundary. ESA 2016.

Other grass species present within the sward, to a varying degree, include red fescue (*Festuca rubra*), creeping bent (*Agrostis stolonifera*), common saltmarsh-grass (*Puccinellia maritima*), marsh foxtail (*Alopecurus geniculatus*). The presence of these species, with the additional records of spear-leaved orache (*Atriplex prostrata*), sea clubrush (*Bolboschoenus maritimus*), and sea aster (*Aster tripolium*) characterises most of the saltmarsh extent, with a little variation when *Elymus* species are absent. On its seaward edge Cuerdley Marsh is characterised by *Puccinellia maritima* with *Spartina anglica* presence, while the landward edge contains false oat-grass *Arrhenatherum elatius* communities, where saline inundation does not occur (Rodwell, 2000; HBC, 2008; EVR, 2011).

3.2 – Mersey Gateway Environment Trust

The Mersey Gateway is a six-lane bridge crossing the river Mersey at the western end of the Upper Mersey Estuary between the towns of Widnes and Runcorn (HBC, 2008). A part of this project was the recognition of an opportunity to contribute to the promotion of biodiversity. In 2010, the Mersey Gateway Environment Trust was set up to implement conservation management and restoration within the Upper Mersey Estuary. The Mersey Gateway Environment Trust is a unique project in the UK in terms of its funding and its relationship with a major civil engineering project (the Mersey Gateway Bridge). The aim of the Trust is to promote the conservation, protection, and improvement of the natural and physical environments in the Upper Mersey Estuary through monitoring and management (Mersey Gateway Environment Trust, 2014). The ecological boundary for the Mersey Gateway Environment Trust is represented in Figure. 3.1. Already, the Trust has supported numerous research projects. These involved the determination of perspectives on landscape ecology, management of urban greenspace utilising the ecosystem approach, and the assessment of future ecosystem services provision (Scott, 2009; Smith, 2013; Drewitt, 2017). The Mersey Gateway Environment Trust incorporates the views of numerous public and private stakeholders into the operation of its projects. One advantage into the selection of the Mersey Gateway Environment Trust area for the current research project is the inclusion of multiple stakeholders, and the opportunity for a cross disciplinary mode of study. This was one of the recommendations of the literature, and in doing so will enable the incorporation of these views into a framework of restoration adaptive to environmental change (Hannah et al., 2002; Collof et al., 2017). All data pertinent to the project will be collected within the Mersey Gateway Environment Trust ecological boundary - at Cuerdley marsh and Upper Moss Side (also known as Norton Marsh) - where access has been permitted by Mersey Gateway Environment Trust and the landowners (Figure. 3.2).

Figure 3.2 – Locations of the two managed sites within the Upper Mersey Estuary.

3.3 – Saltmarsh Satellite Remote Sensing

The following section addresses the requirements for the first research objective by considering methods utilised in the field of remote sensing to characterise saltmarsh vegetation. As identified in Chapter 2, the global coverage of satellite imagery, coupled with the diversity of multispectral, high temporal resolution sensors, establishes remote sensing as a primary data source for mapping habitats and land cover (Bell et al., 2015; Dörnhöfer et al., 2016).

To implement the exploration of such methods within the current study, remote sensing data was collected for a subsample of the saltmarsh habitats in the Upper Mersey Estuary. Permission was granted to conduct the UAV based data collection at Upper Moss Side saltmarsh, however, this was not possible at Cuerdley Marsh due to limitations imposed by the landowner. As such, the spatial scale of the UAV data collection was limited, though it still falls within that of a managed restoration project, a recommendation derived from the literature, and provides an opportunity to assess the value and potential limitations of each remote sensing platform in supporting such a project (Tolvanen and Aronsen, 2016).

Imagery was derived from the European Space Agency's (ESA) Sentinel-2 mission, a multi-spectral space-borne sensor with high temporal resolution and moderate spatial resolution (10m pixel resolution at NIR portion of the spectrum). All Sentinel-2 imagery was acquired through the Semi-Automatic Classification plugin available through QGIS 3.0. This plugin allows the user to pre-process satellite imagery, perform spectral analysis, band calculations, and is pre-set with several pixel-based classifiers. All satellite images were subject to an atmospheric correction, such that the top of atmosphere reflectance was converted to surface reflectance (also known as bottom of atmosphere reflectance), thus removing the impact of the atmospheric conditions from the actual reflectance emitted from the objects under scrutiny (Noi and Kappas, 2018).

First, an exploratory study of range of vegetation indices derived from Sentinel-2 data was undertaken. Vegetation index values were utilised to determine the thresholds between vegetation classes. The mixed saltmarsh community at the study site, Upper Moss Side, is made up of five broad classes: grazed (referred to hereafter as short sward grass), ungrazed (referred to hereafter as long sward grass), reed bed, water, and bare sediment. This study utilised several vegetation indices (VIs) (Table. 1) designed for both aquatic and terrestrial backgrounds, to distinguish the most suitable for separating vegetation cover types in a mixed saltmarsh ecosystem. The vegetation indices displayed in Table 3.1 were calculated from the Sentinel-2 images, the statistics were then compiled from the VI image using 20 training samples per class (Noi and Kappas, 2018). From the derived from the training areas for each VI and cover class, the Jeffries-Matusita distance was calculated. This measure is a qualitative measure of the average distance between pairwise histograms, and has a probabilistic interpretation (Liu et al., 2020). The output of the is measure is a value ranging between 0 (completely separable) to 2 (completely inseparable) with large values indicating greater separability (Liu et al., 2020). This measure was calculated in the SCP plugin to determine class separability for the Sentinel-2 derived data.

The image classification was undertaken on the Sentinel-2 data set for all of the extant saltmarshes in the Upper Mersey Estuary, i.e., those under scrutiny within the context of the current study (Cuerdley Marsh and Upper Moss Side), extended to those present downstream (Astmoor and Widnes Warth), which are also within the remit of the Mersey Gateway Environmental Trust. The classification was also undertaken on the high spatial resolution UAV data set, which is available only for Upper Moss Side due to a lack of landowner permission at Cuerdley Marsh, this analysis will be discussed later in this chapter. The data were classified in ESRI ArcMap, utilising a maximum likelihood, support vector machine and random forest classifier (Noi and Kappas, 2018). The classifiers were trained by collecting 20 samples for each class, a statistically significant sample that is of key importance when using the parametric maximum likelihood classifier (Noi and Kappas, 2018; ESRI, 2018). The study site size and satellite spatial resolution of the satellite derived data limits the number of pixels that can be present in some of the class training samples, however, training size still exceeded 0.25% of the study area recommended in the literature (Noi and Kappas, 2018). The same training samples were utilised for all three classifiers, as while the two machine learning classifiers require fewer samples, including more does not impact the classification accuracy (Nitze et al., 2012; Noi and Kappas, 2018). Classification accuracy was assessed by collecting 500 ground truth points by a random stratification across the study area, and a confusion matrix was computed for each image. The decision to use a 20 m^2 sampling polygon was derived from the discrepancy in positional accuracy derived from Sentinel-2 data, such that the reported mean registration precision from this platform is approximately 15% of the 10 m pixel (Yan et al., 2018). This means that the ground truthing procedure is more likely to locate the same positional area where the classified pixel is located, which is an issue when utilising a single pixel as a sampling unit (Foody, 2010).

In addition to the classifications undertaken on the Sentinel-2 multispectral bands, an image classification was extended to the vegetation indices. The same training area that were used to derive the Jeffries-Matusita Distance separability analysis were utilised to train the Random Forest classifier, as this classifier has been shown to perform well when utilising vegetation index data that has low separability (Liu et al., 2020). A classification image was then produced for each VI that was utilised in this study, for the saltmarshes in the UME.

These images were subject to the same accuracy assessment procedure as the Sentinel-2 classification derived from the image bands.

Table 3.1. – Vegetation Indices applied to the Sentinel-2 data set.

Vegetation Index	**Formula**	**Source**
NDVI – Normalised Difference Vegetation Index	$\frac{\text{NIR - RED}}{\text{NIR+ RED}}$	Rouse et al., (1974)
EVI – Enhanced Vegetation Index	$2.5\frac{\text{NIR - RED}}{\text{NIR + 6RED -7.5BLUE + 1}}$	Huete et al., (1997)
WAVI – Water Adjusted Vegetation Index	$(1+L)\frac{\text{NIR - BLUE}}{\text{NIR + BLUE} \cdot L}$	Villa et al., (2014)
NDAVI – Normalised Difference Aquatic Vegetation Index	$\frac{\text{NIR - BLUE}}{\text{NIR+BLUE}}$	Villa et al., (2013)

3.4 – Saltmarsh Unmanned Aerial Vehicle (UAV) Data Collection

To assess the value of the emerging science of UAV based platforms for vegetation mapping, and to mitigate the risk of cloud cover than satellite-based platforms encounter, data were collected using a UAV system, further addressing Research Objective One, in Chapter 2, Section 2.10. The imagery of the study area was collected by mounting a GPS enabled MAPIR Survey 3 'NGB' (Near Infra-red, Green and Blue bands) band 4.3 mm digital camera to a DJI Phantom 3 standard quadcopter, in addition to the RGB camera that is mounted as stock on the UAV. The MAPIR camera collected radiance in three bands, NIR 850nm, Green 550nm and Blue 450nm, these bands are appropriate for collecting and delineating vegetation data.

Due to limitations in the battery life – less than 20 minutes total flight time – seven flight grids were established across Upper Moss Side. The grids were designed to incorporate 70% image overlap between images; this will assist when matching imagery for orthomosaic generation as the images will contain more shared features, ensuring greater success when mapping homogenous bodies, such as standing water. The MAPIR camera records imagery in RAW format roughly every 5 seconds. To ensure adequate coverage of the grid – and to limit motion blur – the UAV was flown at 4 m/s, and at 80m altitude (Anderson, 2013).

The workflow incorporates several pieces of software at each level of processing. The flight grids were first designed and planned in Pix4D Capture, an application downloaded on to an iPad mini 4. This application was used to monitor the automated flight process in the field. Following the creation of the flight grids, the GPS waypoints and camera trigger locations were uploaded to the UAV system. Following the successful collection of the data, the imagery was pre-processed in MAPIR's own software: using the MAPIR Camera Control the collected RAW imagery was converted to TIFF format. This software also enables an empirical line calibration to be applied to the imagery. Following this, the images are then stitched into an orthomosaic data set using Agisoft Photoscan.

A fundamental stage of image processing is the radiometric calibration, or normalisation. Imaging sensors record radiance in the form of digital numbers (DN). DNs do not reflect the ground surface conditions accurately, as they are a product of atmospheric attenuation, illumination geometry, and the sensor characteristics (Baugh and Groeneveld, 2008). The quantitative value of remote sensing data were derived by calibrating the raw image values to a surface reflectance factor; the reflectance of an object is an inherent physical property that is not subject to external environmental effects (Baugh and Groeneveld, 2008; Laliberte, 2011; Wang, 2015). The most widely used method in UAV and aerial photography is the empirical line method (Wang, 2015). The implementation of this method requires the in-situ placement of panels of known reflectance that the sensor will record. Light and dark coloured targets painted with a Lambertian material are used and placed at the end of each flight line of the grid (Hakala et al., 2013). Once the imagery was collected, the mean pixel value of the calibration target was extracted and plotted against the mean value of each camera waveband (Wang et al., 2015). The technique assumes a linear relationship between DN and ground measured reflectance, and as such, the intercept at the y-axis for each empirical line equation can be interpreted as the calibration parameter for each waveband (Wang et al., 2015). Most studies use two calibration targets of different grey shades to carry out the calibration, however four can be used to improve accuracy (Wang et al., 2015). In this study, four panels of varying reflectance values were captured by the cameras at the start and end of each flight grid. This will allow the variance in illumination conditions throughout the data collection process to be corrected for and allow comparison between multiple dates of data collection, a factor of high importance when considering the use of UAVs for a vegetation monitoring scheme. The calibration procedure was undertaken in the Mapir Camera Control (MCC) application. The panels of known reflectance were also supplied by Mapir. This process was undertaken on both the red, green, and blue and the near infrared, green, and blue data sets.

Following the image processing phase, these data were subject to the same processing and classification techniques as applied to the Sentinel-2 derived data in ESRI ArcMap. To avoid known issues when classifying very high-resolution imagery, i.e., the 'salt and pepper speckle' problem (Dronova, 2015), a mean shift segmentation was first applied to the data before the classification procedures were undertaken (Anderson, 2013; Duffy et al., 2018). Mean shift is a clustering technique used in image segmentation. The process is a form of unsupervised data analysis and does not require prior knowledge of the image set or required number of output clusters. It is therefore pertinent to the current research question where other techniques require user-based parameters to first determine the extent of image objects (Vlachopoulos et al., 2020). The process of OBIA is made up of a series of functions that split an image into a set of distinct objects. The mean shift approach achieves this by grouping adjacent pixels that have similar spectral properties (Duffy et al., 2018). The pixels within an image set that have similar spectral properties and are related spatially are considered an object within this methodology (Blaschke et al., 2000; Myint et al., 2011). This allowed a comparison between the two techniques and aids in determining their appropriateness for monitoring a constrained saltmarsh such as Upper Moss Side. One advantage to the UAV platform in this processing stage is derived from its spatial resolution. One hundred pixels per training sample were collected providing a statistically valid number (Noi and Kappas, 2018). From these sample, Jeffries-Matusita distance was calculated. Image sets were then classified with the maximum likelihood, support vector machine and random forest algorithms.

The verification and accuracy of resultant classifications was derived from sample points. The sample points were derived by random stratification across the study area to avoid biasing results through class bias, and utilised 500 test points (Feng et al., 2015; Noi and Kappas, 2018). The cover class of the 500 stratified random points were ground-truthed during a field survey using a handheld GPS to locate the points, the classes associated with the points was further confirmed by a desk-based operation utilising the RGB band UAV image change. The 500 points were used to establish a sampling polygon rather than utilising the point itself as the sampling unit. The generated point that represents the centre of a 5 m^2 quadrat, which was used to ground truth the landcover. Following Foody (2010), this was achieved by identifying the dominant cover type within the quadrat, which was then utilised to assign the class of the sample point. This was derived during the field survey by utilising the DAFOR relative abundance ranking, where D = Dominant; A = Abundant, F = Frequent, O = Occasional, R = Rare. The utilisation of quadrats, and a collection of pixels rather than a single unit, is an established as means of sampling the data derived from very high-resolution data sets, and UAV derived data, specifically when an object based classification procedure is utilised (Lechner et al., 2012; Anderson, 2013; Duffy et al., 2017). This also addresses the issue when utilising a single pixel of very high-resolution data as a sampling point. In the case of the UAV derived data, determining the exact location of the pixel to be validated would be impossible due to the limitations of positional accuracy of handheld GPS, and the high resolution (3.5 cm) of the image pixel (Foody, 2010).

3.5 – Ecological Surveys

3.5.1 – Target Species – Avifauna

Within the Mersey Gateway environmental statement, there is a description of future measures that are required to increase and maintain levels of biodiversity. During both construction and operational phases of the new road crossing there is a commitment to the maintenance of the saltmarsh habitats and to biodiversity within the Upper Mersey Estuary (HBC, 2008). The management of the habitats should promote species diversity and community assemblage, while making use of traditional management techniques, such as grazing (HBC, 2008). The key objective of the Mersey Gateway Environmental Trust is to increase the available habitat for several target bird species. The presence of breeding lapwing (*Vanellus vanellus*) and redshank (*Tringa totanus*), would be key measures of success for the habitat restoration. The project sought to improve habitat for other passerine species such as reed bunting (*Emberiza schoeniclus*), skylark (*Alauda arvensis*), meadow pipit (*Anthus pratensis*), and the migratory warbler species, sedge warbler (*Acrocephalus scoenobaenus*), reed warbler (*Acrocephalus scirpaceus*) and grasshopper warbler (*Locustella naevia*). Due to the close proximity of the study area within the Upper Mersey Estuary to the Mersey Estuary Special Protection Area (SPA), a site which holds internationally important wetland bird populations, a further objective was to identify whether associated species would move into the UME saltmarshes following management intervention (JNCC, 2017). These species include redshank (*Tringa totanus*), teal (*Anas crecca*) and shelduck (*Tadorna tadorna*). The habitat management was undertaken separately at the two sites, Upper Moss Side and Cuerdley Marsh.

In the winter of 2016 / 2017 a saltmarsh management regime was implemented at Upper Moss Side to improve habitat quality for ground nesting bird species, principally redshank and lapwing. Utilising hardy cattle breeds such as Belted Galloway and Longhorn cattle, is a well-established saltmarsh management technique (Doody, 2008). At Cuerdley Marsh during the same winter, a reedbed cutting cycle was established by which 10 x 10 m^2 areas of reedbed, and reed litter were cleared. This technique promotes structural heterogeneity of the reedbed and has been shown to increase the biodiversity of the reed dwelling species, as these are generally edge dwelling (RSPB, 2014). The design of the habitat interventions provides each unmanaged portion of habitat as the control for the respective managed habitat, i.e., the saltmarsh at Cuerdley Marsh is the control for the managed saltmarsh at Upper Moss Side, and the unmanaged reedbed at Upper Moss Side served as control for those managed at Cuerdley Marsh.

To address research objectives two and three, as stated in Chapter 2, it is required that the ecology of the study site be categorised, and further to determine whether changes in community structure can be represented in a visually engaging way. In keeping with the conservation targets of the managed restoration project within which this research is contextualised, avian species were selected as the key group within the saltmarsh ecosystem.

3.5.2 – Bird Surveys

3.5.2.1 – Common Bird Census

The Common Bird Census breeding bird survey methodology was undertaken at Upper Moss Side and Cuerdley Marshes. This technique has been utilised to document the impact of the management practices implemented during the project on breeding bird populations, and produces maps portraying seasonal breeding territories. The target species for the project conform to those associated with biodiverse saltmarsh habitats. The bracketed colour label after a species' name denotes its UK conservation status. Red is the highest conservation priority describing a species needing urgent action, Amber the next most critical and Green the least. A full description of the criteria assigned to each species is published in Eaton et al., (2015). The target species are northern lapwing (*Vanellus vanellus*) (Red), redshank (*Tringa totanus*) (Amber), skylark (*Alauda arvensis*) (Red), meadow pipit (*Anthus pratensis*) (Amber), reed bunting (*Emberiza schoeniclus)* (Amber), and the summering warbler species, sedge warbler (*Acrocephalus schoenobaenus*), reed warbler (*Acrocephalus scirpaceus*) and grasshopper warbler (*Locustella naevia*). Marsh harrier (*Circus aeruginosus*) (Amber), bearded reedling (*Panurus biarmicus*) (Green), and bittern (*Botaurus stellaris*) (Amber) would be considered an ultimate measure of success within such a restoration project, and such species breeding in the Upper Mersey Estuary could be considered an achievable target within the 30 years of the Mersey Gateway Environment Trust's vision.

Common Bird Census (CBC) is undertaken annually between March-July in accordance with the British Trust for Ornithology and the methodology outlined in Gilbert et al., (1998). During this period, 10 surveys at each site were undertaken to assess avian population size and territory use by recording key indicators of breeding behaviour, namely evidence of nest building activity, feeding activity and territorial behaviour, and singing males (Gilbert et al., 1998; Bibby et al., 1993). The surveys consist of walked route through the study site, making sure to walk within 50m of each key area. It is also recommended to reverse the route walked, so that observations are not biased by time of day. The complete CBC surveys were undertaken yearly for a three-year period. The surveys were initiated in mid-March and repeat visits were made at least ten days apart throughout the season ending in July (Gilbert et al., 1998). All the breeding periods for the bird species will be captured by this technique (Joys and Crick, 2004). It is an assumption of this method that females will be under recorded; but that the sex ratio will be relatively equal (Hill *et al*, 2007). All surveys were carried out during optimal weather conditions for recording bird vocalisation, on days with high winds and consistent rain the surveys were rescheduled. The surveys carried out by pairs of competent surveys to conform to health and safety rules, and to validate the observations made by the lead surveyor. All records in the field were recorded on paper base maps using BTO codes for species and behaviour. The records were then digitised using QGIS 2.16 and an analysis of territories derived following the methods in Bibby et al., (1993). Territories are mapped by a technique that groups temporal observations of male territorial activity, into a cluster. A cluster is accepted as a territory if there are three or more registrations of the species in that area over the ten visits, or, two registrations for a migrant species (Bibby et al., 1993).

3.5.2.2 – Wintering Bird Surveys

To extend the data collected during the CBC surveys, winter bird surveys were also undertaken. These surveys were based on the Wetland Bird Survey methodology and included monthly counts across the study area between the months of August to February. Counts were taken from six vantage points across the study area, and further to this a route was walked across the saltmarshes to ensure all birds were detected (BTO, 2017). The wintering surveys were implemented to detect community changes in the species roosting and feeding on the saltmarsh during the winter months, particularly, species that might also be associated with the Special Protection Area (SPA), such as redshank, teal and shelduck, as a principle aim of the restoration project was to improve habitat connectivity throughout the Mersey Estuary – Upper Mersey Estuary.

3.6 – Statistical Analysis

To address research objectives two and three (Section 2.10), and null hypothesis three: “Habitat management does not impact on bird populations using saltmarsh and reedbed estuarine vegetation”, two statistical tests were undertaken on the bird survey data to test the significance of the observed changes in community. The null hypothesis was tested by addressing several sub-hyptotheses, which are outlined in at the beginning of Chapter 6. These statistical tests are the Mann Whitney-Wilcoxon test and the Kruskal-Wallis test.

The Mann Whitney-Wilcoxon test is a non-parametric alternative of an unpaired t-test and is the equivalent to the Wilcoxon rank sum test. The test compares the median values of non-normal data sets, such as ecological field data, where the generalised null hypothesis is that there is no difference between group medians (Townend, 2005). The basis for the test is the premise that if both populations have a similar distribution, then the values derived from these will be completely interspersed when they are set in rank order, with approximately equal mean ranks. The U-value used in this test is derived from the rank values, from which the probability P-value is derived to determine the likelihood that the observed differences between the medians occurs by chance (Townend, 2005).

The Kruskal-Wallis is a non-parametric alternative to a one-way ANOVA to determine the differences in medians among more than two populations, i.e., across two or more years, or two or more sites. The test works using the same basis as that of the Mann Whitney-Wilcoxon test described above, by placing the samples in rank order. The generalised null hypothesis for this test is that the populations all have the same median (Townend, 2005). A test statistic H-value is then derived from the comparison of the rank means (comparable to the U-value described above) to derive the P-value, which is derived by referencing the H-value and degrees of freedom in a chi-square lookup table (Townend, 2005). This process is completed automatically in Minitab 18, which was the software utilised for these analyses within the current study.

The use of these statistical tests is appropriate when considering data which do not display normality, or data with a small sample size (McDonald, 2016). The applicability of both of these statistical tests to the current research was recently demonstrated in a study conducted by Bonnington and Smith (2018), which utilised bird data collected within both the summer and winter period, and undertook these statistical tests to instead determine the impacts of the construction of the Mersey Gateway Bridge on breeding and wintering bird territory and abundance.

In tandem with the statistical analysis, biodiversity profiles were implemented in this study as a further means to contextualise the ecology of the site. As a means to address the third research objective In Chapter 2, Section 2.10, the biodiversity profiles were calculated for all communities present on site using the total count data based on both breeding and wintering bird surveys as a means to contextualise any significant differences reported by that statistics in terms of biodiversity, and therefore to report changes in community structure in an unambiguous way. While the research is not presented to establish this method as the most appropriate for concise communication of communi9ty change these data are explored to provide context within vulnerability analysis. Due to the nature of the formula underlying a plotted diversity profile, here derived from the Hill numbers, effective species numbers are derived and as such, true comparison between sites, and dates can be made (Hill, 1973; Dodge et al., 2017). The Hill numbers show the relationship between the diversity and evenness indices (Hill, 1973). The commonly used indices of biodiversity (e.g., Shannon or Simpsons indices) order the distribution of an abundance data set only according to the relative aspect captured by each. A change in the choice of index can reverse the order in which groups are ranked by biodiversity (Buckland et al., 2012). The profile reflects diversity as a parametric family and is described as the function of a free parameter λ, where J_j is found by taking the exponential of Renyi's entropy (Hill, 1972; Tothmeresz, 1995; Buckland et al., 2012; Chao et al., 2017). This transformation is derived from the Renyi index of generalised entropy, and was calculated using the following formula (Formula 3.1) (Hill, 1972; Chiu and Chao, 2014):

$$J_j(\lambda) = \left(\sum_{i=1}^{S} p_{ij}^{\lambda} \right)^{\frac{1}{1-\lambda}}$$

Formula 3.1 – Hill's diversity profile.

In this formula, S denotes the number of species, P_i the proportion of species relative to all other detected species and species are indexed by i = 1, 2, 3, 4. (Chao et al., 2017). The value of λ represents the sensitivity, or weight, of the measure to relative abundance, so when λ = 0, all species are considered equally regardless of relative abundance and therefore equates to species richness Buckland et al., 2012;

Chao et al., 2017). When λ approaches 1, this roughly equates to Shannon diversity, i.e., the exponential of Shannon entropy therefore representing the number of common species in an assemblage, which in the context of this equation λ = 1, results in all individuals are considered equally, and species are counted proportionally to their abundance (Chao et al., 2017). When λ = 2, this equates to the inverse of Simpson diversity, which considers the dominant species in an assemblage while disregarding the rarities (Chiu and Chao, 2014; Chao et al., 2017). Rather than representing community as just one of these diversity measures, λ = 0, 1 or 2, where conclusions that are drawn from changes over time are dependent on the choice of parameter, Hill's numbers allow the visualisation of a continuous function of λ, and therefore represent all of the information within the relative abundance distribution (Hill, 1973, Tothmeresz, 1995, Chao and Jost, 2015). Within the continuous plot of these values, if the profiles of assemblages do not cross, then one is unambiguously more diverse than the other. (Chao and Jost, 2015). If they do cross, then only statements in relation to the individual values of λ can be made (Chao and Jost, 2015). The use of the biodiversity profile technique will then enable this research to address a recommendation of the literature, that being to reflect changes in biodiversity in an unambiguous and visually engaging way, which in turn is appropriate within the context of long term vulnerability monitoring (Krolik-Root et al., 2015; Tolvanen and Aronsen, 2016).

The diversity values were calculated on the total number of species rather than mean, as the indices cannot be calculated with decimal values. Rounding the mean would nullify the impact of rare species observations on the index, for example, where one observation of a species was made during the surveys, the value would round to zero. The decision to use the total counts will not change the significance or ranking of the index as the total and mean value for abundance is linked by the constant of the number of survey visits, in this case, the value of twelve (Tothmeresz, 1995; Bibby, 1993). The diversity profiles for each year, using the Hill formula, were calculated in Paleontological Statistics 3.23 (PAST) (Hammer, 2019), an open source population statistics package. The profiles were plotted with the bootstrapping option, providing a

95% confidence limit based on 2000 replicates, to represent statistically significant separation between the plotted profiles (Chao and Jost, 2015; Hammer, 2019).

The statistical analyses described here, the results of which are presented in Chapter 6, are designed to support the generation of the ecosystem vulnerability analysis through the provision of contextual ecological data. While the statistical tests are appropriate for addressing the described aims and objectives, they are of secondary importance within the context of the knowledge generating themes of the thesis.

3.7 – Sea Level Rise Scenarios – Ecosystem Vulnerability

While the impact of sea level rise on saltmarshes may encompass uncertainty due to the multitude of associated processes, it is appropriate in the context of practical conservation to determine the potential for impact on saltmarsh habitats across the range of likely scenarios. It is a focus of this work to utilise elevation data to create a model to determine the sensitivity of the saltmarshes within the Upper Mersey Estuary to sea level rise. The models will incorporate the IPCC and UKCP09 climate change scenarios. A range of scenarios from best to worst case were used to determine the level of flooding that the habitats might see under climate change. There are several approaches within the literature that address the impact of sea level rise on coastal and estuarine communities. These vary from analyses of simple, contour-based intersections and digital elevation model manipulation (Priestnall et al., 2000; Krolik-Root et al., 2015) to dynamic models that simulate the hydraulic effects of land cover and topography (Bates and de Roo, 2000).

Hydrodynamic models are a popular resource for site scale assessments (Battjes and Gerritsen, 2002). However, the computational complexity and calibration effort required to implement finite-difference and finite-element models, especially over large areas, has led to the uptake of more general approaches to flood-risk assessment and sea level rise modelling (Brown, 2006). At its most basic level, the analysis of sea level rise requires only a digital elevation model. This method is known as the inundation model (Mcleod et al., 2010). In this method, a simple calculation using a raster calculator in a commonly used GIS platform (ESRI ArcGIS, QGIS) will provide a representation of tidal inundation (Krolik-Root et al., 2015). Using an elevation model and a raster layer representing a chosen sea level rise scenario Krolik-Root et al., (2015) implement the following formula (Formula 3.2):

$$a \leq b$$

Formula 3.2 – Raster Inundation model.

Where *a* represents the input DEM and *b* the mean high tide scenario the output will represent all areas that will be inundated. To apply this methodology to the current research, tidal gauge data were collected from Fiddler's Ferry in Widnes to represent tide height In the Upper Mersey Estuary. These data were collected online from a long-term tidal data repository supplied by the Environment Agency (2018). Sea level rise projections were derived from IPCC, UKCP09 as presented in Jevrejeva et al., (2014) as well as a worst-case low probability increase presented by those authors. The stated projections were chosen from the described sources as they are the most prominent within the sea level rise projection literature and capture the widest range of sea level rise appropriate to the area of study (Lowe et al., 2009; Jevrejeva et al., 2014; IPCC, 2014). Projections were corrected for isostatic land shift to gain a value for relative sea level rise in the northwest United Kingdom by deriving the yearly land shift and subtracting this yearly value from the projection of sea level rise (Defra, 2009; Nicholls et al., 2013). To maintain focus on the impacts of sea level rise on the ecology of the Upper Mersey Estuary, particularly the avian breeding season, the tidal data from March-September 2018 was analysed. Following this, a series of maps were derived to reflect the increase in tidal inundation under each scenario. Further to this, and to provide a novel application of this methodology within the current study, the analysis was then applied to the breeding season of four threatened species to determine the individual impacts during the breeding season. In this sense, the methods presented here will contribute to gaps within the literature calling for contextual, site-specific sea-level rise analyses (Doody, 2008). This will address research objective three in section 2.10 by addressing the null hypothesis that the current projections of sea level rise, which represent a major source of ecosystem vulnerability, will not impact the key breeding species of the Upper Mersey Estuary.

Chapter 4 – Satellite Remote Sensing

Satellite mounted multispectral sensors, from which environmental data products can be derived, have been the mainstay of environmental remote sensing since the latter part of the 20th century (Campbell, 2002). Applications of remote sensing have been regularly used to identify and monitor the distribution and type of vegetation within a region, and to detect and record changes in land cover (Pande-Chhetri et al., 2017). A great opportunity within this field was afforded when the European Space Agency (ESA) began the operation of the twin satellite Sentinel-2 mission in 2016. The sensors provide remote sensing practitioners with an improved spatial resolution in the red, green, blue and near infrared (NIR) bands, in comparison to the Landsat satellites (10 metres vs 30 metres), and a high temporal and spectral resolution. This means that the system has a greater potential to contribute to the monitoring of land cover across smaller sites. The data are open source, an advantage when considering the relatively low budgets of conservation restoration projects (Duffy et al., 2017).

The following Chapter contains the results of the analyses relating to the Sentinel-2 data covering the saltmarsh habitats of the Upper Mersey Estuary. The chapter aim is to address Research Objective One, and Hypothesis One, as presented in Chapter 2, Section 2.10. To aid comparison, the satellite dataset and the UAV data set were both collected within the same month, and the first cloud free satellite image was acquired. This satellite image was acquired on the 21st May, 2018. Following the collection and pre-processing of the image, the vegetation indices were calculated utilising the formulae presented in Table 3.1 in Chapter 3. A visual representation of the vegetation indices is presented in Figures 4.1 – 4.4. Each index image has been set with a colour-ramp in order to visualise each vegetation index for the saltmarshes in the UME. The index values tend to range between 0-1, where 1 is considered high quality, dense vegetation. Negative values relate to water, and some manmade objects. The band properties of the Sentinel-2 satellite sensor are presented in Table 4.1. These include long sward grass, short sward grass, reed bed, water, and bare sediment. Distinguishing the long and short sward grass coverage is pertinent to the restoration objectives of the Mersey Gateway Environmental Trust (MGET), as ground nesting birds prefer a heterogeneous short sward (Davidson et al., 2017). Statistics were compiled for each of the cover classes associated with the saltmarsh habitat. These were derived from the 20 training polygons per class used within the classification procedure, and from these a pairwise comparison of class separability was calculated using the Jeffries-Matusita distance, presented in Table 4.2. Following this, three classification procedures were undertaken on the image dataset. These were the maximum likelihood, random forest and support vector machine classifiers. In additional to these, a classification was performed on the vegetation index data sets using the random forest classifier (Liu et al., 2020). The justification for these methods is outlined in Chapter 3, Section 3.3.

Table 4.1 – Band properties of Sentinel-2.

Satellite Band	**Central Wavelength (µm)**	**Resolution (m)**	**Bandwidth (nm)**
Band 1 – Coastal aerosol	0.443	60	21
Band 2 – Blue	0.490	10	65
Band 3 – Green	0.560	10	35
Band 4 – Red	0.665	10	30
Band 5 – Vegetation Red Edge	0.705	20	15
Band 6 – Vegetation Red Edge	0.740	20	15
Band 7 – Vegetation Red Edge	0.783	20	20
Band 8 – NIR	0.842	10	115
Band 8A – Narrow NIR	0.865	20	20
Band 9 – Water vapour	0.945	60	20
Band 10 – SWIR – Cirrus	1.375	60	20
Band 11 – SWIR	1.613	20	941
Band 12 – SWIR	2.202	20	851

The pairwise Jeffries-Matusita distance values for the saltmarsh cover classes are presented within Table 4.2. These values represent the separability of the cover classes based on the input bands and VIs and can be interpreted as a reflection confounding classes which may influence overall classification accuracy (Liu et al., 2020). These values were generated using the Semi-Automatic Classification Plugin (SCP). The output values for Jeffries-Matusita distance vary between 0 – 2, where lower values are interpreted as low separability, i.e., highly similar histograms, and values towards 2 with high separability, i.e., a value of 2 would represent an entirely separable histogram. The general distribution of values was similar between those derived from the Sentinel-2 analysis bands and the VIs, these are presented in Table 4.2. Generally, the values which relate to the vegetation classes (long/ short sward grass, and reed bed) were less separable from each other than they were from the non-vegetative classes (bare sediment and water). The values between the vegetative and non-vegetative classes ranged between 1.65 and 1.99 The separability between bare sediment and water was generally low as values ranged between 0.21 and 0.45, with the WAVI index showing the highest separability. For the comparison between the vegetative classes, the WAVI index showed the greatest separability with values ranging between 1.17 for the reed bed vs short sward grass classes, 0.92 for the short sward vs long sward grass classes, and 0.81 for the long sward vs reed bed classes. The pairwise class comparisons between the values derived from the satellite bands was overall of lower separability than those derived from the dedicated VIs.

Table 4.2 – Jeffries-Matusita distance for the five saltmarsh cover types, based on the Sentinel-2 bands, and the vegetation indices.

Sentinel-2 Bands	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.27			
Reed bed	0.19	0.34		
Bare sediment	1.89	1.36	1.41	0.21
Water	1.99	1.67	1.99	

NDVI	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.76			
Reed bed	0.52	0.60		
Bare sediment	1.95	1.65	1.12	0.32
Water	1.98	1.96	1.99	
NDAVI	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.75			
Reed bed	0.58	0.59		
Bare sediment	1.94	1.69	1.54	0.43
Water	1.99	1.99	1.99	
EVI	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.79			
Reed bed	0.64	0.78		
Bare sediment	1.96	1.61	1.87	0.42
Water	1.99	1.99	1.99	
WAVI	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.92			
Reed bed	0.76	1.17		
Bare sediment	1.93	1.65	1.91	0.45
Water	1.99	1.99	1.99	

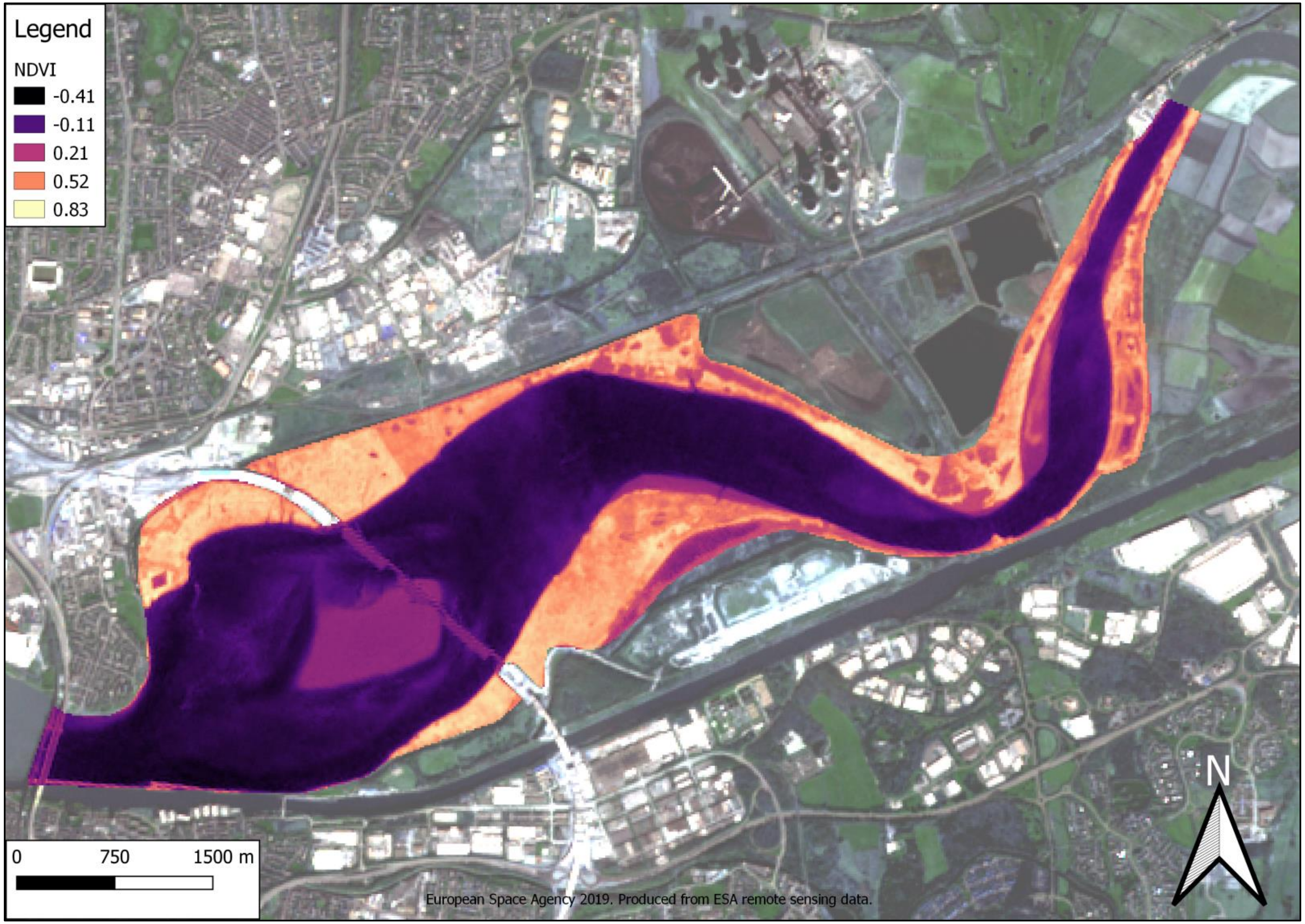


Figure 4.1 – Normalised Difference Vegetation Index (NDVI) of the Upper Mersey Estuary, May 2018.

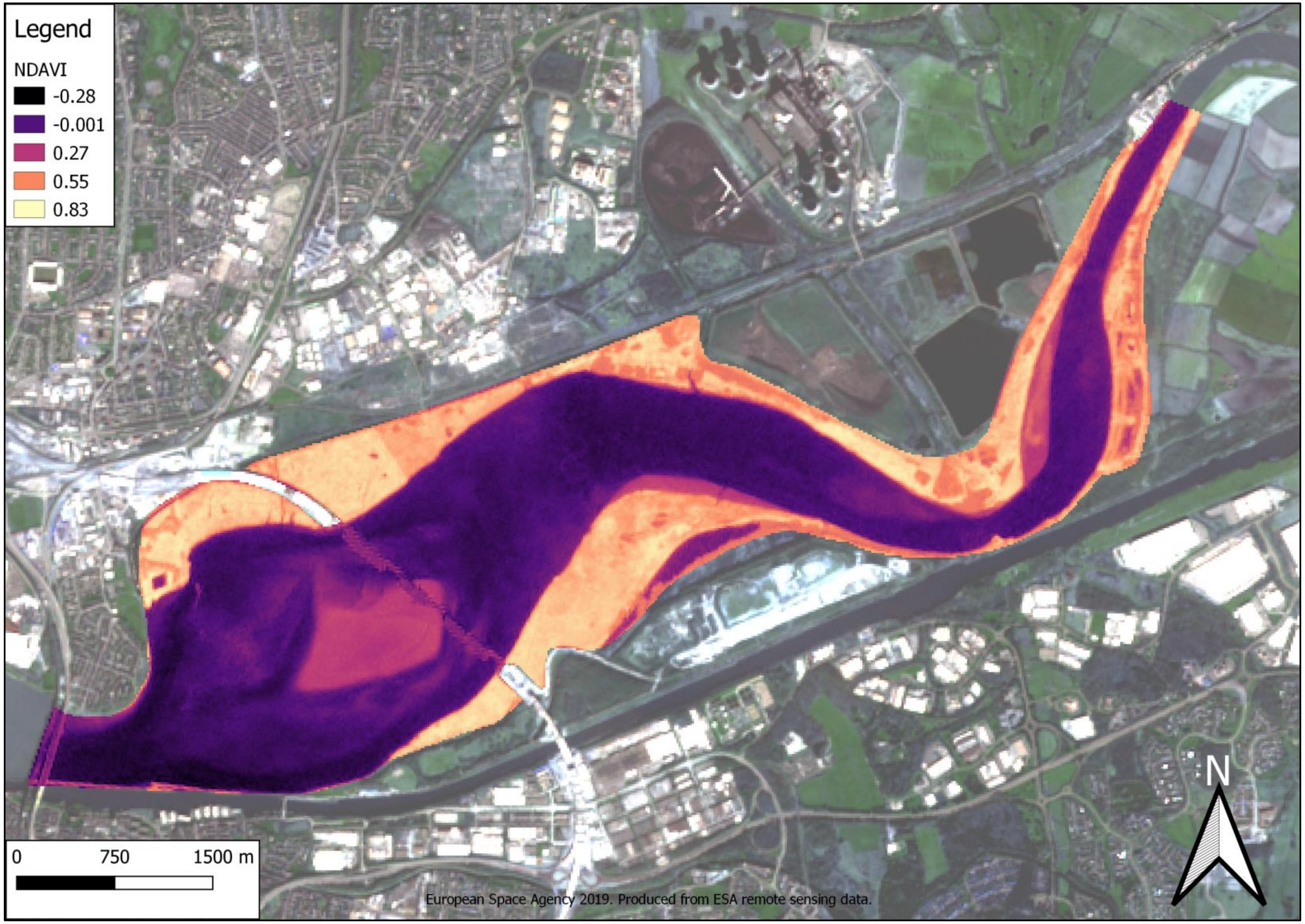


Figure 4.2 – Normalised Difference Aquatic Vegetation Index (NDAVI) of the Upper Mersey Estuary, May 2018.

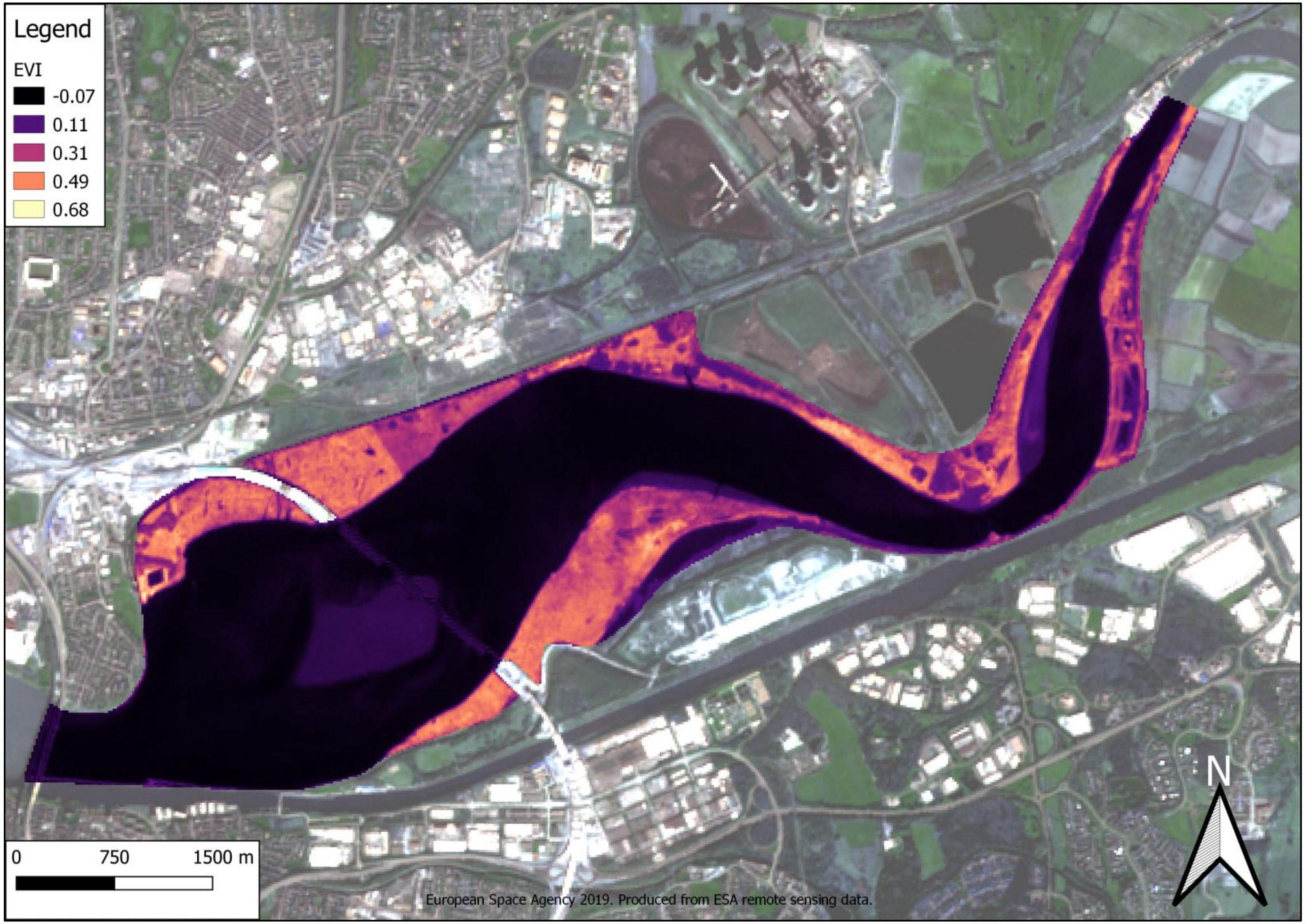


Figure 4.3 – Enhanced Vegetation Index (EVI) of the Upper Mersey Estuary, May 2018.

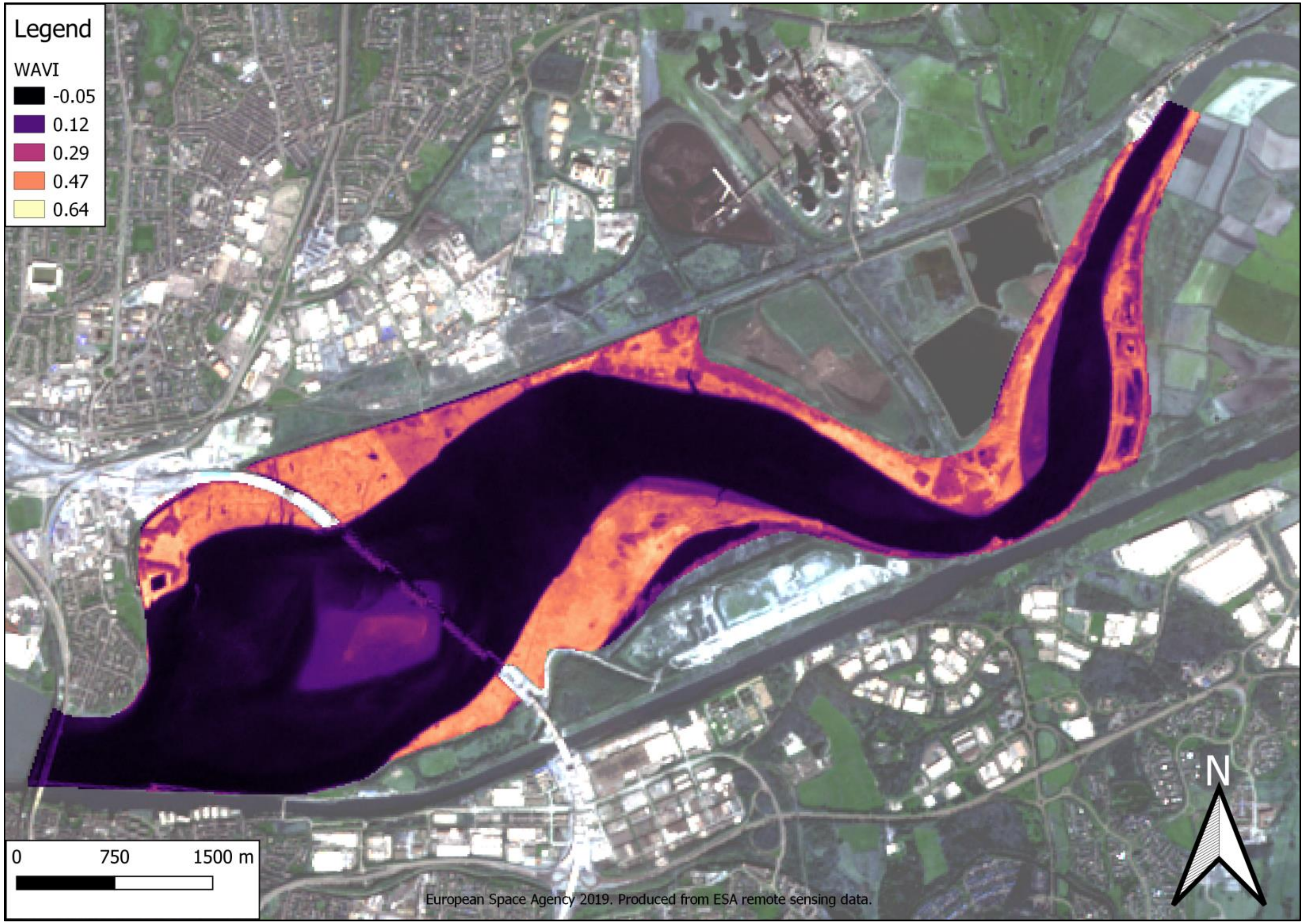
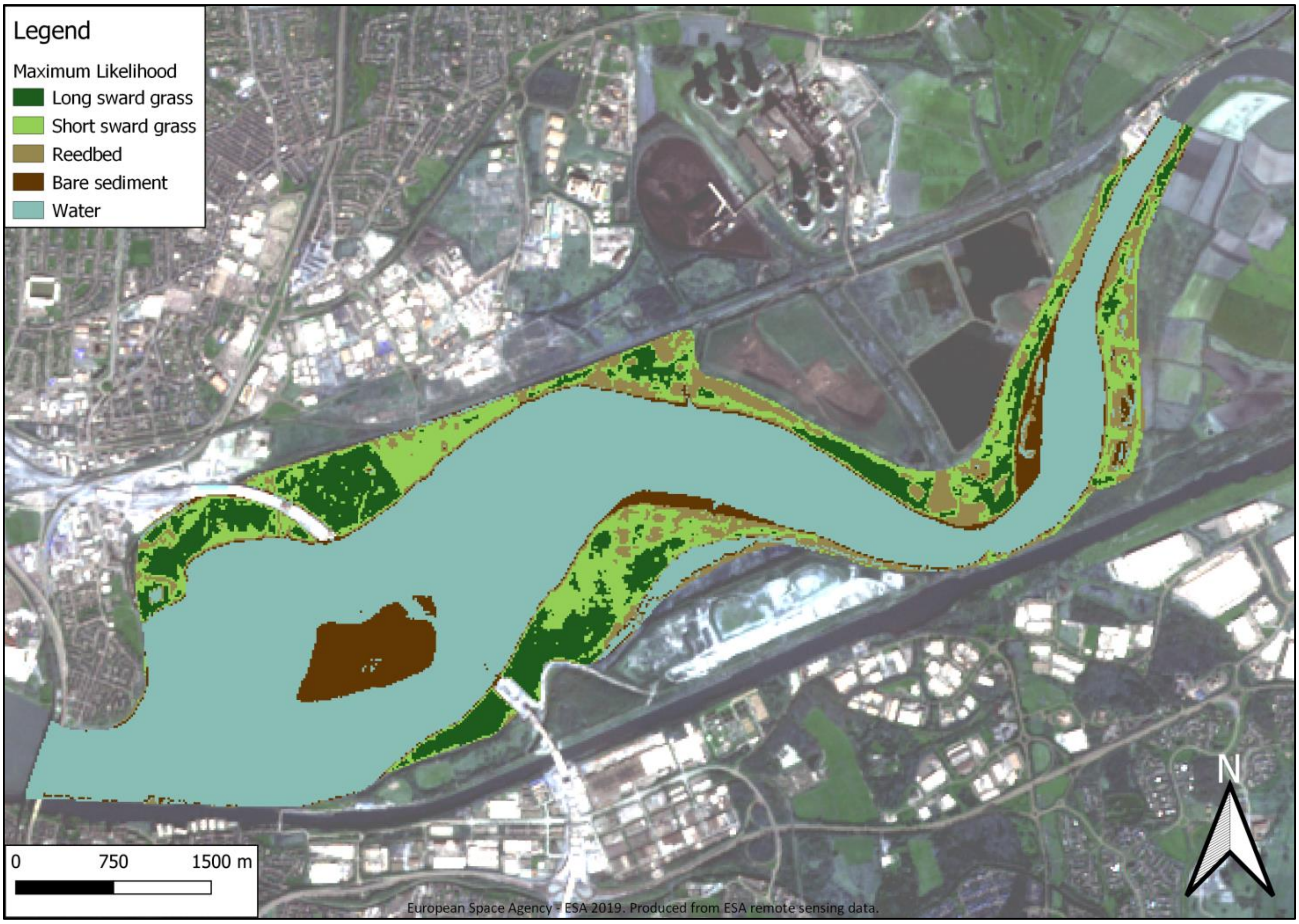


Figure 4.4 – Water Adjusted Vegetation Index (WAVI) of the Upper Mersey Estuary, May 2018.

4.1 – Saltmarsh Vegetation Cover Classification Derived from Sentinel-2 Data

The following section presents data relating to the image classification of Sentinel-2 derived remote sensing data utilising the analysis bands. These data were collected in tandem with an Unmanned Aerial System (UAV) flight at upper Moss Side saltmarsh to enable a comparison in the classification results of the two techniques. The data relating to the UAV remote sensing are presented in Chapter 5. This section helps to further address Research Objective 1 and Hypothesis one in Chapter 2, Section 2.10, by determining the validity of a Sentinel-2 derived data set in classifying the saltmarsh cover of a site within the Upper Mersey Estuary. This will determine whether the technology produces data appropriate within the context of wetland vulnerability analysis, particularly for small area, constrained saltmarshes. The techniques utilised in the classification procedure are described in Chapter 3, Section 3.3, and include the maximum likelihood classifier, support vector machine and random forests classifiers. The results are presented below, for each procedure in turn.

Figure 4.5 – Locations of the 500 sampling points.



European Space Agency - ESA 2019. Produced from ESA remote sensing data.

Figure 4.6 – Maximum likelihood classification of Upper Mersey Estuary Saltmarshes.

Table 4.3 – Confusion matrix for the maximum likelihood classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**108**	45	19	0	0	172	**62**	
Short sward grass	28	**52**	19	1	0	100	**52**	
Reed bed	44	32	**78**	1	0	155	**50**	
Bare sediment	2	1	9	**24**	4	40	**60**	
Water	2	2	0	11	**18**	33	**54**	
Total	184	133	125	37	22	**500**		
P_Acc	**58**	**39**	**62**	**64**	**81**		**56**	
Kappa								**0.4**

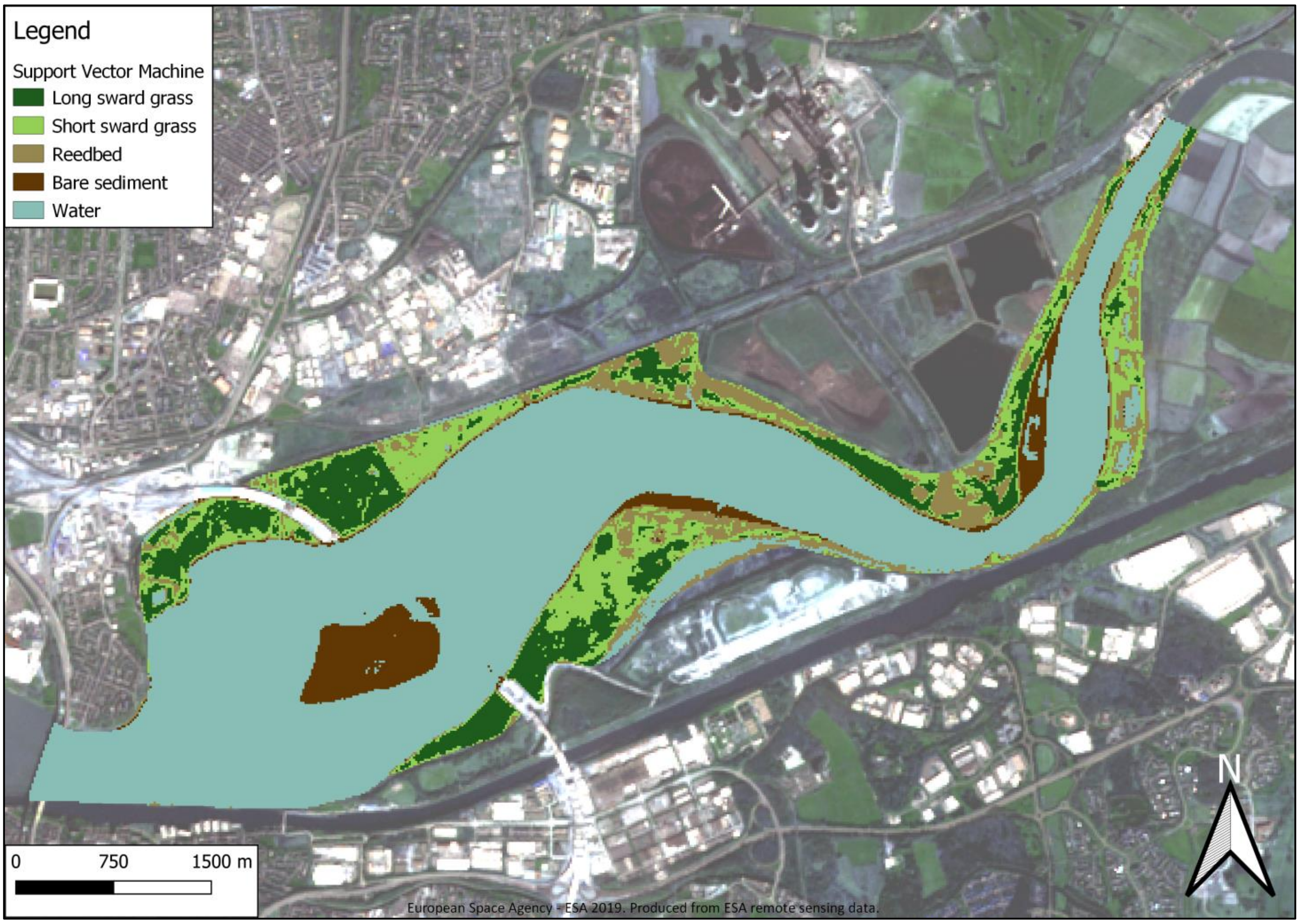


Figure 4.7 – Support vector machine classification of Upper Mersey Estuary Saltmarshes.

Table 4.4 – Confusion matrix for the support vector machine classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**143**	39	12	0	0	194	**73**	
Short sward grass	26	**46**	31	5	1	109	**42**	
Reed bed	13	20	**68**	9	3	113	**60**	
Bare sediment	2	23	12	**19**	5	64	**29**	
Water	0	4	2	4	**13**	23	**56**	
Total	184	132	125	37	22	**500**		
P_Acc	**77**	**34**	**54**	**51**	**56**		**57**	
Kappa								**0.42**

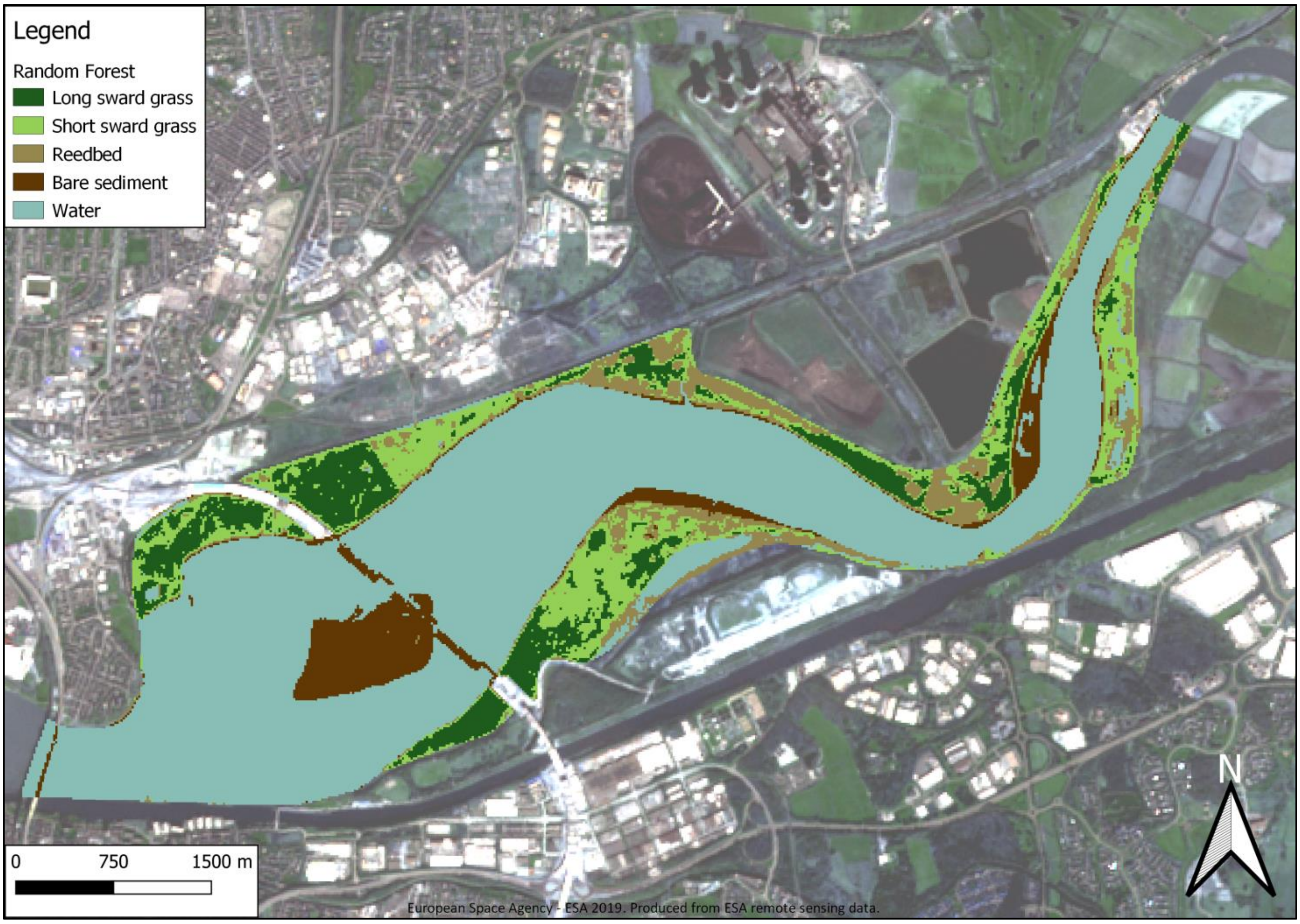


Figure 4.8 – Random forests classification of Upper Mersey Estuary saltmarshes.

Table 4.5 – Confusion matrix for the random forest classification.

Class	Long sward grass	Short sward grass	Reed bed	Bare sediment	Water	Total	U_Acc	Kappa
Long sward grass	**162**	24	0	2	0	188	**86**	
Short sward grass	17	**72**	34	3	2	128	**56**	
Reed bed	4	18	**81**	7	1	111	**72**	
Bare sediment	1	18	8	**21**	1	49	**42**	
Water	0	1	2	4	**18**	24	**75**	
Total	184	133	125	37	22	**500**		
P_Acc	**88**	**54**	**64**	**56**	**81**		**70**	
Kappa								**0.59**

The classification maps for Upper Moss Side saltmarsh are presented in Figures 4.6 – 4.8. An evaluation of the classification accuracy of each is presented in Tables 4.3 – 4.5. Within these, 'P_Acc' and 'U_Acc' refers to the 'producer' and 'user' accuracy. The results of the three classification procedures is 56%, 57%, and 70% respectively, with a Kappa score of 0.4, 0.42, and 0.59 for each of the techniques. The Kappa coefficient reflects the relative accuracy of the classification procedure while also accommodating for the fact that some classes may have been allocated in such a way by chance alone (Foody, 2002). From this, the random forest classifier had the greatest Kappa score, of 0.59.

The interpretation of the error matrices presented in Tables 4.3 – 4.5 enables the determination of the source of the classification errors. The values presented as columns in the matrix represent errors of omission, or false negatives. They are the values of a given class that were predicted to be in a separate class. The errors of commission are presented as rows, represent false positives, they represent values that were predicted to be in a class in which they do not belong. The interpretation of both errors of commission and omission relate only to the values that are off the diagonal, as these represent the number that were classified correctly. Producer accuracy is the probability that a value in a class was classified correctly, and user accuracy is related to the probability that a value predicted to be of a specific class actually is (Campbell, 2003). In Table 4.3, the highest user accuracy for the maximum likelihood is 62%, relating to the long sward grass class, bare sediment is second at 60% user accuracy. The producer accuracy was greatest for water at 81%. Low overall accuracy is the result confusion between classes, particularly reed bed and the short sward class, and bare sediment and reed bed which is also reflected within the Jeffries-Matusita values in Table 4.3. In Table 4.4, the data for the support vector machine classification are presented. The highest user accuracy was the long sward class, with 86%. The long sward grass class had the greatest producer accuracy at 88% with water second at 81%. The lowest accuracy using this classifier was the bare sediment at 42%. Large errors of omission between vegetated classes lowered the producer accuracy for the short sward class and the reed bed class. The random forest classifier in Table 4.5, the highest user accuracy was the long sward class at 86%, the highest producer accuracy was also long sward grass at 88% and water was second at 81%. Relatively large errors of commission and omission were present for the vegetated classes across all three classifiers, though this is in keeping with the low representative Jeffries-Matusita distance values for these.

The second classification procedure was undertaken utilising the individual vegetation index datasets as an input, rather than the Sentinel-2 satellite bands. This utilised the random forest classifier on these data since this has performed well on vegetation index data (Liu et al., 2020). Two of these vegetation indices were specifically designed for aquatic systems, or systems where water may be present within the vegetation. These are the Normalised Difference Aquatic Vegetation Index (NDAVI), and the Water Adjusted Vegetation Index (WAVI) (Villa et al., 2013; Villa et al., 2015). The remaining two indices, the Normalised Difference Vegetation Index (NDVI), and the Enhanced Vegetation Index (EVI) are traditionally used terrestrially, with recent focus being turned to applications within agriculture as a reflection of crop health. The classification maps are presented in Figures 4.9 – 4.12, and the confusion matrices in Tables 4.6 – 4.9. Within these tables, ‘P_Acc’ and ‘U_Acc’ refer to the ‘producer’ and ‘user’ accuracy. WAVI is enlarged (Figure 4.12) as this was the highest accuracy dataset. The classification results utilising the VIs all performed similarly, with greater distinction between vegetated and non-vegetated classes, however, confusion between categories was still prevalent. For the four VIs, the accuracy was 65%, 71%, 68% and 76% respectively, resulting in a kappa of 0.51, 0.61, 0.57 and 0.67. The lowest performing VI was the NDVI, with 0.51 kappa. The water-based VIs all performed greater than the classification procedures based on the satellite bands. Though the random forest classifier utilising the Sentinel-2 bands outperformed the NDVI and EVI classification. The WAVI derived classification utilising the random forest classifier yield the most accurate results of the entire set, with 76% accuracy, and 0.67 kappa. Long grass was best classified with a user accuracy of 80%, the highest producer accuracy was also long sward grass with 85%. Water and bare sediment were the lowest accuracy using the WAVI classifier, with 24% user accuracy for water, and 48% producer accuracy for bare sediment. As is reflected with the Jeffries-Matusita distance values in Table 4.2, the WAVI showed the greatest separability between vegetated and non-vegetated classes. However, as was also reflected by the pairwise comparison within each category, the classification accuracy was inhibited by between class confusion. This was particularly clear between bare sediment and water, and the reed bed and long sward grass classes.

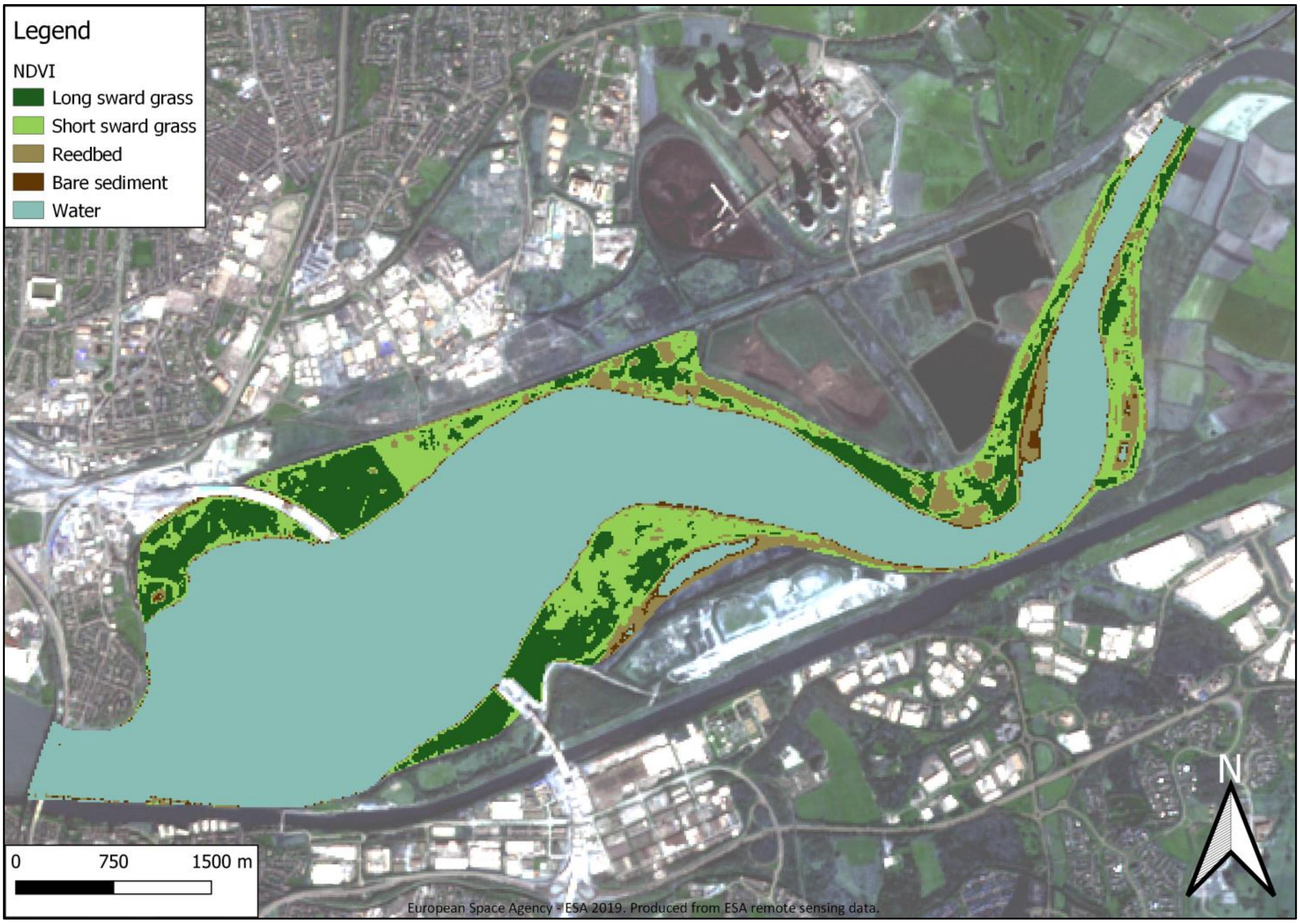


Figure 4.9 – Classification based on the Normalised Difference Vegetation Index (NDVI) class thresholds for the Upper Mersey Estuary.

Table 4.6 – Confusion matrix for the NDVI classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**135**	36	24	0	0	195	**69**	
Short sward grass	22	**74**	19	5	1	121	**61**	
Reed bed	18	21	**81**	11	1	132	**61**	
Bare sediment	3	1	1	**17**	2	24	**70**	
Water	6	0	0	4	**18**	28	**64**	
Total	184	132	125	37	22	**500**		
P_Acc	**73**	**56**	**64**	**45**	**81**		**65**	
Kappa								**0.51**

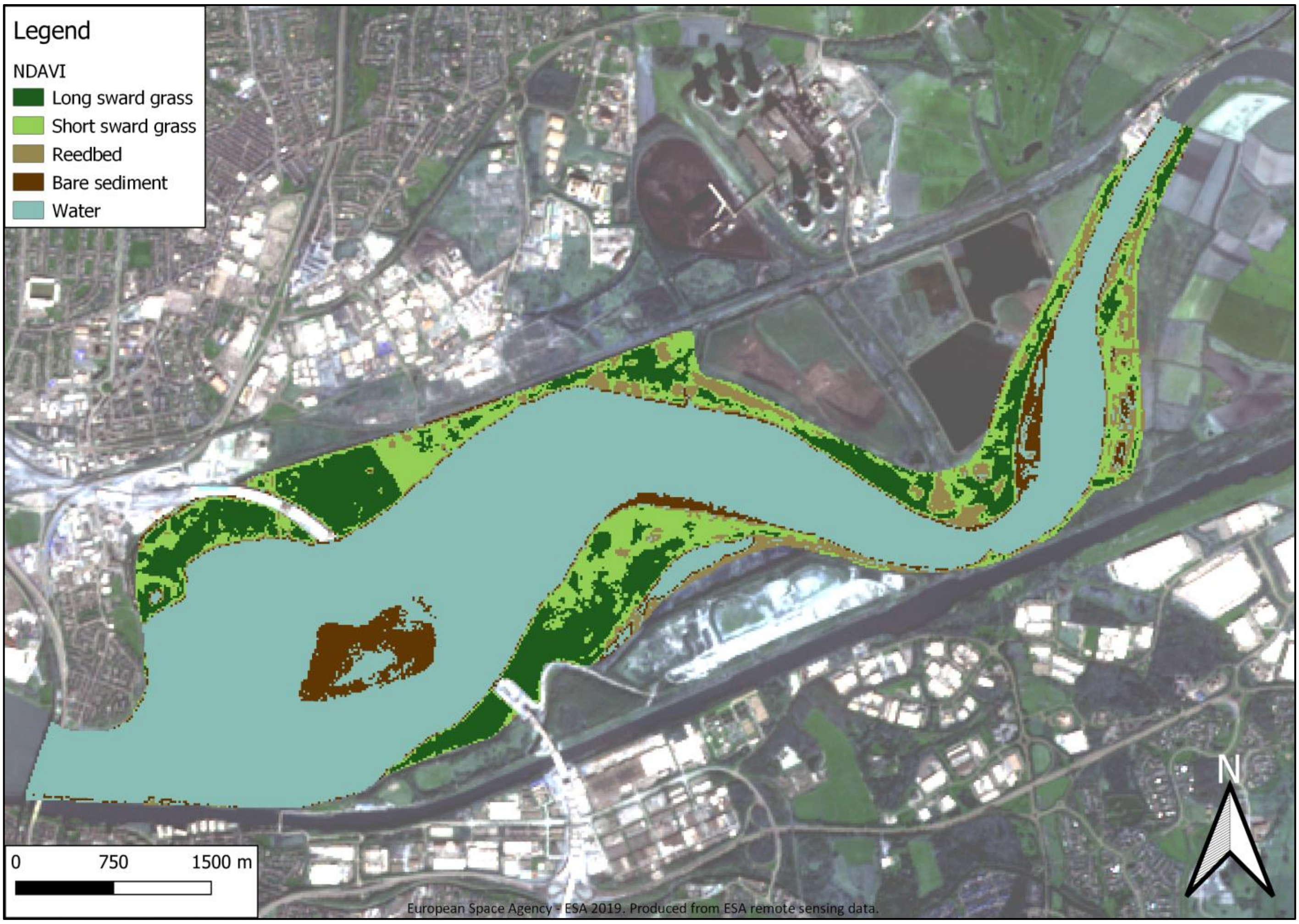


Figure 4.10 - Classification based on the Normalised Difference Aquatic Vegetation Index (NDAVI) class thresholds for the Upper Mersey Estuary.

Table 4.7 – Confusion matrix for the NDAVI classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**144**	22	17	0	0	183	**78**	
Short sward grass	28	**93**	9	8	0	138	**67**	
Reed bed	21	14	**87**	7	1	121	**71**	
Bare sediment	0	3	12	**17**	3	35	**48**	
Water	0	0	0	5	**18**	23	**78**	
Total	184	132	125	37	22	**500**		
P_Acc	**78**	**70**	**69**	**45**	**81**		**71**	
Kappa								**0.61**

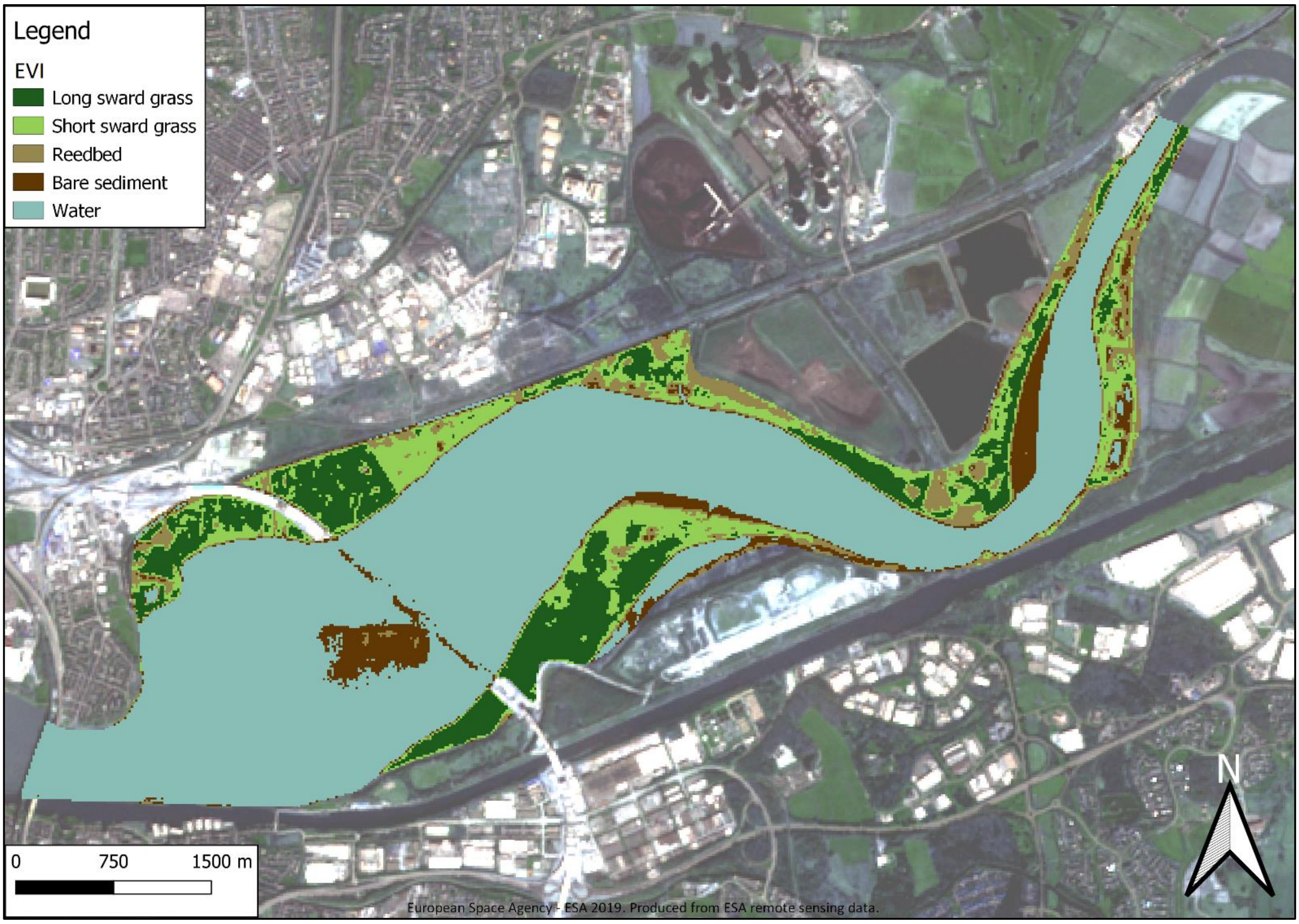


Figure 4.11 - Classification based on the Enhanced Vegetation Index (EVI) class thresholds for the Upper Mersey Estuary.

Table 4.8 – Confusion matrix for the EVI classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**135**	24	15	0	0	174	**77**	
Short sward grass	29	**89**	11	6	1	136	**65**	
Reed bed	11	18	**85**	9	1	124	**68**	
Bare sediment	8	1	12	**16**	1	38	**42**	
Water	1	0	2	6	**19**	28	**67**	
Total	184	132	125	37	22	**500**		
P_Acc	**73**	**67**	**68**	**43**	**86**		**68**	
Kappa								**0.57**

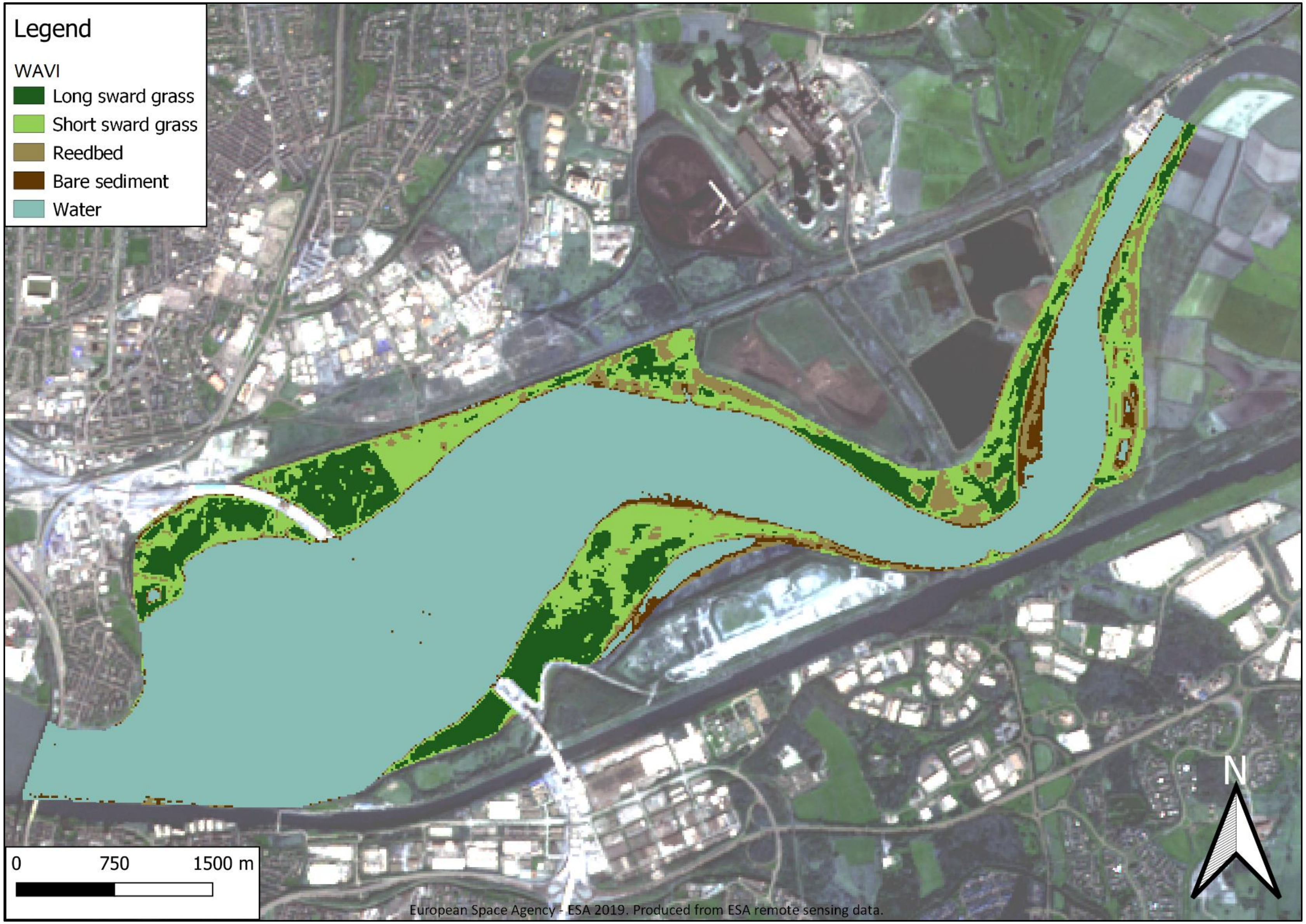


Figure 4.12 - Classification based on the Water Adjusted Vegetation Index (WAVI) class thresholds for the Upper Mersey Estuary.

Table 4.9 – Confusion matrix for the WAVI classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**Water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**157**	26	12	0	0	195	**80**	
Short sward grass	17	**88**	10	4	0	119	**73**	
Reed bed	9	17	**99**	10	1	136	**72**	
Bare sediment	0	1	3	**18**	3	25	**72**	
Water	1	1	0	5	**18**	24	**75**	
Total	184	133	124	37	22	**500**		
P_Acc	**85**	**66**	**79**	**48**	**81**		**76**	
Kappa								**0.67**

Following the analysis of the Sentinel-2 band and vegetation index derived image classification, it can be concluded that for the current study the WAVI has produced the highest accuracy classification. The habitat extent for Cuerdley Marsh and Upper Moss Side is presented in Table 4.10.

Table 4.10 – Total combined habitat area based on the WAVI classification for Upper Moss Side and Cuerdley Marsh.

Saltmarsh Cover Class	**Area in metres squared (m^2)**
Long sward grass	197,223
Short sward grass	43,743
Reed bed	124,220
Bare sediment	10,502
Water	4,223

4.2 – Summary

Data have been presented in this chapter that address the questions raised within the literature, and by utilising methods described in Chapter 3, Section 3.3, and the question put forward as Research Objective One, translated into Hypothesis One. The Water Adjusted Vegetation Index (WAVI) classified with the random forest classifier yielded the classification with the greatest accuracy. Class separability across each input dataset (Sentinel-2 bands, and vegetation indices) shared similar traits in that the vegetated vs unvegetated categories could be well separated, whereas within category separation was much less. A further confounding factor is likely derived from the mixed pixel problem. This problem, where a single pixel reflects multiple cover types, is one of the great challenges when utilising satellite remote sensing data and contributes to the low accuracy of the classification outputs for this site (Campbell and Wynne, 2011). This problem represents a challenge to the field of estuarine remote sensing, and a gap within the literature to be explored, this will be discussed further in Chapter 8. A continued exploration of remote sensing methods is presented in this thesis, and defines the subject of the next chapter, an exploration of an Unmanned Aerial System for saltmarsh vegetation cover mapping.

Chapter 5 – Unmanned Aerial Vehicle (UAV) Data Collection and Analysis

5.1 – Introduction

The reliable and repeatable monitoring of saltmarshes was identified in the literature review (Section 2.10) as a fundamental component in assessing coastal vulnerability. Given both the historic and projected losses of this ecosystem in some parts of the UK, developing up to date monitoring methods of appropriate scale should improve the way that we understand both the drivers of change and how to incorporate these more readily into management objectives (Duffy et al., 2018). Saltmarshes are of particular value in demonstrating how environments can change in response to environmental pressure, and with sea level rise a very real threat globally real-time monitoring of ecosystem response is critical across a range of management applications (Angus, 2017).

The research presented in this chapter investigates three factors relating to the application of lightweight Unmanned Aerial Vehicle (UAV) technology in monitoring saltmarsh ecosystems. These three questions are outline below. The subsequent discussion of these relates to the main research question in Objective One, and the subsequent Hypothesis One - Section 2.10, namely, the requirement for a critical assessment of UAV based remote sensing for monitoring saltmarsh cover types, specifically within a conservation organisation. The three lines of enquiry addressed in this chapter are:

1) Can consumer grade cameras and a lightweight UAV be used to collect proximal remote sensing data of a mixed saltmarsh ecosystem.

2) Can the UAV system provide a classification accuracy greater than the satellite system.

3) How effective are different image classification techniques for mapping saltmarsh cover types.

The limitation of satellite-based remote sensing approaches in monitoring small-scale ecosystems is attributed to a mismatch between the spatial resolution of the sensor, and the observable ecosystem process (Anderson and Gaston, 2013). This was apparent in Chapter 4, Section 4.3, where the relatively large spatial resolution of the Sentinel-2 sensors limited the utility of the data when applied to a narrow, constrained habitat such as the saltmarshes found in the Upper Mersey Estuary. However, this limitation has contributed to the emergence, deployment, and development of UAV technology as a tool for the ecologist (Duffy et al., 2018). The platform of a UAV system offers ecologists cost effective and timely monitoring of environmental phenomena, especially when compared to high-cost aerial photography platforms. The ability to capture data from very low altitude offers a platform that can collect data at sub-decimetre ground sampling distance, thus eliminating issues that may be encountered with the mixed pixel problem in remote sensing (Duffy et al., 2018).

The research presented in this chapter investigates the value of a UAV based monitoring system in contrast to a satellite-based one. The work addresses Research Objective 1, to critically assess the use of remote sensing for mapping and monitoring saltmarsh vegetation cover types at Upper Moss Side Saltmarsh in Warrington. Building on previous work undertaken within the field, this study will incorporate a near infra-red image band and an object-based classification procedure into the analysis (Samiappan et al., 2016; Duffy et al., 2018).

5.2 – UAV System Design and Flight Planning

In comparison to satellite-based data collection – i.e., the download of an appropriate data set from an online repository - the acquisition of UAV data requires more careful planning and consideration. The workflow has two distinct phases before analysis can be considered: planning and data collection. While the use of UAV technology is now established within the scientific literature, there is a lack of a common understanding, and protocol for addressing methodological errors and challenges (Anderson et al., 2017). As a result of this, much of the guidance utilised for designing the data collection procedure is derived from producers of UAV data processing software and included Agisoft, Pix4D, and DJI (Anderson et al., 2017).

The first stage of planning was to confirm, through Civil Aviation Authority (CAA) guidance, that the study area did not fall within a restricted fly zone. The no-fly zones local to the study area are presented in Figure 5.1. The CAA (2018) rules state:

> “Unmanned aircraft weighing more than 7kg are not permitted to be flown in controlled airspace or within an Aerodrome Traffic Zone (ATZ) without the permission of the Air Traffic Control unit responsible for the airspace.”
>
> “Although operators of drones weighing 7 kg or less are not required to have the permission of Air Traffic Control (even when flying within Controlled Airspace or within an ATZ), the Air Navigation Order requires that any person in charge of a small drone:
>
> - may only fly the aircraft if reasonably satisfied that the flight can safely be made, and
> - must maintain direct, unaided visual contact with the aircraft …for avoiding collisions. Note: The use of normal corrective spectacles is acceptable within the term ‘unaided’” (Cunliffe et al., 2017; CAA, 2018).

Following the exploration of the law, and the aviation rules for the area of interest, a UAV system was designed that allowed the fulfilment of the objectives, keeping within the CAA guidelines.

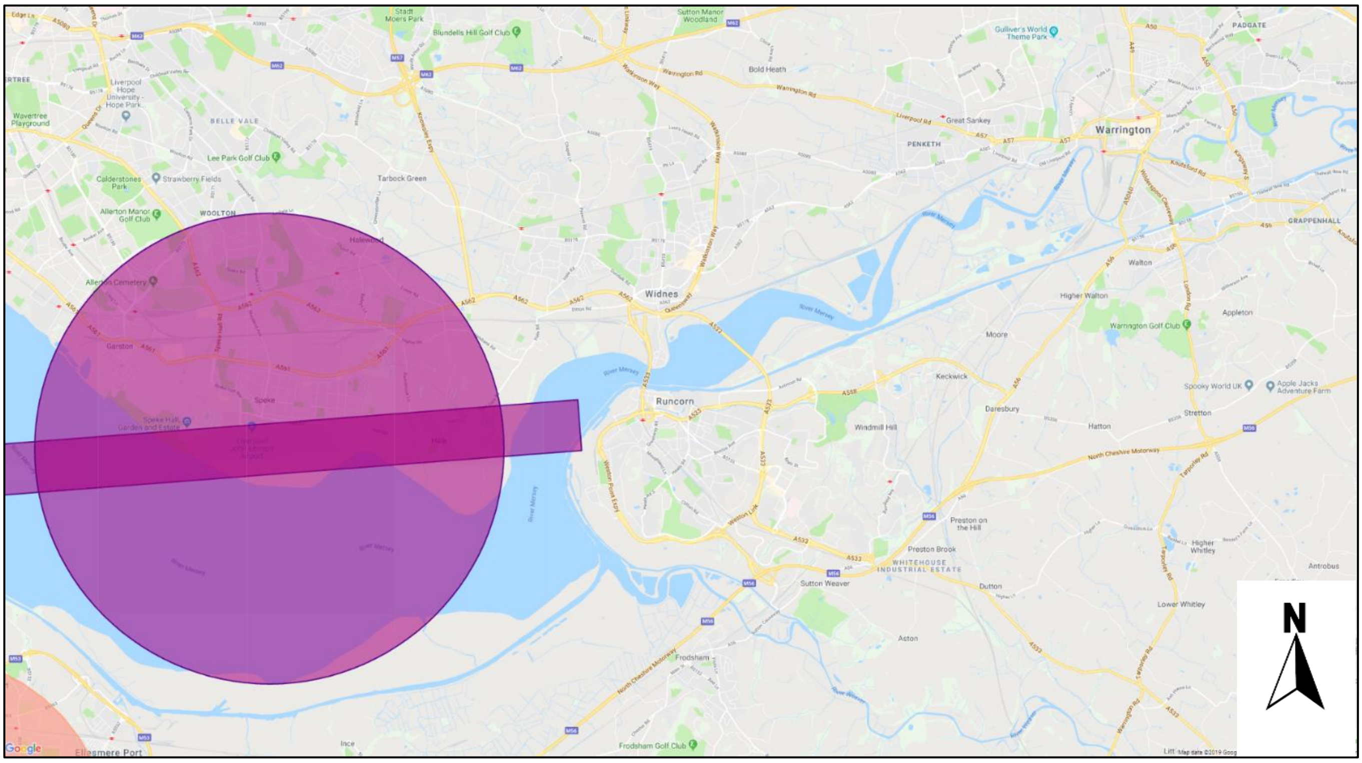


Figure 5.1 – Prohibited area and flight restriction zones local to the Upper Mersey Estuary, obtained directly from www.noflydrones.co.uk, in accordance with CAA rules (Map data ©2018 Google).

Based on the literature, low-cost multi-rotor platforms, such as DJI Phantom quadcopters, are the most used in environmental research, mainly due to the ease of deployment and control of the system (Anderson and Garston, 2013; Hodgson et al., 2016; Duffy at al. 2017; Duffy et al., 2018). The DJI Phantom 3 Standard was selected for this research. This UAV platform includes a pre-installed GPS enabled Red Green and Blue (RGB) camera. To incorporate the Near infra-red band, and to address the research objectives, a second camera – the MAPIR Near infra-red, green and blue (Mapir Survey3W NGB) - was acquired from Peau Productions, Inc. This was then mounted underneath the Phantom 3 UAV chassis with a separate GPS receiver to enable data to be collected across the 4 bands required for this study. In keeping with the CAA guidance for the local area, the fully laden UAV system came to a weight of 1380g (Figure 5.2), and thus it was not required to inform the local ATZ control at Liverpool Airport.

Figure 5.2 – DJI Phantom 3 Standard with a mounted MAPIR Survey3W NGB camera and GPS receiver. The MAPIR calibration target and DJI Phantom controller are also shown in this photograph.

The programme Pix4d Capture (Pix4d, 2018) was used to both design the grids that the UAV will fly (the grids are shown in Figure 5.3), and to control the UAV during its operation. This is a free application that enables the user to select the size of the flight grids, the overlap of the imagery, the altitude at which the UAV flies, and the speed the grid is flown. The software itself was downloaded onto an Apple iPad Mini 4 which was used to connect to the UAV in the field. The procedure for UAV data collection is that a grid is flown, with the cameras in a nadir (vertical) position. Pix4d capture enables the user to determine the size and shape of each grid, the image overlap, the speed at which the UAV will travel, and the elevation from which the data will be collected. Each attribute impacts the quality of the collected data, and the success of the final product.

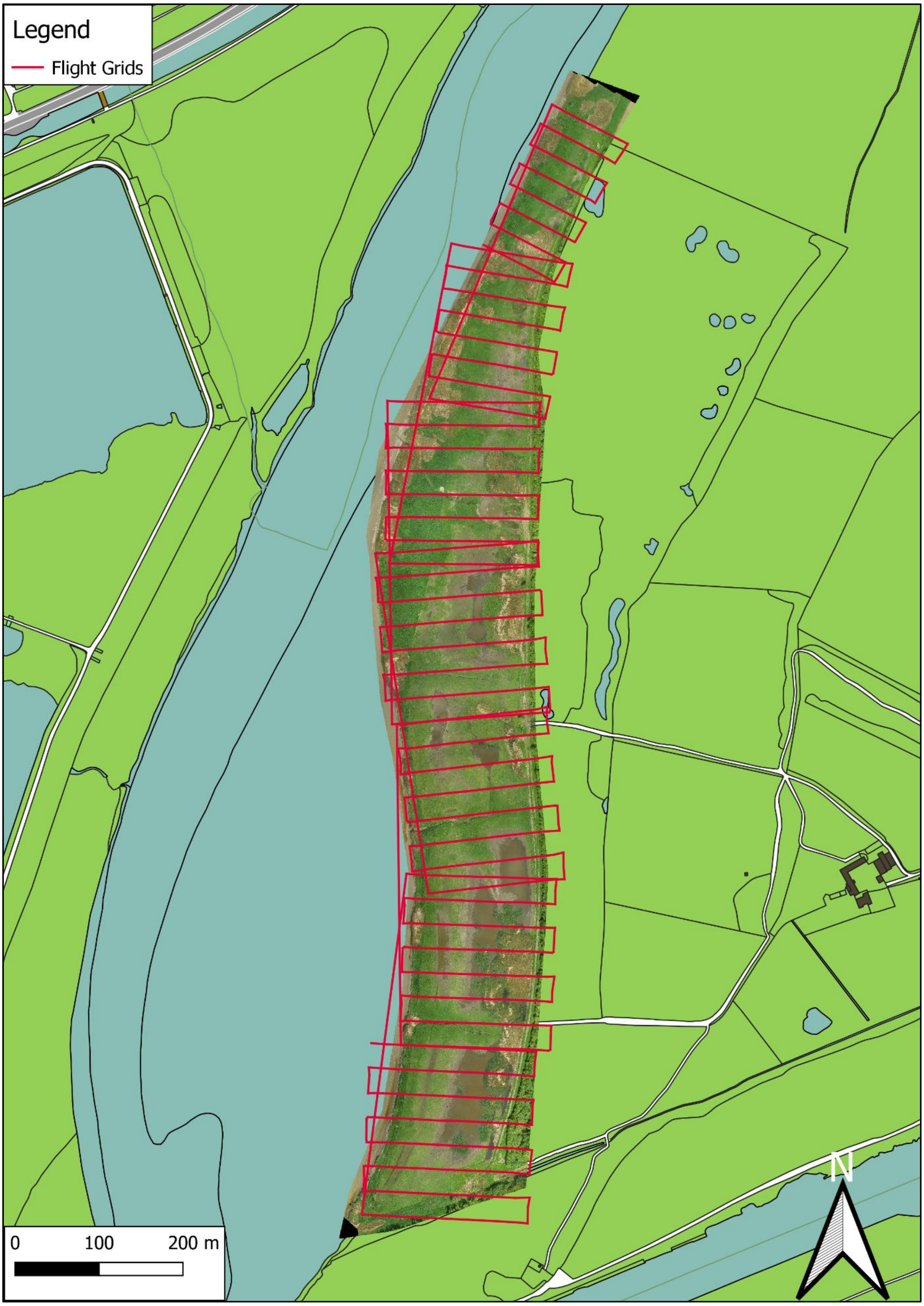
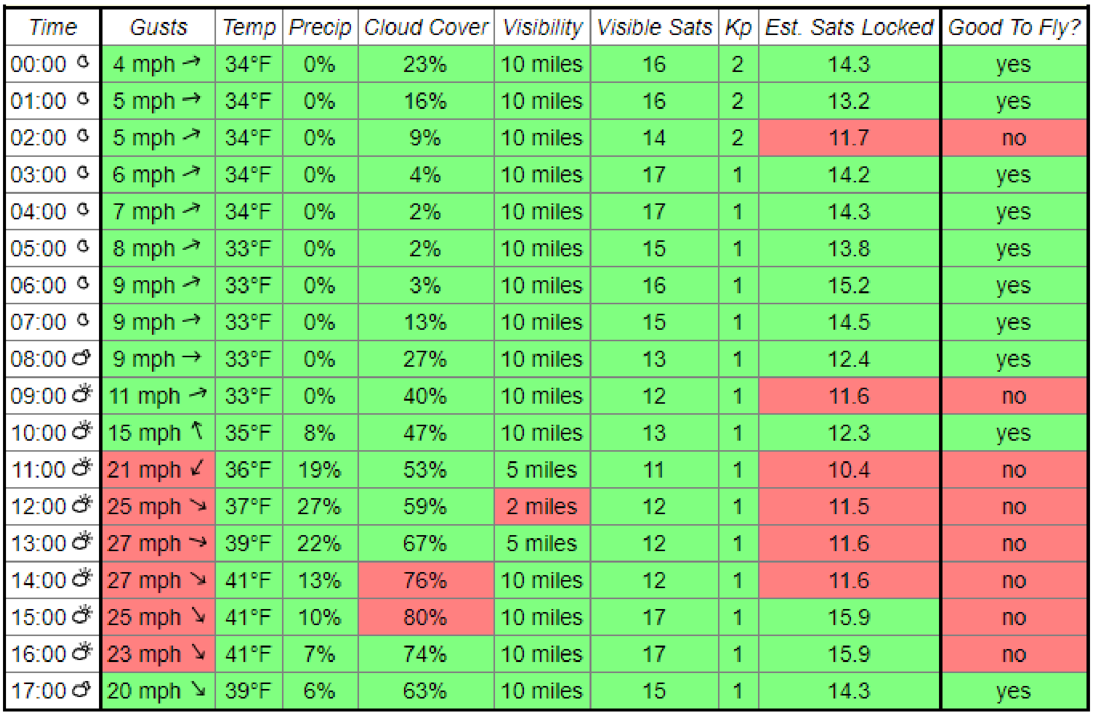


Figure 5.3 – Flight grids and camera trigger locations at Upper Moss Side saltmarsh.

Of key importance is the image overlap, this must be high enough to ensure that all the neighbouring images will share a common feature, so that tie-points can be computed for successful image stitching. The overlap/ sidelap for the flight grids was 85% frontal, and 75% side, which exceeds the recommended guidance detailed by Pix4d (2018). The remaining attributes were selected around the key limiting factors for a flight grid, which are the battery life of the UAV and the capture speed of the mounted cameras. The appropriate flight time was ascertained through several test flights. The Phantom 3 Standard battery lasts for approximately 20 minutes. With the extra weight of the MAPIR camera and GPS unit, this was reduced to around 18 minutes of flight time. Travel to the start of the flight grid and return to the landing area takes 2 minutes in total. Flights were, therefore, conducted at an altitude of 80m and the UAV travelled at a speed of 8 m/s in order to achieve the required flight time for the required image overlap. This enabled the two mounted cameras to take RAW and JPEG photograph every 5 seconds, which was the maximum capture speed of the SD cards within each camera, the Sandisk Extreme Plus 64 gigabyte memory cards. To cover the entire study area, seven flight grids were required with a mean flight time of 12 minutes. The footprint for these, and camera trigger locations are presented in Figure 5.3. A ground sampling distance (GSD) of 3.5 cm was achieved for the RGB camera, and 2.5 cm for the MAPIR NGB camera.

Following a series of test flights, and the recommendations put forward by Duffy, et al., (2017), the maximum permissible wind speed, including gusts, under which a successful flight could be operated was found to be 10 m/s. Under gusts exceeding this value the UAV could be sent off course from its pre-programmed flight grid, the images taken from the mounted NGB camera would vary from a nadir position, and the UAV would have to work harder to counter the wind, thus reducing battery life. To determine whether conditions were suitable to fly, the online resource UAV Forecast (UF, 2018), was utilised. This provides hour by hour forecasts relating to the operation of a UAV (Figure 5.4). Utilising these resources, the date during the peak vegetation period that the UAV data collection was flown, was the 5th May 2018. Following the successful completion of the data collection, the orthomosaic stitching procedure, calibration, and subsequent classification analysis was undertaken. The details of these processes are outlined in Methods, Chapter 3, Sections 3.3, and 3.4.



Time	Gusts	Temp	Precip	Cloud Cover	Visibility	Visible Sats	Kp	Est. Sats Locked	Good To Fly?
00:00	4 mph ↗	34°F	0%	23%	10 miles	16	2	14.3	yes
01:00	5 mph →	34°F	0%	16%	10 miles	16	2	13.2	yes
02:00	5 mph ↗	34°F	0%	9%	10 miles	14	2	11.7	no
03:00	6 mph ↗	34°F	0%	4%	10 miles	17	1	14.2	yes
04:00	7 mph ↗	34°F	0%	2%	10 miles	17	1	14.3	yes
05:00	8 mph ↗	33°F	0%	2%	10 miles	15	1	13.8	yes
06:00	9 mph ↗	33°F	0%	3%	10 miles	16	1	15.2	yes
07:00	9 mph →	33°F	0%	13%	10 miles	15	1	14.5	yes
08:00	9 mph →	33°F	0%	27%	10 miles	13	1	12.4	yes
09:00	11 mph →	33°F	0%	40%	10 miles	12	1	11.6	no
10:00	15 mph ↖	35°F	8%	47%	10 miles	13	1	12.3	yes
11:00	21 mph ↙	36°F	19%	53%	5 miles	11	1	10.4	no
12:00	25 mph ↘	37°F	27%	59%	2 miles	12	1	11.5	no
13:00	27 mph →	39°F	22%	67%	5 miles	12	1	11.6	no
14:00	27 mph ↘	41°F	13%	76%	10 miles	12	1	11.6	no
15:00	25 mph ↘	41°F	10%	80%	10 miles	17	1	15.9	no
16:00	23 mph ↘	41°F	7%	74%	10 miles	17	1	15.9	no
17:00	20 mph ↘	39°F	6%	63%	10 miles	15	1	14.3	yes

Figure 5.4 – An example of data contained in the UAV Forecast tool for flight planning.

5.3 – Results

The two completed orthomosaics from the completed flight at Upper Moss Side saltmarsh are presented in Figures 5.5 and 5.6 respectively for the RGB, and NGB data sets. These images relate to the raw, unprocessed stitching of the photographs collected for each dataset. For the RGB dataset, this was 524 photographs, and for the NGB, 476 photographs. For the purposes of comparison, the three classification techniques, described in Chapter 3 were undertaken on the RGB camera data set and the NGB camera dataset separately. These were maximum likelihood, support vector machine, and random forests. The classifications were undertaken on the output of a mean shift segmentation that was conducted on each orthomosaic image, utilising ESRI ArcMap. The segmented datasets are presented in Figures 5.7 and 5.8, and the Jeffries-Matusita distance scores are presented in Table 5.1.

Figure 5.5 – Red green blue (RGB) orthomosaic of Upper Moss Side saltmarsh.

Figure 5.6 – Near Infrared green blue (NGB) orthomosaic of Upper Moss Side Saltmarsh.

Figure 5.7 – Mean shift segmentation of RGB Image at Upper Moss Side saltmarsh using the base image colour.

Figure 5.8 – Mean shift segmentation of NGB image at Upper Moss Side saltmarsh.

Table 5.1 – Pairwise Jeffries-Matusita distance between each class for the RGB and NGB image sets.

RGB	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.31			
Reed bed	0.42	0.51		
Bare sediment	1.52	1.23	1.21	0.97
Water	1.12	1.02	1.32	
NGB	**Long sward grass**	**Short sward grass**	**Reed bed**	**Water**
Short sward grass	0.56			
Reed bed	0.71	0.98		
Bare sediment	1.71	1.65	1.24	0.89
Water	1.91	1.87	1.81	

5.3.1 – RGB Image Classification

Following the methodology set out in Chapter 3, Sections 3.3 and 3.4, this section presents the outcomes of three classification techniques that were conducted on the segmented RGB data set. The results presented here include three classification maps relating to the five saltmarsh cover classes pertinent to the habitat management at Upper Moss Side (short sward saltmarsh, long sward saltmarsh, reed bed, bare sediment, and water). A confusion matrix for each classification map is also presented as an assessment of accuracy compared to the 500 ground control points shown in Figure 5.9. Figures 5.10, 5.11, and 5.12 present the outputs for the maximum likelihood, support vector machine, and random forest respectively. Tables 5.2, 5.3, and 5.4 relate to the confusion matrices for each classifier. Within these ‘P_Acc’ and ‘U_Acc’ refers to the ‘producer’ and ‘user’ accuracy.

Figure 5.9 – 500 ground sampling points randomly stratified across the study area – Upper Moss Side.

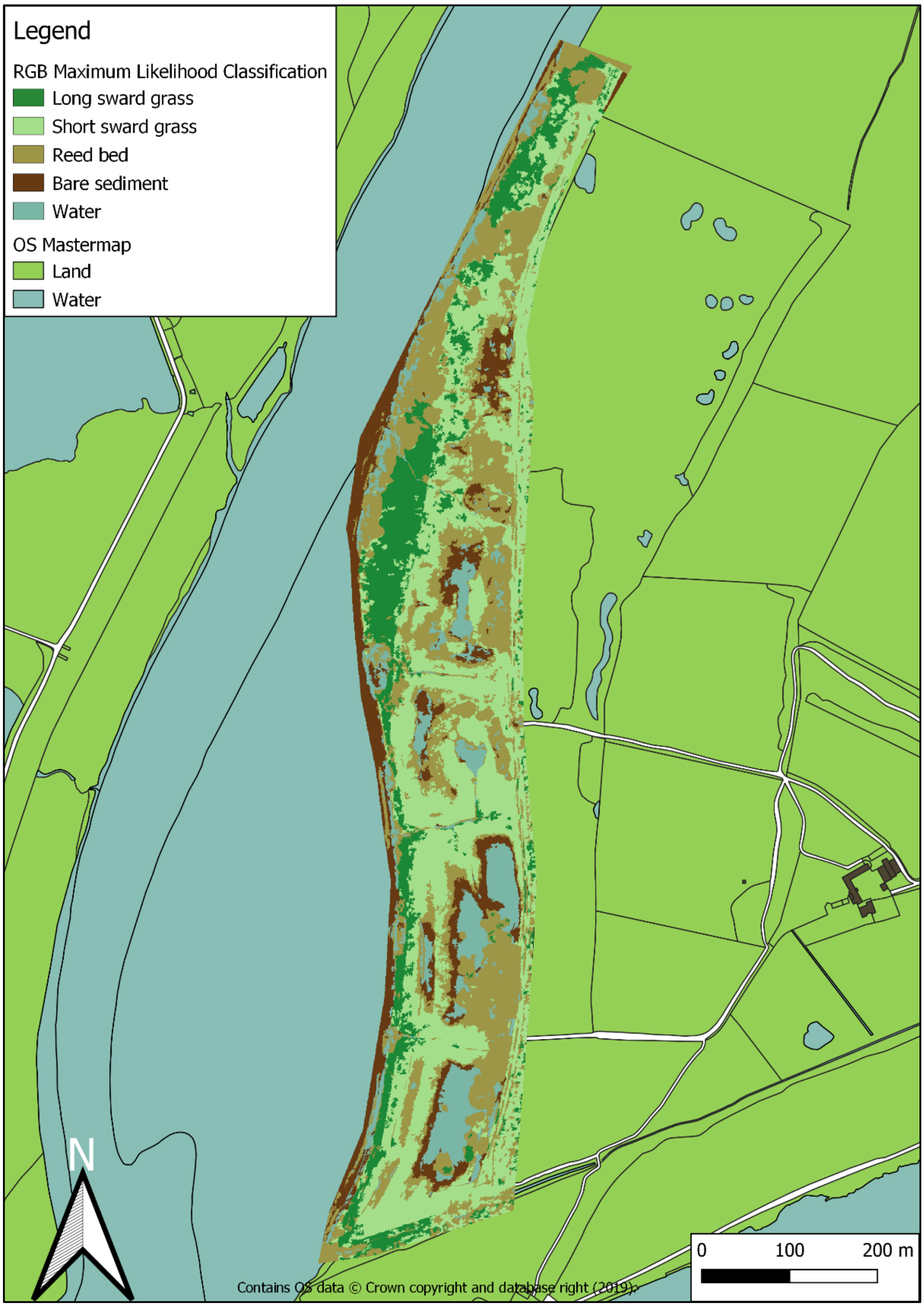


Figure 5.10 – Maximum likelihood classification for the RGB data set.

Table 5.2 – Confusion matrix for the RGB maximum likelihood classification.

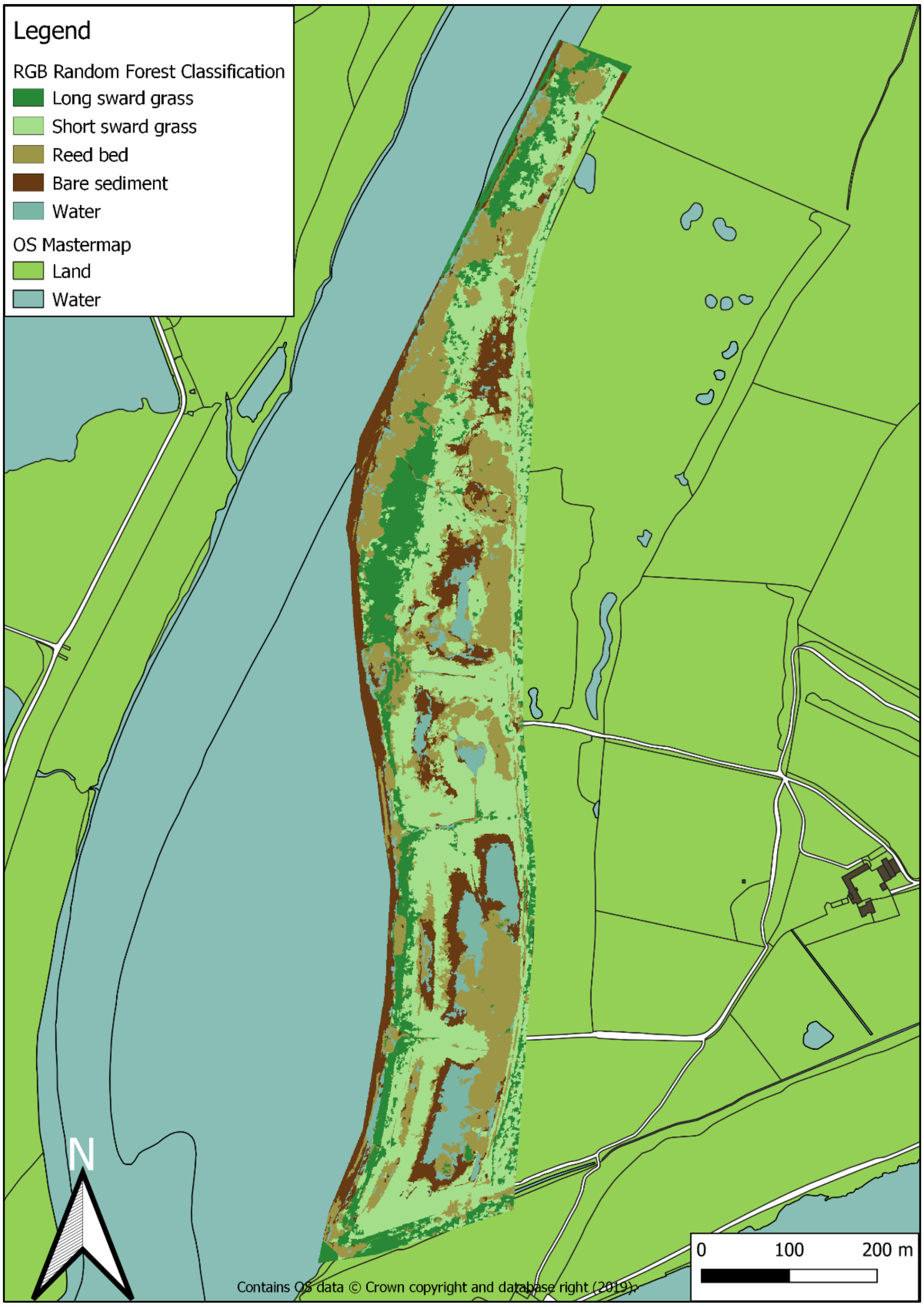
Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**46**	19	8	0	0	68	**60**	
Short sward grass	19	**149**	22	1	0	119	**78**	
Reed bed	4	26	**78**	21	2	136	**59**	
Bare sediment	0	3	4	**51**	26	25	**85**	
Water	0	1	11	7	**26**	24	**57**	
Total	64	198	123	80	30	**500**		
P_Acc	**64**	**75**	**63**	**63**	**86**		**69**	
Kappa								**0.58**

Contains OS data © Crown copyright and database right (2019).

Figure 5.11 – Support Vector Machine Classification for the RGB data set.

Table 5.3 – Confusion matrix for the RGB support vector machine classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**48**	20	9	2	0	79	**60**	
Short sward grass	18	**145**	19	4	0	186	**77**	
Reed bed	2	21	**80**	2	1	406	**75**	
Bare sediment	1	11	5	**65**	3	85	**76**	
Water	0	1	10	7	**26**	44	**59**	
Total	69	198	123	80	30	**500**		
P_Acc	**69**	**79**	**65**	**81**	**86**		**72**	
Kappa								**0.63**



Contains OS data © Crown copyright and database right (2019).

Figure 5.12 – Random forest Classification on the RGB data set.

Table 5.4 – Confusion matrix for the RGB random forest classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**39**	19	10	2	0	70	**55**	
Short sward grass	22	**145**	20	2	0	189	**76**	
Reed bed	2	25	**85**	6	5	123	**59**	
Bare sediment	1	8	4	**63**	3	79	**79**	
Water	0	1	4	7	**22**	34	**64**	
Total	64	198	123	80	30	**500**		
P_Acc	**60**	**79**	**69**	**78**	**79**		**71**	
Kappa								**0.61**

5.3.2 – RGB Interpretation

Table 5.5 – RGB classification summary.

RGB Data	**Maximum Likelihood**		**Support Vector Machine**		**Random Forest**	
Class	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)
Long sward saltmarsh	64.06	60.29	69.56	60.75	60.93	55.71
Short sward saltmarsh	75.25	78.01	73.23	77.95	73.23	76.71
Reed bed	63.41	59.54	65.04	75.47	69.10	69.10
Bare sediment	63.75	85.01	81.25	76.47	78.75	79.74
Water	86.66	57.77	86.66	59.09	73.33	64.70
Overall Accuracy (%)	**69.69**		**72.8**		**71.51**	
Kappa	**0.58**		**0.63**		**0.61**	

The final saltmarsh cover maps derived from the RGB image set are presented in Figures 5.10 – 5.12. An evaluation of the classification accuracy, calculated from the ground control points and presented as a confusion matrix, is presented in Tables 5.2 – 5.4 for each classification procedure respectively. Within these tables, 'P_Acc' and 'U_Acc' refers to the 'producer' and 'user' accuracy. A summary of classification accuracy and Kappa scores are presented in Table 5.4. The evaluation of the classification accuracy for these data show that the overall Kappa and overall accuracy are highest for the support vector machine technique, with 0.63 and 72.8 % respectively. This exceeds the random forest classification with a Kappa of 0.61 and overall accuracy of 71.51%. Maximum likelihood was the lowest with 69.69 % overall accuracy and 0.58 Kappa. The confusion matrices in Tables 5.2 – 5.4 allows determination of which features were associated with the correct cover class, and if they were not, which class they were allocated to. The two types of error derived from the confusion matrix are of omission and commission. An error of omission relates to a ground truth value of a certain class being misclassified as a different class during the classification produce, these classes can be identified by reading along the same row as the class round control point. This error contributes to the producer accuracy, or reliability, value displayed in the confusion matrices and summary tables. An error of commission means that the ground truth of other classes was included in a certain class, these are identified by reading the column of the cover class. Table 5.2 displays the matrix for the RGB maximum likelihood classification. From this, the main sources for errors of omission and commission can be seen, particularly within the vegetative classes, however there is some confusion between the classification of reed bed and bare ground. As sources of omission error in Table 5.2, 22 points of long sward grass resulted as the short sward class and 8 points as reed bed. Nineteen points of short sward were classed as long sward and 22 of reed bed. Of the reed bed ground truth, four were allocated to long sward, 26 to short sward, and 21 to bare sediment. Eleven points that were water were associated with reed bed and 7 as bare sediment. Errors of commission were very much similar in size, though they were marginally more precise overall which can be seen in the overall accuracy values in Table 5.5. Nineteen ground truth points belonging to the short sward class were allocated to long sward. Twenty-six of the reed bed class and 19 of the long sward were allocated to short sward. Twenty-two of the short sward points were allocated to reed bed and 21 of the reed bed class to bare sediment. Because of the misclassification between certain classes, it can be seen that long sward, reed bed, and the water classes have the lowest producer accuracy (Table 5.5). This reflects the probability that a class was correctly classified. The user accuracy is lowest in the water and reed bed class, which reflects the probability that a value predicted to be in a specific class, actually is assigned to that class. As is seen with the comparison between the three classifiers in the RGB imagery, the error values are extremely similar across the three. Despite the long sward class being separable in the reed bed, lack of separability in the remaining bands contributed to the moderate classification accuracy and reliance that a pixel was allocated to the correct class. The low separability is represented by the Jeffries-Matusita distance values as presented in Table 5.1

5.3.3 – Near Infrared Green and Blue (NGB) Image Classification

Following the methodology set out in Chapter 3, Section 3.2, the data presented in this section are the outcomes of three classification techniques that were conducted on the segmented NGB data set. Three classification maps are presented here, pertaining to the five saltmarsh cover classes associated with the habitat found at Upper Moss Side. A confusion matrix for each classification map is presented as an assessment of accuracy compared to the 500 ground control points. Outputs are presented in Figures 5.13 – 5.15 for the maximum likelihood, support vector machine, and random forest in turn. Tables 5.6, 5.7 and 5.8 relate to the confusion matrices for each classifier.

Figure 5.13 – Maximum likelihood classification on the NGB data set.

Table 5.6 – Confusion matrix for the NGB maximum likelihood classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**41**	12	4	0	0	57	**71**	
Short sward grass	9	**116**	11	8	0	144	**80**	
Reed bed	13	68	**106**	27	2	216	**49**	
Bare sediment	1	2	2	**44**	3	52	**84**	
Water	0	0	0	1	**25**	23	**93**	
Total	64	198	123	80	30	**500**		
P_Acc	**64**	**58**	**86**	**55**	**0.83**		**67**	
Kappa								**0.55**

Figure 5.14 – Support vector machine classification on the NGB data set.

Table 5.7 – Confusion matrix for the NGB support vector machine classification.

Class	**Long sward grass**	**Short sward grass**	**Reed bed**	**Bare sediment**	**water**	**Total**	**U_Acc**	**Kappa**
Long sward grass	**53**	27	12	0	0	92	**57**	
Short sward grass	10	**142**	29	6	1	188	**75**	
Reed bed	3	19	**80**	31	0	133	**60**	
Bare sediment	0	7	8	**43**	4	62	**69**	
Water	0	0	1	2	**22**	25	**88**	
Total	66	195	130	82	27	**500**		
P_Acc	**80**	**72**	**61**	**52**	**81**		**69**	
Kappa								**0.56**

Figure 5.15 – Random forest classification on the NGB data set.

Table 5.8 – Confusion matrix for the NGB random forest classification.

Class	Long sward grass	Short sward grass	Reed bed	Bare sediment	water	Total	U_Acc	Kappa
Long sward grass	**49**	5	0	0	0	54	**90**	
Short sward grass	13	**159**	7	1	0	180	**88**	
Reed bed	4	29	**12**	11	1	166	**72**	
Bare sediment	0	2	2	**70**	1	75	**93**	
Water	0	0	2	0	**25**	25	**1**	
Total	66	195	130	82	27	500	**0**	
P_Acc	**74**	**81**	**93**	**85**	**92**		**84**	
Kappa								**0.79**

5.3.4 – NGB Interpretation

Table 5.9 – NGB classification accuracy summary.

NGB Data	**Maximum Likelihood**		**Support Vector Machine**		**Random Forest**	
Class	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)	Producer's accuracy (%)	User's Accuracy (%)
Long sward Saltmarsh	64.06	71.92	80.30	57.60	74.24	90.74
Short sward Saltmarsh	58.58	80.55	72.82	75.53	81.53	88.33
Reed bed	86.17	49.07	61.53	60.15	93.07	72.89
Bare sediment	55.01	84.61	52.43	69.35	85.36	93.33
Water	83.33	96.15	81.48	88.01	92.59	100
Overall Accuracy	**67.07**		**68.01**		**84.8**	
Kappa	**0.55**		**0.56**		**0.79**	

The saltmarsh cover maps derived from the NGB image set are presented in Figures 5.13 – 5.15. An evaluation of the classification accuracy, calculated from the ground control points and presented as a confusion matrix, is presented in Tables 5.6 – 5.8 for each classification procedure respectively. A summary of classification accuracy and Kappa scores are presented in Table 5.9. The evaluation of the classification accuracy for these data shows that the overall Kappa and overall accuracy is highest for the random forest technique: 0.79 and 84.8 % respectively. This exceeds the support vector classification with a Kappa of 0.56 and overall accuracy of 68.01%. Maximum likelihood was the lowest with 67.07 % overall accuracy and 0.55 Kappa. Interestingly, the maximum likelihood and support vector classification were slightly lower than the RGB data set. The highest overall accuracy for this study is derived from the NGB data set. For the maximum likelihood classifier, the NGB images were classified the long sward with greater accuracy than the RGB image set by 0.11 % user accuracy and reliability. The short sward class included 68 points of reed bed as an error of commission, lowering the accuracy compared to the RGB data set. As a result of this, the reed bed class had a reduced reliability compared to the RGB with – 0.1 to the user accuracy at 0.49 %. Error of commission saw 27 points of reed incorrectly classified as bare sediment, further contributing to the decreased accuracy. The support vector classifier had less commission error than the RGB for the long sward class, with a producer accuracy of 80%, fewer pixels of short sward saltmarsh were mistakenly included in this class. The short sward class was classified similarly to the RGB data set: 0.02 difference in the producer accuracy and 0.02 for the user accuracy. For this classification, the bare sediment was the least accurate (52% producer accuracy) due to commission error including 31 points of reed bed as this class. The random forest classifier increased both user and producer accuracy across the five classes: 100% reliability in the water class, 93% for bare sediment, and 90% for the long sward class. Sources of error are derived from omission and commission between the long sward, short sward and reed bed classes, particularly where regions of short sward saltmarsh, long sward saltmarsh, and in some regions, bare sediment are incorrectly classed as reed bed. Despite this, the accuracy was still greater than the other methods. Across all three classifiers water was clearly the highest in reliability and accuracy. The long sward and bare sediment classes were the second and third best in user accuracy for the random forest classification (Table 5.9). This is represented in the Jeffries-Matusita values in Table 5.1, as the inclusion of the NIR band contributed to an increased distinction between vegetated and unvegetated classed. As random forest classifier utilising the camera with the NIR band produced the greatest classification accuracy, this will be used to calculate the habitat extent for Upper Moss Side. These values are presented in Table 5.10.

Table 5.10 – Habitat are in metres squared derived from the random forest classification of the NGB dataset for Upper Moss Side

Saltmarsh Cover Type	**Habitat Extent in Metres Squared (m^2)**
Long sward grass	39,401
Short sward grass	81,012
Reed bed	63,419
Bare sediment	10,742
Pools	12,378

5.4 – Summary

To address Research Objective One, and the Null Hypothesis One, the data presented in this chapter were used to further explore the line of enquiry initiated in Chapter 4, by further exploring methods in remote sensing, and their application to saltmarsh mapping. Overall, two broad contributions can be derived from the work presented in this chapter in relation to the application of these techniques to the remote sensing of saltmarshes. First, the UAV platform and its ability to capture very high spatial resolution imagery addresses the problems derived from the satellite remote sensing data in chapter 4, in that the problems derived from mixed pixels, and the less precise habitat representation are removed. A second contribution included in this chapter is to address the gaps within the literature by including camera which incorporates the NIR band into the classification of saltmarsh vegetation, and by testing the three classification procedures outline in Chapter 3, Section 3.1 (Pande-chhetri et al., 2017; Duffy et al., 2018). While the random forest classifier was clearly the most reliable and accurate within this study, further research is required within this field to determine the value of UAV systems for saltmarsh monitoring and whether the application of such a system is practical within the context of Ecosystem Vulnerability Assessment. The findings within this chapter are in agreement with the recently published literature confirming the random forest classifier an optimal approached compared to other machine learning techniques (support vector machine) and traditional approaches (maximum likelihood). The increase in performance of this classifier is related to the attribute that it performs well with data that has strong ‘noise’ i.e., within wetland ecosystems which contain hydrological fluctuations (Villa et al., 2015; Tian et al., 2016; Liu et al., 2020). Opportunities for further research are described in Chapter 8, in addition to a critical assessment of both techniques. Due to the highest accuracy being derived from the random forest classification, this data set will be utilised an input for the following two chapters, first, as a basemap to represent the ecological data at Upper Moss Side, and second, to contextualise the sea level rise analyses by displaying the extent of the potentially impacted habitat, i.e., the saltmarsh grassland.

Chapter 6 – Characterising Site Ecology and the Impacts of Management – Avian Biodiversity

Since the 1970s there has been a 56 % decline in species in the UK (Hayhow et al., 2016). As was described in Chapter 2, Section 2.7, there are two main attributing factors to this downward trend, habitat loss and deterioration. Continued loss of quality habitat has resulted in a fragmented landscape (Lawton, 2010). In the UK, the value of nature conservation is compounded by the fact that much of the land transformation that has contributed to these losses is to urban and agricultural land use, which interrupts the landscapes natural ecosystem process and ultimately reduces the landscapes ecosystem function (Zipperer, 2011). The recognition of these trends in the UK has prompted a greater move towards landscape linked restoration projects such as those currently an objective of the conservation NGOs, particularly the Wildlife Trusts' 'Living Landscapes', and RSPB's 'Futurescapes' (Adams et al., 2014). In 2010, a key document was published that underpins this focus. The Lawton Report – 'Making Space for Nature' – concluded that the current network of nature reserves in the UK is not sufficient to maintain ecological connectivity, and to reverse the negative impacts that we have seen on species and habitats requires a landscape scale approach to management. These landscape scale approaches require high quality, biodiverse sites to interconnect, enabling species to move between them. The recommendations of the Environment White Paper (Making Space for Nature, Lawton, 2010) are that the extant network of designated sites is managed better, a new series of Ecological Restoration Zones is established, and the current wealth of non-designated sites receive better protection (Lawton, 2010).

Fulfilling the recommendations of the Environment White paper, the Mersey Gateway Environmental Trust initiated a habitat improvement programme in 2016, with the key objective to improve avian biodiversity in both Cuerdley Marsh, on the north bank of the Mersey, and Upper Moss Side, known also as Norton Marsh on the south bank (Chapter 3, Figure 3.1). The work presented in this chapter investigates the change in avian communities across these two managed saltmarshes during 2015 – 2018. Within this chapter is a presentation of a selection of biodiversity data which are used support the data presented in Chapters 4, 5 and 7 by providing ecological context to the central knowledge generating themes of this thesis, that is to say, the development of a vulnerability analysis designed to communicate the pressures facing a wetland ecosystem to non-scientists and stakeholders through the use of remote sensing, habitat maps and sea level rise data. The data and analyses presented here are of secondary importance within this context and are not intended as central to the knowledge generating themes of the research. The analyses presented in this chapter addresses research objectives two and three and null hypothesis three (Section 2.10): Habitat management does not impact on bird populations using saltmarsh and reedbed estuarine vegetation. To address the null hypothesis, the following additional null-hypotheses were explored:

- Breeding territory is not influenced by habitat management period,
- There are no significant variations within species territory, richness and abundance between the management years,
- There is not significant difference between the managed habitat and the control group between species territory, richness and abundance.

6.1 – Site Ecology and Management

The Beyond our Bridges project was set up by the Mersey Gateway Environmental Trust (MGET) as part of a 30-year vision to provide lasting conservation benefit within the Upper Mersey Estuary. The project focuses on the saltmarsh and reed bed habitats present at key sites in the Upper Mersey Estuary (UME): Upper Moss Side and Cuerdley Marsh, both in the Borough of Warrington. Over a three-year timescale, appropriate practical management works were identified and initiated at each site in order to contribute to the conservation of nationally important breeding and wintering bird populations. These species are split into two broad groups related to their habitat type and are presented in Table 6.1. The majority of these species have experienced population declines in recent years, and conservation action is therefore a priority, specifically the Red and Amber list species described by Eaton et al., (2015). Mounting pressure on the populations of these species derived from habitat loss and climate change will only increase unless direct intervention is taken (Lawton et al., 2010; Eaton et al., 2015). Many of the warbler species, which are associated with the reedbed habitats, are migratory, and while two of these species (reed warbler and sedge warbler) are Green list species, these birds are still considered a priority due to their lifecycle and increased sensitivity to change, as changes to wintering habitat conditions can impact population success (Sanderson et al., 2006). Approximately 2 km downstream of the Upper Mersey Estuary, within which the study areas are situated, is the River Mersey Estuary Special Protection Area (SPA). This SPA is designated as it supports internationally important wintering bird populations (JNCC, 2017). Due to the close proximity of this significant area, a broad aim of the conservation project is to increase connectivity between the Upper Mersey and lower Mersey Estuary in terms of bird populations, such that increasing the suitable habitat available in the UME will increase the resilience of these populations to future change. As such, encouraging an increase in wetland species associated with the SPA, e.g., redshank (*Tringa totanus*), teal (*Anas crecca*) and shelduck (*Tadorna tadorna*) either wintering or breeding, would be a key measure of success for the conservation project (MGET, 2014).

Table 6.1 – Target species for the practical conservation work undertaken in the Upper Mersey Estuary (MGET, 2014).

Habitat Type	**Species**	**Conservation Status (Eaton et al., 2015)**
Saltmarsh	Skylark (*Alauda arvensis*)	Red
	Meadow pipit (*Anthus pratensis*)	Amber
	Lapwing (*Vanellus vanellus*)	Red
	Redshank (*Tringa totanus*)	Red
	Eurasian teal (*Anas crecca*)	Amber
	Pink footed goose (*Anser brachyrhynchus*)	Amber
Reedbed	Reed bunting (*Emberiza schoeniclus*)	Amber
	Marsh harrier (*Circus aeruginosus*)	Amber
	Grasshopper warbler (*Locustella naevia*)	Red
	Reed warbler (*Acrocephalus scirpaceus*)	Green
	Sedge warbler (*Acrocephalus schoenobaenus*)	Green
	Cetti's warbler (*Cettia cetti*)	Green

Across both sites, the Mersey Gateway Environment Trust managed different aspects of the available habitat during 2016 – 2018. This provides the opportunity to compare the management impacts of one site to the unmanaged equivalent at the other, which will serve as a control for the analysis. The key focus for the work undertaken at Cuerdley Marsh was the improvement of the reed bed habitat. This was achieved by establishing a seven-year reed bed cutting cycle. During the winters of 2016 and 2017, a network of approximately ten 10 x 10 m patches were cut into the reed beds (accounting for c. 15% of the habitat) using a brush cutter, shown in Figure 6.1 and an example of a cut area in Figure 6.2. This technique is utilised to remove the old reed litter, and dense old growth, and to limit the succession of the bed. The technique increases the structural variation of the reed bed, which in turn has been proven to increase biodiversity as many reedbed birds favour edges, or younger and less dense patches of reed for both breeding and feeding (RSPB, 2014).

Figure 6.1 – The brush cutter used for the practical habitat management – the BCS 630WS Max.

Figure 6.2 – An example of a 10 m^2 cut area of reed bed.

At Upper Moss Side, cattle grazing was utilised as a management technique. Cattle grazing is a long-established method of saltmarsh habitat intervention (Doody, 2008). In the Upper Mersey Estuary, a study undertaken on a grazing programme in 2011 identified clear links between avian biodiversity, and foliage density, and furthermore, an increase in the provision of key ecosystem services (Smith, 2013). When undertaking management at Upper Moss Side Farm the cattle were kept grazing year-round from late winter in 2016 but were taken off for the avian breeding season (March – July). The animals were stocked at a density of 1 animal per hectare, on a rotational basis. The land parcels of Upper Moss Side were split into three, and during the avian breeding season cattle were taken from the saltmarsh parcel to reduce the risk of nest trampling (Sharps et al., 2016). Belted Galloway and English Longhorn cattle were chosen as the grazers (Figure 6.3). These animals are hardy and can stay on pasture during the winter.

Figure 6.3 – The mixed herd of grazing cattle at Upper Moss Side.

The data presented in this chapter are utilised first, to determine whether any key breeding species are present within the study area to inform the sea level rise analysis in Chapter 7, and second, to determine whether there is any evidence that population fluctuations can be attributed to the period of habitat management.

6.2 – Methods

Throughout March – July during 2015 to 2018, Common Bird Census (CBC) breeding bird surveys were undertaken at Upper Moss Side and Cuerdley Marshes. This technique has been utilised to document the impact of the management practices implemented during the project on breeding bird populations, where the output of the analysis is a value for the number of breeding territories. The methodology for this technique is described in Chapter 3, Section 3.5.2.1. In addition to the surveys undertaken as part of the research presented here, the Mersey Gateway Environmental Trust supplied CBC data which was undertaken in 2015, as part of the pre-commencement baseline surveys for the saltmarsh conservation project (MGET, 2014).

In addition to the CBC surveys, a generic wintering bird survey based on the breeding bird survey route was undertaken for the remaining months (September – February) to determine the abundance of wintering birds across the study area, this is described in Section 3.5.2.2. The sum totals of all species, including non-breeding birds, were compiled for the purposes of comparison within this chapter. The breeding territories of key species were then overlain onto the UAV derived habitat map presented in the previous chapter for Upper Moss Side, in addition to other observations of key species of interest for this site, derived from CBC and the generic winter surveys, and community changes across the years of study. The species observation for Cuerdley Marsh will be presented on the basemap derived from the Water Adjusted Vegetation Index (WAVI) classification derived from Chapter 4.

For the purposes of analysis, the breeding species observed on the saltmarsh were assigned to two groups: saltmarsh species and reedbed species. Despite many other species being recorded across the study area, in hedgerows, or trees, these were excluded unless they were deemed to be species that are particularly associated with the habitat types. The timings of the habitat intervention allow for statistics to be undertaken as a function of the management period (i.e., pre-management and during), and the survey year. 2015 and 2016 represent the 'pre-management' condition of the study sites, 2017 and 2018 the 'during' management condition. The statistical analysis described in Chapter 3, Section 3.6 were then undertaken to address the sub-hypotheses and overarching null-hypotheses described at the beginning of this chapter.

The first sub-hypothesis, to determine whether the territory number of breeding bird species was influenced by the habitat management period, was addressed by calculating Mann Whitney-Wilcoxon statistics for the two species groups (saltmarsh and reedbed) against the habitat management period, i.e., before the management intervention had taken place, and during intervention. This was then extended to include the species richness and abundance of all species recorded during the surveys between 2016-2018. The second hypothesis was to determine whether any significant variations within species territory, richness or abundance could be attributed specific years, this was tested with a Kruskal-Wallis test. Third, these tests were repeated to look at variation between the managed habitat and the control sites to determine whether management significantly affected the species group. As with the second hypothesis a Kruskal-Wallis test was used. The diversity profiles technique will accompany these analyses to visualise any significant changes reported by the models.

6.3 – Results

6.3.1 – Habitat Area

The total habitat area was derived from the UAV habitat map from Upper Moss Side (presented in Chapter 5), and the Sentinel-2 WAVI classification map for Cuerdley Marsh, these values are presented in Table 6.2. These values of habitat area represent the post-management period at each of the two saltmarshes. Upper Moss Side holds a much larger area of short sward grass habitat in comparison to Cuerdley, as a result of the grazing regime implemented by the MGET. Both saltmarshes hold a moderate reed bed resource, though the reed bed at Cuerdley Marsh is 21,779 m^2 greater in area, approximately 13,000 m^2 of this habitat was mown each year as part of the cutting cycle, and the removal of c. 15% of the mature reed bed.

Table 6.2 – Measurement of area in metres squared derived from the WAVI classification for Cuerdley Marsh, and the NIR random forest UAV image.

Saltmarsh Cover Class	**Cuerdley Marsh Area m^2**	**Upper Moss Side Area m^2**
Long sward grass	164,252	39,401
Short sward grass	4,721	81,012
Reed bed	85,198	63,419
Bare sediment	1,742	10,742
Water	113	12,378

6.3.2 – Common Bird Census Breeding Bird Surveys

6.3.2.1 – Cuerdley Marsh

The outcome of the Common Bird Census territory analyses for Cuerdley Marsh and Upper Moss Side respectively are presented in Tables 6.3 – 6.5. Within these tables, only the territories of species tied to the two habitat types are presented, these being saltmarsh and reedbed breeding birds.

During the CBC surveys at Cuerdley marsh, only two species were recorded holding breeding territory within the saltmarsh itself (Table 6.3). Skylark (*Alauda arvensis*) held at least one territory between 2015 – 2017 with a peak of three in 2017. During the 2018 season, this species was not recorded holding territory at Cuerdley Marsh. The second species recorded within the saltmarsh habitat of Curedley Marsh was the meadow pipit (*Anthus pratensis*), which held territory consistently through the four survey years, with a peak in 2017 of 20 territories, and a minimum in 2015 of three.

Table 6.3 – Breeding territory at Cuerdley Marsh during the three monitoring years for saltmarsh species.

Species	**2015 Territory**	**2016 Territory**	**2017 Territory**	**2018 Territory**	**Conservation Status**
Meadow pipit	3	15	20	14	Amber
Skylark	1	1	3	0	Red

There were more species breeding in the reed bed habitat at Cuerdley Marsh, with five species recorded as holding territory throughout the survey years (Table 6.4). Cetti's warbler (*Cettia cetti*) showed a steady increase in territory through the study years, from zero held in 2015, to four in 2018. Grasshopper warbler (*Locustella naevia*) only held territory in 2018 at Cuerdley Marsh. Sedge warbler (*Acrocephalus schoenobaenus*), reed warbler (*Acrocephalus scirpaceus*) and reed bunting (*Emberiza schoeniclus*) were present during every survey year. Peak sedge warbler territory was recorded in 2017 and 2018 with six held. Peak reed warbler territory was in 2016 with 25 held, and reed bunting 2016 with 38 held. Figures 6.4 – 6.7 show the approximate territory locations, and changes thereof, at Cuerdley Marsh during the 4 years CBC surveys were undertaken. This data is presented Sentinel-2 WAVI classification map, as this was the vegetation with the highest accuracy for Cuerdley Marsh.

Table 6.4 – Breeding territory at Cuerdley Marsh during the three monitoring years for reedbed species.

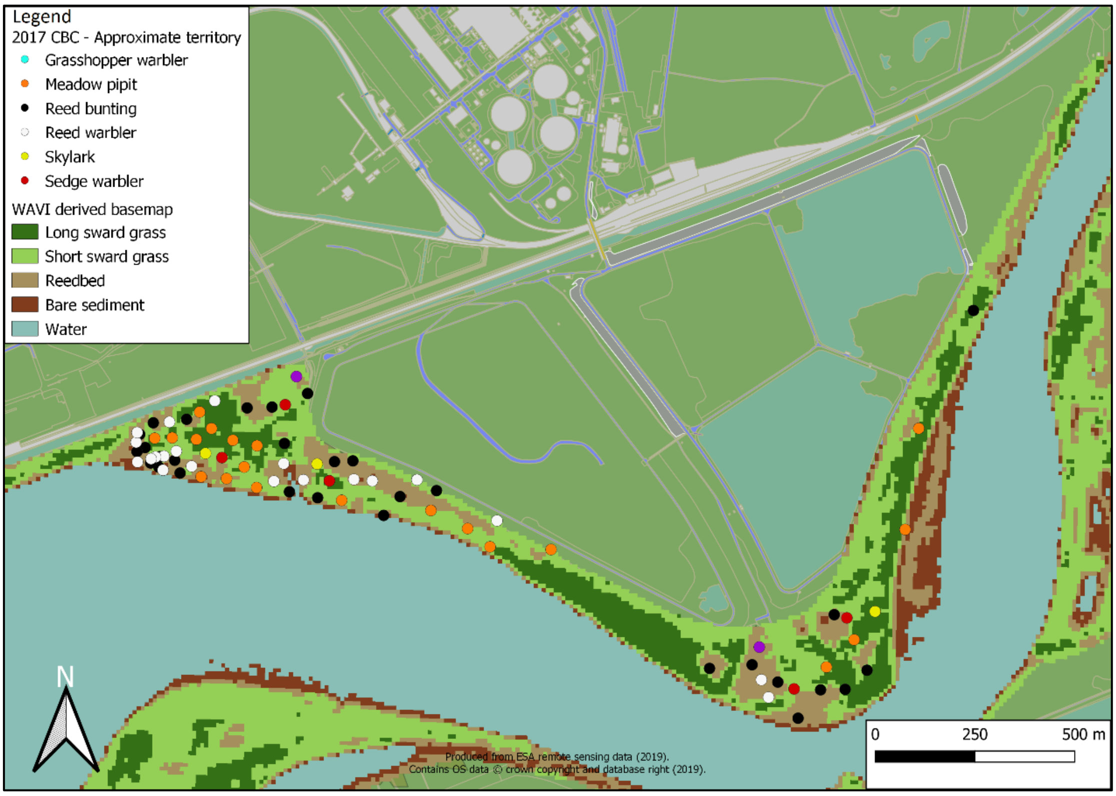
Species	2015 Territory	2016 Territory	2017 Territory	2018 Territory	Conservation Status
Cetti's warbler	0	2	2	4	Green
Grasshopper warbler	0	0	0	1	Red
Reed bunting	34	38	30	30	Amber
Reed warbler	17	25	20	21	Green
Sedge warbler	2	2	6	6	Green

The territories derived from the 2015 - 2018 CBC surveys show that there has been a increase in the reed bunting territories recorded at Cuerdley Marsh (of +13 across the four study years), and a decrease in reed warbler territory (-12) overall during the monitoring period. Meadow pipit territories increased by 17 between 2015 and 2017, and then decreased by 6 during 2018. An increase was seen in sedge warbler (+4) and skylark (+2) by 2017.

Figure 6.4 – Approximate centres of territory for the reedbed and saltmarsh species at Cuerdley Marsh, derived from the 2015 CBC survey data provided by the MGET.

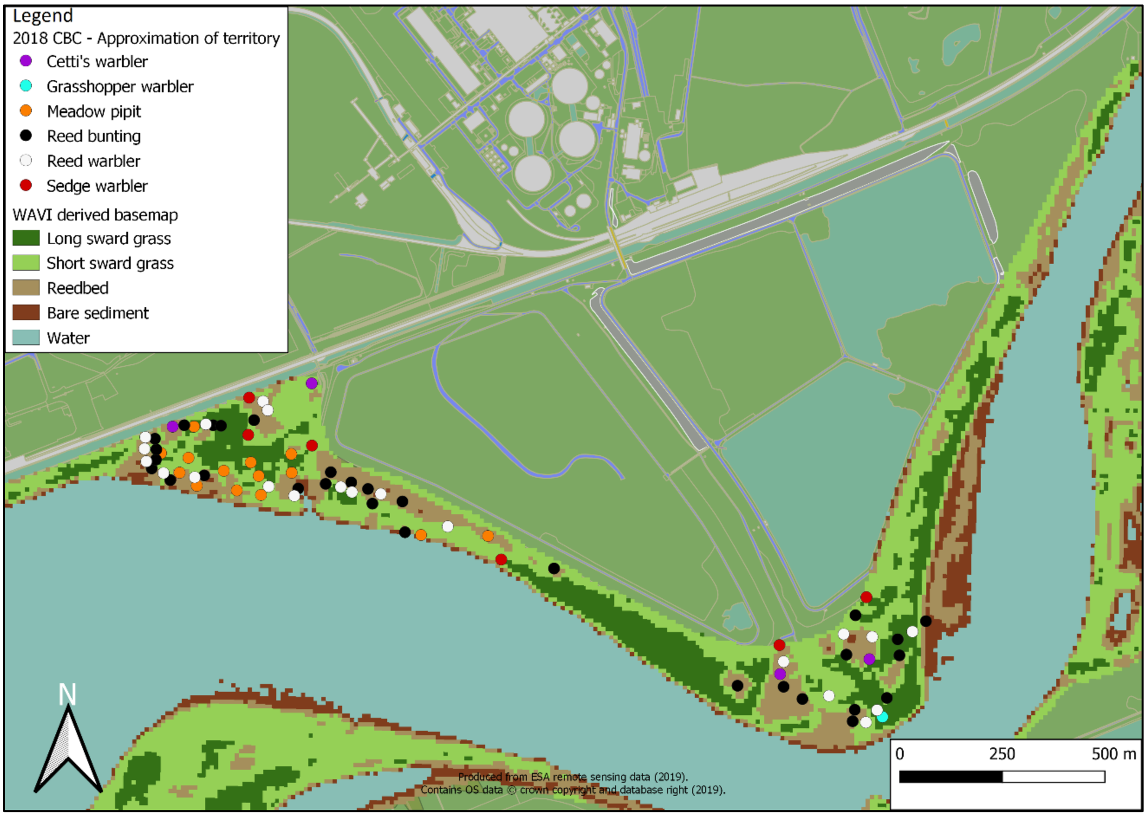
Produced from ESA remote sensing data (2019).
Contains OS data © crown copyright and database right (2019).

Figure 6.5 – Approximate centres of territory for the reedbed and saltmarsh species at Cuerdley Marsh, derived from the 2016 CBC surveys.



Produced from ESA remote sensing data (2019).
Contains OS data © crown copyright and database right (2019).

Figure 6.6 – Approximate centres of territory for the reedbed and saltmarsh species at Cuerdley Marsh, derived from the 2017 CBC surveys.



Produced from ESA remote sensing data (2019).
Contains OS data © crown copyright and database right (2019).

Figure 6.7 – Approximate centres of territory for the reedbed and saltmarsh species at Cuerdley Marsh, derived from the 2018 CBC surveys.

6.3.2.2 – Upper Moss Side

At Upper Moss Side, four species were recorded breeding on the saltmarsh habitat during the survey years (Table 6.5). Meadow pipit were recorded holding territory between 2016-2017 with 5 territories held in the final two years. Northern lapwing (*Vanellus vanellus*), were recorded in 2017 and 2018 with three and four territories held respectively. Redshank (*Tringa totanus*) were recorded holding territory in only the final year, with two observed. Skylark were recorded holding territory during each survey year with a peak of six in 2015, and the low of one in 2017. Figures 6.8 – 6.11 show the approximate territorial centres, and changes to species composition, for the key reedbed and saltmarsh species present throughout the 2015 – 2018 CBC surveys. This data is presented within the context of the habitat map derived from the UAV remote sensing data presented in Chapter 5.

Table 6.5 – Breeding territory at Upper Moss Side during the monitoring years for saltmarsh species.

Species	2015 Territory	2016 Territory	2017 Territory	2018 Territory	Conservation Status
Meadow pipit	0	4	5	5	Amber
Northern lapwing	0	0	3	4	Red
Redshank	0	0	0	2	Amber
Skylark	6	5	1	4	Red

Within the reed bed habitat, four species were recorded (Table 6.6), all of which were recorded as present during each survey year. Grasshopper warbler held peak territory count of four during 2016, reed bunting of 36 during 2016, reed warbler of 26 during 2015, and sedge warbler of 6 during 2016.

Table 6.6 – Breeding territory at Upper Moss Side during the monitoring years for reedbed species.

Species	2015 Territory	2016 Territory	2017 Territory	2018 Territory	Conservation Status
Grasshopper warbler	2	4	2	2	Red
Reed bunting	27	36	33	30	Amber
Reed warbler	26	21	25	20	Green
Sedge warbler	5	6	5	5	Green

At Upper Moss Side, reed bunting territories increased initially by 9 between 2015 – 2016 but decreased by three each of the remaining years. A decrease was seen in skylark (-4) between 2015/2017, however skylark breeding territories increased in 2018 to 4. Sedge warbler remaining stable with 5 across most years with and increase to 6 in 2016. Reed warbler territories increased by 4 between 2016 and 2017, as did meadow pipit by 1, and whitethroat by 1. By 2018 reed warbler territories had decreased by 5. Northern lapwing territories were recorded for the first time within the project with 3 territories centred on the area of the newly created and restored scrape in 2017, and a further territory was recorded in 2018. Two redshank territories were also recorded by 2018.

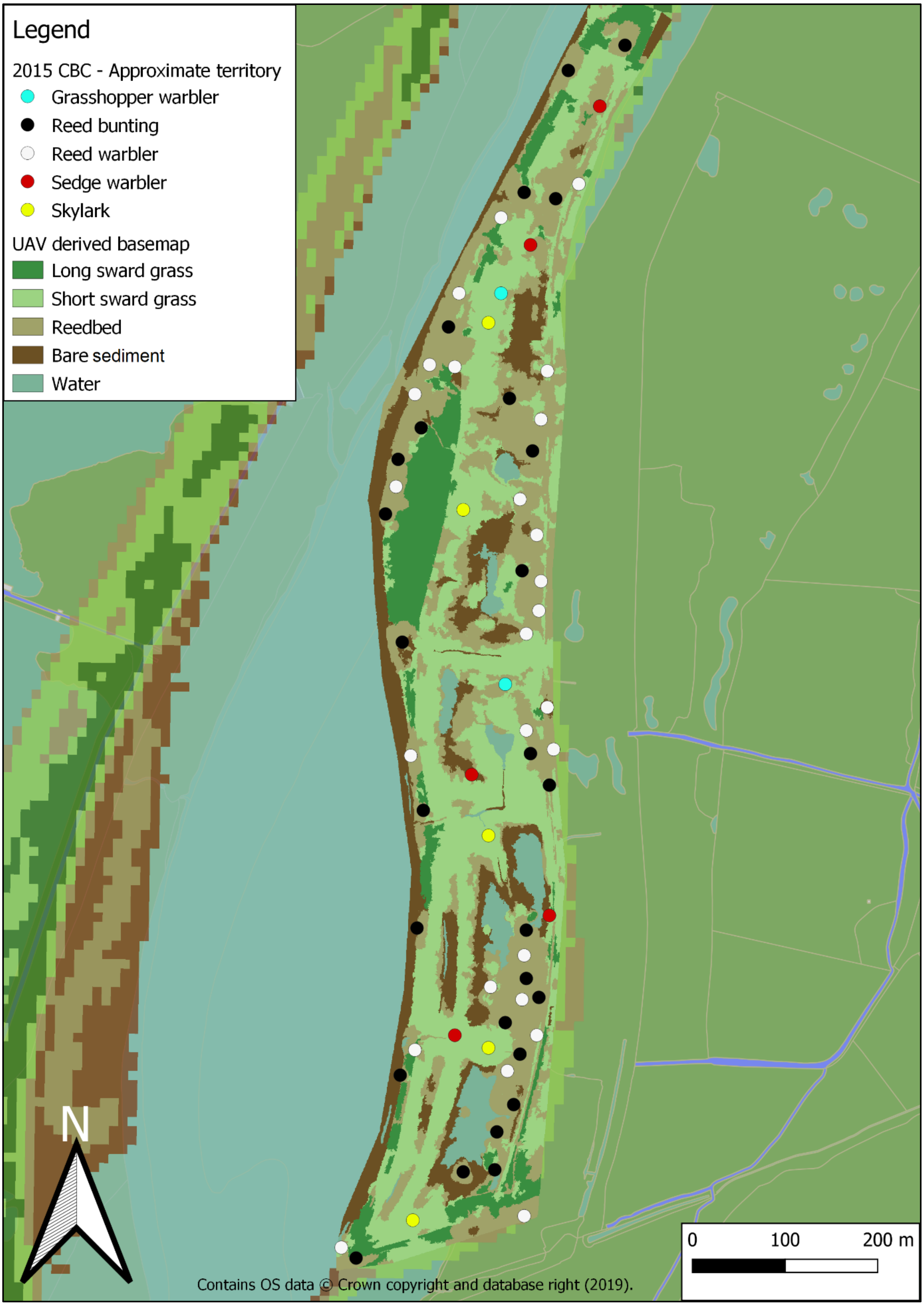
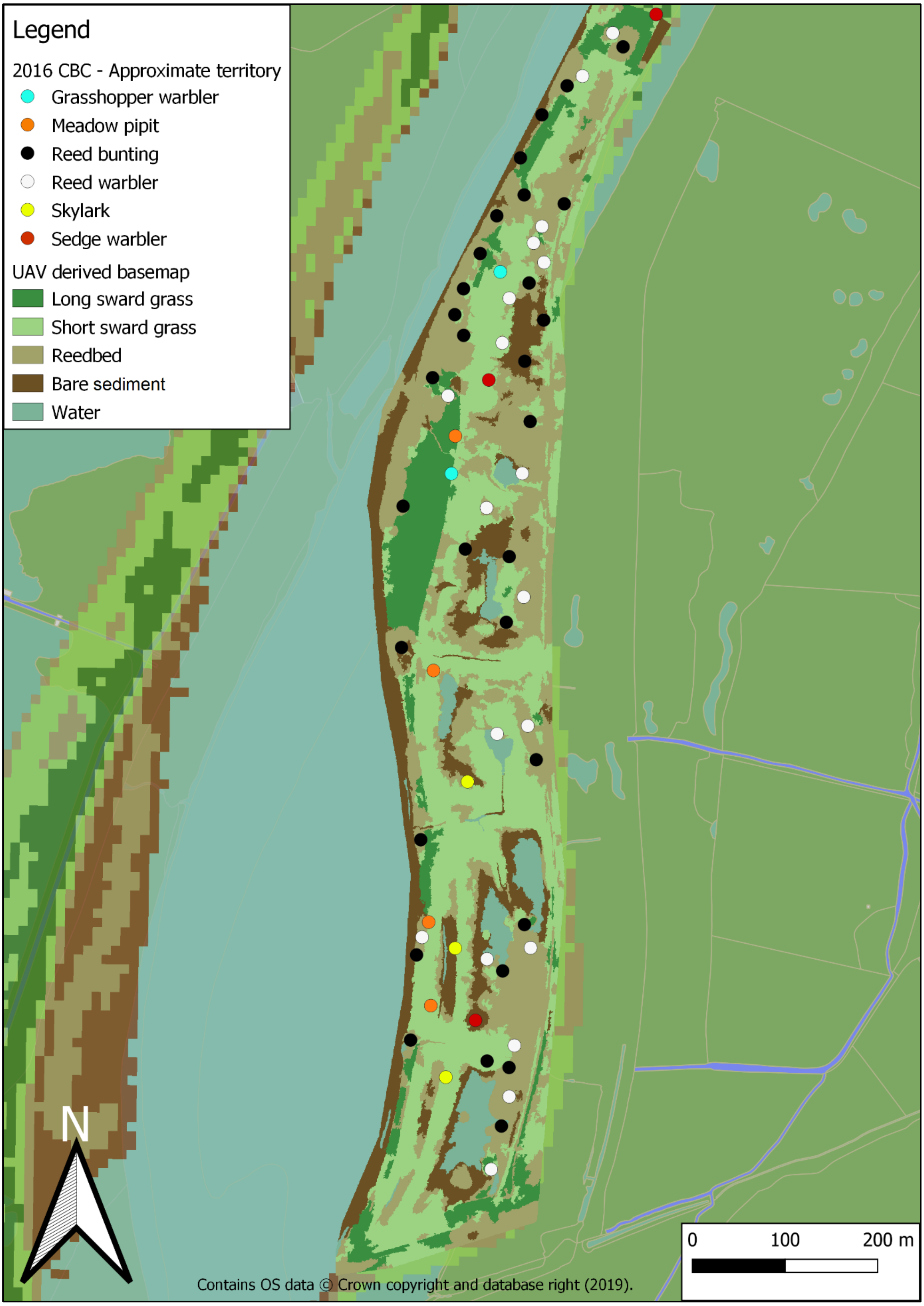


Figure 6.8 - Approximate territorial centres for the reedbed and saltmarsh species at Upper Moss Side, derived from the 2015 CBC survey data provided by the MGET.



Contains OS data © Crown copyright and database right (2019).

Figure 6.9 - Approximate territorial centres for the reedbed and saltmarsh species at Upper Moss Side, derived from the 2016 CBC survey data.

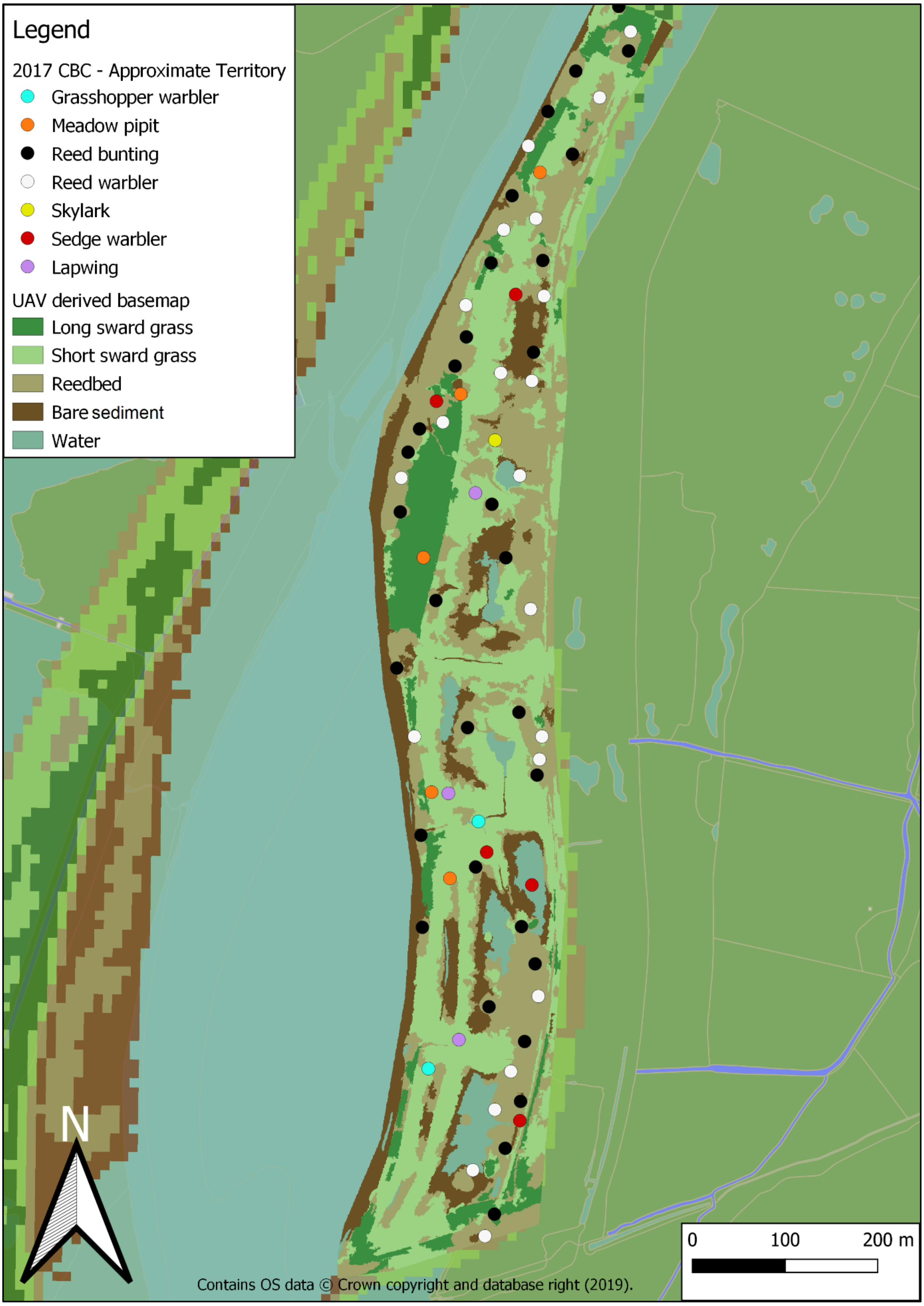


Figure 6.10 - Approximate territorial centres for the reedbed and saltmarsh species at Upper Moss Side, derived from the 2017 CBC survey data.

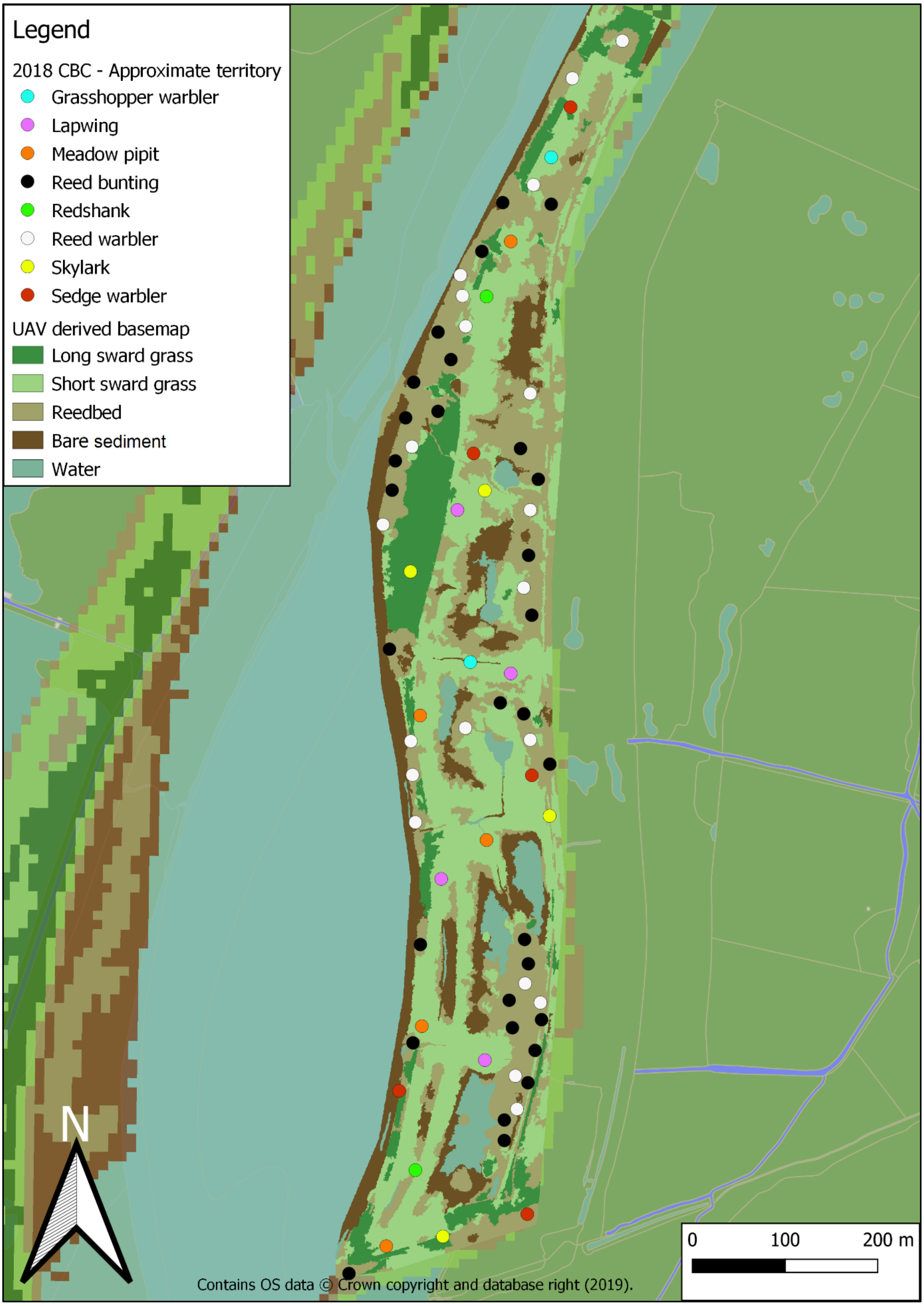


Figure 6.11 - Approximate territorial centres for the reedbed and saltmarsh species at Upper Moss Side, derived from the 2018 CBC survey data.

6.3.3 – Statistical Analysis of Bird Survey Data

6.3.3.1 – Common Bird Census Territory

From the statistical analyses, the null hypothesis has to be accepted, and it can be concluded that the habitat management period, that is to say, before or during habitat management, had no significant effect on the number of held territories within the two groups of breeding birds. This result was returned across of the saltmarshes within the study area and these are presented in Tables 6.7 and 6.8. Despite this, the mean territory during management was higher for all species groups and habitat types than the pre-management value, except for the reedbed species at Upper Moss Side.

Table 6.7 – Mann Whitney-Wilcoxon analysis of the bird territories at Cuerdley Marsh before, and during management. The value in brackets is the range of the recorded territory.

Cuerdley Marsh Species	**Mean territory before management**	**Mean territory during management**	**Mann Whitney-Wilcoxon score**
Saltmarsh			
Meadow pipit	9 (3-15)	17 (14-20)	
Skylark	1 (1)	2 (2-3)	W = 17, P=0.878
Reedbed			
Reed bunting	28 (17-38)	30 (30)	
Reed warbler	29 (25-34)	21 (20-21)	
Grasshopper warbler	0	1 (0-1)	
Sedge warbler	2 (2)	6 (6)	
Cetti's warbler	1 (0-2)	3 (2-4)	W = 25, P=0.676

Table 6.8 – Mann Whitney-Wilcoxon analysis of the bird territories at Upper Moss Side before, and during management. The value in brackets is the range of the recorded territory.

Upper Moss Side Species	**Mean territory before management**	**Mean territory during management**	**Mann Whitney-Wilcoxon score**
Saltmarsh			
Meadow pipit	2 (0-4)	5 (5)	
Skylark	6 (5-6)	3 (1-4)	
Lapwing	0	1 (0-2)	
Redshank	0	4 (3-4)	W = 15, P = 0.468
Reedbed			
Reed bunting	32 (27-36)	32 (30-33)	
Reed warbler	24 (21-26)	23 (20-25)	
Grasshopper warbler	3 (2-4)	2 (2-2)	
Sedge warbler	6 (5-6)	5 (5-5)	W = 29, P = 0.834

6.3.3.2 – Between Year Variation in Bird Communities

In order to extend the analysis and to address the second hypothesis, a Kruskal-Wallis test was applied to all the survey years. In addition to the summer species breeding territory, the species richness and abundance taken from all survey years was incorporated. This included the counts made during the summer CBC surveys as well as the counts recorded during the generic wintering bird surveys.

There was no significant between year effect observed within the saltmarsh and reedbed habitats of Cuerdley Marsh between any of the response variables across the four survey years (Table 6.9). As no significant result was returned, no post-hoc testing was conducted between the individual years.

Table 6.9 - Kruskal-Wallis test between all study years, incorporating abundance and richness measures.

Response Variable	**Comparison between all years (2016 -2018) Kruskal-Wallis test**
Saltmarsh Territory	H = 1.963, P = 0.407
Saltmarsh Abundance	H = 1.954, P = 0.727
Saltmarsh Richness	H = 1.941, P = 0.391
Reedbed Territory	H = 0.614, P = 0.891
Reedbed Abundance	H = 0.192, P = 0.942
Reedbed Richness	H = 1.143, P = 0.498

There was no significant difference between the species measures of the reedbed habitats at Upper Moss Side. The test did return a significant difference (H = 4.15, P = 0.012) for the species richness response variable at this site for the saltmarsh community, and this does indeed translate to a significant increase in total biodiversity. Post-hoc testing, utilising the Mann Whitney-Wilcoxon test (including the Bonferroni adjustment to counteract the problem of multiple comparisons and, as a result of this, results where P < 0.01 are considered significant), returned a significant (P = 0.01) between the year of 2016 and 2017 at this site. These results are presented in Table 6.10.

Table 6.10 - Kruskal-Wallis test between all study years, incorporating abundance and richness measures.

Response Variable	**Comparison between all years (2016-2018) Kruskal-Wallis test**	**2016-2017 (Post-hoc Mann-Whitney-Wilcoxon Test)**
Saltmarsh Territory	H = 1.77, P = 0.595	
Saltmarsh Abundance	H = 4.88, P = 0.08	
Saltmarsh Richness	**H = 4.15, P = 0.0121**	**P = 0.01**
Reedbed Territory	H = 0.14, P = 0.985	
Reedbed Abundance	H = 1.85, P = 0.755	
Reedbed Richness	H = 0, P = 1	

To visualise these changes, and to determine whether the significant different in richness can also be represented as a difference in site biodiversity, the total data utilised in the statistical analysis were plotted as a diversity profile. This includes the full set of records of all species seen interacting with the habitat types over the three-year period, and the data is plotted with the 95% confidence interval to reflect significant difference within the plot. Figure 6.12 displays the data for the saltmarsh group of species for the two survey years at Upper Moss Side, from which the significant difference between species richness data was derived from the Kruskal-Wallis test. The profile indicates a clear separation within the plot line for 2016 and 2017, with the latter year being unambiguously more diverse than 2016. A conclusion can be drawn then that the significant difference between the two survey years does indeed translate to a significant different by an increase in total biodiversity. This contains the total abundance data derived from the surveys at Upper Moss Side over the survey years for the saltmarsh species group. None of the other species groups showed a clear distinction in the biodiversity order as the plots either overlapped, or the confidence intervals overlapped.

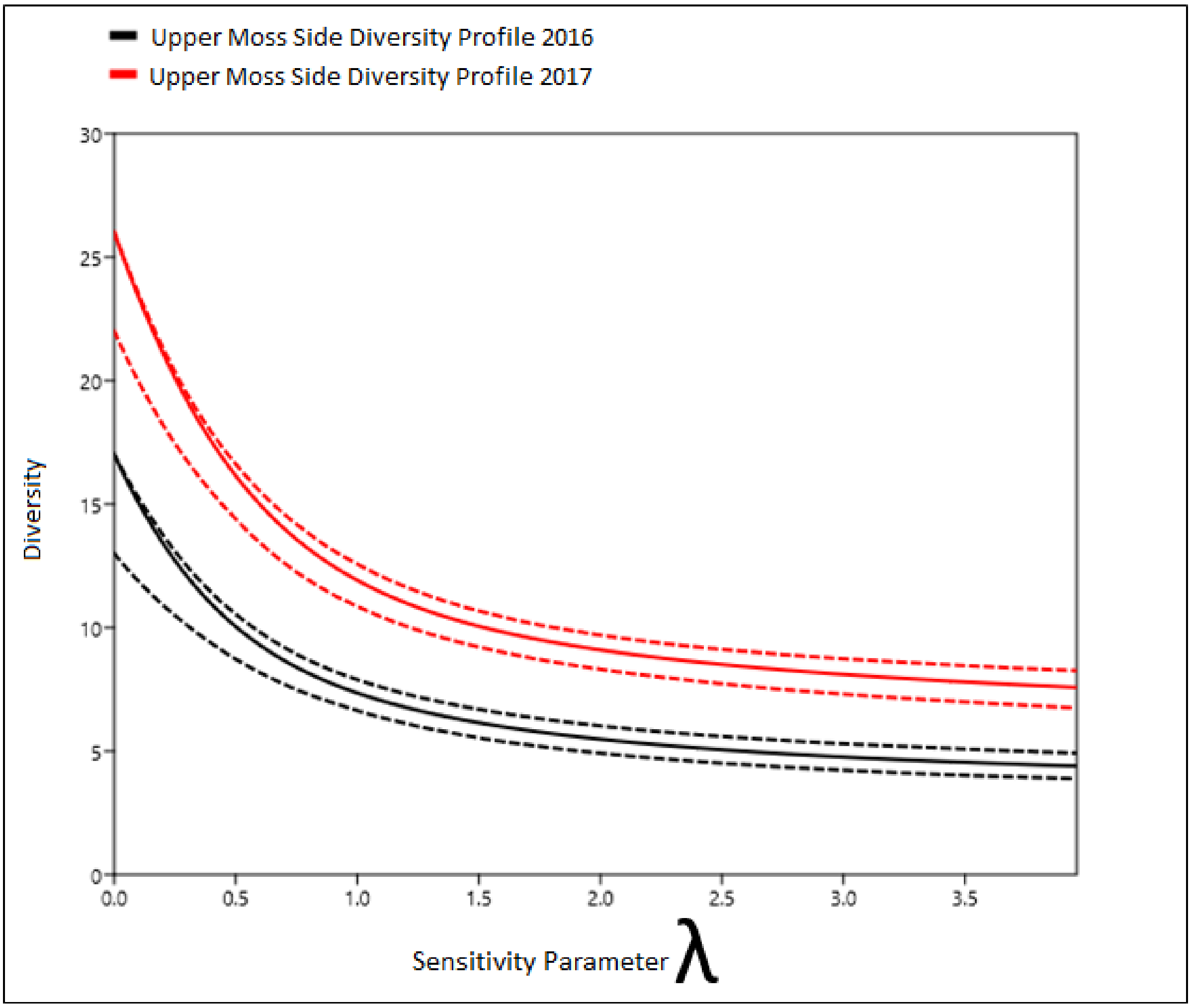


Figure 6.12 – Diversity profile between 2016 and 2017 at Upper Moss Side, the plot shows an unambiguous increase in the saltmarsh biodiversity between the two years. The dashed lines represent the confidence intervals.

This difference between biodiversity order as displayed in Figure 6.12, and the significant difference between these two years coincides with the habitat management, which was undertaken at Upper Moss Side saltmarsh, i.e., cattle grazing to provide a more favourable grass sward. Within the data presented in Table 6.11, derived from the total annual species abundance for the saltmarsh group, the green highlighted rows represent species which were observed using the habitat following the management intervention. These species are presented within the context of the habitat map in Figure 6.13 which represents the increase of wetland species between the years 2016-2017, and visualises the increase in biodiversity, and the significant change in composition as reported by this study.

Table 6.11 – Summary of annual abundance of saltmarsh species present at Upper Moss Side. Rows highlighted in green represent the addition of a species, or an increase in abundance following the management year.

Species	**2016**	**2017**	**2018**	**Species**	**2016**	**2017**	**2018**
Black headed gull	40	51	36	Meadow pipit	46	34	36
Canada goose	0	76	69	Moorhen	0	2	3
Cetti's warbler	2	0	0	Pink footed goose	0	65	97
Curlew	0	13	20	Redshank	0	5	8
Gadwall	2	9	0	Ringed plover	0	2	3
Grey heron	0	5	3	Shelduck	11	4	5
Grey partridge	14	4	0	Shoveler	0	2	3
Greylag goose	1	10	8	Skylark	34	9	11
Jack snipe	0	2	3	Snipe	113	78	62
Kingfisher	1	1	1	Teal	150	125	10
Lapwing	0	115	86	Tufted duck	0	12	13
Linnet	3	3	2	Wheatear	4	6	4
Little egret	0	4	3	Wigeon	10	0	0
Little grebe	0	1	1	Wren	58	54	11

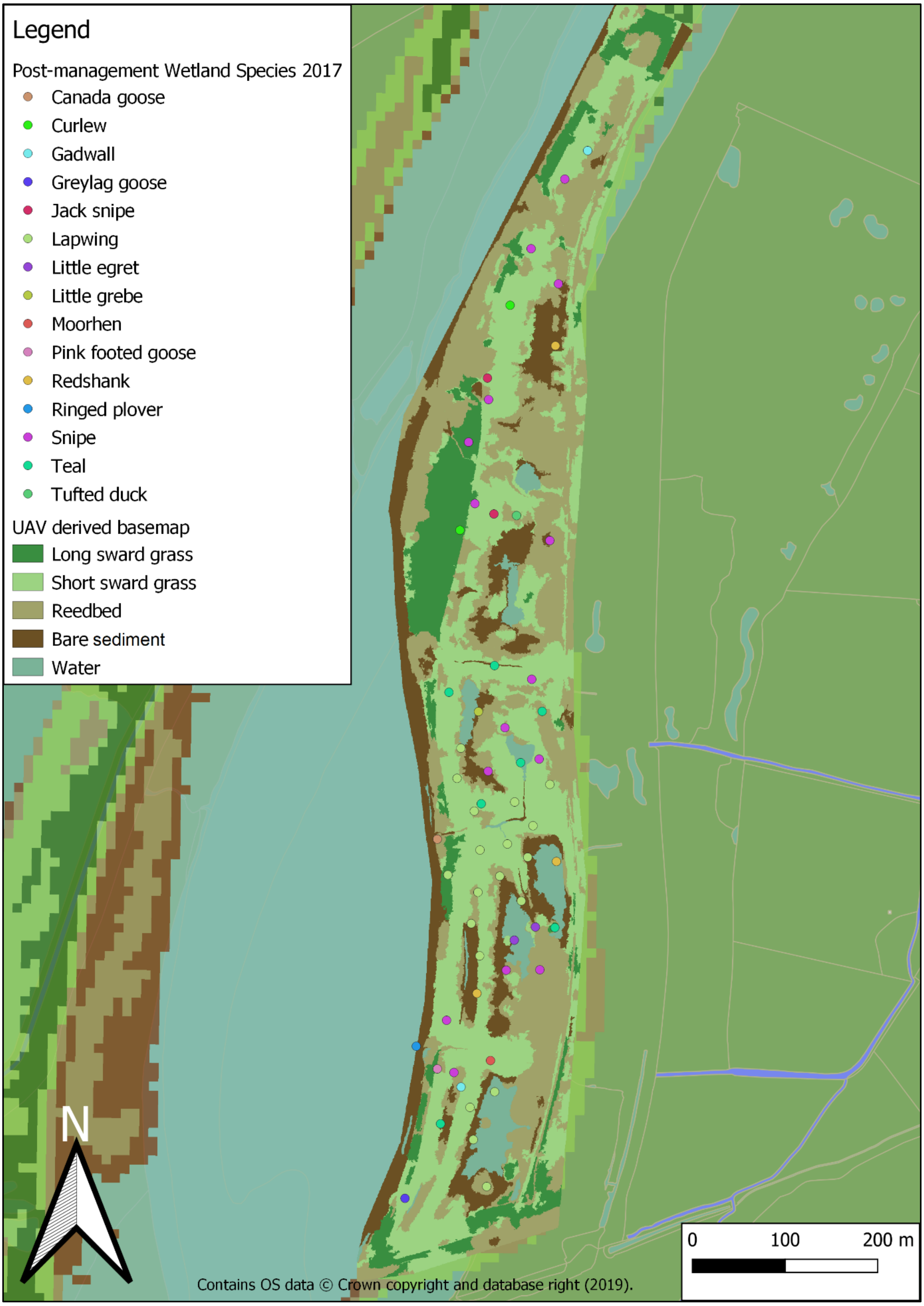


Figure 6.13 – Post-management increase of wetland species, 2017, presented within the context of the Upper Moss Side habitat map.

6.3.3.3 – Between Site Variation in Bird Communities

Tables 6.12 and 6.13 present the outcome of the statistical comparison between each of the study sites before and during management. Both sites contained the same collection of habitats, i.e., reedbed and saltmarsh, however, management for each was undertaken separately at each site. At Cuerdley Marsh only reedbed management was undertaken, leaving the saltmarsh grass sward in an uncut state, at Upper Moss Side only the saltmarsh was managed, leaving the reedbeds. Using each respective unmanaged habitat type as a control, the outcome of the analysis on the breeding bird territories demonstrate that there was no significant difference between the two sites before or during the management interventions.

Table 6.12 - Mann Whitney-Wilcoxon analysis of the bird territories at Cuerdley Marsh and Upper Moss Side before habitat management, years 2015 and 2016. The value in brackets is the range of the recorded territory.

Species Group	**Mean territory before management – Cuerdley Marsh**	**Mean territory before management – Upper Moss Side**	**Mann Whitney-Wilcoxon score**
Saltmarsh			
Meadow pipit	9 (3-15)	2 (0-4)	
Skylark	1 (1)	6 (5-6)	
Lapwing	0	0	
Redshank	0	0	W = 18, P = 1
Reedbed			
Reed bunting	28 (17-38)	32 (27-36)	
Reed warbler	29 (25-34)	24 (21-26)	
Grasshopper warbler	0	3 (2-4)	
Sedge warbler	2 (2)	6 (5-6)	W = 25.5, P = 0.754
Cetti’s warbler	1 (0-2)	0	

Table 6.13 - Mann Whitney-Wilcoxon analysis of the bird territories at Cuerdley Marsh and Upper Moss Side during habitat management, years 2017 and 2018. The value in brackets is the range of the recorded territory.

Species Group	**Mean territory during management – Cuerdley Marsh**	**Mean territory during management – Upper Moss Side**	**Mann Whitney-Wilcoxon score**
Saltmarsh			
Meadow pipit	17 (14-20)	5 (5)	
Skylark	2 (2-3)	3 (1-4)	
Lapwing	0	1 (0-2)	
Redshank	0	4 (3-4)	W = 15, P = 0.471
Reed bed			
Reed bunting	30 (30)	32 (30-33)	
Reed warbler	21 (20-21)	23 (20-25)	
Grasshopper warbler	1 (0-1)	2 (2-2)	
Sedge warbler	6 (6)	5 (5-5)	W = 17, P = 0.885
Cetti’s warbler	3 (2-4)	0	

To determine whether there was a variation between the control sites (Cuerdley saltmarsh and Upper Moss Side reed bed), versus the managed sites (Cuerdley reedbed and Upper Moss Side saltmarsh), a Kruskal-Wallis test was undertaken individually on all of the collected to compare the response variables for each year. The outcome of each test is presented in Table 6.14. There was no significant difference between the control sites vs the managed sites for any of the survey years. As the richness between the saltmarsh variable showed the value closest to the significance threshold, a post-hoc Mann Whitney-Wilcoxon test was undertaken. This returned the significant result between the Upper Moss Side communities between 2016 and 2017, and also a P-value of 0.03 between the saltmarsh communities of the control site (Cuerdley Marsh) and the managed site (Upper Moss Side). This coincides with the period where management was introduced to Upper Moss Side and the reported significant increase in species richness and biodiversity. However, as P = 0.03, this cannot be interpreted as truly statistically significant following the Bonferroni adjustment required when comparing multiple samples.

Table 6.14 – Kruskall-Wallis test undertaken individually for all survey years between the control sites and managed site for each species group.

Response Variable	**Comparison between all years (2016-2018) Kruskal-Wallis test**	**Post-hoc Mann Whitney-Wilcoxon Test**	
Saltmarsh Territory	H = 3.705, P = 0.763		
Saltmarsh Abundance	H = 6.825, P = 0.216		
Saltmarsh Richness	H = 5.304, P = 0.143	**P = 0.01**, 2016 vs 2017 Upper Moss Side	P = 0.03, 2016 Cuerdley Marsh vs 2017 Upper Moss Side
Reedbed Territory	H = 0.7866, P = 0.997		
Reedbed Abundance	H = 0.6215, P = 0.986		
Reedbed Richness	H = 0.4898, P = 0.947		

6.4 – Summary

To determine the relative impacts of both the habitat management schemes implemented by coastal managers and to determine community impacts from environmental change, long-term monitoring programmes need to be initiated. In this chapter the data presented were collected to enable the characterisation of site ecology in the Upper Mersey Estuary targeting avifauna. The identified species were associated with the two key habitat types, saltmarsh and reedbed, and within these species groups, several species of key importance and value in the Upper Mersey Estuary, and estuaries globally, were identified (Doody et al., 2004). From the CBC breeding bird surveys, it was determined that, overall, there have been four species of ground nesting bird that utilise the saltmarshes to breed during the period studied, and five in total within the reedbed. These species are split into two groups: passerines – generally known as perching birds – and non-passerines which in this case include two species of wading bird. The recorded breeding passerines were the skylark (*Alauda arvensis)* and the meadow pipit (*Anthus pratensis*) ground nesting within the saltmarsh, and reed bunting (*Emberiza schoeniclus*), reed warbler (*Acrocephalus scirpaceus*), sedge warbler (*Acrocephalus schoenobaenus*), grasshopper warbler and Cetti's warbler (*Cettia cetti*) within the reedbeds. The wading species recorded were the northern lapwing (*Vanellus vanellus*) and redshank (*Tringa totanus*). All these species were included as target species in the Mersey Gateway Environmental Trusts' management targets (Mersey Gateway Environment Trust, 2015). The two breeding territories held by redshank signify the uptake of the favourable saltmarsh habitat by one of the SPA key species of the Mersey Estuary downstream. The increase in foraging birds associated with the favourable habitat, following the management intervention at Upper Moss Side could represents the increase in ecological connectivity within the estuary entire, as SPA species such as teal were recorded, along other sensitive winter migrants, such as pink footed goose. The records of the breeding territories for the saltmarsh breeding birds will be included in the following section (Chapter 7) as a targeted study on the impacts of climate change derived sea level rise.

The statistical analysis presented here enabled the determination of the specific year and management period of change, as supported by the diversity profile, this enabled a statistically robust, and visually engaging characterisation of an ecological community (Buckland et al., 2012; Krolik-Root et al., 2015; Tolvanen and Aronsen, 2016). With the diversity profile (Figure 6.12) reflecting the disparate measures of species richness, and the dominance and evenness indices as described in the Shannon or Simpson index, within one profile transformed by Hill’s formula a direct comparison between dates and sites can be made. The data presented here reflected a net increase in biodiversity following the management activities described in Section 6.1, at Upper Moss Side only. The continued use of such measures, instead of single biodiversity indices, might be a valuable inclusion into long-term monitoring schemes, particularly when including ancillary data to determine the links between environmental impacts and biodiversity as presented here (Buckland et al., 2012). However, the central design of the analysis presented within this chapter was not to establish these methods for this purpose, but to provide contextual ecological field data to incorporate within the vulnerability analysis, the key theme of this thesis. Future research with a study design focussing on comparative methods for the concise presentation of community change will be better suited to draw such conclusions.

Chapter 7 – Sea Level Rise Impacts on Breeding Avifauna

7.1 – The Impact of Sea Level Rise on Saltmarsh Ecosystems

The literature on the impacts of sea level rise on saltmarshes was critically evaluated in Chapter 2. The worst-case predictions for each mechanism of change reports significant alteration and loss of saltmarsh ecosystems globally, as assessed by multiple sea level rise (SLR) models (Doody, 2004). Despite the extant literature documenting changes in vegetation in response to tidal regime and exposure to salinity, it is still not clear how vegetation communities may change on a site by site basis which limits the exploration of these processes when assessing the impacts on the habitats of the Upper Mersey Estuary. However, the data presented here demonstrate the potential for SLR to impact ground nesting birds by interrupting the breeding species of four key species. This in turn will allow for discourse around saltmarsh vulnerability on a broad scale and the subsequent opportunities for management to mitigate these effects. As such, the study of the impacts of sea level rise on the sensitivity of the saltmarsh avifauna is the focus of this current chapter, and addresses research objective two and three, and null hypothesis four, detailed in Chapter 2, that: sea level rise poses no risk to breeding birds in the Upper Mersey Estuary. The sensitivity of many saltmarsh dwelling birds to sea level rise has the potential to be very high, as most of these species are ground dwelling and nesting (van de Pol et al., 2010). Numerous studies worldwide have focussed on this sensitivity though they have been conducted predominantly in the USA (Knutson and Klaas, 1997; Gjerdrum et al., 2008; Reiley et al., 2017). While this issue has been observed and described in the UK (Greenhalgh, 1971), recent research on the populations sensitivity of ground nesting birds has focussed on disturbance derived from grazing regimes and the loss of nests through trampling (Sharps et al., 2015). Sea level rise scenarios derived from the literature (Table 7.1) are used to determine the derived impacts on four key breeding species in a UK saltmarsh, and to visually highlight habitat that may be sensitive to changes in the tidal regime. The outcomes of this chapter will seek to highlight and portray sensitive areas of habitat under each sea level rise scenario, which will feed into a discussion regarding the ecosystem vulnerability of the area, and the potential management interventions that may serve to mitigate the potential impacts.

7.1.1 – Data

To explore the range of sea level rise scenarios and their impact on the breeding bird species appropriate to this study, several sources of data were acquired. These include the outputs of the previous two chapters, namely the UAV derived habitat cover map produced in Chapter 5, and the territory data of the key species identified in Chapter 6. The base layer for the analysis conducted in the current chapter was derived from the 2017 Environment Agency LIDAR data for the Upper Mersey Estuary in 50 cm spatial resolution (EA, 2017). The data from which the tidal scenarios were calculated is derived from the Fiddler's Ferry tidal gauge, supplied by the National Tidal and Sea Level Facility (2018). This data set contains the daily low, mean, and high water for the six-year period (2012 – 2018), and from this a general approximation of the impacts of sea level rise on the monthly high, and daily tidal cycle can be made. Table 7.1 reflects the tidal range of the Upper Mersey Estuary throughout 2018 and displays the proposed tidal increase at 2095 which are derived from the IPCC, UKCP09 and Jevrejeva et al., (2014). The key breeding bird species associated with the study site were identified during the 2018 Common Bird Census surveys which were conducted as part of the data collection for Chapter 6. These species relate to the management objectives of the Mersey Gateway Environmental trust, and all four are ground nesting, and therefore, potentially susceptible to the secondary impacts of sea level on the saltmarsh habitats through increased inundation and erosion of the saltmarsh platform. These species can be split in to two groups, passerine (perching birds) and non-passerine, in this case, wading species. The two passerine species are the skylark (*Arlauda arvensis*), and the meadow pipit (*Anthus pratensis*), and the wading species the redshank (*Tringa totanus*) and the northern lapwing (*Vanellus vanellus*). The approximate breeding territories of these species are used as the basis for the analysis presented in this chapter. The methods utilised in this chapter are adapted from Krolik-Root et al., (2015), the basis of which is described in Chapter 3. Here, the method is expanded to explore the month/month tidal inundation and a detailed daily comparison of tidal change in relation to avian breeding period and territory. In the first stage of the analysis, an overview of monthly sea level rise was created utilising the 'bath-tub' approach (Krolik-Root et al 2015). The tidal maximum for each month of the breeding season was calculated, and these values formed the basis of input into the Geographical Information systems (GIS) based model.

Utilising the formula: $\boldsymbol{a} \leq \boldsymbol{b}$ (Formula 3.2 in Section 3.6) – where $\boldsymbol{a}$ represents the input digital surface model, and $\boldsymbol{b}$ the elevation – masked layers were produced. For each month seven masks were made representing the mean high monthly tide 2012-2018 and each scenario of sea level rise. The output of a single calculation derived from the above formula is a binary grid where 0 represents the mask where the elevation was excluded and 1 represents values which are equal to and below the $\boldsymbol{b}$ variable. The resulting data includes a grid for each month in the avian breeding season (March – July) and for each sea level rise scenario. The binary grids for each scenario were then combined in a raster calculator utilising a union calculation. For each pixel where a 1 is present in multiple layers, the output will combine them. This then represents the frequency that a specific pixel will be inundated by the high tide based on the mean monthly peak.

This operation was then adapted and repeated to focus on each of the four identified species' breeding periods. Rather than using the monthly high tide data, which does not capture multiple flooding events per month, the procedure was calculated on the 2018 daily tidal gauge data. A decision was made not to calculate the 6-year daily average high tide, due to the nature of the 28-day tidal cycle, all variation in the data set would be lost, and thus would remove the utility of the scenario analysis. The same calculations were carried out on the daily high tide, to determine whether the specific breeding window for the four species would be sensitive to sea level rise. After these processes were implemented, the 2018 avian species territories were used as a layer to import zonal statistics from the sea level rise frequency scenarios. The output of this process reflects the mean and max flooding values for each species territory. These data were then combined and presented as a series of maps which reflect the frequency of tidal inundation per species across the saltmarsh habitat within the breeding season. The saltmarsh cover type was then extracted from the UAV derived classification map and overlain on the inundation map to visually reflect the inundation frequency of the key habitat. Within the work presented here, the basis of the exploratory model assumes that there is no supply and accretion of saltmarsh sediment, and that saltmarsh habitat cover will not change with the increased sea level rise scenarios (Krolik-Root et al., 2015). This work focuses on the potential impact of the sea level rise scenarios interrupting the avian breeding season. Implications of vegetation change are described and discussed in Chapter 8.

This exploration of the sea level rise scenarios in this chapter are focussed on a subset of the Upper Mersey Estuary (UME) at a site known as Upper Moss Side, the site at which the key species were observed as presented in Chapter 6, and where the UAV data collection to produce a habitat map was centred, as is presented in Chapter 5. Within the current chapter, these sources of data will be combined to explore the visual extent and potential impacts of a set of sea level rise scenarios on the breeding ecology of the four target species, as an exploration of an ecosystem vulnerability assessment framework for a managed saltmarsh in the UME.

7.2 – Results – Coastal Vulnerability

The sea level rise scenarios are applied to Environment Agency 2017 digital elevation data, at a spatial resolution of 50 cm (EA, 2017). Environment Agency Lidar data root mean square error is less than ±15 cm, and the absolute spatial error is ± 40cm (EA, 2017). Table 7.1 displays the tidal frame based on the 2017 Tidal Data derived from the National Tidal and Sea Level Facility (2018). This displays current projections derived from the IPCC, (2014), UKCP09, (2009) projections and a worst-case projection of +1.9m cited in Jevrejeva et al., (2014).

Table 7.1 – Tidal values for the River Mersey derived from 2018 tidal gauge, and the mean high water under projected scenarios.

Tidal Categories and Scenarios	**Elevation (m)**
Highest Astronomical Tide (HAS)	5.3
Mean High Water Spring (MHWS)	5.2
Mean High Water Neap (MHWN)	3.2
Mean Low Water Spring (MLWS)	0.7
Mean Low Water Neap (MLWN)	0.3
HAS 2095	6.4
MHWS 2095 High Emission Scenario (+0.7)	5.9
MHWS 2095 Med Emission Scenario (+0.6)	5.8
MHWS 2095 Low Emission Scenario (+0.5)	5.7
Maximum UKCP09 Scenario (0.94 – 1.5)	6.14 - 6.70
Jevrejeva et al., (2014) (+1.9 m)	7.3

7.2.1 – Saltmarsh Avifauna Breeding Season and Sea Level Impacts

The Mersey Gateway Environmental Trust aims to restore the saltmarshes of the Upper Mersey Estuary to a condition favourable for key bird species. The details of the scope and objectives for this project, named Beyond our Bridges, can be found in Chapter Three. As were described in Chapter Three, and identified as breeding at Upper Moss Side in Chapter 6, the four key species relevant to this chapter, are meadow pipit (*Anthus pratensis*), skylark (*Alauda arvensis),* redshank (*Tringa totanus*), and northern lapwing (*Vanellus vanellus*)*.* Data for the breeding ecology of these species are presented in Table 7.2, and is visualised in Figure 7.1, these data represent the date of the first laid clutch are derived from Joys and Crick (2004). The rationale for the selection of these species is that they are ground nesting and are known to breed and raise chicks on saltmarshes, and further, that these species were identified as targets by the live restoration project undertaken by the MGET (Doody, 2004; MGET 2014). Being ground nesting, these species are sensitive to changes in the tidal regime during the summer months and may risk nest loss during catastrophic tidal events (van de Pol et al., 2010).

As can be seen from Table 7.2, the mean date that an egg clutch is laid by the two passerine species: the meadow pipit and skylark is the 19th May. Eggs can be laid earlier in the season: the 5th – 50th percentile date for both species is approximately four weeks before the mean date. The key period of sensitivity to tidal inundation for both ground nesting passerines – taken from the mean date – would include the period of incubation and fledging. Both meadow pipit and skylark chicks are altricial, meaning that they are not yet able to fend for themselves or leave the nest during the fledging period. From the date of eggs laid the sensitivity of a meadow pipit brood to tidal inundation will be 27 days a duration arrived at by adding the mean incubation period and mean fledging to the 19th May. This period is also the same for the skylark when using the values from Joys and Crick (2004) and represents the period of sensitivity from the first brood.

The two wading species differ in their period of breeding. The redshank mean clutch date is the 1st May, whereas the northern lapwing clutch is usually laid by the 12th April. The development of these birds differs from the passerine species. Incubation takes longer: 24 days for the redshank and a mean of 31 for the northern lapwing. Once hatched, the redshank can take 30 days to fledge and the northern lapwing 38. Both species hatch precocial chicks, meaning that the young birds hatch at the developmental stage where they can, to a degree, fend for themselves, potentially reducing the impact of tidal events during this period as the young birds will be mobile and able to move to higher ground if it is possible to do so. In this case, the main period of sensitivity for the redshank is 24 days from the 1st May, and the northern lapwing 31 from 12th April.

Table 7.2 – Date of first clutch, and species breeding ecology (Joy and Crick, 2004).

Species	**Eggs Laid (mean date, and 5th-95th percentile)**	**Incubation (days)**	**Fledging (days)**	**Broods (number)**	**Chick development**
Meadow pipit (*Anthus pratensis)*	19th May (18th April – 16th June)	13 – 15	12 –14	2	Altricial
Skylark (*Alauda arvensis)*	19th May (20th April – 6th July)	13 – 14	11 – 16	1 – 4	Altricial
Redshank (*Tringa totanus)*	1st May (14th April – 7th June)	24	25 – 35	1	Precocial
Northern lapwing (*Vanellus vanellus)*	12 April (25th March – 25th May)	25 – 34	35 – 40	1	Precocial

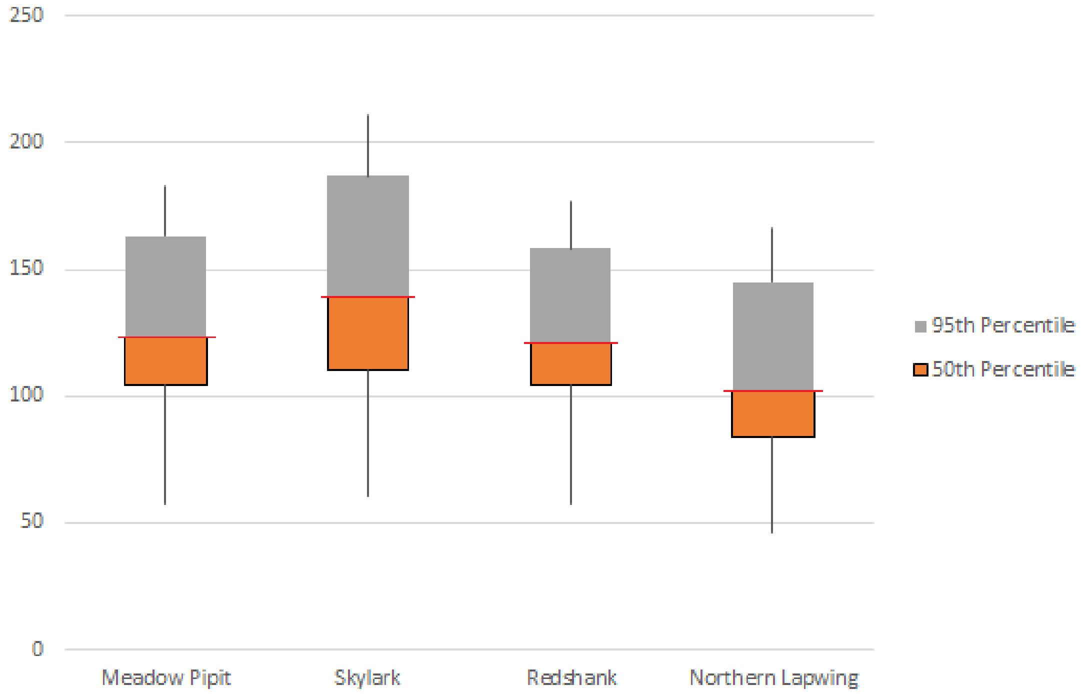


Figure 7.1 – Date of first egg clutch. The date is expressed in number of days, and the red bar represents the mean, or upper limit of the 50th percentile.

Figure 7.2 summarises the mean high tides during the 2012-2018 period with reference to the mean elevation of Upper Moss Side and sea level rise scenarios for 2095. From this period, using the six year mean high tide plot, it can be determined that the passerine breeding season – from mid-May – suffers no inundation as the value for the mean high tide falls below the Upper Moss Side mean elevation. However, it will from the UKCP09 low SLR estimate, the UKCP09 high end estimate and the scenario put forward by Jevrejeva et al., (2014) as these high tide projections exceed that of the Upper Moss Side elevation based on this figure. This is similar for both the redshank and the northern lapwing under the current tidal frame at Upper Moss Side. Figures 7.3– 7.8 visually represent the data displayed in Figure 7.2. They represent the peak high tide for each month between the avian breeding season (March and July) subject to the sea level rise scenarios and the number of inundations each area of saltmarsh will experience under these. The outline of the UAV based habitat map produced in Chapter 5 is overlain on these data to highlight the location of Upper Moss Side within the UME, as this is the site where the study is focussed though these figures provide an overview of the scenarios on the UME in its entirety.

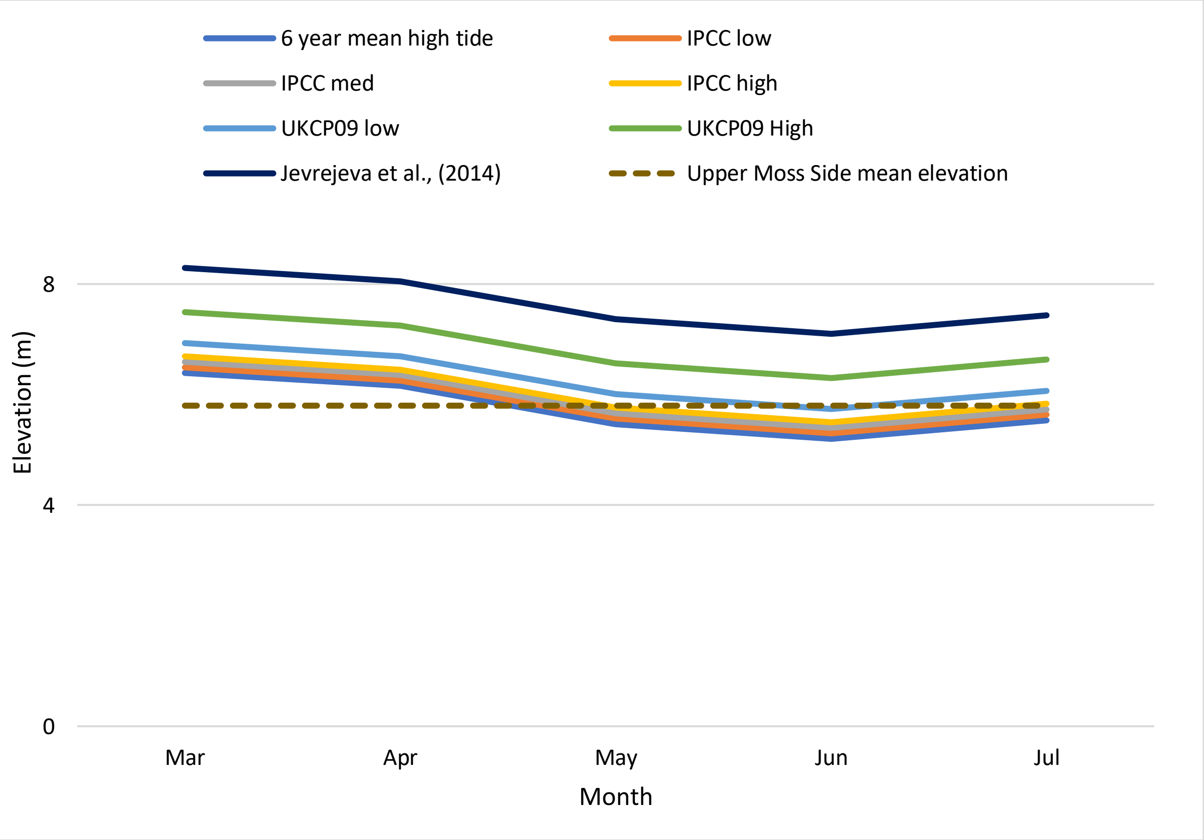


Figure 7.2 – 2012 – 2018 peak mean tide for the breeding season with reference to saltmarsh elevation, and sea level rise forecasts for 2095.

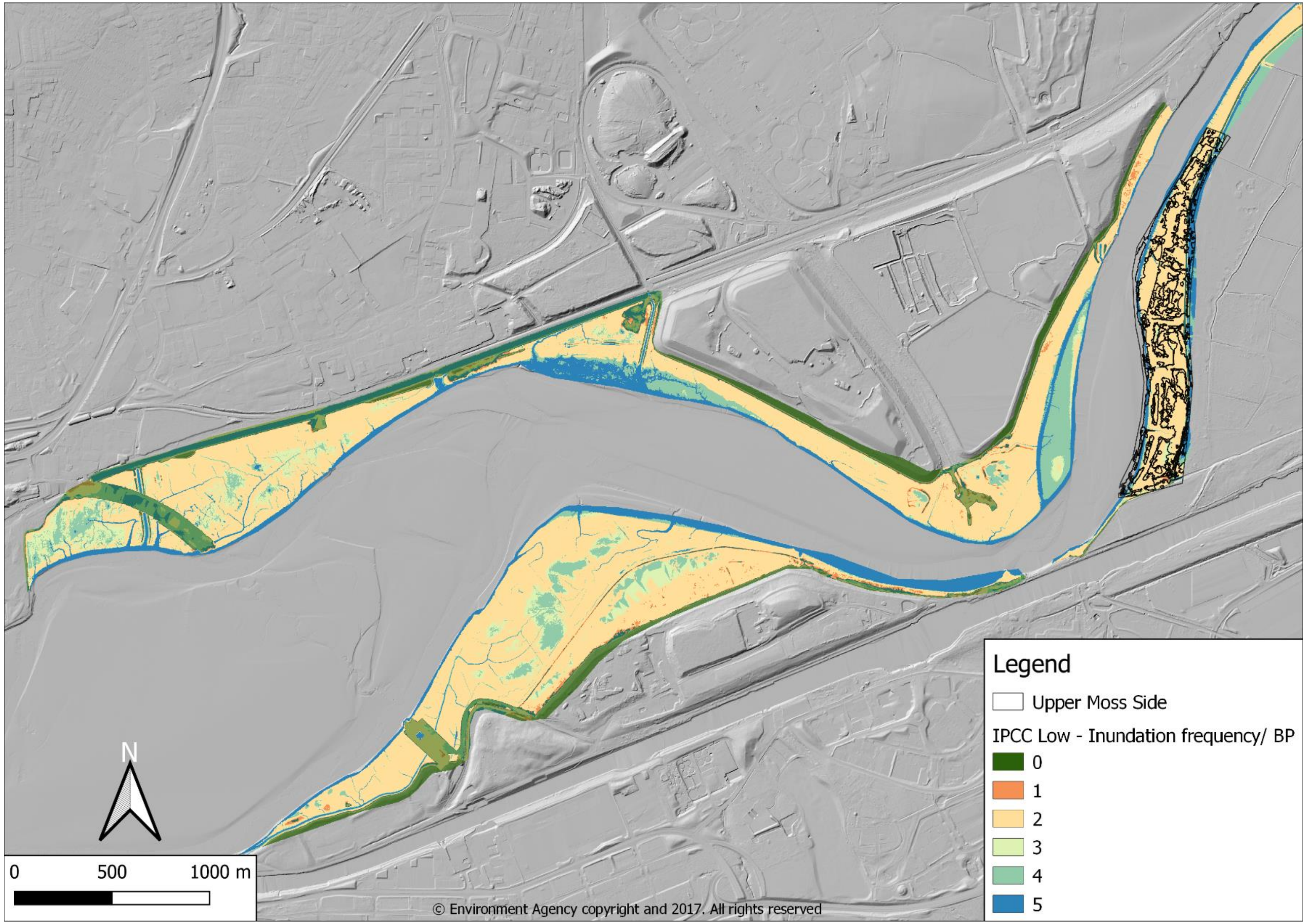


Figure 7.3 - Monthly peak tides based on 2012 – 2018 tidal data from Fiddler's Ferry, Inundation frequency per breeding season.

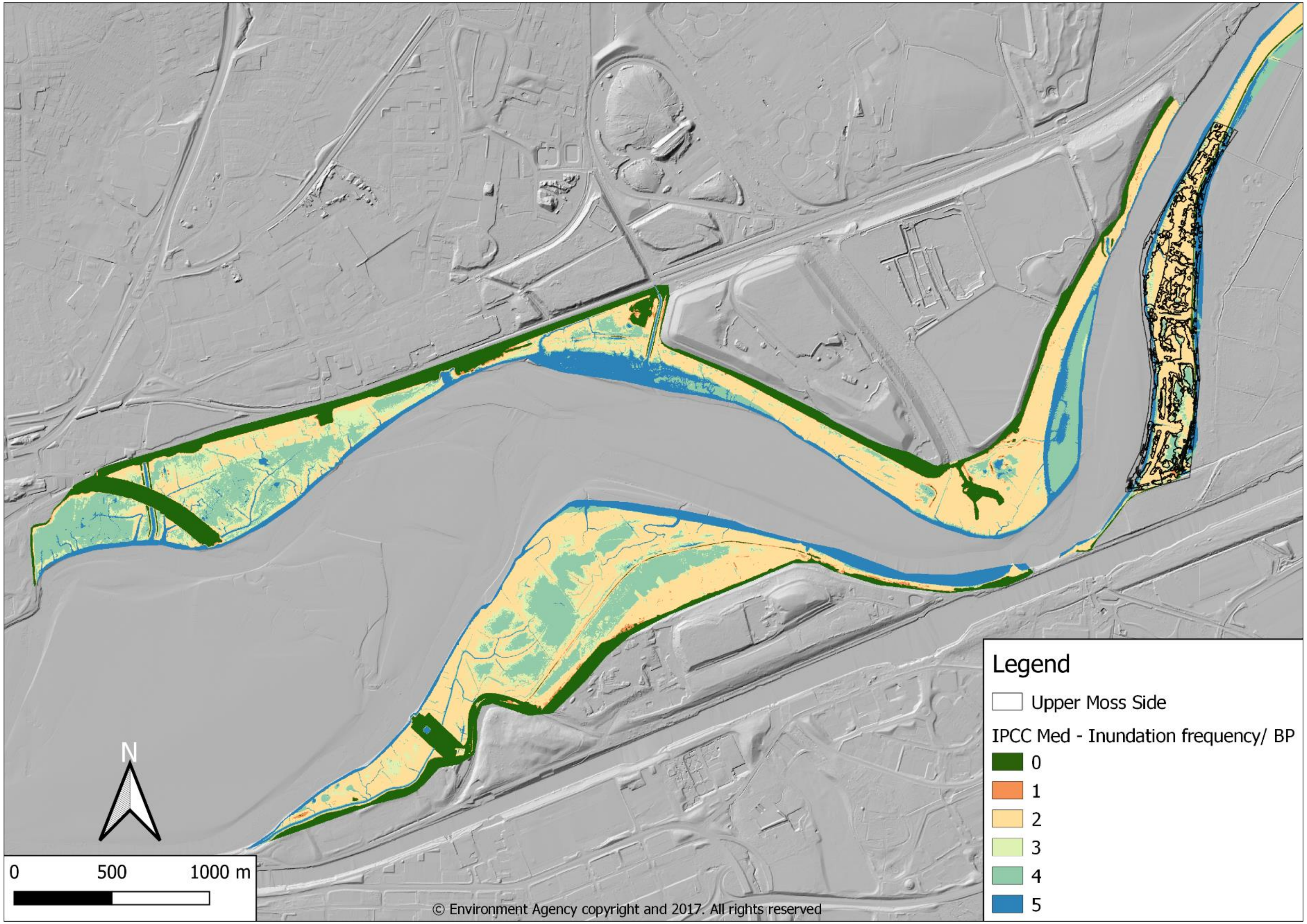


Figure 7.4 - Peak tide inundation based on the IPCC 2095 low emission scenario.

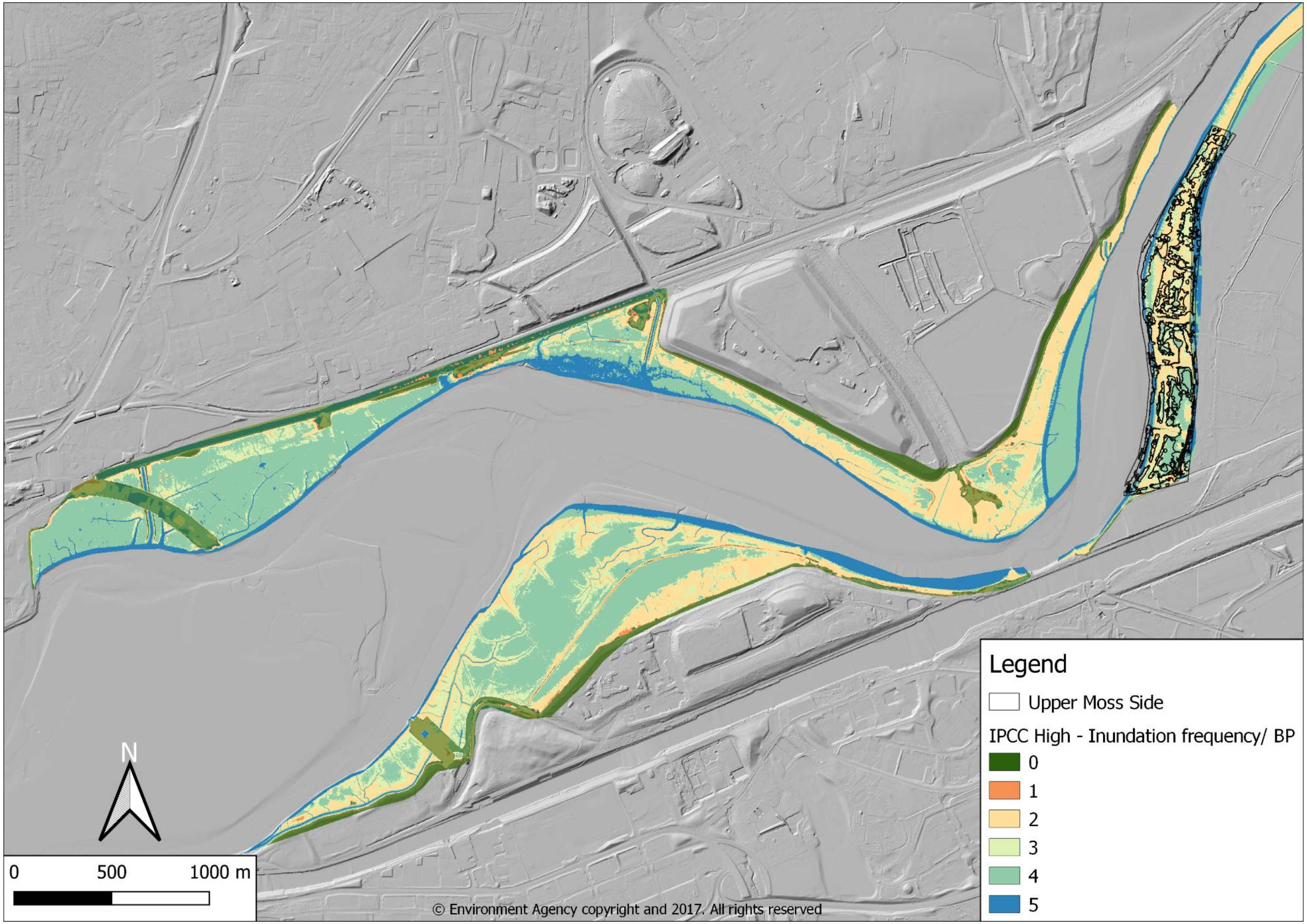


Figure 7.5 - Peak tide inundation based on the IPCC 2095 medium emission scenario.

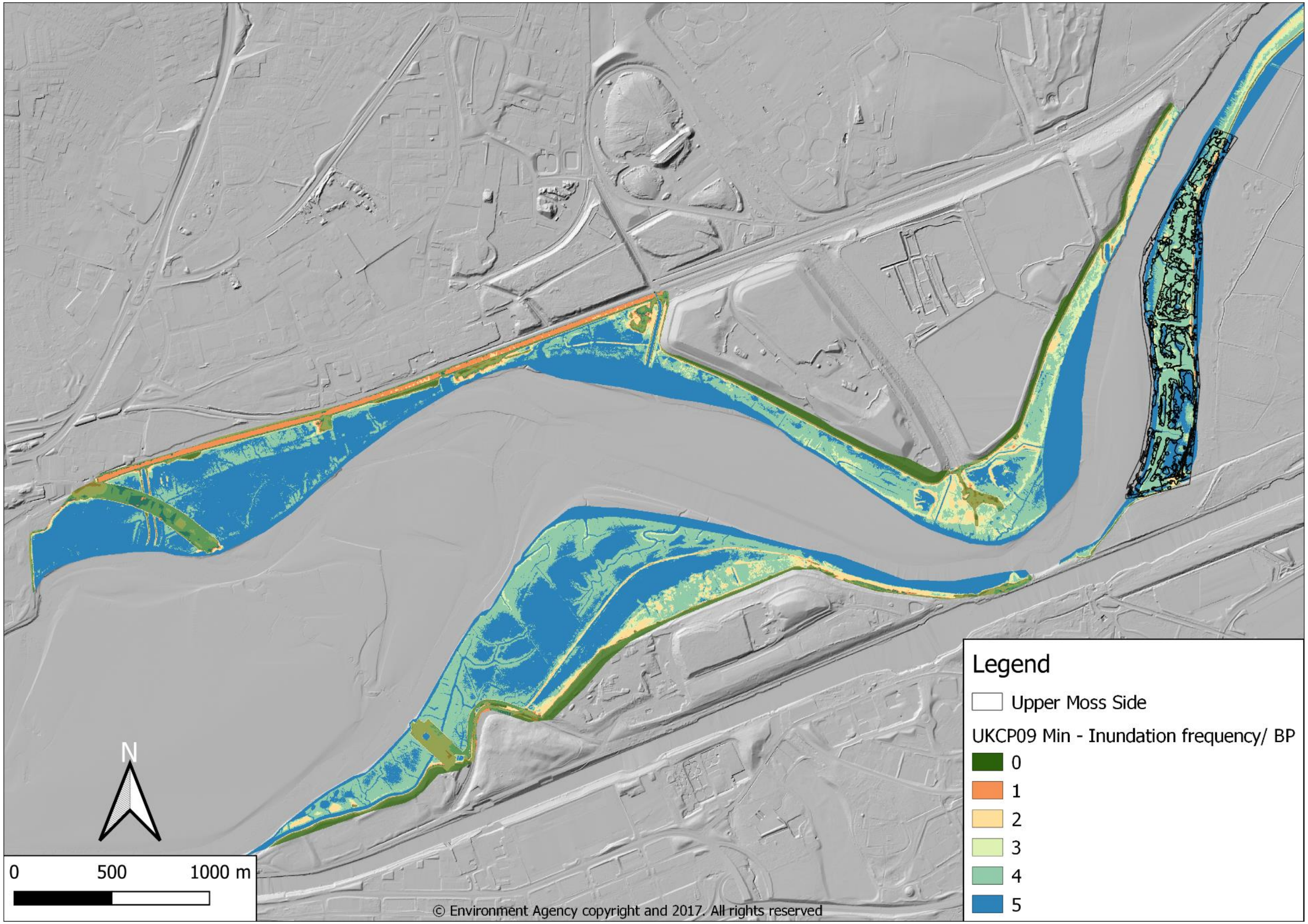


Figure 7.6 - Peak tide inundation based on the IPCC 2095 high emission scenario.

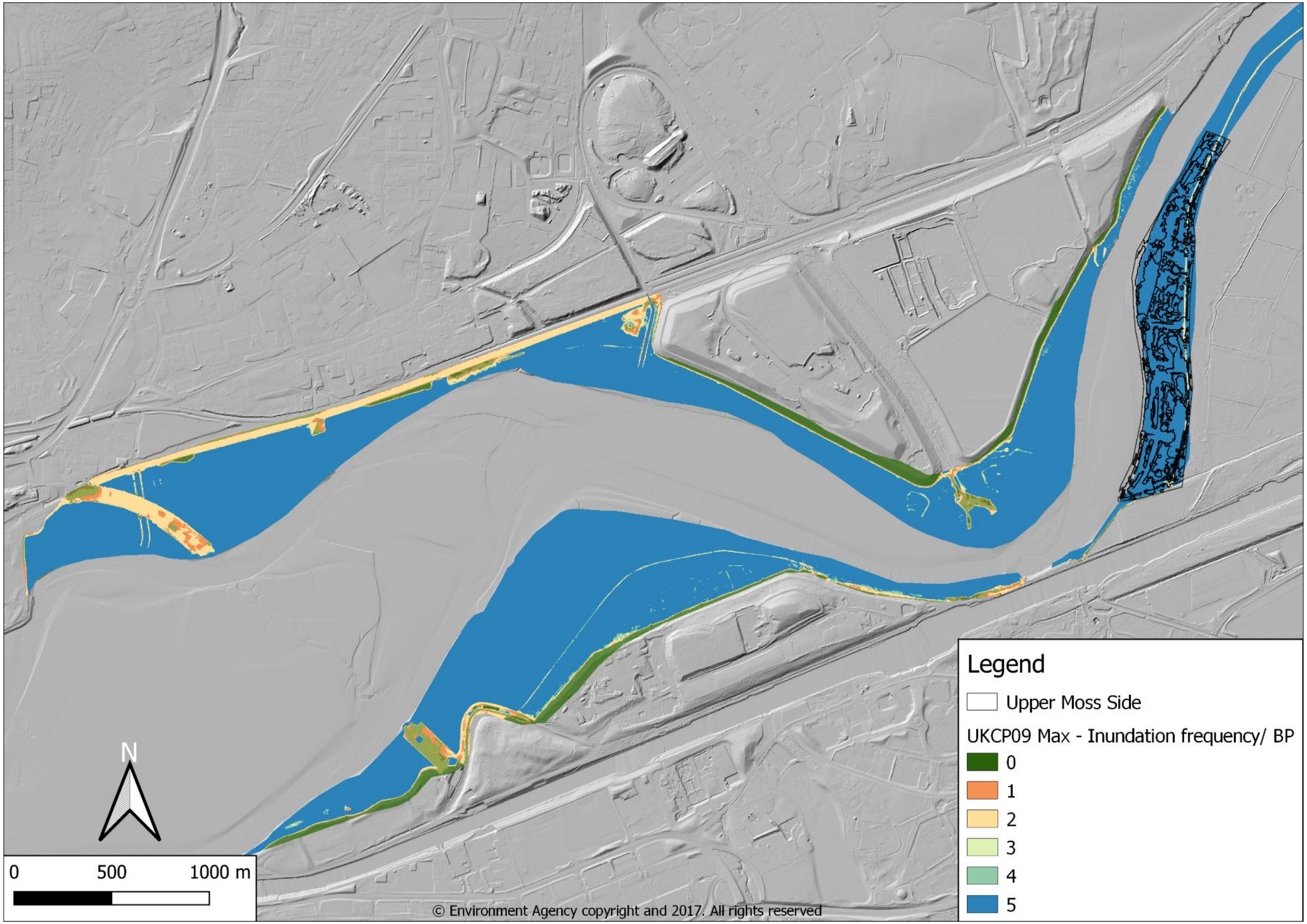


Figure 7.7 - Peak tide inundation based on the UKCP09 2095 minimum scenario

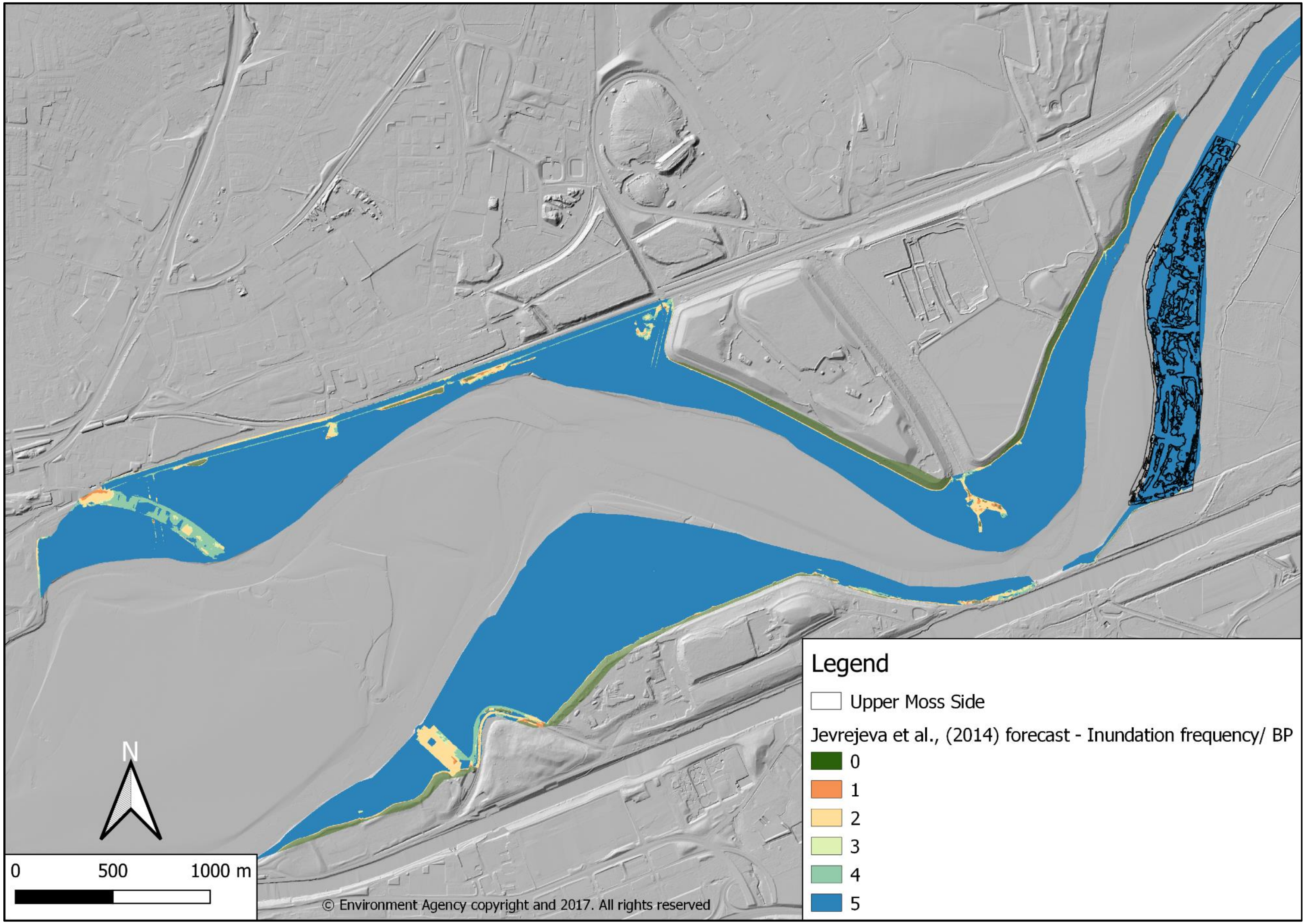


Figure 7.8 - Peak tide inundation based on the UKCP09 maximum scenario

From Figure 7.2 it can be seen that the peak high tides under high sea level rise scenarios will inundate the saltmarshes every month under the UKCP09 maximum forecast and Jevrejeva et al., (2014) forecast, (Figures 7.7 and 7.8). Under these two scenarios, the dates when meadow pipit and skylark species breed coincide with predicted high tides that exceed the average elevation of the saltmarshes and, therefore, there is a high likelihood to impact or interrupt the breeding season of these species. As has been established, the skylark and meadow pipit breeding cycle (egg-laying to fledging) takes around 27 days (Joys and Crick, 2004). The lunar tidal cycle is approximately 28 days between high tides (Gjerdrum et al., 2008). This means that when considering the impact of sea level rise on nest inundation, if only the monthly high tide exceeds the elevation of the saltmarsh, then it may be possible for species to breed uninterrupted in some instances during the May to July period. A 28-day cycle also means that it is likely that some months will see two inundations, a factor which is not expressed within the data above. To explore these issues further the following figures and data represent a daily analysis of saltmarsh inundation based directly around each species breeding period. The data are split into three sections: the passerine species, the redshank, and finally the northern lapwing. The passerine species were grouped as their breeding seasons are during a similar period (Table 7.2 and Figure 7.1).

7.2.2 – Passerine Breeding Season and Sea Level Rise Impacts on 2018 Territory

Figures (7.9 – 7.14) and Tables (7.3 and 7.4) display the outcomes of the sea level rise analysis conducted for the ground nesting passerine species. To base the inundation values on known species territories, the approximate territory centres derived from the analysis in Chapter 6 were utilised to sample these data utilising the zonal statistics function in QGIS. Sea level rise scenarios outlined in Table 7.1 were applied to the daily tidal data for the period of the passerine breeding season. The dates for the breeding season are displayed in Table 7.2 and Figure 7.3. The first date in the series was the mean date of first clutch laid, derived from Joys and Crick (2004). To capture all tidal events within the breeding period for the two species, the study uses tidal data from the 19th May to the 6th July.

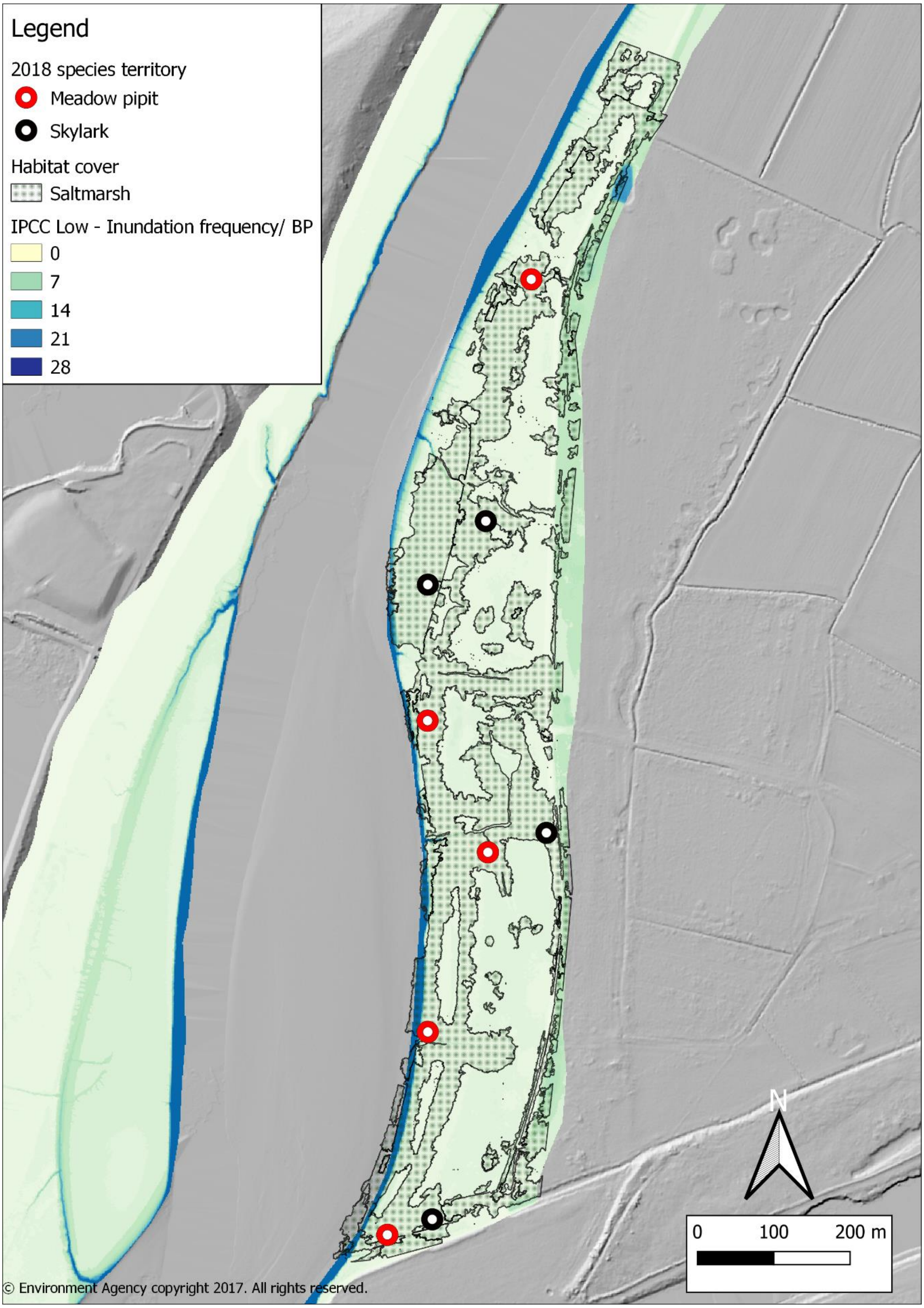


Figure 7.9 - Inundation events based on passerine breeding season under IPCC low emission scenario 2095 per breeding period (BP), March – July.

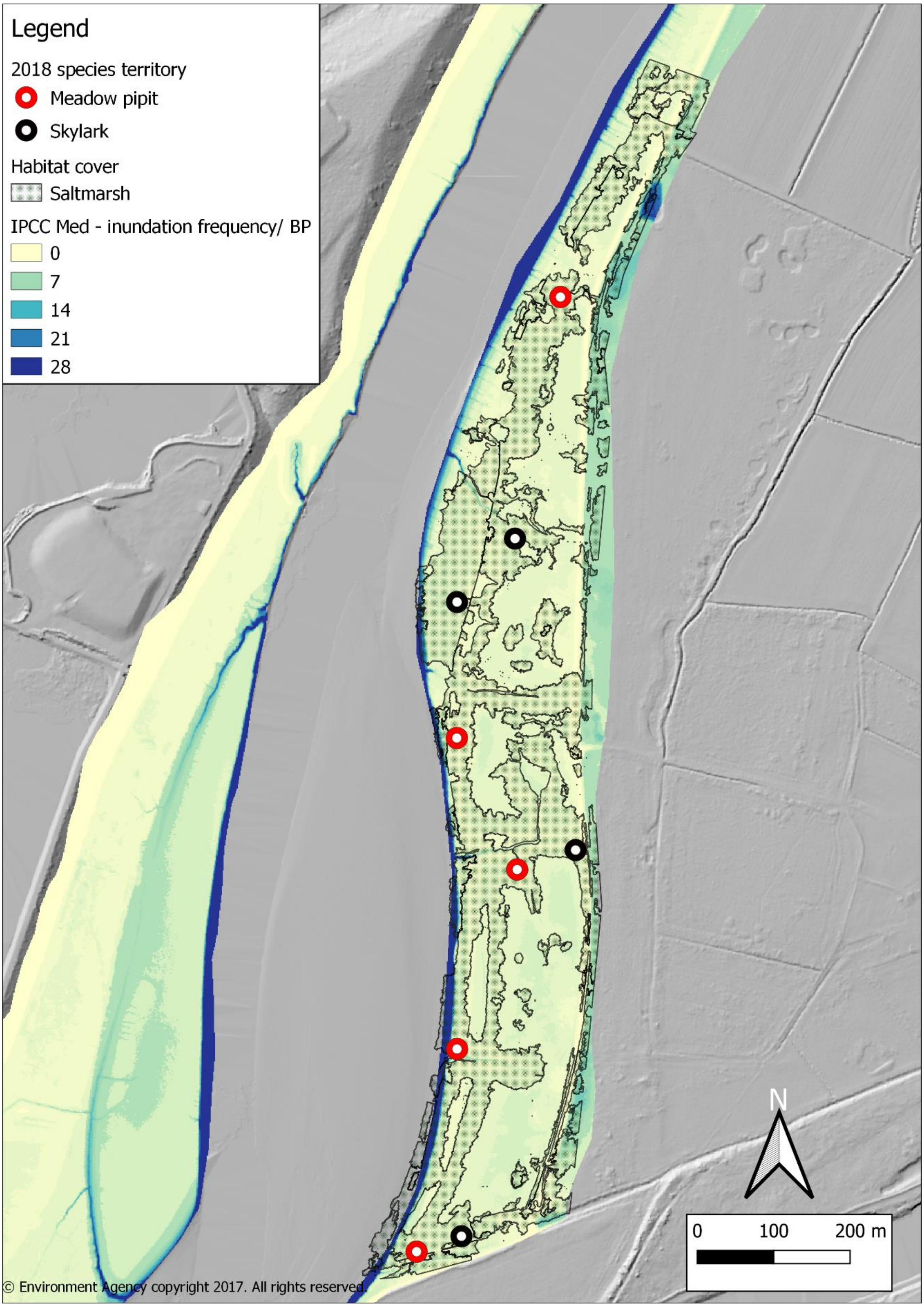


Figure 7.10 – Inundation events based on passerine breeding season under IPCC medium emission scenario 2095 per breeding period (BP), March – July.

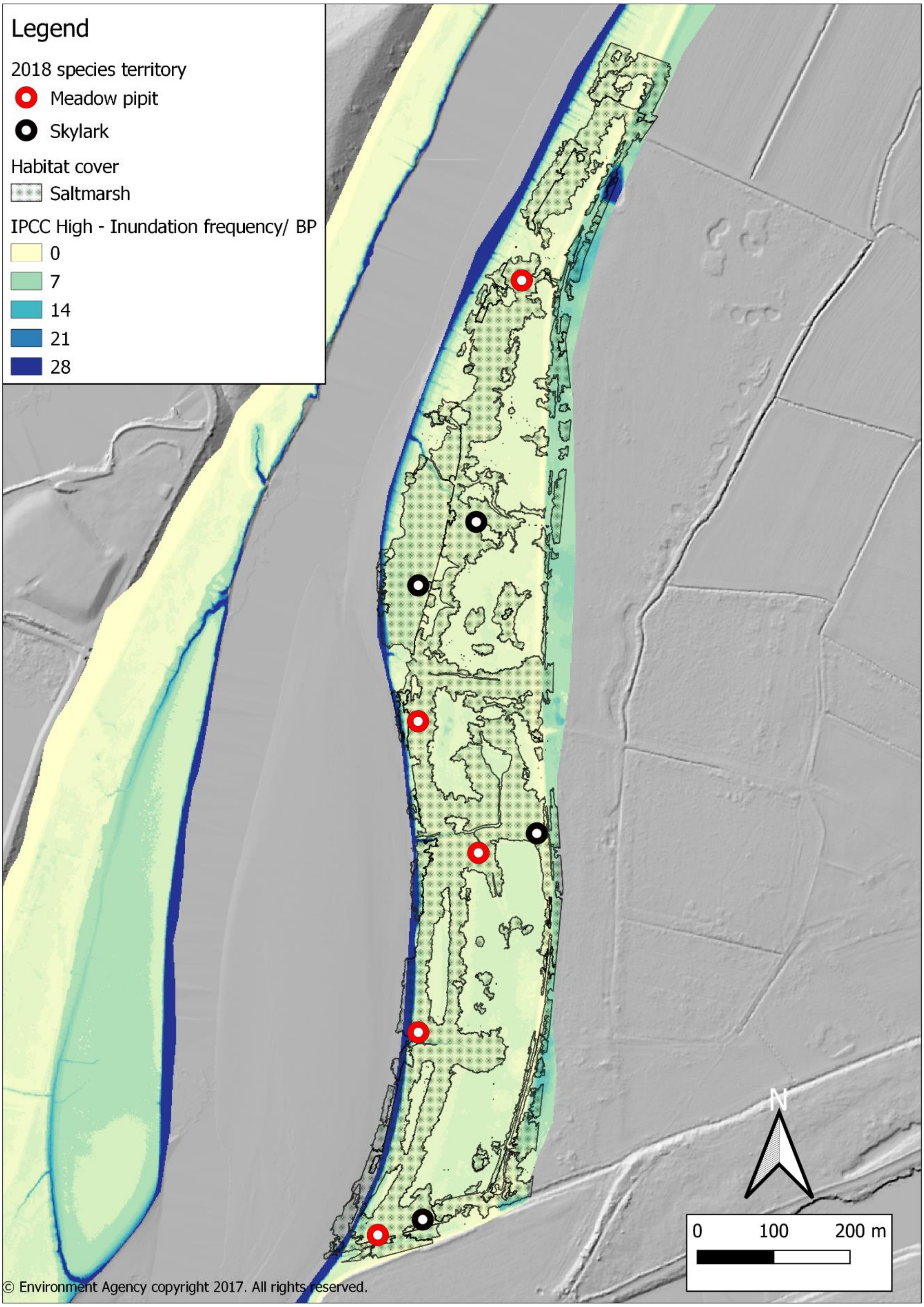


Figure 7.11 – Inundation events based on passerine breeding season under IPCC high emission scenario 2095 per breeding period (BP), March – July.

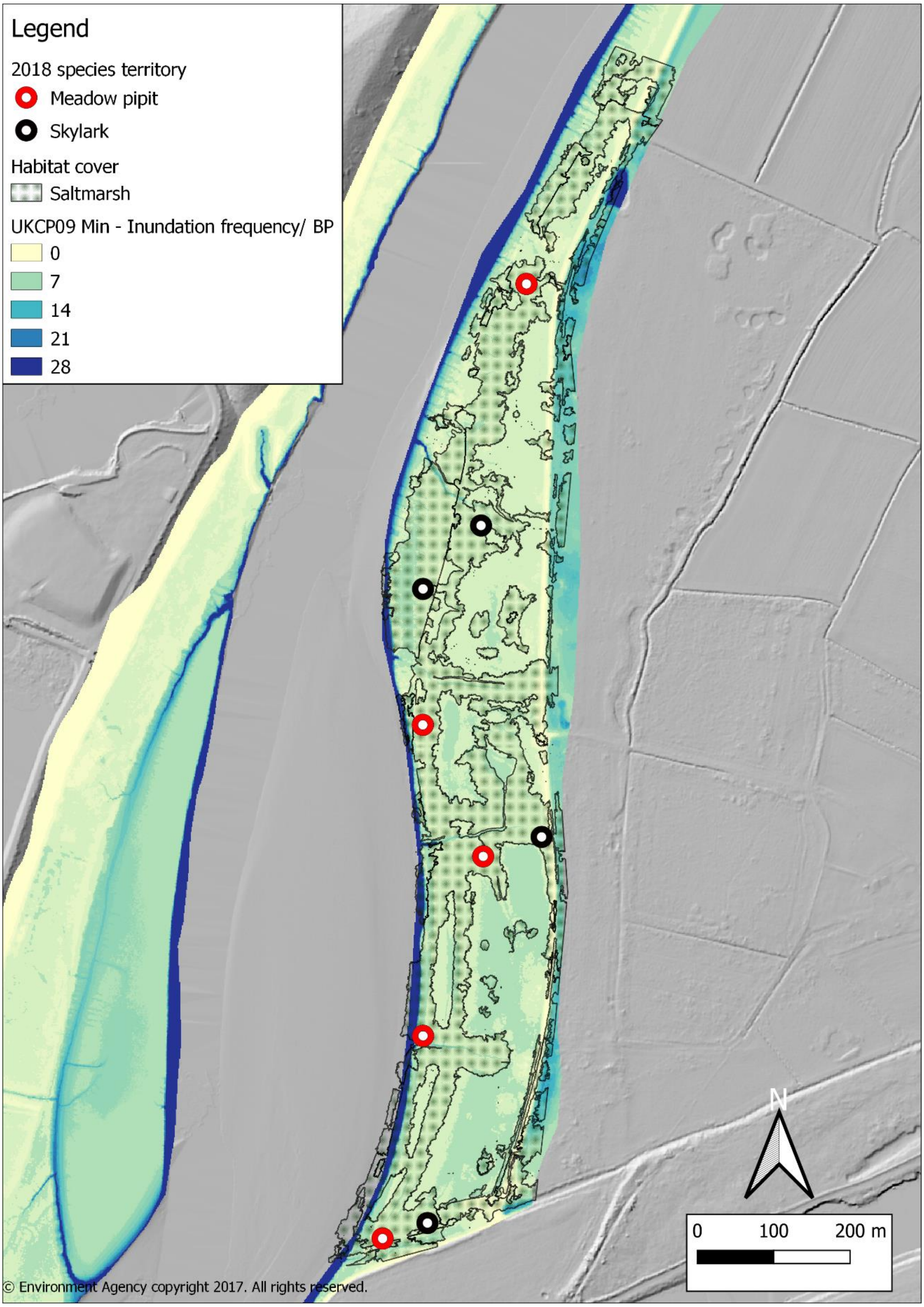


Figure 7.12 – Inundation events based on passerine breeding season under UKCP09 minimum emission scenario 2095 per breeding period (BP), March – July.

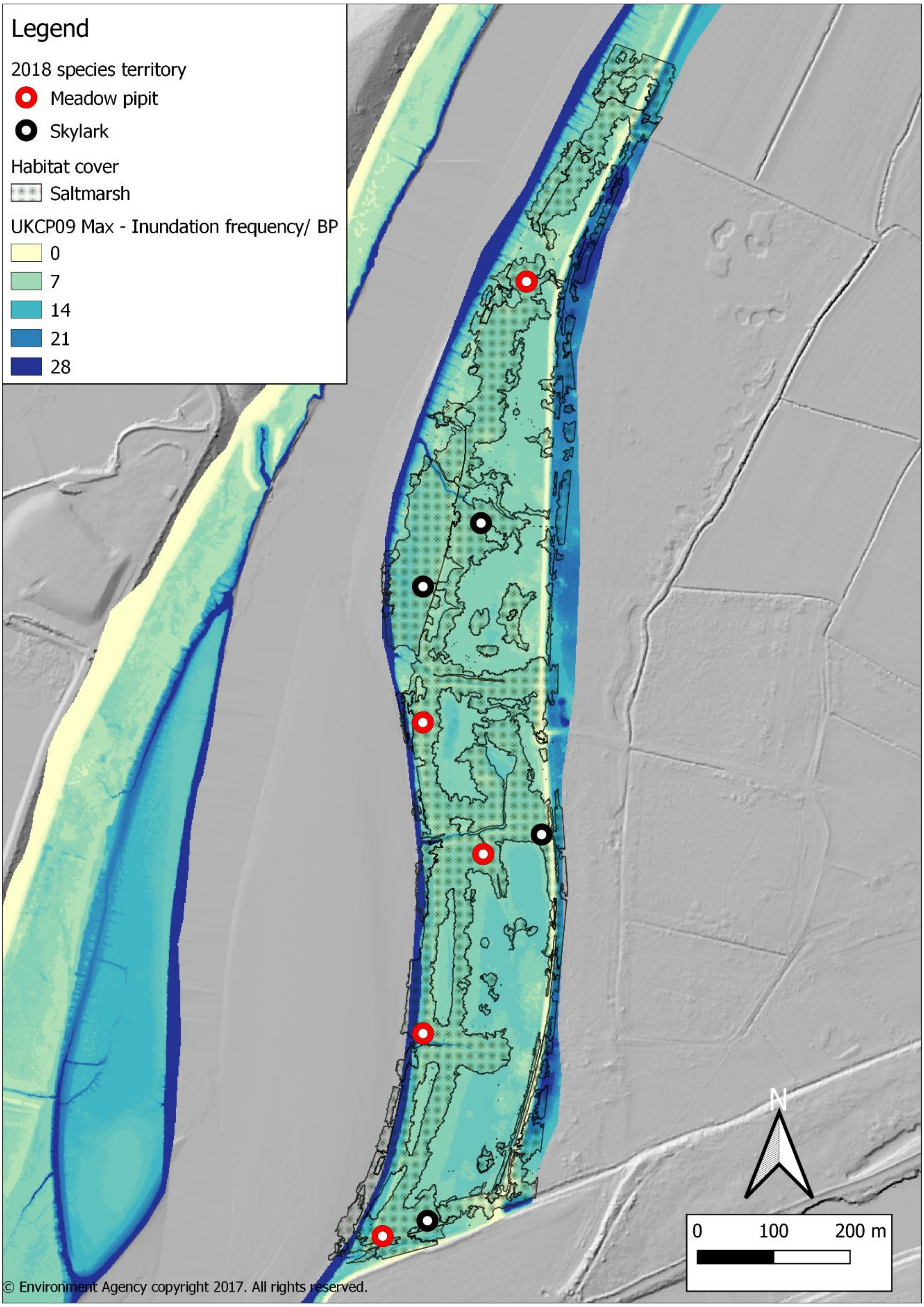


Figure 7.13 – Inundation events based on passerine breeding season under UKCP09 maximum emission scenario 2095 per breeding period (BP), March – July.

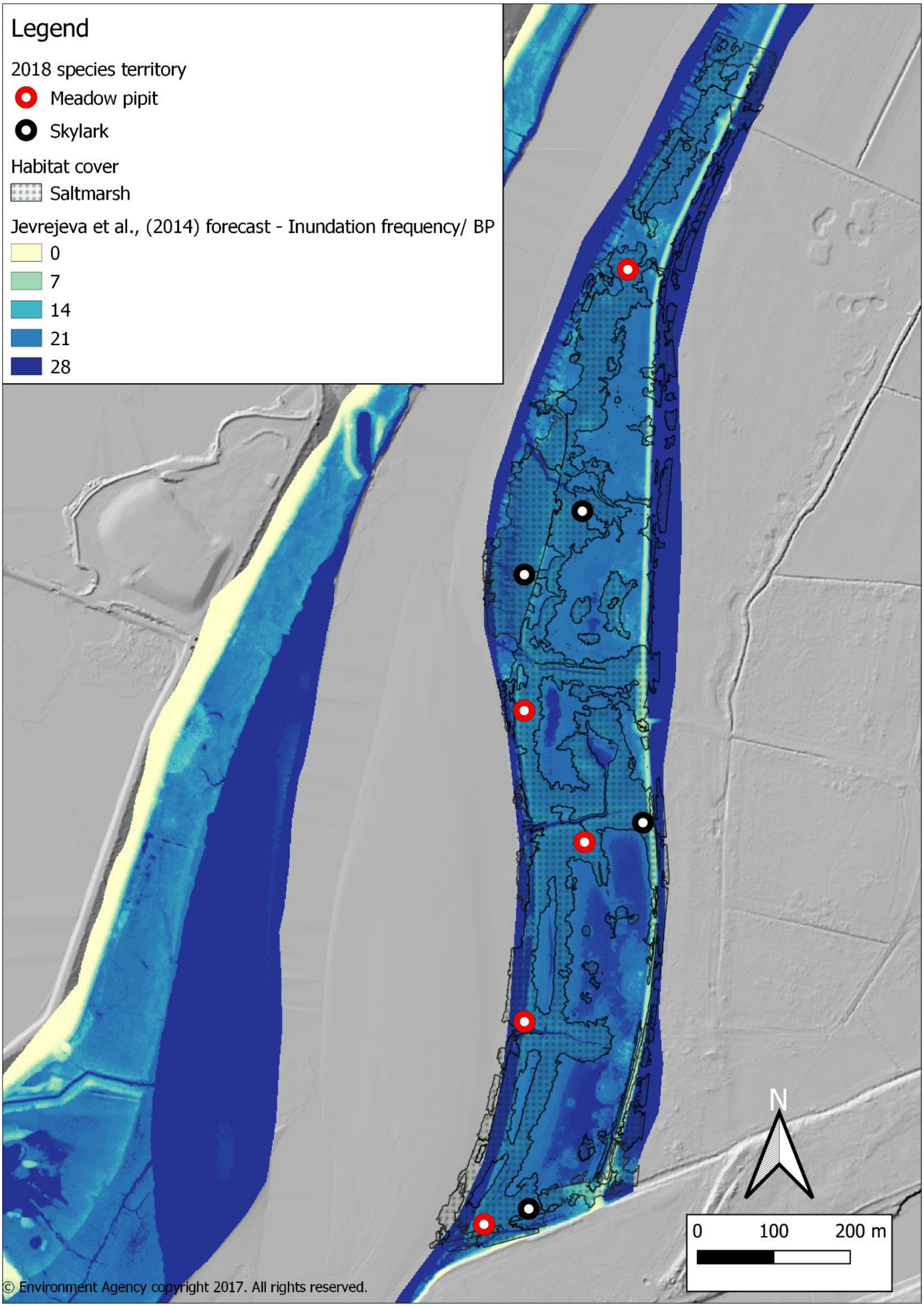


Figure 7.14 – Inundation events based on passerine breeding season under the Jevrejeva et al., (2014) emission scenario 2095 per breeding period (BP), March – July.

Table 7.3 – Descriptive statistics for meadow pipit territory inundation during the breeding period (BP)

SLR scenario	Mean No. of Inundations/ BP	Standard Deviation
IPCC Low	1.1	0.2
IPCC Med	1.6	0.4
IPCC High	2.0	0.33
UKCP09 Min	3.2	0.6
UKCP09 Max	8.5	0.7
Jevrejeva et al., (2014)	21.7	1.1

Table 7.4 - Descriptive statistics for skylark territory inundation during the breeding period (BP).

SLR Scenario	Mean No. of Inundations/ BP	Standard Deviation
IPCC Low	1.1	0.2
IPCC Med	1.7	0.4
IPCC High	2.1	0.3
UKCP09 Min	3.2	0.6
UKCP09 Max	8.7	0.6
Jevrejeva et al., (2014)	21.9	0.9

Table 7.3 displays the sea level rise inundation data associated with meadow pipit territories across Upper Moss Side for the breeding period (19th May – 6th July). The mean number of inundations represents the number of days within the 48-day period that the high tide exceeds the elevation at which the species' territory exists. Figure 7.18 visualises the frequency of inundations graphically with reference to the mean elevation of each of the bird species' territory at Upper Moss Side. Tables 7.5 and 7.6 display the data relating to the longest period without disturbance by flooding and the mean elevation values for both the species territories. The most extreme forecast could see a mean of 21.7 territory inundations with the longest time between these being 22 days (Figure 7.15). The forecast based on the UKCP09 maximum scenario is similar with 24 days being the longest time

between the 21.7 territory inundations. The remaining scenarios see less of an impact, based on the tidal data, than the severe sea level rise scenarios.

The data relating to skylark territory inundation is presented in Table 7.4. The inundation values are nearly identical to that of the meadow pipit territories due to the similarity of elevation and breeding period.

Table 7.5 – Longest period without inundation for meadow pipit territory.

Upper Moss Side Scenario	Longest period without inundation (No. of Days)
IPCC Low	42
IPCC Med	42
IPCC High	41
UKCP09 Min	29
UKCP09 Max	24
Jevrejeva et al., (2014)	23

Table 7.6 – Longest period without inundation for skylark territory.

Upper Moss Side Scenario	Longest period without inundation (No. of Days)
IPCC Low	39
IPCC Med	33
IPCC High	30
UKCP09 Min	24
UKCP09 Max	23
Jevrejeva et al., (2014)	10

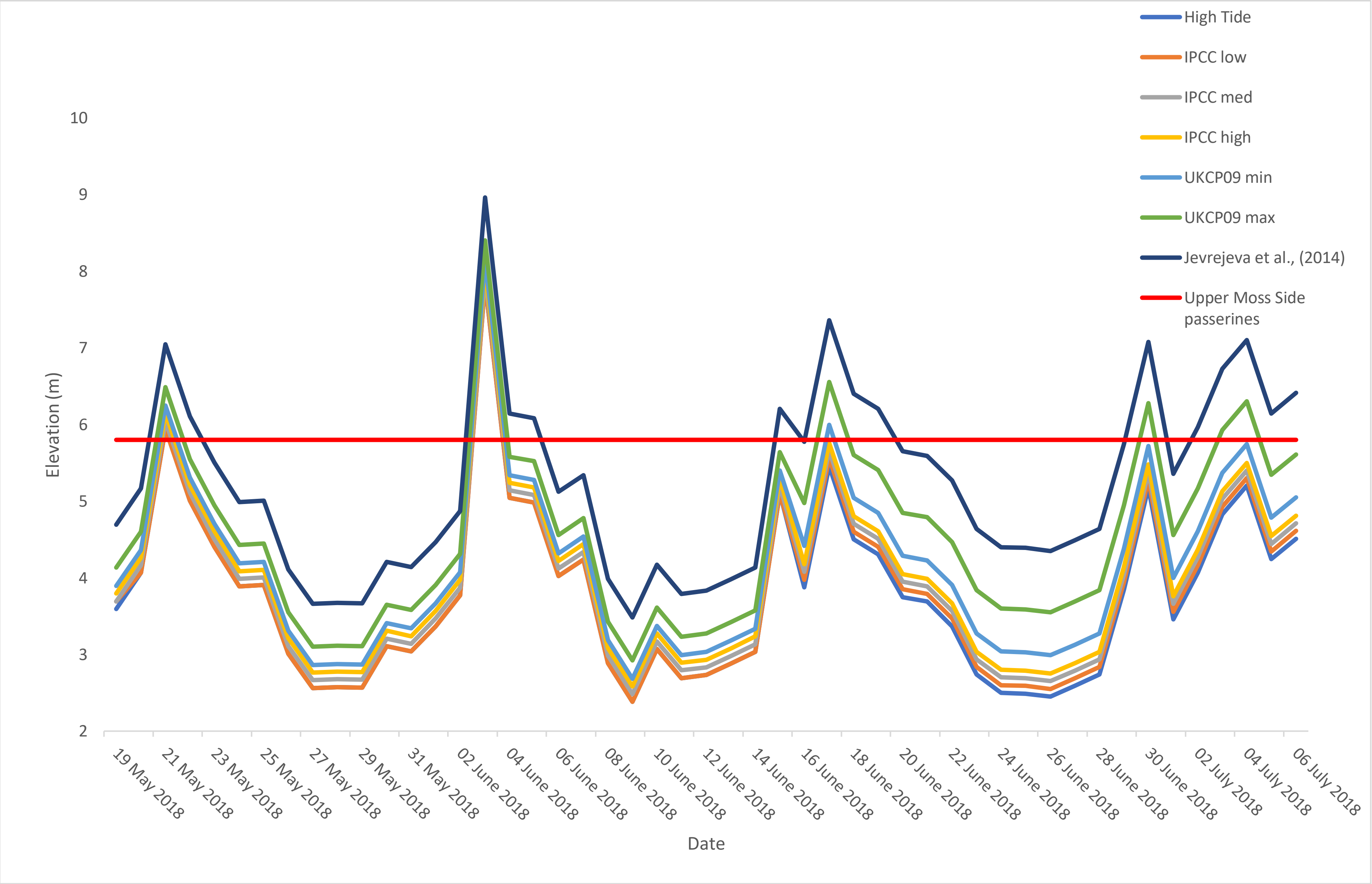


Figure 7.15 – Tidal inundation frequency based on 2018 tidal gauge data under sea level rise scenarios, for the passerine breeding period.

7.2.3 – Ground Nesting Wader Breeding Season and Sea Level Rise impacts on Current Territory

7.2.3.1 – Redshank

Figures 7.16 – 7.21 and Tables 7.7 and 7.8 display the outcome of the sea level rise analysis for the redshank territory at Upper Moss Side. The same procedure was undertaken as outlined above in Section 7.2.2, however the dates used were derived from the redshank breeding season, that is to say between the 1st May and 24th June (Joys and Crick, 2008). Figure 7.22 represents the inundation frequency based on the 2018 tides.

Table 7.7 – Mean inundation for each sea level rise scenario for redshank territory.

Upper Moss Side Scenario	Mean No. of Inundations	Standard Deviation
IPCC Low	1	0
IPCC Med	1	1
IPCC High	1.06	0.2
UKCP09 Min	2.02	0.1
UKCP09 Max	7.8	0.3
Jevrejeva et al., (2014)	16.2	0.7

Table 7.8 – Longest period without inundation for redshank territory.

Upper Moss Side Scenario	Longest period without inundation (No. of Days)
IPCC Low	45
IPCC Med	45
IPCC High	45
UKCP09 Min	44
UKCP09 Max	24
Jevrejeva et al., (2014)	10

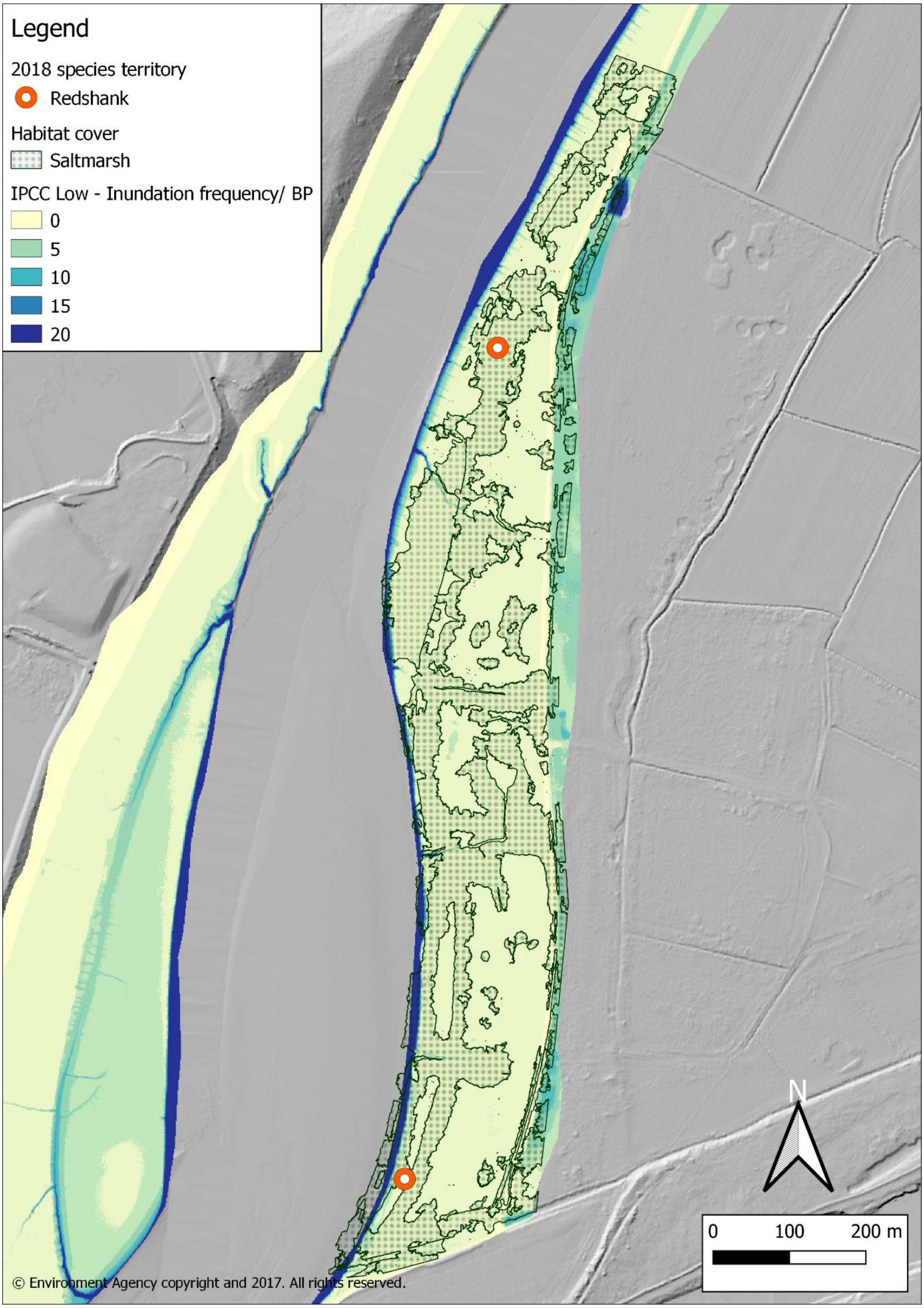


Figure 7.16 – Inundation events based on redshank breeding season under IPCC low emission scenario per breeding period (BP), March – July.

Figure 7.17 – Inundation events based on redshank breeding season under IPCC med emission scenario per breeding period (BP), March – July.

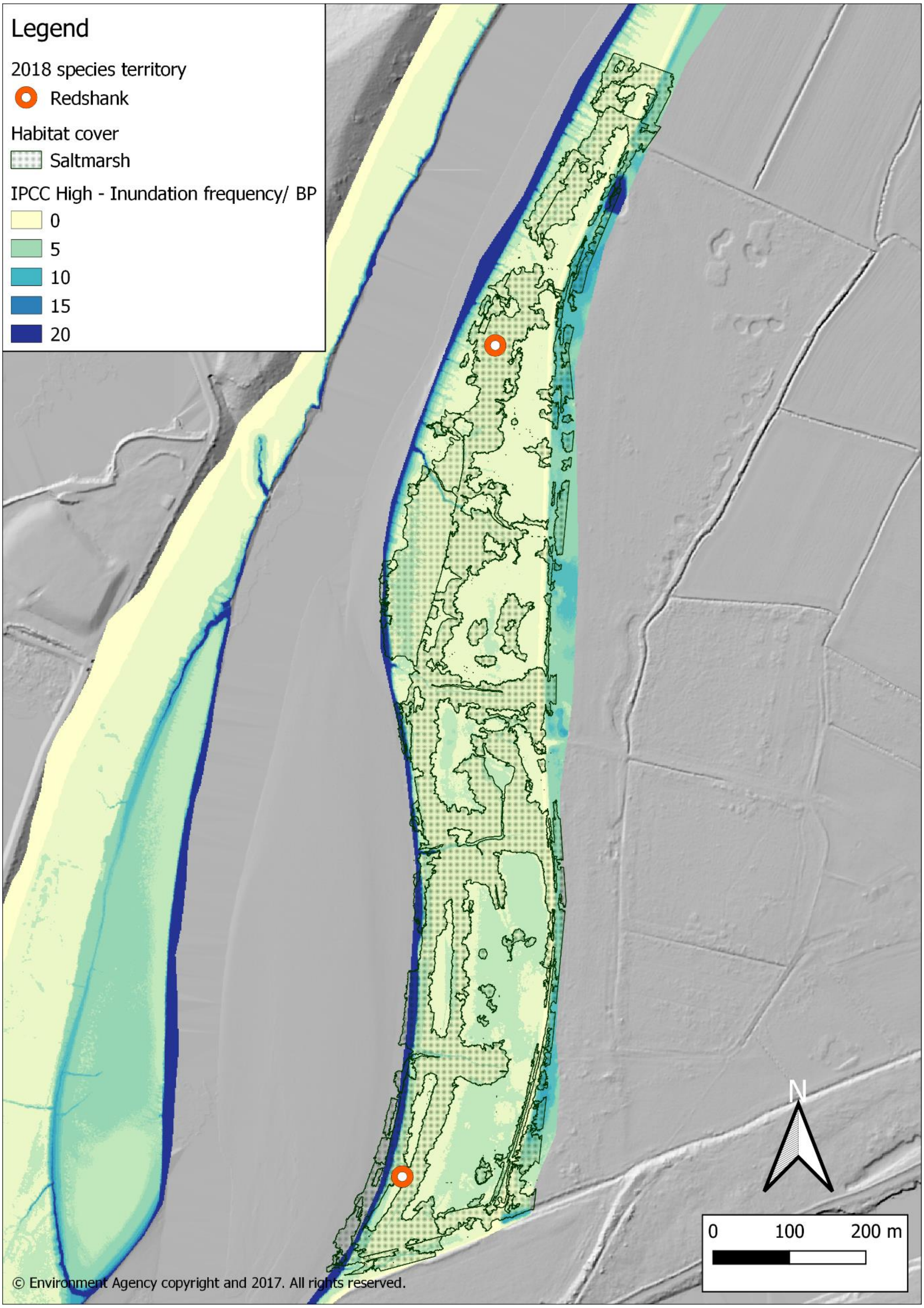


Figure 7.18 – Inundation events based on redshank breeding season under IPCC high emission scenario per breeding period (BP), March – July.

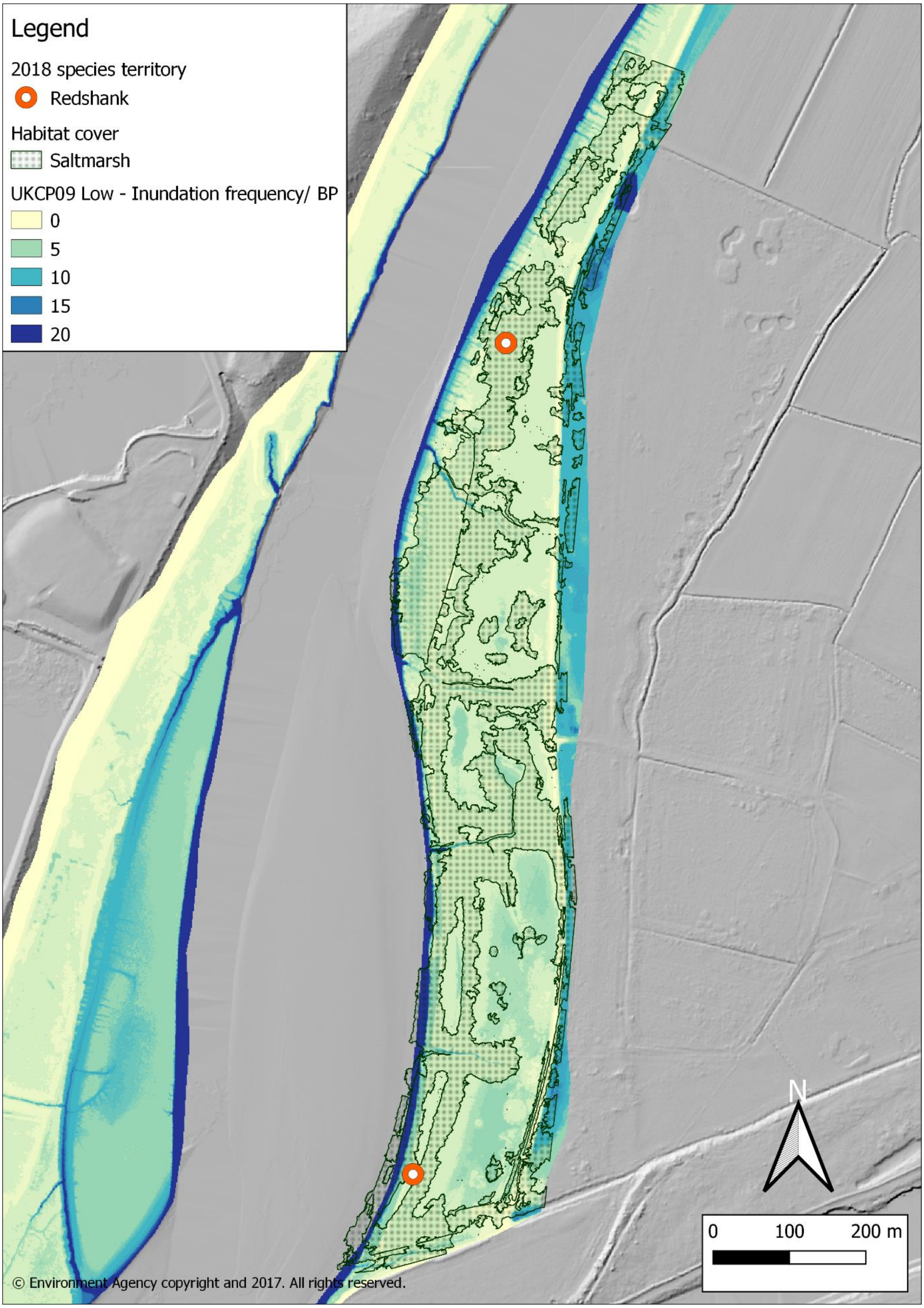


Figure 7.19 – Inundation events based on redshank breeding season under UKCP09 minimum emission scenario per breeding period (BP), March – July.

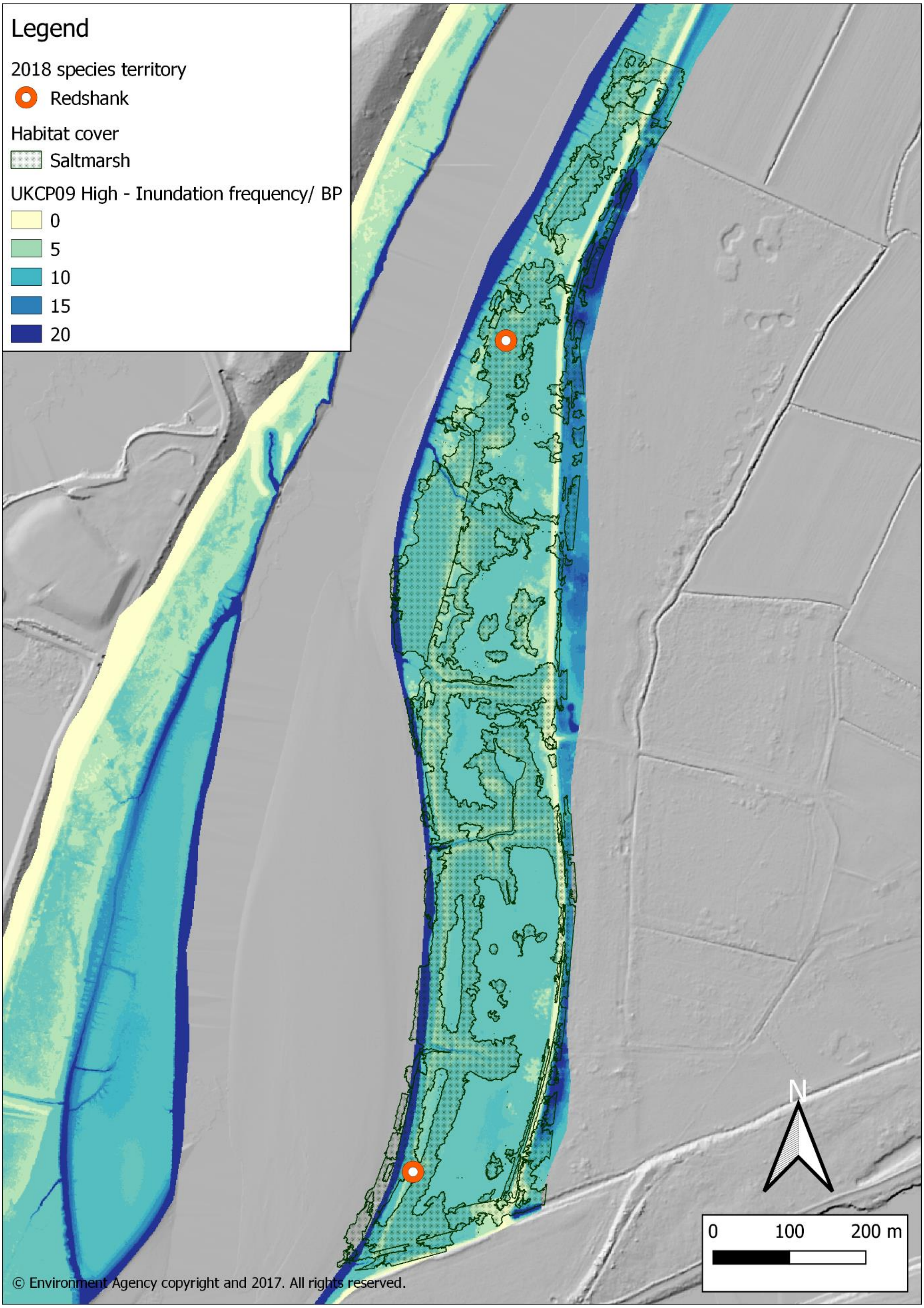


Figure 7.20 – Inundation events based on redshank breeding season under UKCP09 maximum emission scenario per breeding period (BP), March – July.

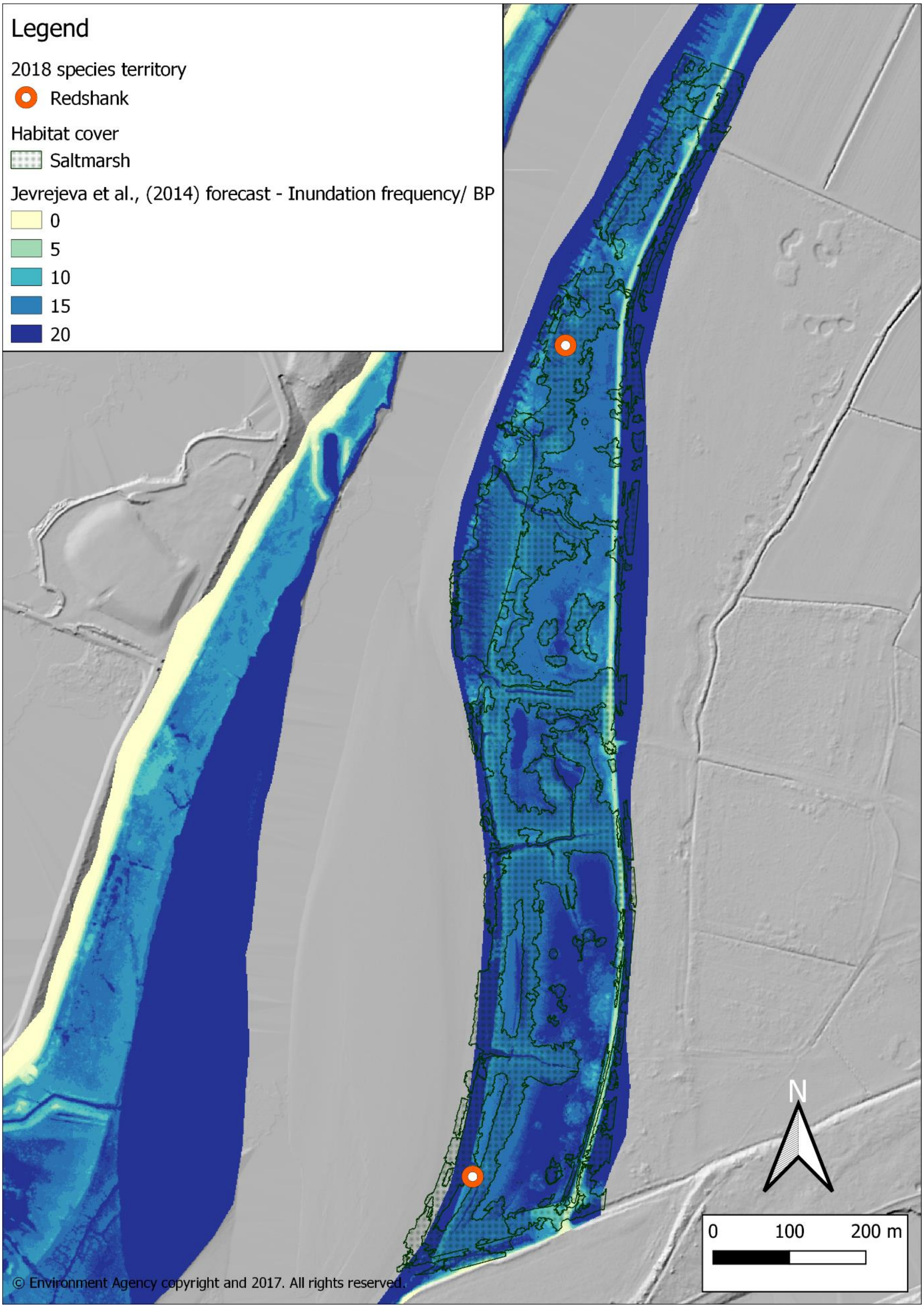


Figure 7.21 – Inundation events based on redshank breeding season under Jevrejeva et al., (2014) emission scenario per breeding period (BP), March – July.

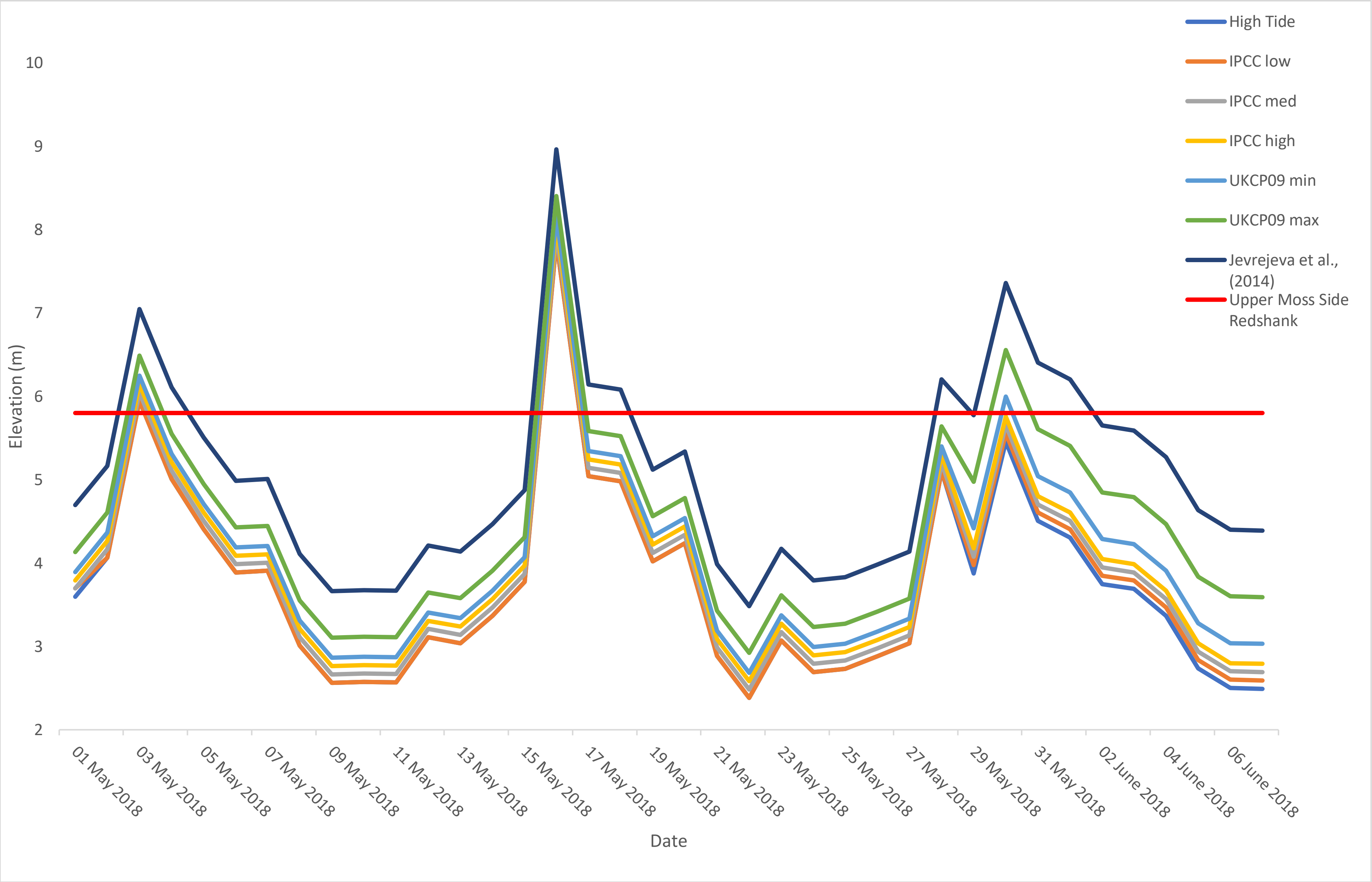


Figure 7.22 – Tidal inundation frequency based on 2018 tidal gauge data, under sea level rise scenarios, for the redshank breeding period.

Figures 7.16 – 7.21 represent the parts of saltmarsh habitat that will be inundated and the frequency of inundation during the redshank breeding period. The data presented in Table 7.7 relate to the mean number of inundations for the redshank territory under the sea level rise scenarios. Due to the relatively late period that this species breeds and the high elevation of the territory at Upper Moss Side, the lower sea level rise scenarios forecast only one inundation under the IPCC predictions. The UKCP09 minimum and maximum range predictions sees 2.02 and 7.8 inundations respectively, and the speculative forecast publish by Jevrejeva et al., (2014) would see the redshank territory inundated 16.2 times based on the 2018 data and current redshank territory. Table 7.8 and Figure 7.22 represents the longest period between inundations under each scenario and a graphical representation of the daily tide heights under the sea level rise scenarios based on the 2018 tidal data. A dissimilarity in the breeding behaviour between the passerine species and the non-passerine, in this case, wading birds, lies in the development of the chicks after hatching. The passerine species are precocial, so are restricted to the nest while the parent birds rear them to fledging. The wading species hatch as altricial, meaning they are mobile as soon as they emerge, meaning that they might only be sensitive to sea level rise during the incubation phase. In redshank, the mean period that eggs are incubated is 24 days, and the fledging period after which the birds can fend for themselves is 36 days. It is the assumption here that once hatched, young birds can avoid inundated areas of the saltmarsh (Redfern, 1982), however, as is seen in the more extreme forecasts represented in the average high tide in figures 7.20 and 7.21, there are few areas that are not inundated. Hence, this period of sensitivity then will remain at the 24 days. As is displayed in Table 7.8 the IPCC forecasts exceed this incubation period: the longest time between inundation is 45 days. The UKCP09 min forecast gives 44 days without inundations, and the max forecast is 24 days which equals the mean of the redshank incubation period. The scenario derived from Jevrejeva et al., (2014) sees only 10 days without inundation. It is clear then that redshank nesting success may be compromised under UKCP09 and Jevrejeva et al., (2014) scenarios, and with Upper Moss Side having a greater elevation than the other marshes in the area this might indicate that redshank across the entire Upper Mersey Estuary are vulnerable.

7.2.3.2 – Northern lapwing

Figures 7.23 – 7.28, and Tables 7.9 and 7.10 display the outcome of the sea level rise analysis for the northern lapwing territory at Upper Moss Side. The same procedure was undertaken as outlined above in Section 7.2.2, however the dates used were derived from the northern lapwing breeding season between the 12th April and 25th May (Joys and Crick, 2004).

Table 7.9 – Mean number of inundations for northern lapwing territories under sea level rise scenarios.

Upper Moss Side Scenario	**Mean No. of Inundations**	**Standard Deviation**
IPCC Low	2	0
IPCC Med	2.02	0.1
IPCC High	2.2	0.5
UKCP09 Min	3.1	0.3
UKCP09 Max	11.80	0.3
Jevrejeva et al., (2014)	22.4	1.2

Table 7.10 – Longest period without inundation for northern lapwing territories.

Upper Moss Side Scenario	**Longest period without inundation (No. of Days)**
IPCC Low	**53**
IPCC Med	**53**
IPCC High	**39**
UKCP09 Min	**39**
UKCP09 Max	**22**
Jevrejeva et al., (2014)	**12**

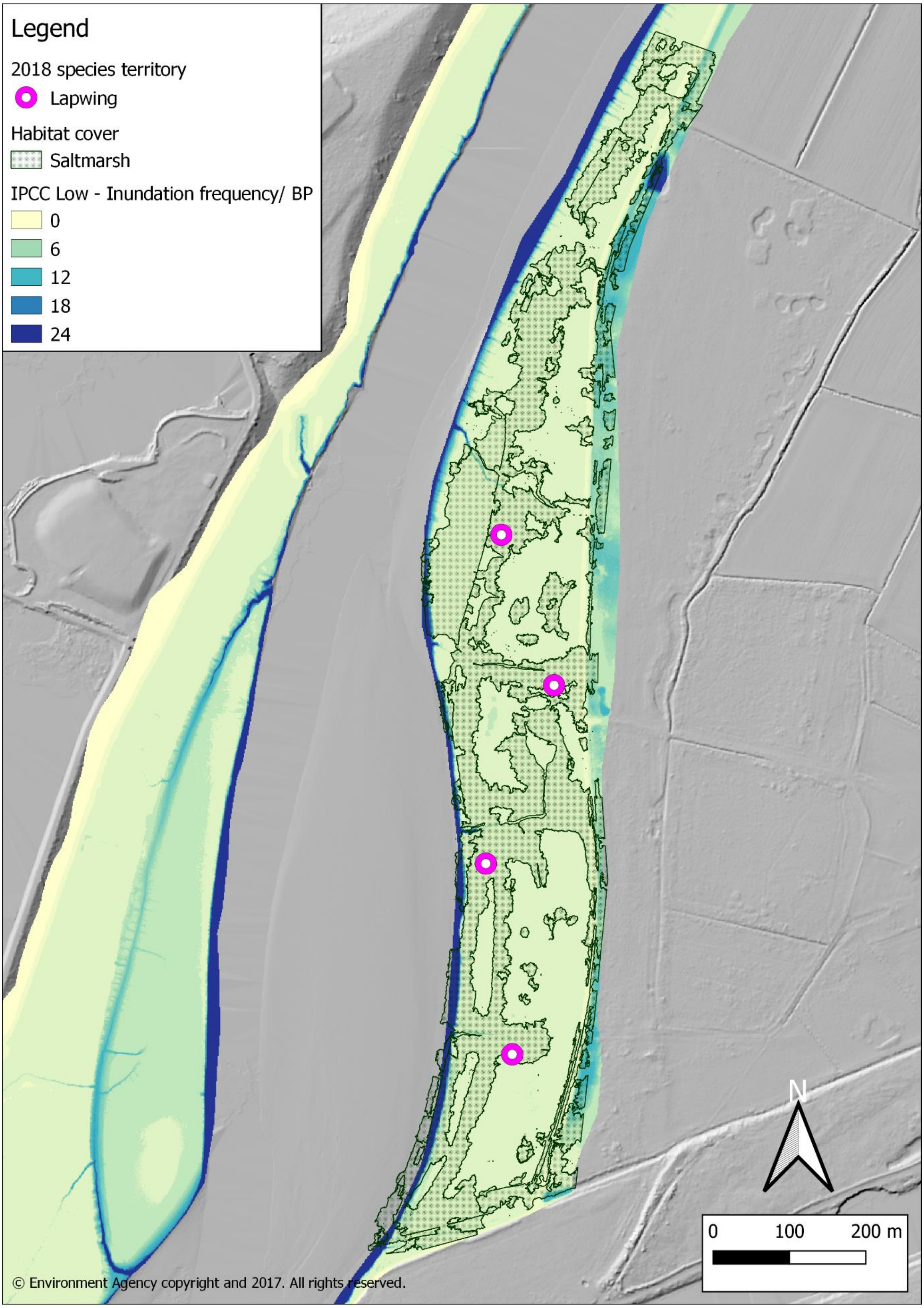


Figure 7.23 – Inundation events based on northern lapwing breeding season under IPCC low emission scenario per breeding period (BP), March – July.

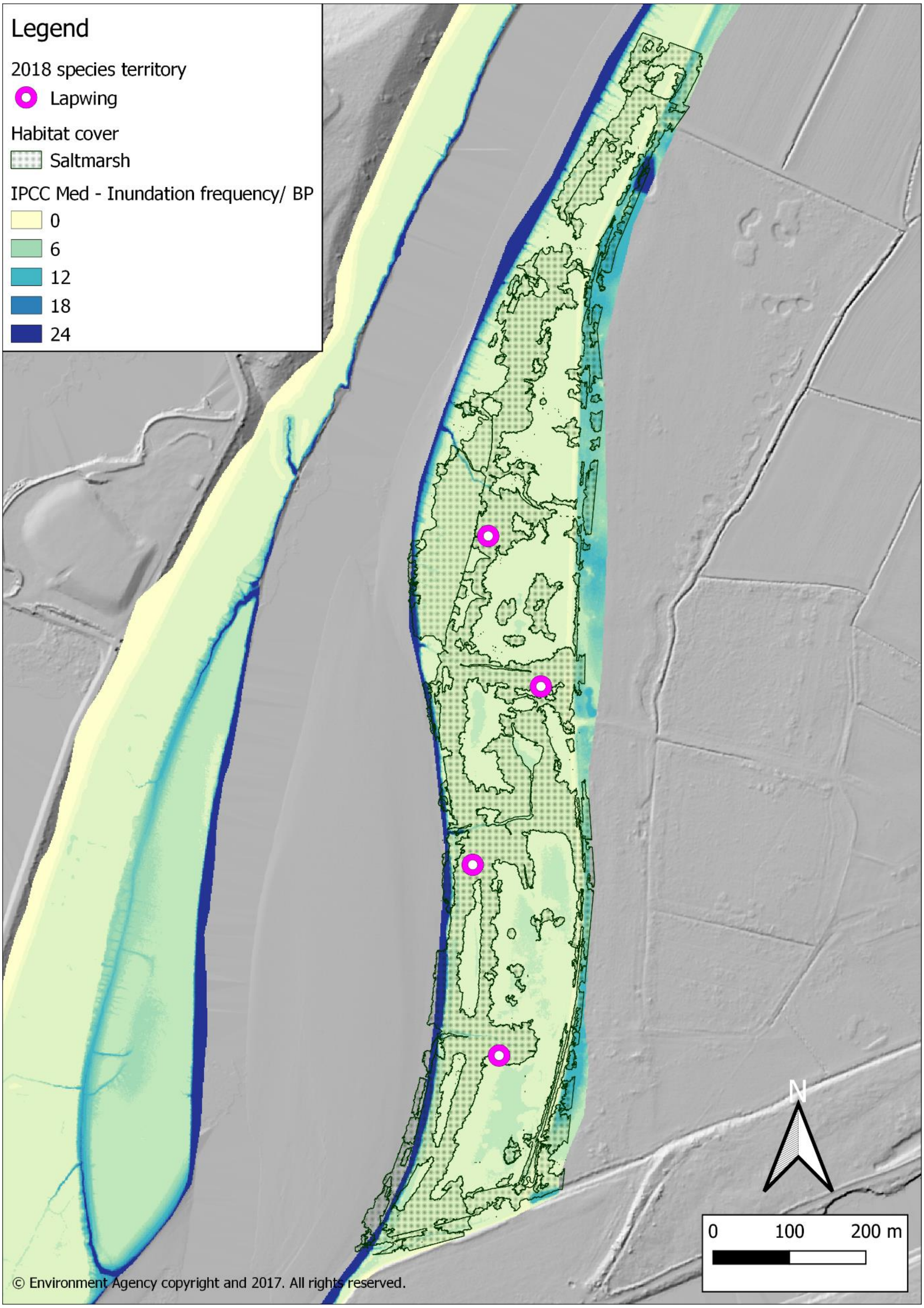


Figure 7.24 – Inundation events based on northern lapwing breeding season under IPCC medium emission scenario per breeding period (BP), March – July.

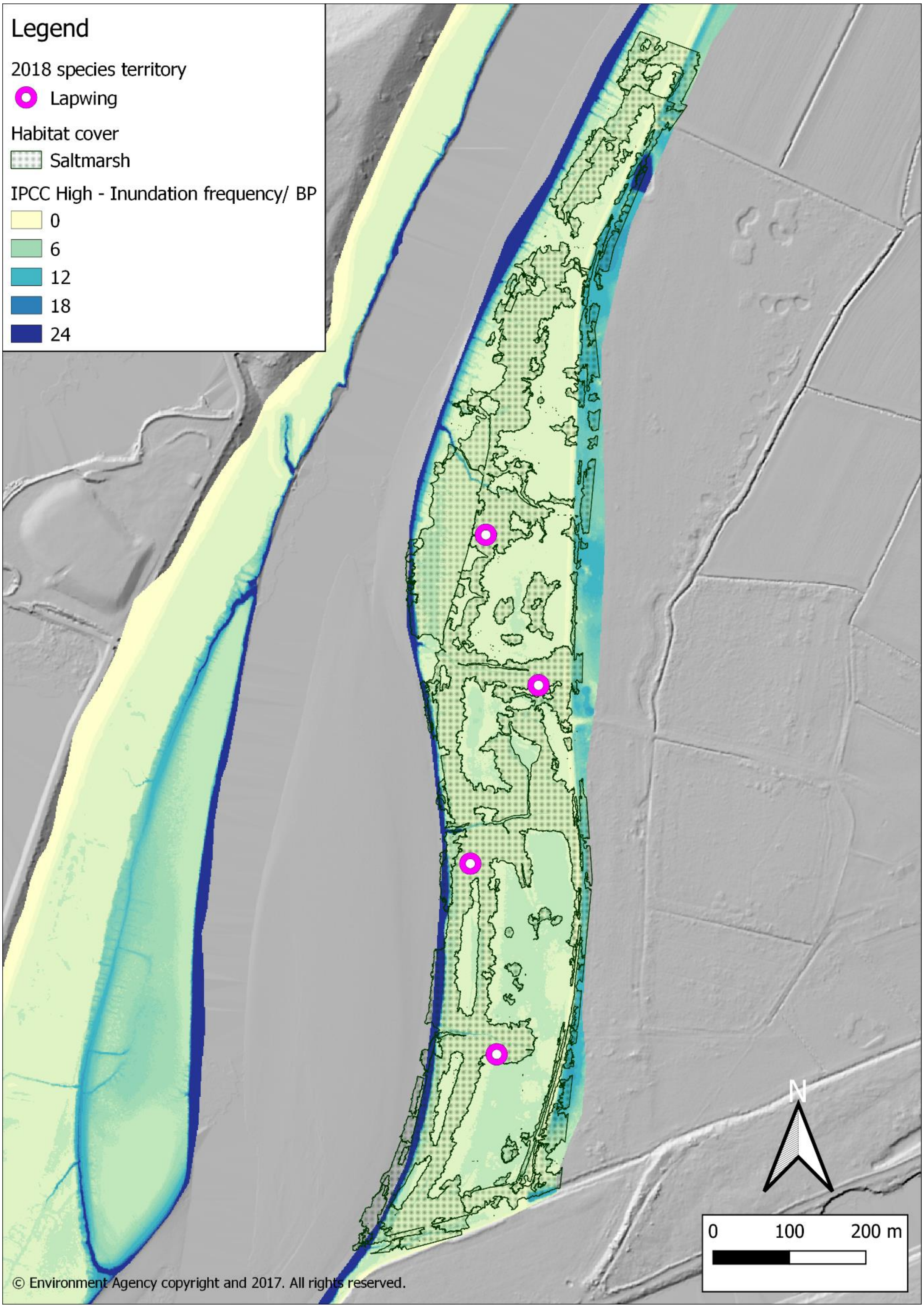


Figure 7.25 – Inundation events based on northern lapwing breeding season under IPCC high emission scenario per breeding period (BP), March – July.

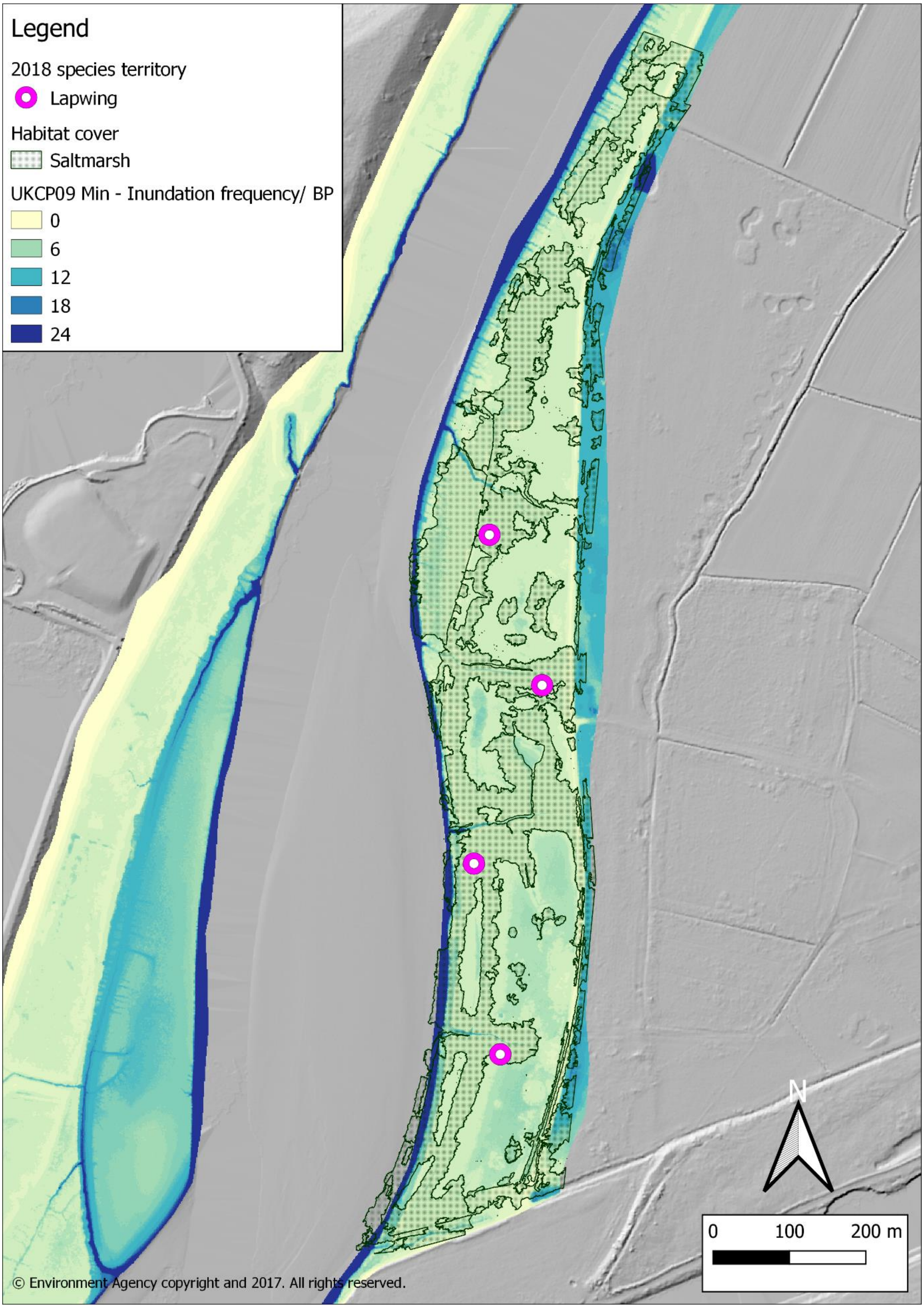


Figure 7.26 – Inundation events based on northern lapwing breeding season under UKCP09 minimum emission scenario per breeding period (BP), March – July.

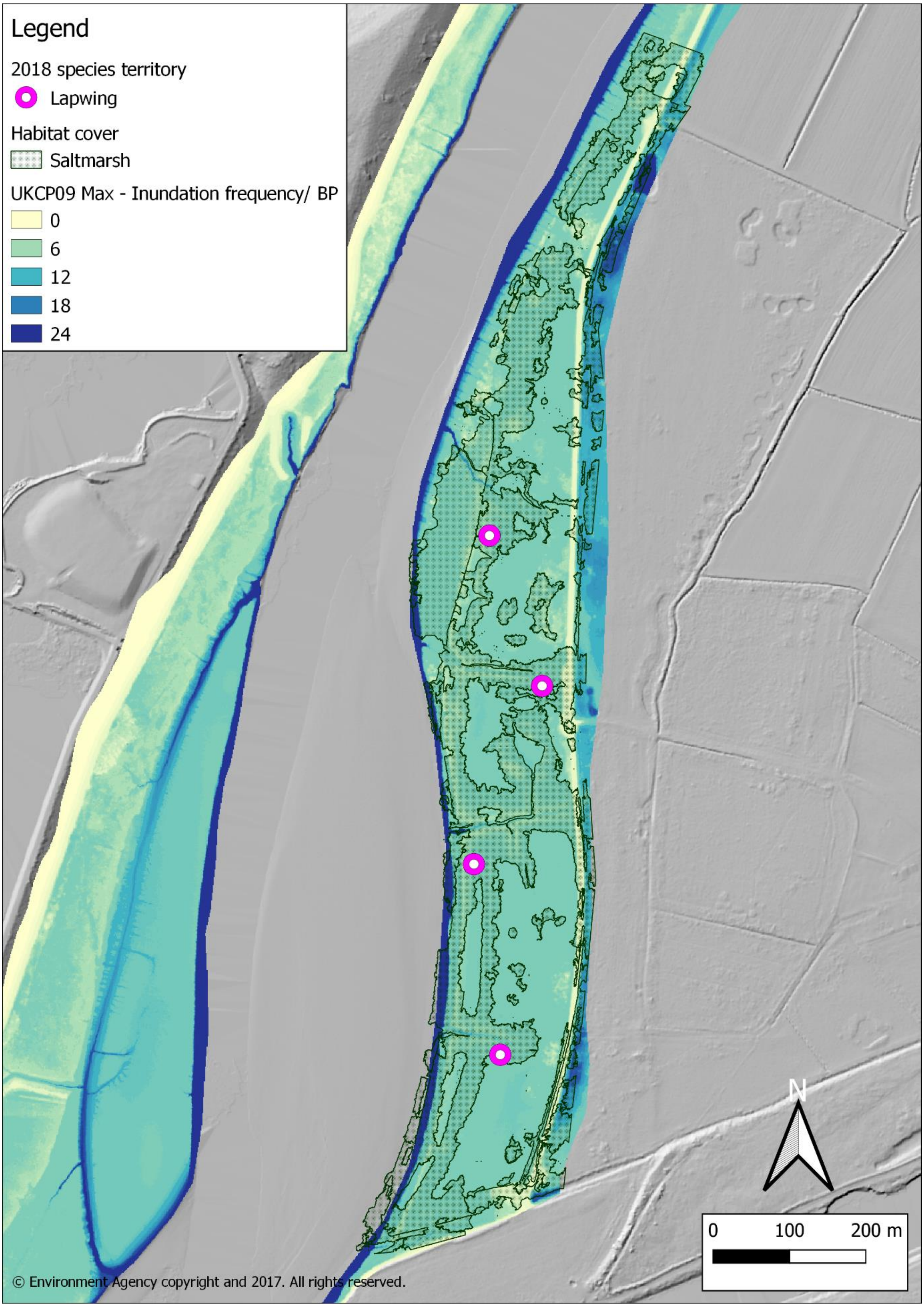


Figure 7.27 – Inundation events based on northern lapwing breeding season under UKCP09 maximum emission scenario per breeding period (BP), March – July.

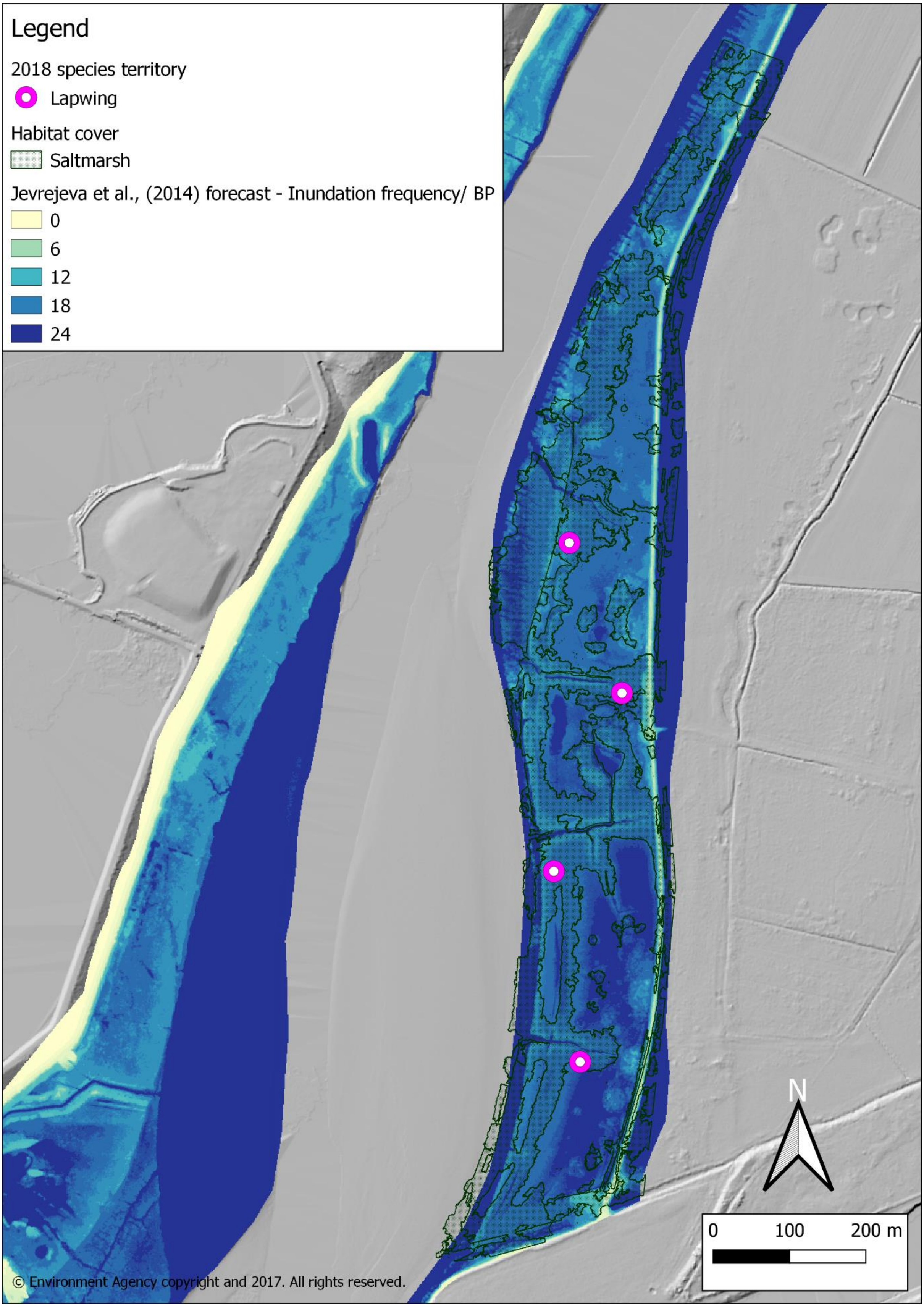


Figure 7.28 – Inundation events based on northern lapwing breeding season under Jevrejeva et al., (2014) emission scenario per breeding period (BP), March – July.

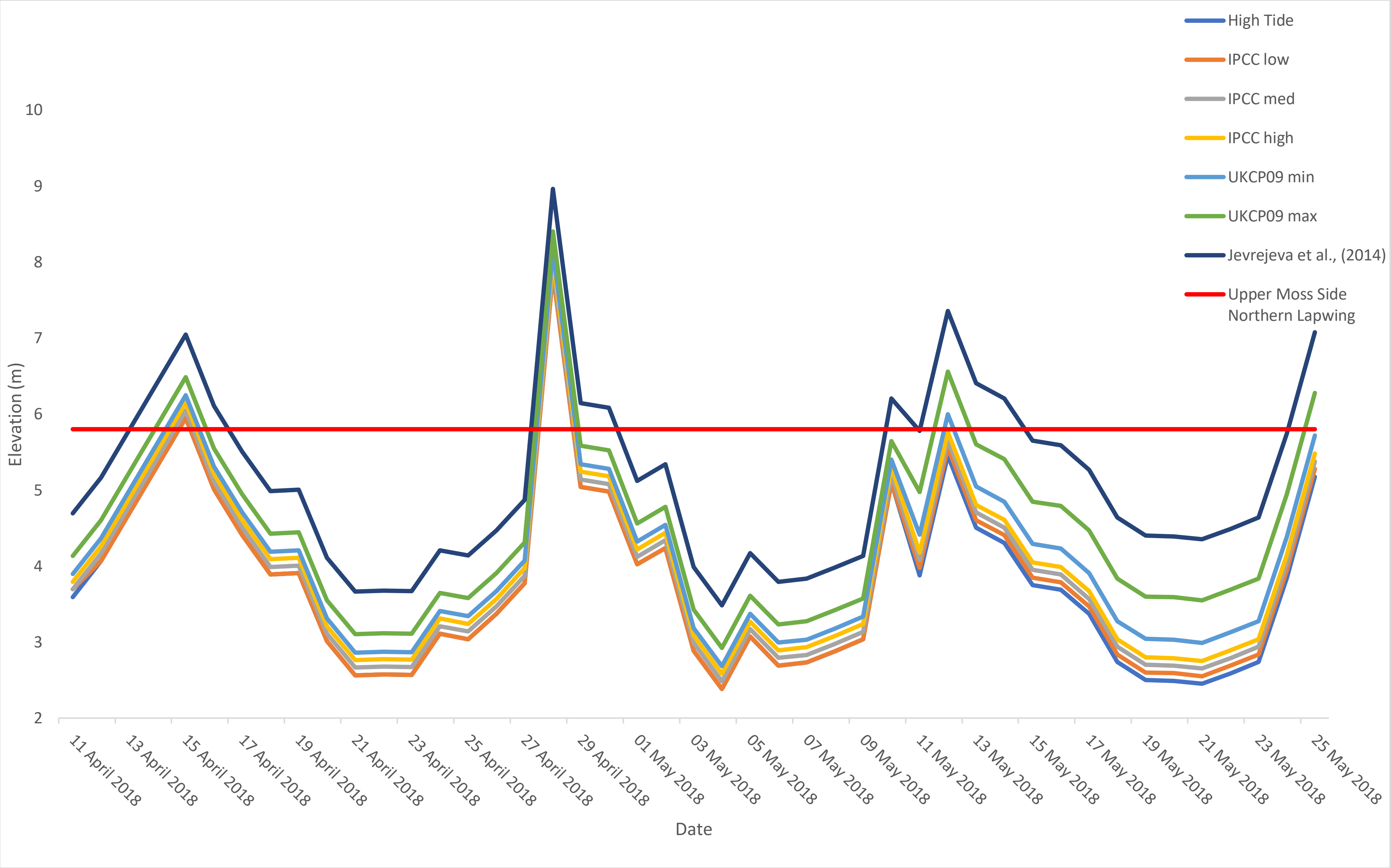


Figure 7.29 – Tidal inundation frequency based on 2018 tidal gauge data, under sea level rise scenarios, for the northern lapwing breeding period.

Figures 7.23 – 7.28 present the data for each sea level rise scenario for the northern lapwing at Upper Moss Side. Each figure communicates the inundation frequency for the saltmarsh habitat at this site in relation to the breeding territory of this species during the breeding period. The data presented in Table 7.9 relates to the mean number of inundations for the northern lapwing territory under the sea level rise scenarios. This species lays eggs between 12th April and 25th May and has a total mean period of 69 days from egg laying to fledging. For this species the IPCC scenarios predict a mean number of inundations of 2, like the redshank, due to the relatively high elevation of the saltmarsh (5.85m). The UKCP09 minimum and maximum range predictions sees 3.10 and 11.80 inundations respectively, and based on speculative forecast published by Jevrejeva et al., (2014) the northern lapwing territory would be inundated 22.4 times based on the 2018 data and current northern lapwing territory locations. Table 7.10 and Figure 7.29 represents the longest period between inundations under each scenario, and a graphical representation of the daily tide heights under the sea level rise scenarios based on the 2018 tidal data. Like the redshank, the northern lapwing chicks hatch as altricial meaning they are mobile as soon as they emerge. In the northern lapwing the mean period that eggs are incubated is 31 days, and the fledging period after which the birds can fly is 36 days. Also following the previous section, it is the assumption here that once hatched, the young birds can avoid inundated areas of the saltmarsh. However, as is seen in the more extreme forecasts, represented in the average high tide data presented in figures 7.27 and 7.28, there are few areas that will not be inundated. This period of sensitivity will, therefore, remain at the 24 days. As is displayed in Table 7.10 the IPCC forecasts exceed this incubation period. The longest time between inundation is 53 days under the IPCC low scenario, and 39 for the IPCC high scenario. The UKCP09 minimum range forecast is for 39 days without inundations and the max forecast is 22 days which equals the mean of the lapwing incubation period. Under the scenario derived from Jevrejeva et al., (2014) the forecast is for only 12 days without inundation. It is clear then that northern lapwing nesting success may be compromised during these two extreme scenarios. And as Upper Moss Side has a greater elevation than the other marshes in the area, northern lapwing breeding success might be compromised across the entire Upper Mersey Estuary under a similar tidal frequency.

7.3 – Summary

The findings reported in this chapter address Research Objective 2, Section 2.10 by visually representing the impacts of sea level rise within a saltmarsh of the Upper Mersey Estuary and determining the potential impacts that sea level rise scenarios would have on the breeding bird species associated with the saltmarsh habitats. This has addressed the recommendation within the literature and represents a novel exploration of breeding data bird data and sea level rise. As has been documented here, it is only under the most extreme scenarios that species-specific breeding seasons in the Upper Mersey Estuary will be an interrupted. While from data presented here it may be determined that the saltmarsh habitats within the Upper Mersey Estuary have a moderate to low vulnerability to sea level rise. This is under the assumption that the avian species will choose to breed at the beginning of a ‘safe’ period the longest period of no flooding. As has been described within the literature, birds do not necessarily have an awareness of changes in tidal flooding cycles and, thus, may still breed within a period that is highly susceptible to flooding (Van de Pol, 2000). Within this chapter the vulnerability of the species breeding habitat to the sea level rise experienced within the Upper Mersey Estuary has been highlighted. Further research will be required, over long-time scales to document species responses to this phenomenon. As the literature recommends it might be appropriate that, regardless of vulnerability, management options should be explored and initiated that protects the ecology of such systems from effects of climate change and sea level rise (Dickinson et al., 2015). Potential management options, and further research that might be derived from the basis of this chapter are explored in Chapter 8.

Chapter 8 – Discussion

8.1 – Introduction to Chapter

The work presented within this thesis has addressed gaps identified within the literature cited in Chapter 2. Pursuing these opportunities for understanding, particularly within the framework of ecosystem vulnerability assessment, has provided new perspectives for the future management of the Upper Mersey Estuary, and for estuaries globally by reinforcing potential risks to these systems under climate change. The findings make important contributions within the now well recognised and globally important field of vulnerability assessment. A key discourse within this field, identified in Chapter 2, relates to environmental uncertainty and how it must be included in the setting of objectives within ecological restoration projects – albeit within the greater framing of environmental conservation – as the uncertainty around the impacts of climate change are irreducible (Dickinson et al., 2015; Collof et al., 2017). The vulnerability of ecosystems needs to be assessed in ways appropriate to their function, and the extent of any vulnerable habitat systems needs to be monitored and mapped. Vulnerability analyses can be derived by examining the sensitivity of component species to changes in key environmental conditions, based on the parameters identified by the IPCC, namely sensitivity, exposure and adaptive capacity. In the case of the research presented here, these parameters relate to the breeding window of bird species and the available breeding habitat within the saltmarshes, and the forecast scenarios of sea level rise. The relationships between these parameters ultimately influences potential impact and subsequent vulnerability of the system to change.

Where vulnerable areas are identified, then appropriate management can be formulated based on those criteria as a response to future predicted changes (Dickinson et al., 2016). Key papers within the literature call for adaptive process to be initiated and adopted widely within conservation and restoration projects (Hannah et al., 2002; Doody, 2008; Lawton, 2012; Dickinson et al., 2016; Wyborn et al., 2016; Collof et al., 2017). These authors identify that a wider application of scenario planning is required to identify robust climate change interventions designed for target species and systems, and that these processes are implemented on a site by site basis.

Systems need to be established to translate climate change scenario impacts on target species into effectively communicable and deliverable, management scenarios (Dickinson et al., 2016). To facilitate the required bridging of the gaps between policy and practice, and the integration of all stakeholders, the consequences and outcomes of different management scenarios should be made as clear as possible through mapping and other forms of communication (Krolik-root et al., 2015; Tolvanen and Aronsen, 2016). These concepts and the associated impacts of change need to be clearly communicated to ley public and non-specialist stakeholders. This is the form that vulnerability analysis needs to take in order to successfully plan for and mitigate change (Gitay et al., 2011). While this area of study is in its relative infancy, and no single approach has been defined, the numerous challenges and gaps within knowledge have been identified. Means to collect spatial and temporal data at scales appropriate to wetland processes is a key area of research. And further, that these data are contextualised by ecological information within complex settings of interactive pressures derived by land use and land ownership is a further area requiring attention (Gitay et al., 2011; IPCC, 2014). Though complex pressures will be entirely unique to each system, the framework of vulnerability assessment can be flexible in its application, such that novel studies are undertaken which are defined both by the aims of a restoration project and likely pressures that the system will face. This collection of ideas, and the gaps knowledge which have been identified are what the research presented within this thesis has sought to address. Within the view of ecosystem vulnerability assessment, the key questions are:

1.) What remote sensing system is best suited to collecting spatial and temporal data of wetlands?
2.) What pressures face wetland ecosystems within a cultural landscape?
3.) Can these issues be communicated in a format suitable for a multi-stakeholder environment?

These questions have been addressed through the following null hypotheses which were derived from the literature review:

1.) Fine scale UAV systems do not produce greater accuracy maps of saltmarsh habitats than satellite derived techniques, 2.) Remote sensing does not provide saltmarsh habitat maps sufficient for a vulnerability analysis,

3.) Habitat management does not impact on bird populations using saltmarsh and reedbed estuarine vegetation,

4.) Sea level rise poses no risk to breeding birds in the Upper Mersey Estuary.

The study was designed in such a way that the individual chapters feed into one another. These data are presented in the following chapters: the empirical findings relating to the saltmarsh vegetation classification (Chapters 4 and 5), and the characterisation of site ecology and the vulnerability of the saltmarshes and breeding bird species to sea level rise (Chapters 6 and 7).The implications derived from the findings, relating to the management of the field of ecological restoration under an uncertain future, is the subject of this chapter. This chapter will conclude by initiating a discourse on the potential future management options implemented in the Upper Mersey Estuary, as a representative of saltmarshes globally, as means to fulfil the recommendations derived from both the literature and from the findings presented in this thesis. The final contribution is to present this thesis as a foundation from which to pursue future research, relating specifically to the adaptive management, vulnerability assessment, and monitoring of estuarine habitats.

8.2 – Employing a Remote Sensing Based System for Vegetation Mapping

A central requirement for the implementation of adaptive management is the repeatable and consistent monitoring of key environmental variables relating to the system under study. This includes the extent of wetland habitats and, the distribution of cover types, and eventually, the within habitat change of the ecosystem. Remote sensing and Geographical Information Systems (GIS) provide scientists with a set of powerful tools to monitor the Earth's surface.

The continued coverage of satellite-based systems allows us to capture an ecosystem at specific moments in time that can then be analysed to provide data products pertaining to a vast array of applications (Whyte et al., 2018). The large capture size, known as a swath width, of satellite sensors allows for the monitoring of large regions, enabling the researcher to collect data at regular intervals without being in contact with the site (Adams et al., 2010). A key application within this field is the derivation of land use and land cover information. This practice, within the context of a monitoring project, can allow for long-term change detection and the monitoring or surveillance of sensitive ecosystems.

The twin-satellite Sentinel-2 mission developed by the European Space Agency (ESA) was identified within the literature as a system appropriate to the study and monitoring of wetland environments. Despite the relatively recent launch of this system (Sentinel-2A launched 23rd June 2015 and Sentinel-2B launched 7th March 2017, 2C and 2D scheduled post-2020), there is a high volume of published work reporting its success and potential in the monitoring of wetland and aquatic systems (Villa et al., 2013; Bresciani et al., 2014; Villa et al., 2014; Statoulias et al., 2015; Villa et al., 2015; Kaplan and Avdan, 2017; Whyte et al., 2018). In order to address the first research objective, this system was adopted within the current study with the aim to evaluate critically the use of the derived products within the context of vegetation mapping within the Upper Mersey Estuary.

Within the context of the current study two products were derived from the Sentinel-2 satellite system, these were vegetation indices, and Sentinel-2 band-based classifications, these data are presented in Chapter 4. That chapter presents an exploration of a saltmarsh land cover classification utilising the Sentinel-2 satellite bands, and a range of vegetation indices across the saltmarsh habitats in the Upper Mersey Estuary. Timely collection of data from which vegetation indices can be calculated allows users to monitor phenological change within a system via the ‘greening up’ vegetation phase, which may be a key indicator of ecosystem alteration as a result of climate change (Adam et al., 2010; Dickinson et al., 2015; Villa et al., 2015). These data were acquired in May 2018 to capture this greening up phase, and to aide comparison with the UAV data set which was collected during the same month (Sun et al., 2016). An exploration of the separability between the saltmarsh cover classes was undertaken utilising the Jeffries-Matusita distance calculation, an established technique which establishes the probabilistic separability between two classes (Liu et al., 2020). The pairwise class separability was calculated for each input; the Sentinel-2 analysis bands, and the four vegetation indices utilised within this study. As was reported within Chapter 4, separability was generally low within category, i.e., vegetated, and non-vegetated, however, between category separability was high. The Water Adjusted Vegetation Index showed the greatest separability between classes, followed by the NDAVI.

This result echoes previous research utilising these indices for reed bed monitoring aquatic vegetation within Lake Garda (Villa et al., 2015). Using the Jeffries-Matusita distance, WAVI and NDAVI outperformed the terrestrial indices when studying reed beds of varying densities and water presence.

Delineating vegetation cover classes are of value both in terms of long-term studies of change and to provide baseline habitat data for key species (Dickinson et al., 2015; Kaplan and Avdan, 2017). The data presented in Chapter 4, Section 4.3, pertain to an exploration of the Sentinel-2 data set as a means to achieving this within the context of a saltmarsh ecosystem. Linking the scale of the study to that of management objectives was a key decision in testing the value of these data for future monitoring (Wyborn et al., 2016; Collof et al., 2017). The utilisation of three relevant pixel-based classification procedures was described in Chapter 3, Section 3.3. These three methods are the maximum likelihood, support vector machine, and random forest. The classification procedure was undertaken on a data set that was collected from the 21st May 2018. The result of these classifications was a user accuracy of 56%, 57%, and 70% for the three methods respectively, and a Kappa coefficient of 0.4, 0.42 and 0.59 (see Tables 4.2 – 4.4). According to the Kappa values the classification yielded moderate agreement for the random forest, with less than 70% of pixels assigned to the correct land cover class. The classification procedure was repeated utilising the random forest technique on the four vegetation index images (Liu et al., 2020). These were the NDVI, NDAVI, EVI and WAVI. The resultant overall classification accuracies were 65%, 71%, 68% and 76% respectively. Overall, the classification results reflected the potential issues highlighted by the separability analysis. There were relatively low errors between categories (vegetated vs non-vegetated), however, with category separability was an issue, and this is due to the similar spectral properties and vegetation ecology of saltmarsh vegetation (Davidson et al., 2017). The WAVI based classification outperformed the other data sets with a Kappa score of 0.67. The also reflects the increased (albeit only slight) separability compared to the other VIs and the Sentinel-2 bands. This was greater particularly between the reed bed class, and the short sward grass class. This is likely due to the background effect of water within the mixed pixel (Villa et al., 2015). Within the matrix of vegetation of the saltmarshes present in the UME, low levels of water is generally present, particularly between the boundary of cover types. Following tidal inundation, the saltmarsh substrate and vegetation will have a ‘background’ presence of water of varying depths. This overall separability is better distinguished by the aquatic VIs which account for this presence – NDAVI and WAVI. This changes when denser, longer sward vegetation is present as the background interference of the tidal water is somewhat obscured, resulting in lower separability, and almost comparable performance to the ‘terrestrial’ vegetation indices such as NDVI or EVI. The WAVI index performing greatest within this context is to be expected, as it derived from the NDAVI, though with the inclusion of a correcting factor for the background influence of water. This means that the index can be adjusted based on the conditions identified (Villa et al., 2020). Further to this, the impacts of the random forest classifier were an increase in accuracy when compared to the other two techniques. As has been noted within the literature, random forest is able to deal with ‘noisy’ data sets, i.e., those with background effects due to water (Tian et al., 2016). The WAVI index performed satisfactorily well, through the lessons learned within the current study, there is potential for future research which may further influence the applicability of this technique for wetland monitoring is discussed at the end of this section.

A key challenge remains within the application of satellite sensors in the monitoring of saltmarsh habitats. This lies in the proportions and distributions of different ground cover types. The zonation and detectability of saltmarsh communities poses a challenge in the field of remote sensing. While these classes are spectrally separable, the steep environmental gradients present in these systems can mean that the detectivity of the vegetation classes is obscured by the spatial resolution of the sensor. Stands of vegetation, ditches, and pools can be smaller in size than the ground pixel size of the common satellite sensors (Adam et al., 2010). Researchers have had difficulties applying satellites of low spatial resolution to the mapping of coastal wetlands on account of this problem (Zomer et al., 2009).

This limitation of traditional remote sensing approaches in monitoring small-scale systems, while derived from a mismatch between the sensors spatial resolution and the ecosystem processes under scrutiny, offers opportunity within the field to test novel methods, and refine data collection techniques (Rosnell et al., 2011; Anderson and Garston, 2013). As a result of this, it was within the remit of the first objective of this research to refine these techniques and explore opportunities for a scale appropriate vegetation monitoring system for application within the Upper Mersey Estuary utilising an Unmanned Aerial Vehicle (UAV). The data associated with the development of this research objective are presented in Chapter 5. Within this study, recommendations were taken from previous research within this field to utilise two consumer grade cameras, one of which collected data in the NIR band, to classify the broad saltmarsh cover classes (Duffy et al., 2018). The novel application of the system described in Chapter 5 establishes this study as a basis for further development within this field, as the application of consumer grade NIR cameras for saltmarsh monitoring was a gap in the literature to be explored (Duffy et al., 2018). The key aim of this chapter relates still to objective one, however, this research sought to improve the accuracy of the classification derived from the Sentinel-2 data whilst also exploring whether the inclusion of the NIR band would assist in a further increase of classification accuracy. The key advantage derived from the consumer grade UAV system is manifested as a trade-off. Ultimately, the system sacrifices the depth of spectral resolution that is associated with satellite platforms for a very high spatial resolution several magnitudes greater than that obtained from the Sentinel-2 system. To determine the relative value of this system three questions were pursued relating to objective one:

1.) Can consumer grade camera and lightweight UAV be used to collect proximal remote sensing data of a mixed saltmarsh ecosystem.
2.) Can the UAV system provide a classification accuracy greater than the satellite system.
3.) How effective are different image classification techniques for mapping saltmarsh cover types.

As outlined in the Methods Chapter of this thesis (Chapter 3), object-based approaches are of value when analysing very high-resolution imagery as they remove the unwanted ‘salt and pepper problem’ of image speckle and noise that will result from pixel-based methods (Dronova, 2015).

Utilising the described methods for data collection and analysis, the three classification methods applied to the Sentinel-2 data were applied to the UAV data sets. For the RGB image set a user accuracy of 69% was reported for the maximum likelihood classifier (Table 5.1), 72% for the support vector machine (Table 5.2), and 71% for the random forest (Table 5.3). The Kappa values were 0.58, 0.63, and 0.61 respectively. For the data set including the NIR band a user accuracy was reported for the maximum likelihood classifier of 67% (Table 5.4), 68% for the support vector machine (Table 5.5), and 84% for the random forest (Table 5.6). The Kappa values were 0.55, 0.56, and 0.79 respectively. Addressing the three questions relating to this chapter, the application of the UAV system was successful in collecting remote sensing data in the saltmarsh environment. Further to this, the classification accuracy reported in Chapter 5 is lower by 5% for the RGB dataset when compared to the Sentinel-2 WAVI derived random forest classifier. The UAV dataset incorporating the NIR band exceeds that of the Sentinel-2 data presented in chapter 4 by an 8% increase, based on the random forest classifier. The NIR classification utilising the random forest classifier, therefore, provided the highest overall classification accuracy of this study, however this was moderately comparable to the Sentinel-2 classification based on the WAVI vegetation index (Section 5.3.3). The random forest classifier produced the highest accuracy classification for both platforms, confirming the validity of this procedure within the classification of wetland systems. This confirms the advantage that has been highlighted within the literature as the classifier performs better than other machine learning algorithms on high noise datasets, such as wetlands or sparsely vegetated drylands (Tian et al., 2016; Noi and Kappas, 2018). It follows, then, that these results establish this technique as an appropriate technique to include within a monitoring strategy for the production of detailed habitat maps for saltmarshes in constrained estuaries, such as the Upper Mersey Estuary. However, though high classification accuracy and detailed habitat distribution were derived from this system, its ease of deployment and computational complexity may hinder the deployment of this system within some contexts. A key advantage to the utilisation of a remote sensing platform in habitat mapping and monitoring is the ability to collect proximal data of hard to reach areas. This advantage is widely cited within the literature and its applicability to satellite derived remote sensing is clear, as the researcher is not necessarily required to visit the site itself (Anderson et al., 2013; Duffy et al., 2017; Duffy et al., 2018). However, the statement cannot truly be applied to the UAV platform in the same way for several reasons, depending on the type of platform used, and the size of the site. UAV flight time is dictated by battery life, which can be further impacted by system weight and wind speed (Duffy et al, 2017). As a result, multiple batteries will be required for medium to large sites (the current study used five), and consequently multiple flight grids will need to be flown. The regulations around UAV flight in the UK dictate that visual contact with the aircraft must always be maintained (Duffy et al., 2017). This means that the researcher will have to be present on site for each grid that is flown, which in the case of the data collection at Upper Moss Side saltmarsh, required seven grids. While flight times can be increased with more expensive multirotor and fixed wing systems, site presence will still be required. The collection of multiple grids across a large site may take several hours from arrival to completion, as it takes time to prepare the battery, deploy the ground reference panels, upload the flight route and move between grids. Within this time, atmospheric conditions, cloud cover, illumination angle and intensity will change such that the collected imagery will require a calibration to account for these changes. This is a procedure that was undertaken within the current study; however, it required several panels of a known reflectance value to be placed throughout each flight grid, such that the calibration could be undertaken. This increases the researchers need to traverse the study area to a greater extent to deploy the calibration targets, or alternatively, to collect radiometric information from features that are present on site. As a result of these reasons, the claim that UAVs enable the proximal collection of remote sensing data in difficult to access, or dangerous to traverse sites is not totally accurate or applicable to this platform. Depending on the choice of the equipment, i.e., a large battery, and the size of the study site, it might be that data can be collected with the surveyor only need to gain access a point at which the system can be deployed (Duffy et al., 2017). However, this would assume that the calibration data would only be collected at the point of take-off and landing and may limit the data quality following processing as variable illumination will influence the final range of digital numbers which represent the radiometric information. Further constrains may lie in the weather conditions appropriate for UAV deployment. Moderate wind speeds, and gusts will prevent the safe flying of the platform and drain battery life, this will be compounded in coastal zone that often exhibit greater wind strength (Anderson et al., 2013; Duffy et al., 2017; Duffy et al., 2018). While the advantage of the UAV platform lies within the ability to deploy data under cloudy conditions, the sensitivity to wind prevents a barrier to data collection. In the current study, this limitation was encountered on multiple occasions, and this may limit the applicability of the UAV approach when timely data is required, i.e., time series monitoring of vegetation. The deployment of the platform requires organisation of resources, and physical assistance such that it may be difficult to remain on 'stand-by' for optimal conditions. With the aforementioned points considered, the UAV system was able to provide a highly detailed habitat map for the saltmarsh at Upper Moss Side, and with the further development of the platform that is still in its relative infancy, the above points will likely be mitigated for (Anderson et al., 2013). The use of UAVs vs satellite platforms needs to be considered with a set of trade-offs. Both platforms offer distinct advantages over the other, and the use of either as a means to provide a representation of habitat distribution will need to be considered along with the project objectives. It is clear from the classification outputs of the current study that the UAV approach succeeds in providing a more detailed habitat cover map for a single site, which is where the larger resolution of the Sentinel-2 data underperforms, as despite the roughly equivalent accuracy of the WAVI derived classification to the UAV system, the pixelated representation will limit how well this output is perceived when communicating the broader ecosystem vulnerability analysis to a wider audience. However, if the project focus is at this wider scale, i.e., the regional coastal zone, the utilisation of the Sentinel-2 platform will provide a rapid and repeatable depiction of saltmarsh extent. The addition of Sentinel-C and D in 2020 and 2021 will only increase this systems applicability like the one currently described, increasing the probability of cloud free data, free of charge, and of high radiometric depth.

It is clear that remotely sensed data provides valuable data from which accurate habitat maps can be derived. In tandem with traditional ground-based techniques, such as condition monitoring, these data will enable the long-term detection of habitat change, both in extent and composition. While remote sensing is not set out here as a replacement for traditional field techniques, it is considered as an approach with a different function. Rapid assessment of habitat extent, and precise georeferenced distribution maps can be produced quickly, and for large geographic areas. The nature of satellite platforms ensures that hard to reach, dangerous areas can be mapped, and therefore can provide data for potentially threatened systems that might not be gained otherwise. These facets determine remote sensing as a valuable source of data for long term vulnerability projects, and future developments within this field will further the ease of uptake, and quality of the derived data products (Doody, 2008; Davidson et al., 2017; Collof et al., 2017).

8.3 – Sea Level Rise Derived Impacts on the Avian Breeding Season

To quantify the avian biodiversity changes because of management across the sites in the Upper Mersey Estuary and to provide ecological context for the sea level rise analysis, an avian monitoring programme was undertaken (Chapter 6, Section 6.3). The programme utilised the Common Bird Census technique to reflect the species assemblage and community structure to the highest achievable precision (Bibby, 2002). After analysis, the field observations of species are transformed to a value representing the number of species breeding territories (Tables 6.1 and 6.2) using a territory mapping method. In addition to territory analysis, this study sought to determine the key periods of community change, and finally took the total number of observations for each year and calculated the effective number of species through diversity profiles (Figure 6.12). The value of diversity profiles in the context of this study is largely twofold. Firstly, the use of effective numbers through the Hill series means that the index is truly comparable between sites and years of study, which is not the case when using only the most common diversity indices alone (Shannon or Simpson etc.) (Jost, 2006; Morris et al., 2014). Incorporating similar metrics into the calculation allows for a rigorous and biological meaningful comparison across communities (Leinster, 2014). Secondly, the nature of the plotted diversity profile makes interpretation clear and easy and allows for the effective communication of diversity changes within a community, which is of high value within the context of the current work (Morris et al., 2014; Krolik-Root, 2015). Based on the profile presented in Chapter 6 (Figure 6.12), the outcome of management had a significant outcome for the short sward saltmarsh at Upper Moss Side in that species richness saw a significant increase during the monitoring years. This was the only community change of significance, as abundance and territory did not increase significantly between the two saltmarshes, and across the pre/during management years. The species representing this change were all favourable indicators of a saltmarsh wetland community, and the species were recorded across the breeding season as well as the winter period. The arrival of these species in 2017 represents the significant community difference reported in Chapter 6. No significant difference was recorded between the following post-management year, 2018, as these communities between these years was similar. The management impact which is statistically linked with this increase in richness fulfilled the key objective of the Mersey Gateway Environment Trust (MGET, 2014), that is, to encourage key bird species to breed within the managed habitat. The two target species which were recorded breeding as result of the management were the redshank (*Tringa totanus*) and northern lapwing (*Vanellus vanellus*). This is in addition to the ground nesting birds which were already on-site pre-management, the skylark (*Alauda arvensis*) and the meadow pipit (*Anthus pratensis*). Importantly, several species which were recorded as utilising this habitat within the UME are associated with the Mersey Estuary SPA and are responsible for its citation (JNCC, 2017). The redshank is one of these species, and its presence both wintering and passage, represents approximately 4% of the British population (JNCC, 2017). The significance of the findings reported here are that the management has been proven to create habitat conditions favourable for this species, both in a capacity to support breeding and wintering birds. At Upper Moss Side this was manifest as an increase in favourable habitat of 81,012 m^2 of short-sward saltmarsh, conditions favourable for breeding waders and ground nesting birds (Sharps et al, 2015; Davidson et al., 2017). Prior to commencement of the habitat management, no suitable habitat was present at Upper Moss Side for ground nesting birds due to dominant and rank saltmarsh grasses, which was identified during pre-commencement surveys conducted by the Mersey Gateway Environmental Trust (MGET, 2014). This increases the resilience of this species to population and habitat changes that may be associated with climate change and sea level rise. The provision of habitat connectivity through management – between the Mersey Estuary SPA and the UME – safeguards this SPA species, fulfilling the aims of the restoration objectives for the Mersey Gateway Environmental Trust's project (MGET, 2014). In addition to the arrival of the SPA species, numerous other wetland species contributed to the increase in species richness. Three species of geese were recorded, pink footed goose (*Anser brachyrhynchus*), greylag goose (*Anser anser*), and canada goose (*Branta canadensis)*, which are species typically associated as indicators of successful marsh restoration (Ladd, Skov, Lewis, & Leegwater, 2018). Waders in addition to the Eurasian lapwing included the nationally threatened curlew (*Numenius arquata*), ringed plover (*Charadrius hiaticula*), and the jack snipe (*Lymnocryptes minimus*) post-2017. Species in addition to these are presented in Table 6.11. Further to the statistically significant increase in species richness, this community change was reflected in the plotted Hill's numbers as shown in the diversity profile in Figure 6.12. This shows a clear separation in the diversity between 2016 and 2017 which corresponds to the statistical measures set out in Table 6.10. This shows clearly that within the context of the current study, statistically significant community changes that are derived from management practices can unambiguously be represented by the Hill's numbers and diversity profiles. This conclusion aligns with the recommendations within the literature, that community changes, either brought about by management, a progressive or acute change in an ecosystems function, needs to be communicated clearly (Collof et al., 2017). The research presented within thesis identified the Hill's numbers as a means to achieve this. Long term monitoring of faunal diversity could include this measure as a rapid, communicable and, most importantly, a statistically comparable measure of changes in community ecology over a period of time (Buckland et al., 2012). However, Chapter 6 was not intended to represent a key theme of knowledge generation within the current thesis, and the study was not designed to compare the analyses used to other methods which may be appropriate for represented community changes in a concise way. As such, while the methods presented here do indeed characterise the communities, an opportunity for future research lies in the rigorous testing of these, along with other appropriate methods.

An imperative recommendation from key sources of literature within the field of ecological restoration and uncertainty relates to approaches in scenario planning (Dickinson et al., 2015; Collof et al., 2017). Uncertainty can then be incorporated by setting goals derived from a range of modelled futures (Dickinson et al., 2015). As part of this method of management the sensitivity and adaptive capacity of a species or functional group can be assessed relative to these projected future scenarios. In tandem with ecological monitoring these methods form the basis of ecosystem vulnerability assessment (Dickinson et al., 2015; Collof et al; 2017). Within the Upper Mersey Estuary, it was identified by pertinent themes within the literature that future vulnerability to climate change is more likely to be derived from the indirect effects of increased tidal flooding than alterations in mean temperature (Doody, 2008; Kirwan et al., 2010; Jevrejeva et al., 2014). In order to determine the impacts of future sea level rise scenarios within the saltmarsh ecosystem, the ecology of these habitats was first categorised (Chapter 6, Section 6.3). Following the analysis of the breeding bird data it was shown that four key species of conservation concern were utilising the saltmarshes as a breeding habitat, moreover, these species were the most likely to be impacted by sea level rise as they nest on the ground. Two species of passerine, the meadow pipit (*Anthus pratensis*) and the skylark (*Alauda arvensis*), and two non-passerine waders, the redshank (*Tringa totanus*) and the northern lapwing (*Vanellus vanellus*), and their breeding habitat were selected as viable subjects for the sea level rise based sensitivity analysis. These species are the subjects of national conservation targets and are key representatives of the saltmarsh ecosystem (Smith, 2012; Dickinson et al., 2015).

Within the Upper Mersey Estuary, to address this problem within the context of vulnerability assessment, a series of scenarios were explored. The scenarios themselves were derived from those of the International Panel of Climate Change (IPCC), the UK Climate Panel (UKCP) and a speculative 'worst-case' scenario all published in Jevrejeva et al., (2014) and the IPCC fifth assessment report (IPCC, 2014). The data were transformed to be applicable to the relative sea level rise rate for the northwest of England by consideration of the regions isostatic adjustment since the Holocene and a summary table is presented in Chapter 7, Section 7.2, Table 7.1. These data allowed for the exploration of a range of severity levels of the ecological impact of sea level rise, particularly focussing on the avian breeding season (Dickinson et al., 2015). In Chapter 7 data were presented relating to sea level rise impacts on the avian breeding season and whether under sea level rise the species-specific breeding season would in fact be interrupted resulting in the potential loss of young and an unsuccessful season for an already threatened group of species. As presented in the chapter, for all four species studied, it was only under the most extreme scenarios – those proposed as the top end of those interpreted from the UKCP09, and Jevrejeva's (2014) speculative forecast – that the species-specific chick rearing period would see an interruption (see Table 7.5 for the meadow pipit data, Table 7.6 for the skylark data, Table 7.8 for the redshank data and Table 7.10 for the lapwing data). This interruption was ascertained in this study by deriving the mean clutch laying dates and chick rearing dates from a species and then determining whether in this breeding window there was a suitable flood free period in the forecasted high tides (Joy and Crick, 2004). This interruption free period, however, assumes that the birds will immediately lay a second clutch following the loss of the first, though this area knowledge within the ornithological research literature is lacking. Addressing objectives two and three, it must then be concluded, based on these data, that the species and habitats within this saltmarsh ecosystem in the Upper Mersey Estuary in fact have a relatively moderate sensitivity to sea level rise based on its primary effects, however, scenario-based management plans need to incorporate the uncertainty within the sea level rise projections and plan for all cases (Jevrejeva et al., 2014; Dickinson et al., 2015).

8.4 - Future Management and Implications of Change

The visualisation of habitat extent, in addition to the contextual ecological information as presented within this thesis is recommended as the first stage of a wetland vulnerability analysis (Gitay et al., 2011). An exploration of the physical impacts of sea level rise on a target species or group of species allows for the subsequent setting of management targets, restoration goals and potential responses to sea level rise events in estuaries such as the UME (Wahl et al., 2017). The key gaps cited within this field are within the lack of spatial and temporal data at appropriate scales, an understanding of the multiple interactive pressures facing a site, and the limited understanding of the adaptive capacity of wetlands (Gitay et al., 2011). The geographical context and scale of a site are critical factors influencing the vulnerability assessment process, and the derivation of vulnerability will be intimately linked to these. The UME provides a clear example of the consideration of these multiple pressures that must be considered before the assessment includes future pressures and scenario planning. The UME represents an area where a multi-stakeholder landscape may influence how successful future management may be before it is undertaken. This was partly addressed within the context of the UME by Drewitt (2017) who identified the array of stakeholders and their potential objectives. Certain sites may not be released to conservation practitioners if they are within the remit of a landowner that is not willing to invest the time, or money, hence the requirement for explicit communication within the sciences, and its subsequent value within the context of ecosystem vulnerability analysis (Collof et al., 2017). If this is achieved, site specific and local information which contrasts plausible future narratives can be used to articulate interactions and the education of the public and stakeholders (Gitay et al., 2011; Collof et al., 2017). This communication as an awareness raising exercise is fundamental to the success of such projects, as these systems will have to be maintained for many years into the future, spanning decades of monitoring and adaptive management (Downing and Doherty, 2004; IPCC, 2014). The engagement through effective communication and the involvement of stakeholders throughout the process is a well repeated recommendation throughout the literature, though the stakeholder identification was not a part of the research presented here as this has been undertaken for the UME within the last decade, effective communication was addressed within the scope of the current project (Bugliss et al., 1999).

The research presented within this thesis contributes to the field of wetland vulnerability assessment in multiple ways. Foremost, the key species present with the UME were identified, and their distribution and climate derived pressures were mapped explicitly. Two systems for the rapid assessment and mapping of saltmarsh habitat extent were identified and tested. And, an approach derived from statistical analysis was utilised to reflect community change. Each of these contributing sections links to one another, to provide a system for assessing the ecosystem vulnerability of the UME, with a focus on threatened bird species. This was represented within Chapter 7, as the outputs of each preceding chapter were combined to reflect the avian community, and the associated habitat, that may be impacted by climate change derived processes in the future. The findings outlined within this thesis represent the very earliest stages of a wetland vulnerability assessment, however this research addresses the gaps within the extant literature by using the UME as a case study. The next stage within an assessment such as this relates to the identification of management options in order to mitigate the identified risks (Gitay et al., 2011).

The impact of an increase in the frequency of seasonal flooding is likely to have wider array of impacts on the ecology of the UME, which in turn has implications for management. The restoration of degraded marshes is becoming more widespread within wetland management, though there have been issues in restoring sites to a condition comparable to a natural reference sites, at least in the short term (Hughes and Paramor, 2004; Mossman et al., 2012; Ladd, Skov, Lewis, & Leegwater, 2018). Many of these restored sites are derived from managed realignment projects which is the process of breaching the flood defences to allow the land beyond to be reclaimed as saltmarsh. There are numerous examples of these projects throughout the United Kingdom, a notable example being Hesketh Out Marsh on the Ribble Estuary (Ladd, Skov, Lewis, & Leegwater, 2018). Restoring a wetland to a ‘functional’ state is an issue which needs to be successfully addressed to mitigate for projected marsh loss, though the mechanisms that influence the characteristics of a reference system are multifaceted and complex. Historically, the colonisation of a marsh by halophytic vegetation has been considered a measure of success (Ladd, Skov, Lewis, &

Leegwater, 2018). The lack of comparability with reference sites is generally due to a different vegetative dominance (Mossman et al., 2012). While species richness is usually comparable, realigned sites are colonised rapidly by halophytic, early successional species. Mossman et al., (2012) noted that the shrub *Atriplex portulacoides* was significantly more abundant at realigned sites, preventing or inhibiting other species' colonisation due to its growth form. This species is fast growing, long lived and bares many fruits in contrast to species such as *Limonium vulgare and Puccinellia maritima* which exhibit long reproductive cycles and low seed viability (Davy et al., 2011). Further to this, managed realigned sites tend to have more bare ground, which can either indicate bioturbation, or represent a characteristic of an early successional state (Mossman et al., 2012). However, these factors may also indicate that the soil sediment is less oxygenated than the saltmarsh conditions at a comparable elevation on a reference site (Davy et al., 2011). This phenomenon is sediment redox potential and may inhibit the colonisation of species which are tolerant to waterlogged conditions, i.e., those species typical of mid-marsh succession and as such the realigned site is colonised and dominated by pioneer species (Davy et al., 2011). Sediment redox potential was found to be comparable in the high marsh when compared to reference sites, however, they were also dryer, and more terrestrial in vegetative composition (Mareno-mateos et al., 2012). A lower abundance of vegetation is likely to impact the saltmarsh ecosystem. With a mix of terrestrial and salt tolerant grasses dominating, and a subsequent lower proportion of flowering species. Faunal diversity will be reduced as many invertebrates depends on plants such as *Limonium vulgare*, which was recorded infrequently on many realigned marshes (Agassiz et al., 2000, Castillo and Ferguson, 2009). It is clear then, that managed realignment projects do not yet compare to natural systems, this is a serious consideration for wetland managers. If the aim is to provide comparable, functioning systems to natural saltmarshes, then large scale hydrological and geo-engineering, and the provision of topographic heterogeneity may be required to address the issues relating to the characteristics of soil sediment (Mareno-mateos et al., 2012). Further to this, the planting of upper and mid-marsh species might also increase recruitment and stabilisation towards natural reference conditions (Mossman et al., 2012). Authors have commented that marsh restoration and mitigation for losses due to climate change, or any other anthropogenic activity, may not satisfy the requirements of current EU legislation relating to saltmarshes, among other habitats, within the EU Habitats Directive (Mossman, et al., 2012). The implications of this will be discussed towards the end of this section. What is clear, is that for some systems, particularly those constrained by urban areas such as the UME, managed realignment may be the only long-term option to mitigate the projected rates of SLR. If the UME lacks the ability to maintain elevation in the tidal frame through sediment accretion, then large-scale, high impact management approaches, such as managed realignment, might be appropriate (Pontee, 2017). This would involve the removal of parts of the flood defence walls, particularly those situated on the eastern side of Upper Moss Side saltmarsh, to enable the ecosystems natural migration inland. As yet, it is not very well understood how an increase in flooding events, and the associated increase in salinity pulses, will affect European saltmarsh communities. This has been studied in the USA, and while the species differ, the conclusions drawn by the response the vegetation communities are that an increase in salinity exposure and an increase in inundation frequency leads to a reduction of stem density and biomass (Howard and Mendolssohn, 2000). However, authors have noted that sediment redox potential of some US saltmarshes is not comparable to those in the UK and Europe (Davy et al., 2011). Under the assumption that the oligohaline communities present in European saltmarshes will react in the same way as those in the Americas, these findings may represent further impacts to the resilience of saltmarshes to sea level rise. Changes in community structure can remove the value of the saltmarshes for feeding bird species, across all seasons, as valuable seed-bearing food sources are replaced by more salt tolerant plants (Hughes, 2004). Differences in the sediment binding properties may be a further driver of change, as the saltmarsh loses stability, and perhaps is unable to track sea level rise (Hughes, 2004). This interaction of salinity with vegetation community structure, particularly within the upper/mid marsh zones, provides an opportunity for valuable research in the UK, and in tandem with a long term, managed realignment project.

It might be that future management needs to look beyond the current structure of the specific habitat type, or ecosystem, under scrutiny to fulfil conservation targets and provide true ecological resilience. There is inherent variation in natural saltmarshes and projected environmental change. Policies set out within the EU Habitats Directive, which require management to produce almost exact equivalence between created marshes and references sites, may not be achievable based on our current understanding of saltmarsh ecology (Mossman et al., 2011). Accepting this and shifting our definition of restoration might be required for the successful management of wetlands under projected climate change and sea level rise, at least in the short term. Our current systems for restoration are as yet unsuccessful in restoring true vegetative function, and as this is intimately linked to wider trophic groups, this is a key consideration (Mossman et al., 2011). Therefore, current managed realignment and restoration does not satisfy adherence to the EU Habitats Directive which requires that the compensatory measures are comparable to the habitats and species negatively affected (Mossman et al., 2011). It might be that a minimum level of certain functions should be defined by the project, such as the presence of breeding birds, colonisation by pioneer species, and a 'live' sediment containing invertebrate faunas an initial indicator of success for managed realignment or restoration (Atkinson et al., 2004). This, in a way, would mirror the US Clean Water act, that requires no net loss of wetland habitat on larger spatial scales (Ladd, Skov, Lewis, & Leegwater, 2018). This would in turn require holistic management at the catchment level which might overshadow the ecological importance of some sites, for example, the Upper Mersey Estuary and its proximity to the Mersey Estuary SPA and SSSI (JNCC, 2017; Ladd, Skov, Lewis, & Leegwater, 2018). Replicating the tenets outlined in the 2010 UK Environment White Paper "Making Space for Nature" might be the most appropriate way in which to view the future of restoration (Lawton, 2010). That is, we need more habitat of higher quality with a greater level of connectivity (Lawton, 2010). This is of particular importance when considering constrained ecosystems such as the Upper Mersey Estuary. In some contexts, the mitigation of habitat loss through management decisions may not always be possible because of socio-economic considerations, spatial limits, and local development plans (Smart et al., 2016). In this case, projects could mitigate for this by creating, or restoring inland freshwater grassland that may prove an important option for the conservation of breeding waders (Smart et al., 2016). The variation in habitat across the landscape scale including taller, rougher patches of vegetation, has also been shown to reduce predation effects on breeding waders, perhaps of value as this threat increases with sea level rise (Laidlaw et al., 2015; Thorne et al., 2019). Increasing the network of scrapes and wet ditches may aid lapwing chick survival as mammalian predator species find it difficult to navigate the inundated marsh or wet grassland (Laidlaw et al., 2017); this in turn may encourage a greater nesting density where the lapwing predator-mobbing behaviour may reduce nest predation (MacDonald and Bolton, 2008). Without continuous and specialised surveillance and monitoring, it will be difficult to detect shifts in abundance after ecological changes for species, especially those with low dispersal (Takekawa, 2015).

Impacts such as these, however localised, are a conservation concern when attempting to ascertain the best approach to dealing with the challenges of habitat management for sea level rise resilience and species conservation. Species of conservation concern are generally restricted to small habitat fragments, and many coastal nesting birds are strict habitat specialists, so it is down to restoration practitioners to assist their adaptation to an uncertain future (Wilson, 2005; Van de Pol et al., 2010). This fact is compounded by a reported worryingly low-level or complete lack of adaptive response of saltmarsh nesting birds to flooding (Trilateral Wadden Sea Plan, 1997, cited in Van de Pol et al., 2010). Novel management practices will have to be implemented on both newly restored and existing saltmarshes to maximise avian biodiversity. These should be implemented through site specific research programmes backed up by a monitoring strategy tailored to the species, or group under study, and including consideration of the local ecological network (Doody, 2008; Van de Pol et al., 2010; Smart et al., 2016).

8.5 – Future Research

An increased frequency of inundation on the saltmarsh, or an increase in the frequency of extreme storm events derived from climate change, can alter habitat availability in tidal ecosystems. Changes such as these have long-term effects on the ecology of a site as population dynamics are fundamentally influenced by the availability of habitat (Thorne et al., 2019). These secondary community effects provide both a basis for future exploration within research, and the justification for the long-term monitoring of the communities that have been identified as under threat (Collof et al., 2017; Thorne et al., 2019). An area of value for both research and management is the analysis of the potential changes in predator-prey interactions because of climate change induced sea level rise, both in terms of high impact storm induced flooding events, and the progressive rise of tide levels. Predation pressure is enhanced already for endemic tidal marsh species due to the seasonal impacts of spring tides. The impact of this change on the predation pressure for saltmarsh species depends on the spatial-temporal dynamics of the saltmarsh being flooded, which is influenced by the creek structure, habitat structure, marsh elevation, and presence of sea walls (Traill et al., 2011). These factors will influence the marsh dwelling species risk to predation. Predator-prey relationships around saltmarshes are also influenced by the structure of adjacent land-use which can increase predation type and density (Traill et al., 2011). Variation in the availability of habitat for small mammals is linked to the impacts of predation on bird populations; establishing patches of taller vegetation, scrub and hedges, provides more habitat for rodents, and increase in the presence of these species reduces the impact of red fox (*Vulpes vulpes)* and mustelids on ground nesting bird populations (McDonal et al., 2000; Dell'Arte et al., 2007; Smart et al., 2016).

Research has documented the link between satellite derived vegetation indices and ecology, and methods documented here might be valuable within the context of the saltmarsh ecosystems explored in the Upper Mersey Estuary. The synoptic coverage of habitats and ecosystems using remote sensing technology, whilst invaluable for vegetation studies, provides potential for correlation through the trophic levels with wildlife data to inform species distribution modelling, habitat suitability indices, and other ecological interactions (Bradley & Fleishman 2008; Villa et al., 2014). The long-term application of which might be valuable when considering species vulnerability assessments under climate change and sea level rise. Buermann et al., (2008) found that the inclusion of vegetation variables, such as Leaf Area Index, into a species distribution model improved the accuracy of prediction. The inclusion of these data provides a more continuous data set when compared with coarse resolution land cover, climate, and topographic variables as these variables better reflect the scale of the habitat/species interaction and often outrank predictive power of discrete variables. This is a phenomenon also observed with NDVI measures, with unclassified images performing as well as traditional land cover classification (Seto et al., 2004; Bradley & Fleishman 2008; Buermann et al., 2008; Goetz et al., 2008; Duro et al., 2014; Sheeren et al., 2014). The utilisation of VIs for predicting species richness has been demonstrated in a growing body of literature. Methods have been demonstrated across varying spatial scales with most studies focussing on individual species (Gottschalk et al., 2005; Mcfarland et al., 2012). Seto et al., (2004) use mean NDVI values in a desert ecosystem to test the correlation between bird and butterfly richness. The authors report the NDVI derived plant productivity correlates positively with each group at varying sampling grains, and that vegetation indices may be useful in future studies across differing taxa (Seto et al., 2004). Inclusion of NDVI measures into the riparian habitat modelling of the southwestern willow flycatcher (*Empidonax traillii extimus*) demonstrated an increase in the ability to predict breeding habitats (Hatten and Sogge, 2007). Though there has been difficulty in extending the models to describe community structure, work has been implemented with moderate levels of success. Mcfarland et al., (2012) implemented a study to test whether the inclusion of NDVI has a greater correlation with species richness and avian abundance when compared with variables measured on the ground. Habitat preference and species abundance was successfully predicted for some key species, as with a number of studies within the same region (Hatten and Sogge, 2007). However, the majority of the R^2 values were low, and the current methods were not appropriate for species richness. The authors recommend continued focus on VIs for habitat suitability across other watersheds and for a range of species with potential for model refinement to utilise the method for a rapid assessment of potential species richness (Mcfarland et al., 2012). VIs have been shown to be positively correlated with species richness at coarse resolution across a large spatial scale in previous work (Foody, 2005; Mcfarland et al., 2012). NDVI, and the implicit potential of other vegetation indices, has been utilised by ecologists to quantify the effects vegetative vigour and phenology has on the upper trophic levels. This enables the potential for more robust predictions of the impacts of future environmental change as we develop knowledge of the responses of organisms to such scenarios (Pettorelli et al., 2005). NDVI has been linked to avifauna presence by representing increased primary productivity and increasing food abundance and variation within the NDVI values indicates habitat heterogeneity (Gordo 2007; St-Louis et al., 2009), for example, temporal variation of NDVI derived ecological conditions demonstrates habitat suitability and breeding success in the European range of the barn swallow (*Hirundo rustica*), and white stork (*Ciconia ciconial*) (Saino et al., 2004; Pettorelli et al., 2005).

In the context of the research presented in this thesis, determining the link between bird species richness and saltmarsh productivity through vegetation indices might be valuable to pursue as future research within the Upper Mersey Estuary to assist in determining the impact of habitat changes on the ecological structure (Ding et al., 2006).

Historically, the use of satellite remote sensing in ecological studies has utilised land cover classification as the environmental layer. This use of discrete variables for predicting ecological patterns has some limitations. Chiefly, it ignores within class variability that will not be captured by one broad class for a habitat type (St-Louis, 2009). It is well known that dynamic habitat structure on grasslands and saltmarshes promotes species diversity, so it is inappropriate to utilise an environmental measure that fails to capture this variation (Doody et al., 2008). A common measure of vegetation structure in ornithological studies is the foliage height diversity (FHD), which measure vertical and horizontal structure (Wood et al., 2013). Image texture is a measure derived from remotely sensed images that has been used to distinguish habitat suitability within grasslands (St-Louis, 2009). It is a measure of spatial variation in image tone values and has been shown to assist the prediction of habitat occupancy, habitat selection and species diversity of grassland meadows (St-Louis, 2009; Wood et al., 2013).

Extending the remote analyses towards a time-series approach would be a valuable contribution to the research presented within this thesis. Vegetation classes will exhibit different spectral characteristics throughout the growth season (Sun et al., 2016). The inclusion of a Sentinel-2 vegetation index time-series, with a focus on the Water Adjusted Vegetation Index (WAVI), may lead to increased classification accuracy when monitoring habitats long term (Villa et al., 2015, Sun et al., 2016, Liu et al., 2020). Increasing data integration with traditional field techniques, for example condition monitoring, may reveal thresholds of habitat change that can be detected within long term monitoring (Hurford, 2006). Further to this, an exploration of 'fuzzy' classification methods would be a further contribution and gap to address within wetland remote sensing and may increase accuracy of classification maps when dealing with narrow successional gradients (Zomer et al., 2009).

Building upon the methods presented in Chapter 5 and the literature just described, future studies might focus on including texture into the classification procedure. Texture in some studies has led to an increase in accuracy when compared to pixel-based methods of between 10 % – 31% (Franklin et al., 2000; Laba et al., 2010; Dronova, 2015). In wetlands, particularly, texture could be a critical feature in the delineation of feature classes as it can compensate for a lack of richness in spectral resolution (Samiappan et al., 2016). Samiappan et al., (2016) report high classification accuracy when utilising a range of texture-based variables when distinguishing common reed (*Phragmites australis*) stands in a mixed wetland. Accuracy varied between 89% – 99% depending on the classification.

In Chapter 7 data were presented relating to the impacts of relative sea level rise and its impacts on avian species breeding season within the Upper Mersey Estuary. A limitation of the simplistic, 'bathtub model' that was utilised in this research is that future projections of sea level rise assume that the vertical frame of the landscape is static (Brown, 2006; Kirwan et al., 2016). The topography and structure of estuaries is dependent on the local characteristics. A key attribute is the supply of fluvial sediment and the availability of sediment that is brought in on tidal water (Kirwan et al., 2016). This determines the resilience of saltmarshes to the eroding forces of tidal water and the ability of the saltmarsh to maintain its vertical position within the tidal frame (Kirwan et al., 2016). The Sea Level Affecting Marshes model (SLAMM) method is advantageous when compared with more straightforward techniques through its incorporation of a sediment variable. This 'modified bath-tub' approach resolves some of points of criticism encountered using simpler GIS based approaches that do not incorporate assumption relating to the dynamic nature of saltmarshes (Kirwan et al., 2016). Incorporating an assumption of annual vertical sediment accretion enables a truer value to be derived, and a better representation of relative sea level rise when forecasting the sensitivity of coastal ecosystems (Davies et al., 2016; Kirwan et al., 2016).

While the inundation approach can provide a 'quick' analysis of the vulnerability of an area to sea level rise, the interpretation and application of the results must recognise that important feedback processes might be missing (Mcleod et al., 2010). These relate to the geomorphological attributes discussed previously as well as feedbacks among biological, ecological, and social process, for example how human adaptive process might impact the planning and mitigation of sea level rise at a specific site (Mcleod et al., 2010). Uncertainty must also be considered as an implicit aspect of sea level rise models. Projections of climate change and sea level rise are limited by uncertainty (IPCC, 2014). Primarily this is due to uncertainty in the contribution of the Greenland and West Antarctic ice sheets, perhaps contributing an additional 1-5m on current projections (IPCC, 2014).

To determine the impact of relative sea level rise, a GIS-model based on, or similar to the Sea Level Affecting Marshes Model (SLAMM) framework would be a useful application for estuarine research. SLAMM operates through decision tree rules and calculates water elevation and the subsequent inundation and response of habitats (Murdukhayeva et al., 2013). The model incorporates the rate of sea level change through time to project scenarios. Depending on the local conditions the output maps will portray expected habitat classes after inundation and the area of habitat that will be lost (NOAA, 2016). A limitation to this model is the hard coding of the North American Nation Wetland Inventory as the representative landcover classes used to model vegetation change. This limits the models use outside of the USA unless the program is manually rewritten (Murdukhayeva et al., 2013).

8.6 – Summary

With climate change a very real threat, and its derived impacts widespread, it is clear that we have entered a period of pervasive change, one which brings about new challenges for conservation planning and restoration, particularly within the coastal environment (Heller and Zavaleta, 2009). The practice of conservation science developed during a time before the dynamic nature of the natural world was truly understood (Collof et al., 2017). Some regard the current era, characterised by change and complexity, as a ‘post-normal’ world (Funtowitz and Ravitz, 1993 cited in Collof et al., 2017). The ‘normal’ frameworks of the past —based on a static view of nature — may be less useful when approaching the problems present in today’s social-ecological systems (Collof et al., 2017). Instead, the science of this ‘post-normal’ age will be based on unpredictability and incomplete control; the peer community will also have to be extended to include all those with a stake in the issue (Funtowitz and Ravitz, 1993, cited in Collof et al., 2017). The challenges of the current era signal that a shift in approach is required. Change will be rapid and widespread, and the impacts irreversible (Heller and Zavaleta, 2009). The past decade of research within climate adaptation has produced numerous tools, guidelines, and alternative frameworks to assist in understanding, communicating and mitigating climate change impacts on biodiversity (Wyborn et al., 2016). As the literature in this field grows; recommendations for the future implementation of conservation practice, policy, and the potential barriers to their success, become clearer.

Human-induced climate change is a new threat, there is still much to learn about its associated impacts and secondary effects on ecological communities. Vulnerability to these effects will be mediated not only by the environmental processes themselves, but also how we as a society manage them (Dawson et al., 2011). While the model of vulnerability assessment and adaptive management may provide robust options for managers to incorporate into planning, it is still an emerging science and has yet to be incorporated into planning and policy (Dickinson et al., 2015; Wyborn et al., 2016). As a result, the implementation of these approaches in informing wetland vulnerability assessment is challenging. Is it a central to vulnerability assessment that what we do know is made explicit, and that we incorporate uncertainty. The task at hand is one that needs to transcend the disciplines and the research forum to extend into working practice and discourse. The research presented within this thesis has sought to incorporate the challenge facing a constrained saltmarsh system, the Upper Mersey Estuary, within the framework of wetland vulnerability assessment. Through this framework, the threats, the sensitivity of the system, and the potential for adaptation have been identified and contextualised by the aims of the restoration practitioners managing the sites (The Mersey Gateway Environmental Trust). The research through which the habitats, key faunal communities and future threats have been described link to the first stages of ecosystem vulnerability assessment for the Upper Mersey Estuary. The mapping and statistics which have been utilised to characterise the site have been made as explicit as possible to aide future communication, and to provide a benchmark for continued research and monitoring of this system. Future research will be required to further understand the thresholds of change, particularly in relation to saltmarsh vegetation, which will be required to successfully restore and potentially extend the wetland in this region. To address these challenges on a global scale, management of these systems needs a holistic view, so that we move away from a model where research only supplies information, and not a clear pathway for adaptation (Collof et al., 2017). Studies such as this represent only the first stage in a commitment to the adaptive management and conservation of these systems.

References

Adam, E., & Mutanga, O. (2009). Spectral discrimination of papyrus vegetation (*Cyperus papyrus* L.) in swamp wetlands using field spectrometry. *ISPRS Journal of Photogrammetry and Remote Sensing*, *64*(6), 612–620.

Adam, E., Mutanga, O. & Rugege, D. (2010). Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. *Wetlands Ecology and Management*, *18*(3), 281–296.

Adam, E., Mutanga, O., Odindi, J., & Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, *35*(10), 3440–3458.

Adams, W. M., Hodge, I. D., Macgregor, N. A., & Sandbrook, L. (2016). Creating restoration landscapes: partnerships in large-scale conservation in the UK. *Ecology and Society, 21*(3):1

Agassiz, D., (2000). Lepidoptera of British saltmarshes. In B.R. Sherwood, B.G. Gardiner & T. Harris (Eds.), *British Salt-marshes* (pp. 303–308). London: Linnaean Society of London.

Anderson, K. & Gaston, K. J. (2013). Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment*, *11*(3), 138–146.

Araujo, M.B., & New, M., (2007). Ensemble forecasting of species distributions. *Trends in Ecology and Evolution*, *22*(1), 42–47.

Armitage, R. P., Ramirez, A. F., Danson, F. M., & Ogunbadewa, E. Y. (2013). Probability of cloud-free observation conditions across Great Britain estimated using MODIS cloud mask. *Remote Sensing Letters*, *4*, 427–435.

Artigas, F. J. & Yang, J. S. (2005). Hyperspectral remote sensing of marsh species and plant vigour gradient in the New Jersey Meadowlands. *International Journal of Remote Sensing*, *26*(23), 5209–5220.

Atkinson, P. W., Crooks, S., Drewitt, A., Grant, A., Rehfisch, M. M., Sharpe, J., & Tyas, C. J. (2004). Managed realignment in the UK - the first 5 years of colonization by birds. *Ibis*, *146*(SUPPL.1), 101–110. https://doi.org/10.1111/j.1474-919X.2004.00334.x

Ausden, M. (2014). Climate Change Adaptation: Putting Principles into Practice. *Environmental Management*, *54*(4), 685–698.

Balvanera, P., Pfisterer, A. B., Buchmann, N., He, J., Nakashizuka, T., Raffaelli, D., & Schmid, B. (2006). Quantifying the evidence for bio- diversity effects on ecosystem functioning and \services. *Ecology Letters*, *9*, 1146–1156.

Balvanera, P., Pfisterer, A. B., Buchmann, N., He, J.-S., Nakashizuka, T., Raffaelli, D., & Schmid, B. (2006). Quantifying the evidence for biodiversity effects on ecosystem functioning and services: Biodiversity and ecosystem functioning/services. *Ecology Letters*, 9(10), 1146–1156.

Bates, P. D., & De Roo, A. P. J. (2000). A simple raster-based model for flood inundation simulation. J*ournal of Hydrology*, *236*, 54–77.

Battjes, J. A, & Gerritsen, H., (2002). Coastal modelling for flood defence. *Philosophical transactions. Series A, Mathematical, physical, and engineering sciences, 360*, 1461–75.

Baugh, W. M., & Groeneveld, D. P. (2008). Empirical proof of the empirical line. *International Journal of Remote Sensing*, *29*(3), 665–672.

Baugh, W. M., & Groeneveld, D. P., (2008). Empirical proof of the empirical line. *International Journal of Remote Sensing*, *29*, 665–672.

Bayliss, B., Brennan, K., Eliot, I., Finlayson, M., Hall, R., House, T., … Waterman, P. (1997). *Vulnerability assessment of predicted climate change and sea level rise in the Alligator Rivers Region, Northern Territory Australia. Supervising Scientist Report 123.* Retrieved from www.environment.gov.au/ssd/publications/ssr/123.html.

Bell, G., Neal, S., & Medcalf, K. (2015). Use of remote sensing to produce a habitat map of Norfolk. *Ecological Informatics, 30*, 293–299.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., & Courchamp, F. (2012). Impacts of climate change on the future of biodiversity. *Ecology Letters*, *15*(4), 365–377. https://doi.org/10.1111/j.1461-0248.2011.01736.x

Bengtsson, J., Angelstam, P., Elmqvist, T., Emanuelsson, U., Folke, C., Ihse, M., … Nyström, M. (2003) Reserves Resilience and Dynamic Landscapes. *Ambio, 32*(6), 389–396.

Bennie, J., Hodgson, J. A., Lawson, C. R., Holloway, C. T. R., Roy, D. B., Brereton, T., … Wilson, R.J. (2013). Range expansion through fragmented landscapes under a variable climate. *Ecology Letters*, *16*(7), 921–929.

Berkes, F., & Folke, C. (editors). (1998). *Linking social and ecological systems: management practices and social mechanisms for building resilience*. Cambridge: Cambridge University Press.

Berkes, F., Colding, J. & Folke, C. (2008). Rediscovery of traditional ecological knowledge as adaptive management. *Ecological Applications*, *10*(5), 1251–1262.

Bibby, C. J., Burgess, N. D., & Hill, D. A., (1992). *Bird census techniques*. Academic Press. London, UK 257.

Blaschke, T., Lang, S., Lorup, E., Strobl, J., & Zeil, P. (2000). Object-Oriented Image Processing in an Integrated GIS / Remote Sensing Environment and Perspectives for Environmental Applications. *Training, 2*, 555–570.

Bonnington, C., & Smith, D. (2018). Do bridge construction activities influence birds using the River Mersey, in northwest England? *Bird Study*, *65*(3), 346–356. Retrieved from https://doi.org/10.1080/00063657.2018.1513988.

Both, C., Van Asch, M., Bijlsma, R.G., Van Den Burg, A. B., & Visser, M. E. (2009). Climate change and unequal phenological changes across four trophic levels: Constraints or adaptations? *Journal of Animal Ecology*, *78*(1), 73–83.

Bradley, B. A., & Fleishman, E. (2008). Can remote sensing of land cover improve species distribution modelling? *Journal of Biogeography*, *35*(7), 1158–1159.

Breiman, L. (2001). Random Forests. *Machine Learning*, *45*, 5.

Brooker, R. W, Travis, M. J., Clark, E. J., & Dytham, C. (2007). Modelling species' range shifts in a changing climate: The impacts of biotic interactions, dispersal distance and the rate of climate change. *Journal of Theoretical Biology, 245*(1), 59–65.

Brotons, L., De Cenceres, M., Fall, A., & Fortin, M. J. (2012). Modeling bird species distribution change in fire prone Mediterranean landscapes: Incorporating species dispersal and landscape dynamics. *Ecography*, *35*(5), 458–467.

Brown, I. (2006). Modelling future landscape change on coastal floodplains using a rulebased GIS. *Environmental Modelling and Softwa*re, *21*, 1479–1490.

Buckland, S. T., Baillie, S. R., Dick, J. M. P., Elston, D. A., Magurran, A. E., Scott, E. M., … Watt, A. (2012). How should regional biodiversity be monitored? *Environmental and Ecological Statistics*, *19*(4), 601–626.

Buermann, W., Saatchi, S., Smith, T. B., Zutta, B. R., Chaves, J. A, Milá, B., & Graham, C.H. (2008). Predicting species distributions across the Amazonian and Andean regions using remote sensing data. *Journal of Biogeography*, *35*(7), 1160–1176. https://doi.org/10.1111/j.1365-2699.2007.01858.x

Bullock, J. M., Aronson, J., Newton, A. C., Pywell, R. F., & Rey-Benayas, J. M. (2011). Restoration of ecosystem services and biodiversity: Conflicts and opportunities. *Trends in Ecology and Evolution*, *26*(10), 541–549.

Campbell, J. & Wynne, R. (2011). *Introduction to Remote Sensing*. New York: Guildford Press.

Carpenter, S. Walker, B., Anderies, J. M., & Abel, M. (2001). From Metaphor to Measurement: Resilience of What to What? *Ecosystems*, 4(8), 765–781.

Carter, R. W.G. (1988). *Coastal Environments. An Introduction to the Physical, Ecological and Cultural Systems of Coastlines*. London, UK: Academic Press.

Castellari, S., & Kurnik, B. (2017). *Climate change, impacts and vulnerability in Europe 2016* (Issue 1). https://www.eea.europa.eu/publications/climate-change-adaptation-and-disaster

CBD., (2000). *CBD Adopting the Ecosystem Approach Annex III to the Convention of Biological Diversity.* 15-26 May 2000, Nairobi.

Champion, M. H., & Ashton, P. A. (2010). Reedbed Habitat Restoration at the Wigan Flashes: Restoring the Post-Industrial Landscape for Wildlife Conservation. Restoration and Recovery: Regenerating Land and Communities. *Whittles Press*, 206-223.

Chao, A., Gotelli, N. J., Hsieh, T. C., Sander, E. L., Ma, K. H., Colwell, R. K., & Ellison, A. M. (2014). Rarefaction and extrapolation with Hill numbers: A framework for sampling and estimation in species diversity studies. *Ecological Monographs*, *84*(1), 45–67. https://doi.org/10.1890/13-0133.1

Chen, X., Zou, I., & Xu, L. (2013). Research on the correlation of bird changes with the net primary productivity in the pearl river estuary wetlands a case of Mai Po Inner Deep Bay Ramsar Site. *2nd International Conference on Agro-Geoinformatics: Information for Sustainable Agriculture, Agro-Geoinformatics,* 239–242.

Chirayath, V., & Earle, S. A., (2016). Drones that see through waves e preliminary results from airborne fluid lensing for centimetre-scale aquatic conservation. *Aquat. Conserv*. *26*, 237–250.

Chiu, C.H., L. Jost, and A. Chao. 2014. Phylognetic beta diversity, similarity, and differentiation measures based on Hill numbers. *Ecological Monographs*, *84*, 21–44.

Chust, G., Galparsoro, I., Borja, Á., Franco, J., & Uriarte, A. (2008). Coastal and estuarine habitat mapping, using LIDAR height and intensity and multi-spectral imagery. *Estuarine, Coastal and Shelf Science*, *78*, 633–643.

Clausen, K. K., & Clausen, P. (2014). Forecasting future drowning of coastal waterbird habitats reveals a major conservation concern. *Biological Conservation*, *171*, 177–185.

Clewell, A, Aronson, J., & Winterhalder, K. (2004). The SER International primer on ecological restoration. *Ecological Restoration*, *2*(2), 206–207

Clough, J. S., Park, R.A., & Fuller, R. (2010) *SLAMM 6 beta Technical Documentation.* Warren, WC: Warren Pinnacle Consulting, inc.

Colloff, M. J., Lavorel, S., van Kerkhoff, L. E., Wyborn, C. A., Fazey, I., Gorddard, R., … Degeorges, P. (2017). Transforming conservation science and practice for a post-normal world. *Conservation Biology,* 31, 1–18.

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *92*, 79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013

Colston, A. (2003). Beyond preservation: the challenge of ecological restoration. 247- 267: in W. M. Adams, and M. Mulligan, editors. *Decolonizing Nature: strategies for conservation in a post-colonial era*. London: Earthscan

Congalton, R. & Green, K. (2008). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices,* Second Edition. Boca Raton: CRC Press.

Cooper, H. M., Fletcher, C. H., Chen, Q., & Barbee, M. M. (2013). Sea-level rise vulnerability mapping for adaptation decisions using LiDAR DEMs. *Progress in Physical Geography, 37*, 745–766.

Cordell, S., Questad, E. J., Asner, G. P., Kinney, K. M., Thaxton, J. M., Uowolo, A., Brooks, S., & Chynoweth, M. W. (2017). Remote sensing for restoration planning: how the big picture can inform stakeholders. *Restoration Ecology*, *25*, S147–S154. https://doi.org/10.1111/rec.12448

Cox, K. D., Black, M. J., Filip, N., Miller, M. R., Mohns, K., Mortimor, J., Freitas, T. R., Greiter Loerzer, R., Gerwing, T. G., Juanes, F., & Dudas, S. E. (2017). Community assessment techniques and the implications for rarefaction and extrapolation with Hill numbers. *Ecology and Evolution*, *7*(24), 11213–11226. https://doi.org/10.1002/ece3.3580

Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A., & Totterdell, I. J. (2000). Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature*, *408*(6809), 184–187.

Cundy, A. B., & Croudace, I. W. (1996). Sediment accretion and recent sea-level rise in the Solent, southern England: Inferences from radiometric and geochemical studies*. Estuarine Coastal and Shelf Science*, *43*(4), 449–467.

Cunliffe, A. M., Anderson, K., Debell, L., & Duffy. J. P. (2017). A UK Civil Aviation Authority (CAA) -approved operations manual for safe deployment of lightweight drones in research. Int. J. *Remote Sens*. *38*, 2737–2744.

Davies, F. E., Robins, P. E., Skov, M. W., & Jago, C.F. (2016). Impact of climate change on UK estuaries: A review of past trends and potential projections. *Estuarine, Coastal and Shelf Science*. *169*, 119–135.

Davy, A. J., Brown, M. J. H., Mossman, H. L., & Grant, A. (2011). Colonization of a newly developing salt marsh: Disentangling independent effects of elevation and redox potential on halophytes. *Journal of Ecology*, *99*(6), 1350–1357. https://doi.org/10.1111/j.1365-2745.2011.01870.x

Defra., (2009). *Adapting to climate change UK Climate Projections*. UK Climate Projections 52.

Delegido, J., Verrelst, J., Alonso, L., & Moreno, J. (2011). Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content. *Sensors*, *11*(12), 7063–7081.

Dell'Arte, G.L., Laaksonen, T., Norrdahl, K., & Korpimäki, E. (2007). Variation in the diet composition of a generalist predator, the red fox, in relation to season and density of main prey. *Acta Oecol, 31*, 276–281.

Dickinson, M., Prentice, I. C., & Mace, G. M. (2015). *Climate change and challenges for conservation.* Grantham Institute Briefing paper, (13).

Doerr, V. A. J., Barrett, T., & Doerr, E. D. (2011). Connectivity, dispersal behaviour and conservation under climate change: A response to Hodgson et al. *Journal of Applied Ecology*, *48*(1), 143–147.

Doody, J.P. (2008). Saltmarsh Conservation, Management and Restoration. In: U. Haq. *Coastal Systems and Continental Margins. 12*, 217–312. New York: Springer.

Dörnhöfer, K., & Oppelt, N., (2016). Remote sensing for lake research and monitoring – Recent advances. *Ecological Indicators*, *64*, 105–122.

Downing, T., & Dougherty, B. (2004). *Toward a core methodology for climate vulnerability and adaptation.* Stockholm: Stockholm Environment Institute. Retrieved from www.vulnerabilitynet.org.

Drewitt, A. (2017). *An ecosystem approach assessing the impacts of the construction and operation of the Mersey Gateway Crossing on the Upper Mersey Estuary*, PhD thesis, University of Salford.

Dronova, I. (2015). Object-based image analysis in wetland research: A review. *Remote Sensing*. *7*, 6380–6413.

Duffy, J. P., Cunliffe, A. M., DeBell, L., Sandbrook, C., Wich, S. A., Shutler, J. D., … Anderson, K. (2017). Location, location, location: considerations when using lightweight drones in challenging environments. *Remote Sensing in Ecology and Conservation*, 1–13. http://hdl.handle.net/10871/28157.

Duffy, J. P., Pratt, L., Anderson, K., Land, P. E., & Shutler, J. D. (2018). Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone. *Estuarine, Coastal and Shelf Science*, *200*, 169–180.

Duro, D.C., Girard, J., King, D. J., Fahrig, L., Mitchell, S., Lindsay, K., & Tischendorf, L. (2014). Predicting species diversity in agricultural environments using Landsat TM imagery. *Remote Sensing of Environment*, 144, 214–225.

Eaton, M. A., Brown, A. F., Hearn, R., Noble, D. G., Musgrove, A. J., Lock, L., Stroud, D., & Gregory, R. D. (2015). Birds of conservation concern 4: the population status of birds in the United Kingdom, Channel Islands and Isle of Man. *British Birds*, *108*, 708–746.

EC, (2009a). *The economics of climate change adaptation in EU coastal areas. Country overview and assessment: Outermost regions.* Brussels: European Commission.

Elmqvist, T., Folke, C., Nyström, M., Peterson, G., Bengtsson, J., Walker, B., & Norberg, J. (2003). Response diversity, ecosystem change, and resilience. *Frontiers in Ecology and the Environment*, *1*(9), 488–494.

Elvidge, C. D., & Chen, Z. (1995). Comparison of broad-band and narrow-band red and nearinfrared vegetation indices. *Remote Sensing of Environment*, *54*(1), 38–48.

Erwin, K. L. (2009). Wetlands and global climate change: the role of wetland restoration in a changing world. *Wetlands Ecology and Management*, *17*(1), 71–84.

Fagherazzi, S., Kirwan, M. L., Mudd, S. M., Guntenspergen, G. R., Temmerman, S., D'Alpaos, A., … Clough, J. (2012). Numerical models of salt marsh evolution: Ecological, geormorphic, and climatic factors. *Review of Geophysics*, *50*(2011), 1–28.

Farina, A., Johnson, A. R., Turner, S. J., & Belgrano, A. (2003l). "Full" world versus "empty" world paradigm at the time of globalisation. *Ecological Economics, 45*(1), 11-18.

Farrelly, R. (2013). Setting the record straight. *British Journal of Nursing*, *22*(19), 1145.

Folke, C. Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C. S., Walker, B. (2002). Resilience and Sustainable Development Building Adaptive Capacity in a World of Transformations. *Ambio*, *31*(5), 437–440.

Foody, G.M., (2005). Mapping the richness and composition of British breeding birds from coarse spatial resolution satellite sensor imagery. *International Journal of Remote Sensing*, *26*(18), 3943–3956.

Forman, R. T. T. (2014). Basic Principles for Molding Land Mosaics. In: F. O. Ndubisi, (Ed.), *The Ecological Design and Planning Reader*. Washington, DC: Island Press 299–319.

Foster, N. M., Hudson, M. D., Bray, S., & Nicholls, R. J. (2013). Intertidal mudflat and saltmarsh conservation and sustainable use in the UK: A review. *Journal of Environmental Management*, *126*, 96–104.

Foster, N.M., Hudson, M.D., Bray, S., & Nicholls, R.J. (2013). Intertidal mudflat and saltmarsh conservation and sustainable use in the UK: A review. Journal of Environmental Management. *Journal of Environmental Management*, *126*, 96-104

Franklin, J.F., Lindenmayer, D. B., MacMahon, J. A., McKee, A., Magnusson, J., Perry, D. A., (…) Foster, D.R. (2000). Threads of continuity: ecosystem disturbances, biological legacies and ecosystem recovery. *Conservation Biology in Practice*, *1*, 8-16.

Funtowicz, S. O., & Ravetz, J. R. (1993). Science for the post-normal age. *Futures 25*, 735−755.

Gao, B.C., (1996). NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, *58*(3), 257–266.

Gedan, K. B., Silliman, B. R., & Bertness, M. D. (2009). Centuries of human-driven change in salt marsh ecosystems. *Annual Review of Marine Science*, *1*, 117–141. https://doi.org/10.1146/annurev.marine.010908.163930

Gedan, K.B., Kirwan, M.L., Wolanski, E., Barbier,E.B., & Silliman, B.R. (2011). The present and future role of coastal wetland vegetation in protecting shorelines: an answering recent challenges to the paradigm. *Climatic Change*, 106, 7-29.

Gedan, K.B., Silliman, B.R., & Bertness, M.D. (2009). Centuries of human-driven change in salt marsh ecosystems. *Annual review of marine science, 1*, 117–141.

Gilbert, G., Gibbons, D.W., & Evans, J. (1998). *Bird Monitoring Methods – A Manual of Techniques for Key US Species*. Sandy: RSPB.

Gitay, H., Finlayson, C.M. & Davidson, N.C. 2011. A Framework for assessing the vulnerability of wetlands to climate change. Ramsar Technical Report No. 5/CBD Technical Series No. 57. Ramsar Convention Secretariat, Gland, Switzerland & Secretariat of the Convention on Biological Diversity, Montreal, Canada. ISBN 92-9225-361-1 (print); 92-9225-362-X (web).

Giuliani, S.; Bellucci, L. (2019). Salt Marshes: Their Role in Our Society and Threats Posed to Their Existence. In C. Sheppard (Ed.)*, World Seas: an Environmental Evaluation (Second Edition) Volume III: Ecological Issues and Environmental Impacts* (pp. 79-101). Waltham, MA: Academic Press.

Gjerdrum, C., Sullivan-Wiley, K., King, E., Rubega, M. A., & Elphick, C. S. (2008). Egg and Chick Fates During Tidal Flooding of Saltmarsh Sharp-Tailed Sparrow Nests. *The Condor*, *110*(3), 579–584.

Glick, P., Stein, B. A., & Edelson, N. A. (2011). *Scanning the Conservation Horizon: A Guide to Climate Change Vulnerability Assessment*. Washington, DC: National Wildlife Federation.

Glick, P., Stein, B. A., & Edelson, N. A. (2011). Scanning the Conservation Horizon: a guide to climate change vulnerability assessment. *National Wildlife* (Issue May). Retrieved from www.nwf.org/vulnerabilityguide.

Goetz, S.J., Gardiner, N., & Viers, J.H. (2008) Monitoring freshwater, estuarine and nearshore benthic ecosystems with multi-sensor remote sensing: An introduction to the special issue. *Remote Sensing of Environment*, *112*(11), 3993–3995.

Gonçalves, J.A., & Henriques, R. (2015). UAV photogrammetry for topographic monitoring of coastal areas. *ISPRS J. Photogramm. Remote Sens. 104*, 101–111.

Gordo, O. (2007). Why are bird migration dates shifting? A review of weather and climate effects on avian migratory phenology. *Climate Research*, *35*(1-2), 37–58.

Gottschalk, T. K., Huettmann, F., & Ehlers, M. (2005). Thirty years of analysing and modelling avian habitat relationships using satellite imagery data: a review. *International Journal of Remote Sensing*, *26*(12), 2631–2656.

Greenwood, O., Mossman, H. L., Suggitt, A. J., Curtis, R. J., & Maclean, I. M. D. (2016). Using in situ management to conserve biodiversity under climate change. *Journal of Applied Ecology*, 885–894. https://doi.org/10.1111/1365-2664.12602

Greig-Smith, P. (1983). *Quantitative Plant Ecology*, 3rd edn. Oxford: Blackwell Scientific Publications.

Grenfell, S. E., Callaway, R. M., Grenfell, M. C., Bartelli, C. M., Mendzil, A. F., & Tew, I. (2016). Will a rising sea sink some estuarine wetland ecosystems? *Science of the Total Environment*, *5*, 276–292.

Haggerman, S. M., & Satterfield, T. (2014). Agreed but not preferred: expert views on taboo options for biodiversity conservation, given climate change. *Ecological Applications, 24*, 548–559.

Hakala, T., Honkavaara, E., Saari, H., Mäkynen, J., Kaivosoja, J., Pesonen, L., & Pölönen, I. (2013). Spectral Imaging from UAVs Under Varying Illumination Conditions. In G. Grenzdörffer, & R. Bill (Eds.), *International Archives of the Photogrammetry, 4–6 September 2013* (pp. 189-194). Rostock: Germany.

Halcrow Ltd. (2010). *North West England and North Wales Shoreline Management Plan SMP2*. (1) Swindon: Halcrow Group ltd

Handbook, T. R., & Behavior, D. (2011). The Routledge handbook of deviant behavior. *Routledge International Handbooks*, *2*, 618 – 618.

Hannah, L., Midgley, G., Andelman, S., Araújo, M., Hughes, G., Martinez-Meyer, E., … Williams, P. (2007). Protected area needs in a changing climate. *Frontiers in Ecology and the Environment*, *5*(3), 131–138.

Harris, J. A., Hobbs, R. J., Higgs, H., & Aronson, J. (2006). Ecological restoration and global climate change*. Restoration Ecology*, *14*(2), 170–176.

Hatten, J. R., & Sogge, M. K. (2007). Using a remote sensing/GIS model to predict Southwestern Willow Flycatcher breeding habitat along the Rio Grande, New Mexico. *U.S. Geological Survey Open-File Report,* 1207.

Hawke, C. J. & José, P. V. (1996). *Reedbed Management for Commercial and Wildlife Interests.* Sandy: RSPB.

Hayhow, D. B., Burns, F., Eaton, M. A., Al Fulaij, N., August, T. A., Babey, L., … Gregory, R. D. (2016). *State of Nature 2016*. The State of Nature Partnership, 1.

HBC., (2008). *The Mersey Gateway Project. Environmental Statement. 1, 7. Runcorn.* Halton Borough Council.

Heller, N. E., & Zavaleta, E. S. (2009). Biodiversity management in the face of climate change: A review of 22 years of recommendations. *Biological Conservation, 142*(1), 14–32.

Hestir, E. L., Brand, V. E., Bresciani, M., Giardino, C., Matta, E., Villa, P., & Dekker, A. G. (2015). Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission. *Remote Sensing of Environment*, *167*, 181–195.

Hill, D., Fasham, M., Tucker, G., Shewry, M., & Shaw, P. (2007). *Handbook of Biodiversity Methods. Survey, Evaluation and Monitoring.* Cambridge: Cambridge University Press.

Hill, M. O. (1973). Diversity and evenness: a unifying notation and its consequences. *Ecology 54*, 427-432.

Hodgson, J. A., Thomas, C. D., Wintle, B. A., & Moilanen, A. (2009). Climate change, connectivity and conservation decision making: Back to basics. *Journal of Applied Ecology*, *46*(5), 964–969.

Hodgson, J. C., Baylis, S. M., Mott, R., Herrod, A., & Clarke, R. H. (2016). Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports*, 6(March), 1–7.

Holzinger, B., Hullber, K., Camenisch, M. & Grabherr, G. (2008). Changes in plant species richness over the last century in the eastern Swiss Alps: elevational gradient, bedrock effects and migration rates. *Plant Ecology, 195*, 179–196.

Houghton, R. A., Davidson, E. A., & Woodwell, G. M. (1998). Missing sinks, feedbacks, and understanding the role of terrestrial ecosystems in the global carbon balance. *Global Biogeochemical Cycles*, *12*(1), 25–34.

Howard, R. J., & Mendelssohn, I. A. (2000). Structure and composition of oligohaline marsh plant communities exposed to salinity pulses, *Aquatic Botany, 68*, 143–164.

Huete, A. R., Justice, C., & Liu, H. (1994). Development of Vegetation and Soil Indexes for Modis-EOS. Remote Sensing of Environment, 49(3), pp.224–234

Hughes, R.G. (2004). Climate change and loss of saltmarshes: Consequences for birds. I*bis, 146,* 21–28.

Huntley, B., Berry, P. M., Cramer, W., & McDonald, A. P. (1995). Modelling Present and Potential Future Ranges of Some European Higher Plants Using Climate Response Surfaces. *Journal of Biogeography*, *22*(6), 967–1001.

Huntley, B., Collingham, Y. C., Willis, S. G. & Green, R. E. (2008). Potential impacts of climatic change on European breeding birds. *PLoS One*, 3, 1439.

Hurford, C. (2006) *Monitoring Nature Conservation in Cultural Habitats: A Practical Guide and Case Studies.* London: SpringerLink - Springer e-Books.

IPCC. (2007). *Climate Change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the Intergovernmental Panel.* Geneva, Switzerland: IPCC

IPCC. (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva, Switzerland, 151.

Jevrejeva, S., Grinsted, A., & Moore, J. C. (2014). Upper limit for sea level projections by 2100. *Environmental Research Letters, 9*(10), 104008 (9pp)

Jevrejeva, S., Moore, J. C., & Grinsted, A. (2012). Sea level projections to AD2500 with a new generation of climate change scenarios. *Global and Planetary Change*, *80-81*, 14–20.

Jha, V. N. (1991). *Proceedings of the National Seminar on Environmental Awareness Reflected in Sanskrit Literature.* Poona: University of Poona,

JNCC, (2010), *Handbook for Phase 1 habitat survey – a technique for environmental audit*. Peterborough: JNCC ISBN 0 86139 636 7.

JNCC. (2015) *The UK Biodiversity Indicators 2015*. Peterborough: JNCC

JNCC. (2017) *SPA description*. Mersey Estuary. http://jncc.defra.gov.uk/page- 1986. Accessed 14 July 2017

Jordan, W. R., & Lubick, G. M. (2011). *Making Nature Whole: A History of Ecological Restoration.* Washington, DC: Island Press, 272

Jost, L. (2006). Entropy and diversity. *Oikos, 113*, 363–375.

Joys, A. C. & Crick, H. Q. P. (2004). *Breeding Periods for Selected Bird Species in England.* BTO Research Report No. 352. Thetford: BTO.

Kaplan, G., & Avdan, U. (2017). Mapping and monitoring wetlands using SENTINEL-2 satellite imagery. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *4*, 271–277.

Kirwan, M. L., Guntenspergen, G. R., D'Alpaos, A., Moris, J. T., Mudd, S. M., & Temmerman, S. (2010). Limits on the adaptability of coastal marshes to rising sea level. *Geophysical Research Letters*, *37*(23), 1–5.

Kirwan, M. L., Temmerman, S., Skeehan, E. E., Guntenspergen, G. R., & Fagherazzi, S. (2016). Overestimation of marsh vulnerability to sea level rise. *Nature Climate Change, 6*(3), 253–260.

Klemas, V. (2013). Remote Sensing of Coastal and Wetland Biomass: An Overview. *Journal of Coastal Research, 29*(5), 1016–1028.

Knorr, W., Prentice, I. C., House, J. I., & Holland, E. A. (2005). Long-term sensitivity of soil carbon turnover to warming. *Nature*, *433*(7023), 298–301.

Knutson, M. G., & Klaas, E.E. (1997). Declines in abundance and species richness of birds following a major flood on the Upper Mississippi River. *Auk, 114,* 367–380.

Koh, L. P., & Wich, S. A. (2012). Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science*, 5(2), 121–132.

Konteos, C., & Stakenborg, J. (1990). Availability of cloud-free Landsat images for operational projects. The analysis of cloud-cover figures over the countries of the European Community. *International Journal of Remote Sensing*, *11*, 1599–1608.

Krebs, C. J. (2001). *Ecology; The Experimental Analysis of Distribution and Abundance,* 5th ed. San Francisco: Benjamin Cummings.

Krolik-Root, C., Stansbury, D. L., & Burnside, N. G. (2015). Effective LiDAR-based modelling and visualisation of managed retreat scenarios for coastal planning: An example from the southern UK. *Ocean and Coastal Management, 114*, 164–174.

Kumstatova, T., Brinke, T., Tomkova, S., Fuchs, R., & Petrusek, A. (2004). Habitat preferences of tree pipit (*Anthus trivialis*) and meadow pipit (*Anthus pratensis*) at sympatric and allopatric localities. *Journal of Ornithology, 145*, 334–342.

Laba, M., Blair, B., Downs, R., Monger, B., Philpot, W., Smith, S., … Baveye, P. C. (2010). Use of textural measurements to map invasive wetland plants in the Hudson River National Estuarine Research Reserve with IKONOS satellite imagery. *Remote Sensing of Environment*, *114*(4), 876–886.

Ladd, C., Skov, M., Lewis, H., & Leegwater, E. (2018). *Climate change and marine conservation: Saltmarsh* Lowestoft, MCCIP. doi: 10.14465.2018. ccmco.005-smr

Laidlaw, R. A., Smart, J., Smart, M. A., & Gill, J. A. (2015). The influence of landscape features on nest predation rates of grassland-breeding waders. *Ibis*, 157, 700–712.

Laliberté, E., Wells, J. A., DeClerck, F., Metcalfe, D. J., Catteral. C. P., Queiroz, C. … Mayfield, M. M. (2010). Land-use intensification reduces functional redundancy and response diversity in plant communities. *Ecology Letters*, *13*(1), 76–86.

Langlois, E., Bonis, A., & Bouzille, J. B. (2003). Sediment and plant dynamics in saltmarshes pioneer zone: *Puccinellia maritima* as a key species? *Estuarine, Coastal and Shelf Science*, *56*(2), 239–249.

Lawton, J. H., Brotherton, P. N. M., Brown, V. K., Elphick, C., Fitter, A. H., Forshaw, J., … Wynne, G. R. (2010). *Making Space for Nature: A review of England's Wildlife Sites and Ecological Network.* Report to Defra.

Legendre, P. & Legendre, L. (1998). *Numerical ecology,* 2nd English edition. Amsterdam: Elsevier Science BV.

Leinster, T. (2014). Measuring diversity: The importance of species similarity. *Ecology.* 93(3) 477-489. https://doi.org/10.1890/10-2402.1

Leisler, B., Ley, H. W., & Winkler, H. (1989). Habitat, Behaviour and Morphology of Acrocephalus Warblers: An Integrated Analysis. *Ornis Scandinavica, 20,* 181-186.

Leo, K. L., Gillies, C. L., Fitzsimons, J. A., Hale, L. Z., & Beck, M. W. (2019). Coastal habitat squeeze: A review of adaptation solutions for saltmarsh, mangrove and beach habitats. *Ocean and Coastal Management*, *175*, 180–190. https://doi.org/10.1016/j.ocecoaman.2019.03.019

Lillesand, L. M., Kiefer, R. W., & Chipman, J. W. (2008) *Remote Sensing and Image Interpretation.* 6th Edition. New York: John Wiley & Sons.

Lissner, J. & Schierup, H.-H., (1997). Effects of Salinity on the Growth of *Phragmites australis*. *Aquatic Botany*, *55*(4), 247-260.

Liu, H., Zhang, F., Zhang, L., Lin, Y., Wang, S., & Xie, Y. (2020). UNVI-based time series for vegetation discrimination using separability analysis and random forest classification. *Remote Sensing*, *12*(3), 1–20. https://doi.org/10.3390/rs12030529

Lowe, J. L. (2009). *UK Climate Projections Science Report: Marine and Coastal Projections* Exeter, UK: Met Office Hadley Centre.

Lubick, W. R., & Jordan, G. M. (2012). *Making nature whole: a history of ecological restoration.* Washington, D.C.: Island Press.

Lurgi, M., Brook, B. W., Saltré, F., & Fordham, D. A. (2015). Modelling range dynamics under global change: Which framework and why? *Methods in Ecology and Evolution*, *6*(3), 247–256.

MA. (2005). *Ecosystems and Human Well-being: A Synthesis.* Washington, D.C: Island Press.

MacArthur, R. H., & E. O. Wilson. 1967. The theory of island biogeography. Princeton University Press, Princeton, New Jersey, USA

MacDonald, M.A., & Bolton, M. (2008). Predation on wader nests in Europe. *Ibis, 150,* 54–73.

Mace, G.M., (2014). Whose conservation? *Science*, *345*(6204), 1558–1560.

Martay, B., Brewer, M. J., Elston, D. A., Bell, J. R., Harrington, R., Brereton, T. M., … Pearce-Higgins, J. W. (2017). Impacts of climate change on national biodiversity population trends. *Ecography*, *40*(10), 1139–1151. https://doi.org/10.1111/ecog.02411

Martimort, P. Arino, O., Berger, M., & Biasutti, R. (2007). Sentinel-2, the optical high-resolution mission for GMES operational services. *Remote Sensing of Environment, 131,* 2677–2680.

Massachusetts Climate Action Partnership (MCAP) (2015), Massachusetts Wildlife Climate Action Tool. *University of Massachusetts Amherst.* Accessed 27th November, 2019, https://climateactiontool.org/>.

Maturo, F., & Di Battista, T. (2018). A functional approach to Hill's numbers for assessing changes in species variety of ecological communities over time. *Ecological Indicators*, *84*(January), 70–81. https://doi.org/10.1016/j.ecolind.2017.08.016

Mawdsley, J. (2011). Design of conservation strategies for climate adaptation. Wiley *Interdisciplinary Review, 2*(4), 498–515.

Mawdsley, J. R., O'Malley, R., & Ojima, D.S. (2009). A review of climate-change adaptation strategies for wildlife management and biodiversity conservation. *Conservation Biology*, *23*(5), 1080–1089.

McCauley, D. J., (2006). Selling out on nature. *Nature*, *443*(7107), 27–28.

McDowell, M., & O'Connor, J, (1977). *Hydraulic Behaviour of Estuaries*. London: Macmillan.

Mcfarland, T. M., Van Riper, C., & Johnson, G.E. (2012). Evaluation of NDVI to assess avian abundance and richness along the upper San Pedro River. *Journal of Arid Environments*, *77*(1), 45–53.

McLaughlin, J. F., Hellmann, J. J., Boggs, C. L., & Ehrlich, P.R. (2002). Climate change hastens population extinctions. *PNAS, 99*(9), 6070–6074 https://doi.org/10.1073/pnas.052131199

Mcleod, E., Poulter, B., Hinkel, J., Reyes, E., & Salm, R., (2010). Sea-level rise impact models and environmental conservation: A review of models and their applications. *Ocean & Coastal Management, 53*, 507–517.

MGET (2014), MGET (online). Available at: http://www.merseygateway.co.uk/merseygateway-environmental-trust/ [Accessed: 23/02/2017].

Millar, C. I., & Brubaker, L. B. (2006). Climate Change and Paleoecology: New Contexts for Restoration Ecology. In M. Palmer, D. Falk, & J. Zedler (ed.) *Foundations of restoration ecology*: 315–40. Washington (DC) & London: Island Press.

Milton, E. J., Fox, N. P., & Schaepman, M. E. (2006). Progress in field spectroscopy. *International Geoscience and Remote Sensing Symposium (IGARSS*), Denver, CO, 1966–1968.

Mithen, S. J. (2004). *After the ice: a global human history, 20,000-5000 BC*. Cambridge: Cambridge University Press.

Moreno-Mateos, D., Power, M. E., Comín, F. A., & Yockteng, R. (2012). Structural and functional loss in restored wetland ecosystems. *PLoS Biology*, *10*(1). https://doi.org/10.1371/journal.pbio.1001247

Morgan, J. L., Gergel, S. E., & Coops, N. C. (2010). Aerial photography: A rapidly evolving tool for ecological management. *BioScience*, *60*(1), 47–59. https://doi.org/10.1525/bio.2010.60.1.9

Mori, A. S., Furukawa, T., & Sasaki, T. (2013). Response diversity determines the resilience of ecosystems to environmental change. *Biological Reviews, 88*(2), 349–364.

Morris, E. K., Caruso, T., Buscot, F., Fischer, M., Hancock, C., Maier, T. S., … Rillig, M. C. (2014). Choosing and using diversity indices: insights for ecological applications from the German Biodiversity Exploratories. *Ecology and Evolution*, *4*(18), 3514–3524.

Morris, J. T., Sundareshwar, P. V., Nietch, C. T., Kjerfve, B., & Cahoon, D. R. (2002). Responses of coastal wetlands to rising sea level. *Ecology 83*, 2869–2877.

Mossman, H. L., Davy, A. J., & Grant, A. (2012). Does managed coastal realignment create saltmarshes with "equivalent biological characteristics" to natural reference sites? *Journal of Applied Ecology*, *49*(6), 1446–1456. https://doi.org/10.1111/j.1365-2664.2012.02198.x

Murdukhayeva, A., August, P., Bradley, M., LaBash, C., & Shaw, N. (2013). Assessment of Inundation Risk from Sea Level Rise and Storm Surge in Northeastern Coastal National Parks. *Journal of Coastal Research, 291*, 1–16.

Nicholls, R. J., Townend, I. H., Bradbury, A. P., Ramsbottom, D., & Day, S. A., (2013). Planning for long-term coastal change: Experiences from England and Wales. *Ocean Engineering, 71,* 3–16.

Nitze, I., Schulthess, U., & Asche, H. (2012). Comparison of Machine Learning Algorithms Random Forest, Artificial Neural Network and Support Vector Machine To Maximum Likelihood for Supervised Crop Type Classification. *Proceedings of The 4th GEOBIA, May 7-9 - Rio de Janeiro - Brazil*, (April 2015), 35–40.

Noi, P. T., & Kappas, M. (2018). Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using sentinel-2 imagery. *Sensors* (Switzerland), *18*(1): 18. 10.3390/s18010018

Nuse, B. L., Cooper, R. J. & Hunter, E. A. (2015). Prospects for predicting changes to coastal wetland bird populations due to accelerated sea level rise. *Ecosphere,* 6(December), p286.

O'Connor, B. A. (1987). Short and long term changes in estuary capacity. *J. Geological Society, 144,* 187–195.

Ouyang, Z. T., Zhang, M. Q., Xie, X., Shen, Q., Guo, H.Q., & Zhao, B., (2011). A comparison of pixelbased and object-oriented approaches to VHR imagery for mapping saltmarsh plants. *Ecological Informatics, 6,* 136–146.

Pal, M., (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, *86*(4), 554–565.

Pande-Chhetri, R., Abd-Elrahman, A., Liu, T., Morton, J., & Wilhelm, V. L. (2017). Object-based classification of wetland vegetation using very high-resolution unmanned air system imagery. *European Journal of Remote Sensing, 50*(1), 564–576.

Parmesan, C. (1999) Poleward shifts in geographical ranges of butterfly species associated with regional warming. *Nature, 399*, 579–583.

Pearson, R. G., & Dawson, T. P. (2003). Predicting the impacts of climate change on the distribution of species: Are bioclimate envelope models useful? *Global Ecology and Biogeography, 12*(5), 361–371.

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J-M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology and Evolution, 20*(9), 503–510.

Pontee, N.I., (2011). Reappraising coastal squeeze: a case study from north-west England. *Maritime Engineering, 164*(3), 127-138.

Poulin, B., Davranche, A., & Lefebvre, G., (2010). Ecological Assessment of *Phragmites australis* Wetlands using Multi-Season SPOT-5 Scenes. *Remote Sensing of Environment, 114*(7), 1602-1609.

Pressey, R. L., Cabeza, M., Watts, M. E., Cowling, R. M., & Wilson, K. A. (2007). Conservation planning in a changing world. *Trends in Ecology and Evolution*, *22*(11), pp.583–592.

Priestnall, G., Jaafar, J., & Duncan, A., (2000). Extracting urban features from LiDAR digital surface models. Computers. *Environment and Urban Systems,* 24, 65–78.

Raposa, K. B., Weber, R. L. J., Ekberg, M. C., & Ferguson, W. (2017). Vegetation Dynamics in Rhode Island Salt Marshes During a Period of Accelerating Sea Level Rise and Extreme Sea Level Events. *Estuaries and Coasts*, *40*(3), 640–650. https://doi.org/10.1007/s12237-015-0018-4

Redfield, A. C. (1972), Development of a New England salt marsh. *Ecol. Monogr., 42*(2), 201–237. Doi: 10.2307/1942263

Redford, K. H., & Adams, W. M., (2009). Payment for ecosystem services and the challenge of saving nature: Editorial. *Conservation Biology, 23*(4), 785–787.

Reiley, B. M., Benson, T. J., Everitts, J., & Bednarz, J. C. (2017). Does flooding effect the apparent survival and body condition of a ground foraging migrant passerine? *PLoS ONE 12*(4), e0175179.

Robins, P. E., Skov, M. W., Lewis, M. J., Giménez, L., Davies, A. G., Malham, S. K., … Jago, C. F. (2016). Impact of climate change on UK estuaries: A review of past trends and potential projections. *Estuarine, Coastal and Shelf Science*. *169*, 119–135.

Rodwell, J. S., Pigott, C. D., Ratcliffe, D. A., Malloch, A. J. C., Birks, H. J. B., Proctor, M. C. F., … Wilkins, P. (2000). *British Plant Communities. Volume 5. Maritime communities and vegetation of open habitats.* Cambridge: Cambridge University Press.

Roser, M., & Ortiz-Ospina, E. (2019). *Global Extreme Poverty*. Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/extreme-poverty' [Online Resource]

Rosnell, T., Honkavaara, E., & Nurminen, K. (2011). On Geometric Processing of Multi-Temporal Image Data Collected by Light UAV Systems. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *2011-1/*(September), 63–68.

Rupprecht, F., Möller, I., Paul, M., Kudella, M., Spencer, T., van Wesenbeeck, B. K., Wolters, G., Jensen, K., Bouma, T. J., Miranda-Lange, M., & Schimmels, S. (2017). Vegetation-wave interactions in salt marshes under storm surge conditions. *Ecological Engineering*, *100*, 301–315. https://doi.org/10.1016/j.ecoleng.2016.12.030

Saino, N., Szép, T., Romano, M., Rubolini, D., Spina, F., & Møller, A. P. (2004). Ecological conditions during winter predict arrival date at the breeding quarters in a trans-Saharan migratory bird. *Ecology Letters, 7*(1), 21–25.

Sala, O. E., Chapin, F. S. Ill, Armesto, J. J., Berlow, E., Bloomfield, J., Poff., N. L. (2000). Global biodiversity scenarios for the year 2100. *Science*, *287*(5459), 1770–1774.

Samiappan, S., Turnage, G., Hathcock, L., Casagrande, L., Stinson, P., Moorhead, R. (2017). Using unmanned aerial vehicles for high-resolution remote sensing to map invasive *Phragmites australis* in coastal wetlands. *International Journal of Remote Sensing, 38,* 2199–2217.

SC. (2013). North West Estuaries Processes Reports: Mersey Estuary. Volume 3, Sefton:

Schröter, D., Cramer, W., Leemans, R., Prentice, C., Araújo, M. B., Arnell, N. W., … Zierl, B. (2005). Ecosystem Service Supply and Vulnerability to Global Change in Europe. *Science*, *1333,* 1115-1233.

Scott, A. V. (2009). *The Landscape Scale Approach to Urban Nature Conservation: Implementation, Critical Appraisal of Policy Interactions and New Opportunities for Urban Biodiversity Enhancement.* PhD Thesis. The University of Salford, Salford.

Scriven, S. A., Hodgson, J. A., McClean, C. J., & Hill, J. K. (2015). Protected areas in Borneo may fail to conserve tropical forest biodiversity under climate change. *Biological Conservation*, *184*, 414–423.

Seto, K. C., Fleishman, E., Fay, J. P., & Betrus, C. J. (2004). Linking spatial patterns of bird and butterfly species richness with Landsat TM derived NDVI. *International Journal of Remote Sensing*, *25*(20), 4309–4324.

Sharps, E., Garbutt, A., Hiddink, J. G., Smart, J., & Skov, M. W. (2016). Light grazing of saltmarshes increases the availability of nest sites for Common Redshank *Tringa totanus*, but reduces their quality. *Agriculture, Ecosystems and Environment*, *221*, 71–78.

Sharps, E., Smart, J., Skov, M. W., Garbutt, A., & Hiddink, J. G. (2015). Light grazing of saltmarshes is a direct and indirect cause of nest failure in Common Redshank *Tringa totanus*. *IBIS, 157*(2), 239–249.

Sheeren, D., Bonthoux, S., & Balent, G. (2014). Modeling bird communities using unclassified remote sensing imagery: Effects of the spatial resolution and data period. *Ecological Indicators, 43*, 69–82. Available at: http://dx.doi.org/10.1016/j.ecolind.2014.02.023.

Silva, T. S. F., Costa, M. P. F., Melack, J. M., & Novo, E. M. L. M. (2008). Remote sensing of aquatic vegetation: Theory and applications. *Environmental Monitoring and Assessment, 140*(1-3), 131–145.

Silvestri, S. & Marani, M. (2004). Salt-Marsh Vegetation and Morphology: Basic Physiology, Modelling and Remote Sensing Observations. *Ecogeomorphology Tidal Marshes, 59*, 5–25.

Smart, J., Gill, J. A., Sutherland, W. J., & Watkinson, A. R. (2006). Grassland-breeding waders: Identifying key habitat requirements for management. *Journal of Applied Ecology*, *43*(3), 454–463.

Smith, D. J. (2013). *Changes in Perspectives of the Values and Benefits of Nature.* PhD Thesis, The University of Salford, Salford.

Soule, M. (2014). Also seeking common ground in conservation. *Conservation Biology, 28*(3), 637–638.

Stagg, C. L., Krauss, K. W., Cahoon, D. R., Cormier, N., Conner, W. H., & Swarzenski, C. M. (2016). Processes Contributing to Resilience of Coastal Wetlands to Sea-Level Rise. *Ecosystems, 19*, 1445–1459.

St-Louis, V., Pidgeon, A. M., Clayton, M. K., Locke, B. A., Bash, D., & Radeloff, V. C. (2009). Satellite image texture and a vegetation index predict avian biodiversity in the Chihuahuan Desert of New Mexico. *Ecography, 32*(3), 468–480.

Stratoulias, D., Balzter, H., Sykioti, O., Zlinszky, A., & Tóth, V. R. (2015). Evaluating Sentinel-2 for Lakeshore Habitat Mapping Based on Airborne Hyperspectral Data. *Sensors, 15*(9), 22956–22969. Doi: 10.3390/s150922956.

Stratoulias, D., Balzter, H., Zlinszky, A., & Tóth, V. R. (2015). Assessment of ecophysiology of lake shore reed vegetation based on chlorophyll fluorescence, field spectroscopy and hyperspectral airborne imagery. *Remote Sensing of Environment, 157*, 72–84.

Sun, C., Liu, Y., Zhao, S., Zhou, M., Yang, Y., & Feixue, L. (2016). Classification mapping and species identification of salt marshes based on a short-time interval NDVI time-series from HJ-1 optical imagery. *International Journal of Applied Earth Observations and Geoinformation, 45*, 27–41.

Taft, J. B., Hauser, C., & Robertson, K. R. (2006). Estimating floristic integrity in tallgrass prairie. *Biological Conservation*, *131*(1), 42–51. https://doi.org/10.1016/j.biocon.2006.02.006

Takekawa, J. Y., Ackerman, J. T., Brand, L. A., Graham, T. R., Eagles-Smith, C. A., Herzog, M. P., … Athearn, N. D. (2015). Unintended consequences of management actions in salt pond restoration: Cascading effects in trophic interactions. *PLoS ONE, 10*, e0119345

Tallis, H., Kareiva, P., Marvier, M., & Chang, A. (2008). Ecosystem Services Special Feature: An ecosystem services framework to support both practical conservation and economic development. *PNAS, 105*(28), 9457–9464.

Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J., Collinghamn, Y. C., … Williams, S. E. (2004). Extinction risk from climate change. *Nature*, 427(6970), 145– 148.

Thorne, K. M., Spragens, K. A., Buffington, K. J., Takekawa, J., & Rosencranz, J. A. (2019). Flooding regimes increase avian predation on wildlife prey in tidal marsh ecosystems. *Ecology & Evolution, 9*(2), 1–12.

Thuiller, W., Albert, C., Araújo, M. B., Berry, P. M., Cabeza, M., Guisan, A., & Zimmermann, N. E. (2008). Predicting global change impacts on plant species' distributions: Future challenges. Perspectives in Plant Ecology. *Evolution and Systematics*, *9*(3-4), 137– 152.

Tian, S., Zhang, X., Tian, J., & Sun, Q. (2016). Random forest classification of wetland landcovers from multi-sensor data in the arid region of Xinjiang, China. *Remote Sensing*, *8*(11), 1–14. https://doi.org/10.3390/rs8110954

Tolvanen, A., & Aronson, J. (2016). Ecological restoration, ecosystem services, and land use: A European perspective. *Ecology and Society, 21*(4): 47 https://doi.org/10.5751/ES-09048-210447

Tóthmérész, B. (1995). Comparison of different methods for diversity ordering. J. *Veg. Sci. 6,* 283–290.

Tovey, E. L., Pontee, N., & Harvey, R. (2009). Award Winning Managed Realignment: Hesketh Out Marsh West. Manchester: Halcrow.

Townend, JA (2005). *Practical Statistics for Environmental and Biological Scientists*. Sussex, Wiley and Sons Ltd.

Traill, L. W., Perhans, K., Lovelock, C. E., Prohaska, A., McFallan, S., Rhodes, J. R., & Wilson, K. A. (2011). Managing for change: Wetland transitions under sea-level rise and outcomes for threatened species. *Diversity and Distributions, 17*, 1225–1233.

Travis, J. M. J., Delgado, M., Bocedi, G., Baguette, M., Bartoń, K., Bonte, D., … Bullock, J. M. (2013). Dispersal and species' responses to climate change. *Oikos, 122*(11), 1532–1540.

Tsao, D. C., Takekawa, J. Y., Woo, I., Yee, J. L., & Evens, J. G. (2009). Home range, habitat selection, and movements of California black rails at tidal marshes at San Francisco Bay, California. *The Condor, 111*, 599– 610.

UK-NEA. (2011). *The UK National Ecosystem Assessment: Chapter 1. Introduction to the UK National Ecosystem Assessment.* Cambridge: UNEPWCMC

United Kingdom Marine Monitoring and Assessment Strategy (UKMMAS). (2010). *Charting Progress 2 Feeder Report: Ocean Processes* (Ed J. Huthnance.). Department for Environment Food and Rural Affairs on Behalf of UKMMAS, 279pp.

Van de Koppel, J., van der Wal, D., Bakker, J. P. & Herman, P. M. (2005). Self-Organization and Vegetation Collapse in Salt Marsh Ecosystems. *The American Naturalist, 165*(1), 1–12.

Van der Putten, W.H., Macel, M., & Visser, M.E., (2010). Predicting species distribution and abundance responses to climate change: why it is essential to include biotic interactions across trophic levels. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1549), 2025–34.

van der Wal, D., & Pye, K., (2004). Patterns, rates and possible causes of saltmarsh erosion in the Greater Thames area (UK). *Geomorphology, 61*(3-4), 373–391.

Van Duin, W. E., Dankers, N.M.J.A., Dijkema, K. S., Van Eeden, S., Sleutel, A., Wolff, W. J., et al. (1996). Results from the Dutch team. In J. C. Lefeuvre (Ed.), *The effects of environmental change on European salt marshes: Structure, functioning and exchange potentialities with marine coastal waters* (pp. 6). Rennes: University of Rennes.

van Kerkhoff L. E., & Lebel L., (2015). Coproductive capacities: rethinking science-governance relations in a diverse world. *Ecology and Society, 20*(1): 14.

Ventura, D., Bruno, M., Jona Lasinio, G., Belluscio, A., & Ardizzone, G. (2016). A low-cost drone based application for identifying and mapping of coastal fish nursery grounds. *Estuar. Coast. Shelf Sci., 171*, 85–98.

Villa, P. (2013). A remote sensing approach to monitor the conservation status of lacustrine *Phragmites australis* beds. *Wetlands Ecology and Management, 21*(6), 399– 416.

Villa, P., Bresciani, M., Bolpagni, R., Pinardi, M., & Giardino, C. (2015). A rule-based approach for mapping macrophyte communities using multi-temporal aquatic vegetation indices. *Remote Sensing of Environment, 171,* 218– 233.

Villa, P., Bresciani, M., Braga, F., & Bolpagni, R. (2014). Comparative assessment of broadband vegetation indices over aquatic vegetation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7*(7), 3117–3127.

Villa, P., Mousivand, A., & Bresciani, M. (2014). Aquatic vegetation indices assessment through radiative transfer modeling and linear mixture simulation. *International Journal of Applied Earth Observation and Geoinformation, 30*(1), 113–127.

Vlachopoulos, O., Leblon, B., Wang, J., Haddadi, A., LaRocque, A., & Patterson, G. (2020). Delineation of Bare Soil Field Areas from Unmanned Aircraft System Imagery with the Mean Shift Unsupervised Clustering and the Random Forest Supervised Classification. *Canadian Journal of Remote Sensing*, *0*(0), 1–12. https://doi.org/10.1080/07038992.2020.1763789

Walther, G.-R., (2010). Community and ecosystem responses to recent climate change. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *365*(1549), 2019–2024.

Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T. J. C., … Bairlein, F. (2002). Ecological responses to recent climate change. *Nature, 416,* 389–395.

Walther, G.-R., Roques, A., Hulme, P. E., Sykes, M. T., Pyšek, P., Kühn, I., … Settele, J. (2009). Alien species in a warmer world: risks and opportunities. *Ecology Letters, 24*(12), 686–693.

Wan, H., Wang, Q., Jiang, D., Fu, J., Yang, Y., & Liu, X. (2014). Monitoring the invasion of *Spartina alterniflora* using very high resolution unmanned aerial vehicle imagery in Beihai, Guangxi (China). *The Scientific World Journal,* 2014: 638296 doi: 10.1155/2014/638296.

Wang, C., & Myint, S.W. (2015). A Simplified Empirical Line Method of Radiometric Calibration for Small Unmanned Aircraft Systems-Based Remote Sensing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote* Sensing, 8, 1876–1885.

White, G., (2009). *The Future of Reedbed Management*. Sandy: RSPB. Accessed On-line 19/11/15

Wilson, E. O. (1984). *Biophilia.* Cambridge, Mass: Harvard University Press

Wolf, P., Roßler, S., Schneider, T., & Melzer, A. (2013). Collecting in situ remote sensing reflectances of submersed macrophytes to build up a spectral library for lake monitoring. *European Journal of Remote Sensing, 46*(1), 401–416.

Wolters, M., Bakker, J., Bertness, M. D., Jefferies, R. L., & Möller, I. (2005). Saltmarsh erosion and restoration in south-east England: squeezing the evidence requires realignment. *Journal of Applied Ecology, 42*(5), 844– 851. https://doi.org/10.1111/j.1365-2664.2005.01080.x

Woodworth, P. L., Teferle, F. N., Bingley, R. M., Shennan, I., & Williams, S. D. P. (2009). Trends in UK mean sea level revisited. *Geophysical Journal International, 176,* 19–30.

Wyborn, C., van Kerkhoff, L., Dunlop, M., Dudley, N., & Guevara, O. (2016). Future oriented conservation: knowledge governance, uncertainty and learning. *Biodiversity and Conservation, 25*(7), 1401–1408.

Yachi, S., & Loreau, M. (1999). Biodiversity and ecosystem productivity in a fluctuating environment: the insurance hypothesis. *PNAS, 96*(4), 1463–1468.

Yoccoz, N. G., Nichols, J. D., & Boulinier, T. (2001). Monitoring of biological diversity in space and time. *Trends in Ecology and Evolution*, *16*(8), 446–453. https://doi.org/10.1016/S0169-5347(01)02205-4

Yuan, H., Van Der Wiele, C. F., & Khorram, S. (2009). An automated artificial neural network system for land use/land cover classification from landsat TM imagery. *Remote Sensing, 1*, 243–265.

Yvon-Durocher, G., Jones. J. I., Trimmer, M., Woodward, G., & Montoya, J. M. (2010). Warming alters the metabolic balance of ecosystems. *Philosophical Transactions of the Royal Society B: Biological Sciences, 365*(1549), 2117– 2126.

Zipperer, W. C. (2011). The process of natural succession in urban areas. In: I. Douglas, D. Goode, M. Houck, & R. Wang (eds.) *The Routledge Handbook of Urban Ecology.* London: Routledge Press. 187-197.

Zomer, M. J., Bunce, R. G. H., Jongman, R. H. G., Sayre, R., Trabucco, A., & Metzger, R. (2013). A high-resolution bioclimate map of the world: A unifying framework for global biodiversity research and monitoring. *Global Ecology and Biogeography, 22*(5), 630–638.