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Assessing high resolution climate data to inform landscape management of climate risk at different scales.

A thesis submitted for the degree of Doctor of Philosophy

Lucia Zagora Watts

School of Natural Sciences, Thoday Building, Bangor University, Bangor, Gwynedd, LL57 2DF

Declaration

I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.
I confirm that I am submitting this work with the agreement of my Supervisor(s).

Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw'r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o'r blaen ar gyfer unrhyw radd, ac nid yw'n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy.
Rwy'n cadarnhau fy mod yn cyflwyno'r Gwaith hwn gyda chytundeb fy Ngoruchwylwr (Goruchwylwyr).

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Abstract

Climate change is one of the greatest threats in the 21st century to all inhabitants of the planet. Conservation organisations in the UK are interested in understanding this risk to their sites, and in integrating climate adaptation into management plans. This research assesses the use of high resolution UKCP18 projections for three case studies managed by the National Trust in Wales. The case studies cover a range of expected climate impacts to, bird species distributions, wind on parkland trees and fire in peatland areas. Predictions are at a range of scales from a single property through to the UK scale. Results are presented for three time frames of 20-year averages; 1980 to 2000 (1990s), 2020 to 2040 (2030s) and 2050 to 2080 (2070s).

Bird species in the UK uplands, especially habitat specialists, are vulnerable to climate change. For the species distribution study current and future distributions of five bird species found in the uplands of Britain were modelled using the Maxent model. Results at 2.2 km and 12 km scales were compared, with baseline and projected habitat layers included to investigate land cover change. Species-specific, local scale species distribution models outperformed those at the larger spatial scale. Habitats were found to be more limiting than climate, with all species increasing ranges under climate change alone.

Fire risk on peatlands is increasing, with risks to important habitats and carbon stores. The Canadian Forest Fire Danger Rating System (CFFDRS) was tailored to an upland peatland and predicted three metrics of future fire risk: 1. Fire Weather Index (FWI), a measure of fire risk, 2. Head Fire Intensity (HFI), the strength of a potential fire and 3. fire season length. The metrics were validated using dates of known fire at the site. All metrics of fire risk increase from the 1990s to 2070s with reductions in risk in the 2030s. Validation results suggest FWI is a better predictor of fire risk than HFI. Current conservation and farming practices may need to adapt to consider risk from fires all year round.

High wind speeds have a direct impact on tree health and lifespan in forests and parklands, and consequently affect visitor safety. Tatter flags were used to quantify the exposure of individual parkland trees to wind speeds and direction, with baseline data gathered from a year-long fieldwork study. The number of times the site may have to close due to high winds above pre-determined thresholds were also calculated. Trees are more likely to become more exposed to high winds in autumn and winter seasons, with a decrease in exposure in the spring and summer months. Wind directions are predicted to continue as a prevailing south-westerly, but likely to experience more wind from the north-west. Closures are predicted to increase, especially around Christmas and Easter holidays. The current site plan may not be viable in the future, with exploration around new access routes and species a potential next step.

Finally, we conducted a feedback study with staff at each site to explore understanding about the results from the data chapters. We developed all chapters and outputs iteratively with staff using an online questionnaire. Staff found that results presented about their case study site would be useful when thinking about conservation planning and adaptation for the future.

Overall, most results suggest a decrease in risk from climate change in the 2030s, and an increase in the 2070s compared to the 1990s. We found that, as expected, tailoring models to a site or species produces results of a greater degree of accuracy, and therefore are a greater useful contribution to conservation. Finally, we have demonstrated the versatility of high-quality local scale climate data in a range of scenarios as useful data to explore future risk at the site scale.

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Chapter 1: General introduction

Here I provide a general introduction to this thesis and the surrounding research with a focus on current and future impacts of climate change to biodiversity. This includes, the data used and how these have evolved over time, differences in scale and need between conservation management and processes impacted by climate change, and finally consideration of the requirements of conservation practice in communicating these impacts. This chapter, while a thesis introduction, provides a review of the relevant literature as well as outlining the rest of the thesis.

1.1 Climate change and biodiversity

Climate change, directly impacted by anthropogenic activity (Mooney *et al.*, 2009; Haustein *et al.*, 2019; Basińska *et al.*, 2020), will be the most important threat to, and primary driver of increasing vulnerability and loss to biodiversity by 2100 (Klausmeyer *et al.*, 2011; Pautasso, 2012; Scheffers *et al.*, 2016; Brandt *et al.*, 2017; Synes *et al.*, 2020). Disruptions to ecosystems from this change are unlike any previous disturbance, with threat of a sixth mass extinction (Barnosky *et al.*, 2011; Bellard *et al.*, 2012). Global biodiversity is declining faster than at any time in human history with devastating implications for all species (Diaz *et al.*, 2019). Other impacts, such as habitat fragmentation, land use change and agriculture also negatively affect biodiversity (Sozanska-Stanton *et al.*, 2016), and are exacerbated by climate change. Average global temperatures are predicted to exceed 1.5°C of warming above pre-industrial levels at the earliest by 2030 (IPCC, 2018; Masson-Delmotte *et al.*, 2018a), with warnings of irreversible changes to ecosystems and Earth systems processes. Impacts to weather events over recent decades in the United Kingdom have already been directly attributed to global greenhouse gas (GHG) emissions (Pall *et al.*, 2011). These impacts are mirrored in the natural world, with increases in risks of droughts, wildfires and flooding (Arnell *et al.*, 2021). Extreme weather events in the UK are becoming more common and severe, and are expected to become more frequent with climate change (Arnell *et al.*, 2021; Clarke, Otto and Jones, 2021). Considerable evidence highlights the need for developing good quality habitats through actions such as wetland restoration and land use changes to sequester carbon, reduce GHG emissions and increase biodiversity in priority habitats in the UK and beyond (e.g. Sozanska-Stanton *et al.*, 2016; Morecroft *et al.*, 2019; Field *et al.*, 2020; Rowland *et al.*, 2021a; Smith *et al.*, 2022). Through reduction of these emissions, change may be slowed, extreme events lessened and ecosystems likely to become more resilient to change although global progress on emissions reduction is falling short of both commitments and requirements to avoid the worst climate change.

This thesis focuses on local-level impacts of climate change to conservation sites in Wales owned and/or managed by the National Trust, and in this, explores some of the risks to Wales. These risks have been recognised since the 1990s, with recognition that costs will far outweigh the benefits of warmer winters and wetter summers (Hurst, 1997; Farrar *et al.*, 2000). Average temperatures in Wales have increased by almost 1°C since the mid-1970s, with significant heatwaves in 2019 and 2022 (Netherwood, 2022). Under high emissions scenarios estimating future average global temperatures exceeding 4^{o}C, average temperatures in Wales could increase by 2.3^{o}C by the 2080s, with a greater number of risks associated with these increases identified in the most recent Climate Change Risk Assessment (CCRA3) (Climate Change Committee, 2021; HM Government, 2022). Met Office predictions show similar trends (Met Office, 2018), with Welsh climates under high emission scenarios potentially experiencing summer rainfall decreasing by over 50 % and temperatures increasing by up to 6^{o}C. Winter months are also predicted to see increases in temperature of up to 4^{o}C with precipitation up to 29 % wetter than current averages. These changes could see negative impacts to species and landscapes in Wales such as losses to habitats, although little research has explored these impacts at the Welsh scale. Recent studies have explored the significant impacts of climate in Wales to hydrology (Dallison, Patil and Williams, 2021), buildings (Hayles *et al.*, 2022) and forestry (Ray *et al.*, 2015), but with little exploration into the impacts to species and habitats. One paper (Arnell, Freeman and Gazzard, 2021) explored how climate change may affect fire danger in the UK, with a Welsh case study which predicts between a 78 to 98 % likelihood of Wales experiencing more days than the current average at very high danger from fire. This highlights the importance of conducting research at the local-level for Wales due to the scarcity of research investigating climate change impacts, but the high risk found in studies which have explored risks to the area.

Nearly 60 % of species in the UK are showing long term negative trends in abundance and distribution (Hayhow *et al.*, 2019), with agricultural policies and climate change highlighted as key reasons for declines. Previously, the Lawton *et al.*, Report (2010) emphasised that England's ecosystems are highly degraded and unable to respond to climate change and changes in land use. This limits not only the species and habitats present, but also the capability of these landscapes to deliver important ecosystem services, from recreation to carbon sequestration. Without understanding how these unprecedented impacts may affect sites managed for nature, experts will be unable to put useful, sustainable practices in place to bolster ecosystems and potentially lessen the effects of negative change. There is potential for some species to benefit from climate change, through new colonisations or increases in suitable range (Thomas *et al.*, 2011), especially through the protected area network (Johnston *et al.*, 2013). Targeting management to areas that are more likely to protect diversity of species, and facilitate species distribution shifts, could focus resources to and increase positive outcomes from the perspective of climate change.

There is an understanding of these threats and the scale of potential change, depending on different scenarios, but there is less understanding on the most effective ways to react to this change (Cook, Hockings and Carter, 2010). Evidence-based decisions and action will help nature to become more resilient to, and better aligned with, change and even help slow global average temperatures (Stafford *et al.*, 2021). There could be several options for a site or area (McLaughlin *et al.*, 2022), with conflicting requirements and limited resources for implementation. Analysis of change and impacts at the local scale leads to greater understanding of risk and opportunity (Glad and Mallard, 2022) and provides evidence to decide the most effective ways to manage change.

1.2 What can we do about climate change? A brief introduction to UK climate policy and targets.

Nature is essential for meeting worldwide agreements such as the Sustainable Development Goals to ensure a liveable planet, many of which have already been exceeded (Pecl *et al.*, 2017). As a global community we have already missed seemingly vital targets to enhance biodiversity as set out by the Convention on Biological Diversity (CBD) (Lawton *et al.*, 2010; Mace *et al.*, 2010). Even though these targets were criticised as being unrealistic, with recommendation for a smaller number of specific targets, we have seen little positive change towards worldwide goals. Transformative change is required to meet any global targets set for emissions reductions, area of land within conservation designation or sustainability goals. For example, the ambitious proposal to protect or conserve at least 30 % of the planet by 2030 (Convention on Biological Diversity, 2020), will require coordinated efforts between countries and experts to meet this goal.

Within the UK, the Climate Change Act (2008) forms the basis for responding to climate change, primarily through the reduction of GHGs, but also through identifying vulnerability via climate change risk assessments (UK Government, 2008). In Wales, this catalysed the formation of the Environment (Wales) Act 2016, which contains targets for an 80 % reduction in GHG emissions by 2050, compared to 1990 levels (Welsh Government, 2016). These are strong targets, requiring updates and innovative measures to meet more recent 'net zero' emissions targets for the UK as set in 2019, also to a 2050 deadline (BEIS, 2021). In England, the UK Government's 25-Year Plan for the Environment commits, albeit without specific recommendations, to do what is necessary to adapt to the effects of a changing climate (DEFRA, 2018). This plan has also come under scrutiny as it is unlikely to fit with some approaches to protecting nature, such as more innovative, experimental ideas (Dempsey, 2021) such as rewilding projects. The Plan does provide strong targets and recognises the broad benefits nature brings to the table, but without implementation and ongoing research into adaptation need, these targets are unlikely to be met. Additionally, with the continuing relaxation of regulations following the UK exit from the European Union in 2016, and further damaging of shields against development on legally protected land in recent Conservative announcement and budgets, these policies may amount to little.

From a Welsh perspective, the Wellbeing of Future Generations (Wales) Act (2015) includes commitments to protect the natural environment to enhance a healthier, globally responsible, and resilient Wales. Climate change is at the centre of the Act (ASC, 2016), with one wellbeing goal the 'Resilience Goal' specifically highlighting the need for adaptation. Wales's natural environment is worth £8 billion to the Welsh economy (Welsh Government, 2015), and also recognised for its intrinsic, cultural values and positive impact to sustainability. Recent pledges by Welsh Government to uphold fracking bans are hopeful signs that these goals will be respected, but political climates often only examine the short term whereas our planetary climate requires much greater temporal scales of investigation and care.

To analyse risks to the UK from changing climates, the UK Climate Change Risk Assessments (UK CCRA) were developed as a requirement of the Climate Change Act in 2008. Three CCRAs published in 2012, 2017 and 2022 (CCRA3) (HM Government, 2022) have assessed future impacts and the actions required to mitigate and adapt to them, including our commitment to net zero. Main points from CCRA3 surround the large economic cost of climate change and highlight the case for acting now rather than later, especially to prevent locking-in large future impacts. The report recognises that small average changes can lead to large changes in extreme events, but also that climate change will present some opportunities for the UK, although these centre around international trade rather than the natural world. Nevertheless the key risks and priorities recognised by CCRA3 and the prior independent review (Climate Change Committee, 2021) highlight risks to terrestrial species and habitats from temperature changes, wind speeds and wildfires, all of which are explored in this thesis. The CCRA3 identified 61 risks to Wales from climate change, with all but eight requiring further investigation or more action (Netherwood, 2022). This suggests a lack of useful evidence or resources to assess these risks. Three risks to Wales in the CCRA3 have particular relevance to this research project. One relates to the risks and opportunities presented in natural carbon stores, with healthy environments contributing to carbon sequestration, but degraded and more at risk stores potentially shifting to become sources of GHG emissions. Another risk with an associated opportunity is to terrestrial species and habitats which are at risk from changing climatic conditions and extreme events, as described above. There could be some opportunities to these terrestrial species through potential for new species colonisation, although this could lead to negative impacts from invasive species. Finally, there has been a recognised risk and potential opportunity from climate change to natural heritage and landscape character. The urgency score for this sector has been updated from '*watching brief*' in CCRA2 to '*further investigation*' in CCRA3 (Netherwood, 2022) suggesting that these risks have increased in scale from previous risk assessments.

Evidence of current change and increases in risks (Arnell *et al.*, 2021) support development of national and local climate and resilience policy. Many climate variables, such as wind gusts (Schindler *et al.*, 2013) and precipitation, are highly variable and likely to become more so (Pendergrass *et al.*, 2017), and therefore understanding local risk and putting into place local policy and plans are likely to have greater positive outcomes. However, this is likely to be resource intensive and requires a thorough understanding of local risks and variability.

1.3 Using conservation management to react to processes impacted by climate change: scale and need

There are impacts of climate change to ecosystems that have been understood for many years now (Thomas *et al.*, 2004; Chambers *et al.*, 2007; Lawton *et al.*, 2010; Johnston *et al.*, 2013; Turetsky *et al.*, 2015; Liang *et al.*, 2018; Hayhow *et al.*, 2019; Loisel *et al.*, 2020). However, identifying and assessing the vulnerability of species, habitats and processes to climate related change is complicated (Clark *et al.*, 2010; Pacifici *et al.*, 2015), and often an overlooked step in conservation planning (Pearce-Higgins *et al.*, 2011).

For example (Pearce-Higgins *et al.*, 2017), identified the most vulnerable species through considering alterations to species ranges sizes with climate change, and combining species distribution modelling techniques (Beale, Brewer and Lennon, 2014) with species risk assessments (Thomas *et al.*, 2011). These results were found to be highly species-specific and therefore using broad species categories can be problematic as many individual species respond differently to even closely related cousins. A meta-analysis (Radchuk *et al.*, 2019) found that climate change has advanced phenological traits, such as migration, in birds. This could greatly affect timings of management on site, such as cutting or burning as species could be at great risk from disturbance or loss of habitat. However, whilst these impacts of climate change are being experienced on sites, many site managers are yet to include climate change adaptation in conservation plans (Duffield, Le Bas and Morecroft, 2021).

The need for evidence-based management for UK conservation has been recognised (Sutherland *et al.*, 2010) with priority policy options able to guide scientific research. This need can be met through the tailoring of research around the type of decisions that are made about a certain species or habitat requiring conservation (Schwartz, 2012). Yet there have been relatively few case studies of scenario-led adaptation (Green and Weatherhead, 2014). This is potentially due to a lack of resources, considerable uncertainties around models and future conditions, and data intensive methods (Green and Weatherhead, 2014). Scenario-led adaptation could be developed through co-designed research between academics and practitioners with significant inputs from stakeholders at all stages of research which can increase the uses, reach and scope of a desired outcome (Kurle *et al.*, 2022). When stakeholders bring a scenario to researchers this can lead to tailoring of outputs to what people actually need on the ground, and while these could become highly specific to a place or impact, they can also clead to the formation of new ideas for wider conservation management.

In this thesis, I explore the needs of the National Trust (NT) a non-governmental organisation (NGO) in understanding climate risk to places it manages, and how these risks can be adapted to bolster resilient sites. The NT has a commitment to preserve nature and heritage across England and Wales, to protect important sites and ensure that these areas can be enjoyed by everyone. There is a clear recognition for the need to protect sites from climate change and the NT is leading the way in sustainable practices such as energy generation at its properties. As part of this, in 2015 the NT identified climate change as the greatest threat to the organisation in the 21st century (National Trust, 2015), and yet is unsure exactly what this will mean for properties and how to plan for these impacts. Much of the evidence for change was reactionary, in understanding events that had already occurred in the context of climate change. Current academic research surrounding the impacts of climate change to the NT has focused on energy (Blades *et al.*, 2018) and risks to historic interiors (Lankester and Brimblecombe, 2012). There has been investigation into sustainable heritage tourism at the National Trust and this commitment to climate change (Floy, 2015), but little research into how climate impacts may threaten nature on its sites. When considering the NT role in climate change adaptation, and wider nature conservation, there is a responsibility not just to the natural world, but to members of the charity. The NT has a bold commitment of 'For ever, for everyone', with an explicit promise to maintain and enhance land and property within its care. Additionally, the NT is facing similar challenges to other nature conservation organisations like the Royal Society for the Protection of Birds (RSPB) and the Wildlife Trust. These three organisations all have sites that are open to the public to encourage people to enjoy and learn about nature with a dedication to the protection and conservation of the natural world.

I have worked in collaboration with the National Trust through funding from the Knowledge Economy Skills Scholarship (KESS2) programme (kess2.ac.uk). The scholarship is supported by the European Social Fund, and through Welsh Government links organisations with all Welsh universities to undertake collaborative research. This not only trains research students and enables them to further their education, but also puts small-to-medium enterprises at the heart of research. This collaboration highlights the importance of evidence-based decision making for conservation organisations and the usefulness of conducting scientific research to aid in these decisions. The project was part-funded by the National Trust directly by the three case study sites explored in this thesis due to their interest in the impacts of climate change and risks at each site. Properties were visited at the commencement of research to understand more about the current impacts and the potential risks that managers were concerned about in the future. This ongoing collaboration helped to strengthen the project and keep it focused on organisational need as well as scientific advancement.

1.4 Communicating the impacts

There is little point in researching and quantifying impacts of climate change to ecosystems, if the understanding gained is not passed on to relevant organisations and stakeholders. However, this communication of impacts is often overlooked, with a widening gap between research and practice. While there is an increasing focus on applied research that delivers impact, recognising and quantifying this impact once research is conducted can be lacking (Yates *et al.*, 2018; Fabian *et al.*, 2019). Numerous studies have investigated ways to bridge this gap. There is recognition that the published science is useful in conservation management and used if appropriately provided (Fabian *et al.*, 2019), but that barriers to uptake by stakeholders include time constraints, access to journals and lack of specialised scientific expertise. This has led to decisions in the past being mostly experience-based (Pullin *et al.*, 2004) with reliance on traditional land-management practices, which may not be suitable under future climates. Decision makers need access to reliable evidence-based information, presented in readable form, to enable the best responses to climate change risks and assess opportunities for adaptation (Harrison *et al.*, 2013). Decisions may also need to be made quickly in reaction to impacts (Cook, Hockings and Carter, 2010), with sometimes little time for assessment of evidence-based literature. Integration of stakeholders from the onset of a project has been highlighted as an important step in communicating impacts and developing projects that meet stakeholders needs (Harrison *et al.*, 2013; Samson *et al.*, 2017; Fabian *et al.*, 2019). Additionally, local perspectives on environmental change are important as these communities are the ones who experience the change and often have a greater wealth of knowledge on the area than potentially outside researchers (Palacios-Agundez *et al.*, 2013).

Several methods have been used to bridge this science-practice gap and produce outputs which are useful and accessible for local nature conservation. Community-based scenario planning puts locals at the heart of a project, which revealed local perspectives on environmental change, visions for their community and actions to aid in community adaptation to change (Bennett, Kadfak and Dearden, 2016). Early engagement of stakeholders and practitioners is a key step in producing results useful and wanted for practice (Samson *et al.*, 2017), with ongoing engagement throughout a project providing stakeholders with ownership of a project (Shaw *et al.*, 2009). Additionally, visualisation of an impact or a solution aids in better understanding and acceptance (Milligan *et al.*, 2009). Projects like the CLIMSAVE platform (Harrison *et al.*, 2013; Harrison, Holman and Berry, 2015) provide an interactive tool which practitioners can use to assess impacts under different scenarios and adaptation measures. This open access participatory modelling tool provided a high level of customisability and was developed with stakeholders through a number of workshops to develop scenarios and adaptation responses (Harrison, Holman and Berry, 2015). While this is an innovative approach, it requires a certain level of knowledge from stakeholders and could be fairly time intensive.

Other repositories of information collated to assist in environmental decision making include the Conservation Evidence website (Sutherland *et al.*, 2004, www.conservationevidence.com) which is designed to suggest conservation actions based on keywords, species and habitats, and the country in question. For example, searching "*adaptation*" for the United Kingdom returns 15 actions which could be used to conserve biodiversity. Searching "*climate change*" as a keyword also for the UK returns 22 actions, with information on the effectiveness of these actions and links to multiple open access journal papers in that area. However, these actions are based around specific species and habitats which may not be useful to stakeholders if they are interested at a site or landscape-scale level. Recently, the British Ecological Society published a new open-access journal *Ecological Solutions and Evidence* to foster communication between practitioners, policy makers and academic researchers in the sharing of ideas and ecological system management (Cadotte, Jones and Newton, 2020). However, these papers are still only likely to be accessible to those with time and knowledge of their availability, even with the inclusion of shorter form papers designed to share practice in applied management.

Communication of environmental research to stakeholders is vital to ensure uptake and use of ideas and results in decision-making. These must be accessible through face-to-face meetings, stakeholder-led initiatives, interactive online programmes, or open-access easily understandable research. Projects developed with stakeholders are likely to be more successful if stakeholders are included in all aspects of a project (Samson *et al.*, 2017), and there may be scope to design, run and publish research in direct collaboration with stakeholders. The research within this thesis creates links between science and practice. Throughout my PhD research I worked collaboratively with a range of partners within the National Trust from the conception of the individual site-based projects throughout my research through iterative feedback loops. The recognised value in integrating stakeholders from the onset of a project as shown in previously mentioned research (Shaw *et al.*, 2009; Bennett, Kadfak and Dearden, 2016; Samson *et al.*, 2017) was the reasoning behind developing each project directly with the National Trust, so that the results were more likely to be integrated into current and future nature conservation and land management planning.

1.5 The case studies

This thesis presents three chapters exploring through spatial and temporal data the local effects of three different situations for which the increasing impacts of climate change are likely to be common issues for UK nature conservation bodies. Three case study sites (figure 1.1) chosen for their popularity with visitors, observed impacts of climate change and previous management activities are the focus of each chapter. These sites also represent values the National Trust aims to uphold across its entire site portfolio of, among others, nature conservation, heritage value and community. The impacts studied represent a variety of issues the National Trust faces when properties are affected by the impacts of climate change, and I provide information about how trends of these impacts may develop. Each site is at a different spatial scale to explore differences in trends and useability of UKCP18 climate. Abergwesyn Common is at the largest scale being an upland common approximately 20 km in length. The Ysbyty Ifan Estate is marginally smaller at 10 X 12 km with Chirk Castle at the finest spatial scale of just over 1 X 1 km. These case study sites are explored in more detail below, with a data chapter focusing on each site individually.

For more information about the differences between scale, which are continued throughout this thesis, local refers to the Met Office UKCP18 climate projections used in all analyses, while site scale refers to the scales at which each case study site is at. These site scales are similar, but differ slightly due to the physical size of the sites included in this thesis, and the scope of each chapters research as mentioned above.

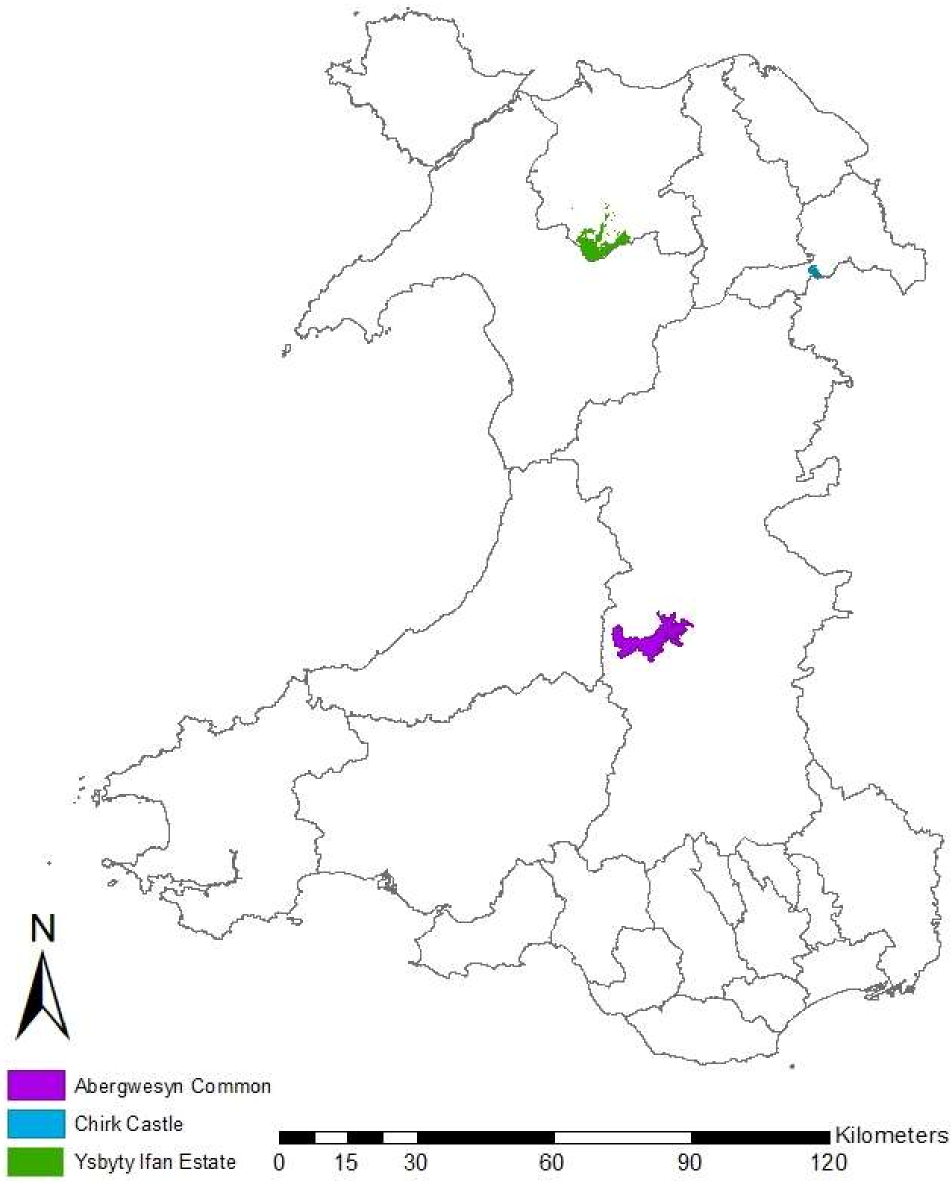


Figure 1.1: The location of the three case study sites in Wales, UK. Each study site is a property or land owned and/or managed by the National Trust.

1.6 Thesis aims and objectives

Accounting for adaptation to climate change in conservation planning at the site level was recommended in the recent CCRA3 technical report as being important to develop ongoing successful adaptive management (HM Government, 2022). Overall, this thesis has three main objectives;

1. To assess if local scale UKCP18 data together with existing models is useful in identifying and quantifying climate risks,
2. To assess how climate change is likely to affect ecosystems at different scales and for different impacts to explore usefulness of modelling outputs at different scales, and
3. To understand how to communicate these risks and provide more insight into bridging the gap between science and practice.

These objectives work towards an overall aim to evaluate the extent to which integrating high scale climate data into landscape management improves the information provided and enables climate change to be integrated into these management plans.

Here I aim to highlight the importance of process-based site-specific, but transferable modelling that is able to enhance adaptation management as an additional layer of information in conservation planning. Tailoring models to sites and impacts provides useful insights into local scale changes which could be tested at other sites and scales. The transferability and connection to Welsh conservation, in this case through the National Trust, is vital to ensure implementation of research which may add to the current wealth of information professionals use on sites to adapt to climate change. Local scale climate projections are assessed for useability in these models to test predictions at similar scales to conservation management needs and associated processes. The outcomes of this research provide more evidence on the impact of climate change at the site-level through three specific risks and how modelling projects can bridge the science – practice gap. Through three case studies, this thesis meets the overall aim and objectives through:

1. Quantifying the change in suitable climate and habitat space for distributions of five bird species found in the uplands of Wales and Great Britain and assess the predictive power of default and species-specific inputs, with a case study in mid-Wales at Abergwesyn Common (20 km length of site) (chapter 2).
2. Assessing the future impacts of fire risk and severity to an upland peatland in North Wales and investigate the applicability of a Canadian fire risk model in this context focusing on a case study at the Ysbyty Ifan Estate (10 X 12 km) (chapter 3).
3. Assessing the capability of tatter flag methods to quantify the current impacts of wind speed and direction to parkland trees and develop future predictions of the risks of exposure to these individual trees, focusing on a case study at Chirk Castle (1 X 1 km) (chapter 4).
4. Investigating the needs and requirements of National Trust staff in developing robust conservation planning essential to delivering resilient ecosystems and understand further the barriers and opportunities in the interface between science and practice (chapter 5).

Chapter 2: Data and data use in environmental modelling: what do we need and how do we use it?

2.1 Climate change data and accessibility

The basis of evidence and information needed to prioritise action for biodiversity should come from an understanding of current and past conditions of species and habitats, and take into account projected future change (Thomas *et al.*, 2011). Identification of trends through spatial modelling highlights costs and opportunities through the testing scenarios and tailoring inputs to modelling. Projections of future climates are at the heart of research understanding climate impacts to species and habitats. The Met Office has released four iterations of climate projections for the UK in 1998 (Hulme and Jenkins, 1998), 2002 (UKCP02) (Hulme *et al.*, 2002), 2009 (UKCP09) (Murphy *et al.*, 2009) and 2018 (UKCP18) (Lowe *et al.*, 2018) to provide a range of plausible scenarios based on individual data for different environmental variables. Overall trends for all iterations of climate projections predict in general, warmer, wetter winters and hotter, drier summers for the UK (Hulme and Jenkins, 1998; Hulme *et al.*, 2002; Murphy *et al.*, 2009; Lowe *et al.*, 2018). The scale of change has been updated over time with new information on global emissions and greater predictive power for models. In particular this relates to spatial scales available for modelling future climates and impacts. The first predictions in 1998 were available at one spatial scale which matched that of the HadCM2 emissions scenarios at approximately 295 km X 278 km (Hulme and Jenkins, 1998). Greater geographical resolution was requested for subsequent iterations of projections, with 2002 predictions available at a finer 50 km scale (Hulme *et al.*, 2002). At the time, users of these models were warned about "over-interpreting the significance of geographical differences on these small scales" (Hulme *et al.*, 2002) as these regional models were driven by a global climate model. Further iterations of UKCP models increased spatial scales of predictions further, with UKCP09 projections available at 25 km resolution, with Weather Generator predictions at 5 km (Jenkins *et al.*, 2009; Murphy *et al.*, 2009). This allowed greater exploration of projections and impacts at regional scales (Jenkins *et al.*, 2009), those which are more likely to match with species movements and conservation management decisions. The UKCP18 climate projections provide future trends of climate at the greatest range of spatial and temporal scales, from local 2.2 km, regional 12 km and 25 km, and larger resolution 60 km scale to investigate landscape-scale impacts (Lowe *et al.*, 2018). Daily projections have been included for the first time, and a wider range of emissions scenarios are available. This increase in resolution and scenarios allows exploration of change at the scale at which ecosystems are likely to change enabling management to respond in kind. While there are higher uncertainties surrounding high spatial scale climate projections, these data are especially useful for the examination of extreme risk and weather events which could have large impacts to the natural world. Climate trends, weather events and tipping points for individuals and communities of species can be predicted using these Met Office projections under a range of climate scenarios, and spatial and temporal scales. Research has explored the useability of these projections (Tang and Dessai, 2012), as there has often been a disconnect recognised between climate impact science and the writing and implementation of conservation decisions and policies. This research found that although the UKCP09 data was perceived to be robust and useful by adaptation stakeholders, actual use of projections was dependent on scientific competence which was often lacking (Tang and Dessai, 2012).

The UKCP18 data provides projections at higher spatial resolutions without further manipulation of the data sets being required when compared to UKCP09. One large difference between the 2009 and 2018 iterations of projections is the increase in temporal scale in raw projections. A number of papers explored the use of the UKCP09 Weather Generator which was able to calculate hourly predictions of weather variables for a location (Eames, Kershaw and Coley, 2011a; Kershaw, Eames and Coley, 2011; Watkins, Levermore and Parkinson, 2011; Dunn *et al.*, 2012; Jack and Kelly, 2012; Lankester and Brimblecombe, 2012; Mylona, 2012). This Weather Generator was used, for example, to create wind speed and direction variables at an hourly temporal resolution (Eames, Kershaw and Coley, 2011b), which were not previously available. However, the creation of such files was not without requiring computational skill to ensure that these Weather Generator outputs were useful for the task at hand. Therefore, the Weather Generator highlighted the importance of using projected weather files to identify smaller temporal scale changes, but that there was a high level of uncertainty (Mylona, 2012) and computational requirements in the creation and comparison of these files. Flexibility of climate projections in developing weather files for a specific area, for example, can enhance useability of the data for those with available technology and skills, but may exclude some users from fully accessing the data. UKCP18 went a step further by providing a larger range of projections of climate variables at a variety of temporal and spatial scales (Lowe *et al.*, 2018). This data is relatively new with the literature exploring a variety of uses for the models from using the Climate Projections User Interface (Reeves *et al.*, 2022) to download ready-made products of future climate, to the calculation of decadal averages from raw data to aid in analysis (Dallison, Patil and Williams, 2021). However, these are at broader spatial scales of 12 km (Dallison, Patil and Williams, 2021) and 25 km (Reeves *et al.*, 2022), which provide important regional predictions, but give less information at the local scale. The UKCP18 projections provide predictions of future climate at a 2.2 km spatial scale (Lowe *et al.*, 2018) which can be especially useful for highly spatially variable metrics such as wind and precipitation. Assessing the accuracy of these predictions is ongoing as high spatial and temporal scales can be highly variable. However, these local scale variables are being explored and they are able to predict observed climate patterns to a high degree of accuracy (Chen, Paschalis and Onof, 2020). In this thesis, I explore the potential use of 2.2 km UKCP18 climate projections from the Convection Permitting Model (CPM) (Kendon *et al.*, 2019) to explore local-scale impacts. The CPM allows for high spatial and temporal predictions of future climate if a high emissions scenario (RCP 8.5) is experienced (Kendon *et al.*, 2019). The Representative Concentration Pathway 8.5 is the worst case scenario of change utilised by the IPCC and relates to a predicted global temperature increase of approximately 4.5°C (van Vuuren *et al.*, 2011). While this is unlikely to occur if emissions targets are met, it represents a worst case scenario, which can be useful in planning responses. Additionally, this greater spatial and temporal scale allows for change to be modelled at a scale that matches local processes and impacts, such as those for an individual species (Boulangeat, Gravel and Thuiller, 2012) or site (Coll *et al.*, 2010).

2.2 What are we talking about when we talk about model results?

When thinking about how well a model explains a hypothesis or answers a question, there are a number of things to consider. These include, the accuracy and reliability of input data, model methods and analysis, how the model is validated and compared to real-time data, and the precision of the results which in turn could dictate how useful they are. However, detail on what is meant by terms such as 'accurate' can be lacking which in turn, can be misleading in scientific text. Below, I outline the definitions of commonly used language when explaining scientific models. For all mentions of these terms in the rest of the thesis, refer back to this section for definitions.

Accuracy is often used to describe for example, how close predicted results match known values or trends. The higher the accuracy of a model or result, the higher the likelihood of these results being useful in contributing to answering questions about a system. If a result is not accurate, decisions could be made that negatively impact the study system or research may not provide the answers required. Understanding and clearly reporting the accuracy of a model or result is vital in evidence-based decision making to ensure that subsequent actions are made from the best information possible.

Reliability assesses if the findings produced from a study are good and useful. It refers to if a result can be trusted, and if decisions can be made based on the results. A more reliable result may lead in larger changes being made based on what the results show. For example, this could refer to greater financial backing or time spent on an action made in response to a study producing reliable results. Reliability can be tested through comparisons of predicted known distributions of a species or event to actual data of these predicted. The closer predictions are to known values, the more reliable we can ascertain the model to be.

2.3 Shared methods and data within this thesis

The main research and presentation of results in this thesis is separated into four data chapters, chapters 3, 4, 5 and 6. While the majority of methods are unique to the specific chapter, there are some shared methods across the thesis. In this next section, I will go into detail about these shared methods. These methods will be mentioned in each subsequent data chapter, but this section will provide the greatest detail.

2.3.1 Emissions scenario usage

The Intergovernmental Panel on Climate Change (IPCC) set out four climate scenarios of future average global temperature increases based on future levels of greenhouse gas (GHG) emissions. Within this thesis, one emissions scenario is used throughout, that at the Representative Concentration Pathway (RCP) 8.5. This pathway represents a 'worst case scenario' in which global emissions continue to increase from the present day up to 2100, unchecked by policy, government, or individual action (IPCC, 2014). Under this pathway, average global temperatures are predicted to increase by over 4.5^{o}C, which would have catastrophic impacts to the natural and anthropogenic worlds. It is thought that this future would be unlikely to occur, however, understanding a worst case scenario ensures that

Climate projections are available at a range of 'global futures' i.e. what the world could feel like, in terms of the climate variables explored, depending on the rate of GHG emissions and, in some cases, the level of adaptation and mitigation to climate change in place. These projections are detailed below to give an idea of the range of futures explored in climate change impact research, and the range of futures scientists conclude have the potential to occur. A representation concentration pathway is that that represents a possible range of radiative forcing values in the year 2100. Therefore, a RCP of 8.5 indicates a radiative forcing of 8.5 W per m^2.

2.3.2 UKCP18 climate change projections

This thesis explores the use of local scale UKCP18 climate projections, developed by the Met Office, to analyse the impacts of climate change to three National Trust properties and sites in Wales. But what does all this mean in terms of the data used to assess these impacts?

I used one data set from the UKCP18 climate projections, raw climate data from the Convection Permitting Models at the local spatial scale of 2.2km (see table 2.1 for details about other climate projection data).

Table 2.1: Details about the Met Office UKCP18 climate projection datasets (Lowe *et al.*, 2018; Kendon *et al.*, 2019)

Type	Spatial Scale	Temporal Scale	Time Frame	Emissions Scenarios	Description
Probabilistic projections	25km	Monthly Seasonal Annual	1961 – 2100	RCP2.6 RCP4.6 RCP6 RCP8.5 SRES A1B	- Probabilistic changes in future climate - Based on uncertainties in emission scenarios, key processes in climate models - Characterises future extremes in risk assessment
Global model projections	60km	Daily Monthly Seasonal Annual	1900 – 2100	RCP2.6 RCP8.5 2^{o}C world 4^{o}C world	- 28 projections - How climate may change in 21st century - Long time series - Has raw data
Regional model projections	12km	Daily Monthly Seasonal Annual	1981 - 2100	RCP8.5	- 12 projections - Downscaled from global projections - Has raw data - Extremes in climate are improved
Convection permitting model	2.2km	Sub-daily (some variables) Daily Monthly Seasonal Annual 20/30-year means	1981 – 2000 2021 – 2040 2061 – 2080	RCP8.5	- Predictions can be made at local spatial scales - 12 projections - The most spatially detailed picture of future climate - Provides information about localised rainfall and extreme events

The Convection Permitting Model (CPM) provides predictions of local effects of climate, and is downscaled from the regional climate models. These models provide credible climate information at sub-daily timescales, but cannot be substituted for real-time weather forecasts, they are still climate predictions and exist to provide trends at high resolutions and to explore extreme events.

When evaluating if climate projections have accurately represented know time periods in terms of climate trends, both Met Office (Lowe *et al.*, 2018) and independent (Tucker *et al.*, 2022) reports indicate that current trends are simulated in climate projections, giving users high confidence in these predictions of future change. While this independent report (Tucker *et al.*, 2022) does focus on the regional 12km projections, the local 2.2km projections are downscaled from those analysed in the study, and therefore confidence in the projections can be gathered.

2.3.4 Ensemble members of climate change projection data

The Convection Permitting Model (CPM) consists of 12 members, all assuming no reduction of greenhouse gas emissions to 2100, but each member differing due to natural climate variability and uncertainties in global model physics (Kendon *et al.*, 2019). However, uncertainty in the CPM model members has not been sampled by the Met Office, and therefore uncertainties in the climate predictions are underestimated. Predictions of climate by the CPM do not differ greatly from the rest of the UKCP18 ensemble, and headline impacts remain that future conditions are likely to be warmer and wetter in the winter, and hotter and drier in the summer (Lowe *et al.*, 2018). Rainfall predictions are those most different to the regional climate model (RCM) ensembles, with rain less often in the future, but when rainfall is predicted, it is heavier in the CPM compared to the RCM (Kendon *et al.*, 2019).

This thesis uses the first model member (01) and unfortunately, does not include an ensemble mean approach to the climate variables. As the raw daily data was used in analysis, data processing was extensive, and there was not enough time during the studies to pull out the data for all members and compute an average, or run the models for multiple members. This was especially challenging due to my own coding and data processing skills as the researcher as throughout the PhD research study period, I was learning to code in R, process huge data sets and run these models as I was going along. I recognise the limitations only using one model member adds to my research, and the results presented in this thesis. However, this thesis provides a step forward in the use of local-scale climate impact modelling for understanding further how climate change is likely to affect nature at the site scale, and therefore can be seen as a strong starting point for further research. Not only is the use of higher spatial resolution climate data a plus to the research, but the development of individual research skills, especially through coding, and experience and comfort with novel, large data sets only a benefit to the research sphere.

Met Office guidance suggests that the 2.2km spatial scale predictions are to be used where *improved 'representation of extremes or spatial detail is more important than exploring a wider range of future outcomes'* (Kendon *et al.*, 2019). As this thesis is focused on improving the information provided in making decisions about future conservation management at the local/site scale, exploring these higher resolution data is paramount, and therefore even assessing one model member, provides more information, and furthers science, than modelling only at lower spatial resolutions, even if this data may be easier and faster (computationally) to process.

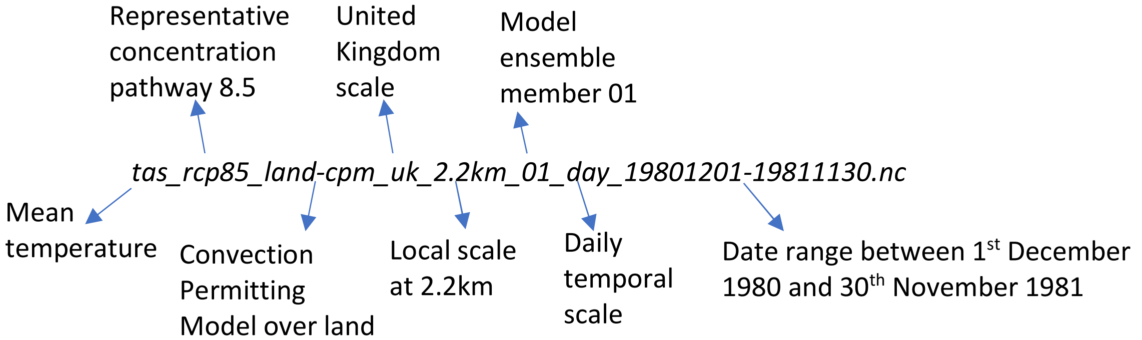
The first model member (01) of the CPM used in this thesis is without perturbed physics, and can be thought of as the default model in the projection members. Perturbation of model variables means that values of some variables within the model outputs are tested and changed for each member. This provides analysis of uncertainty and recognises that there are a range of plausible values for each model parameter which may control the processes informing climate change (Sexton *et al.*, 2017). Future research could utilise multiple model members in analysis, either as a full ensemble of all members, or one that included lower, median and upper extremes of uncertainty within the overall model to reduce computational requirements.

I used this first model member in this research with the recognition that this only provides information about one potential future of change and that there are a range of futures simulated within the UKCP18 projections. Therefore, this research provides a single picture of potential impact, due to computational and researcher limitations, and that updating these results in the future with an ensemble projection would provide greater detail of plausible change.

2.3.5 Shared data processing

All climate data was processed once, and used in the same format for each thesis chapter, with the only alterations being in geographical space, and with some unit changes (see chapter 4). In this section, I describe the common methods used in all chapters in regards to the processing of the raw climate data projections. This data processing was carried out using R 4.0.2 (R Core Team, 2020), the sf (v0.9-8; Pebesma, 2018), ncdf4 (v1.17; Pierce, 2019), raster (v3.4-10; Hijmans, 2021), rgdal (v1.5-23; Bivand *et al.*, 2021)and PCICt (v0.5-4.1; Bronaugh and Drepper, 2018) packages. Data at two spatial scales was extracted from the Met Office UKCP18 directory within the Atmospheric Data repository in the Centre for Environmental Data Analysis Archive (data.ceda.ac.uk/badc/ukcp18) from Model 01 (as described above in 2.3.4). These spatial scales were the 12km regional data and the 2.2km local scale data, both at the daily time steps to accurately compare the same temporal time scales.

All data were downloaded as netCDF files which contained a yearly time step of the climate variable in question. Below is an explanation of the data within an example file name,



Baseline data for the study was the 20-year daily average between 1980 and 2000 (1990s), with two 20-year daily average future time frames between 2020 and 2040 (2030s), and 2060 and 2080 (2070s). Hereafter and throughout the rest of the thesis, the time periods will be referred to as the 1990s, 2030s and 2070s. Full reproducible code is available in on request with further detail on extracting and averaging data at both spatial scales in published blogs at *luciazwatts.wordpress.com* which are included in Appendix 1.

Data processing for each spatial scale were completed in similar ways, with some differences which I will detail below. As mentioned previously, netCDF files for each year of the 1990s, 2030s and 2070s were downloaded from the online repository. The data was in a 360 day format, which presents variables as 360 day years and each month as 30 days. Therefore, each netCDF file contained 360 layers of a variable as individual days, which were extracted as separate files to facilitate the creation of multi-decadal averages. Data at both spatial scales were extracted from the netCDF files using R 4.0.2 (R Core Team, 2020) with individual days of data saved as .TIF files. All data was required to be at the British National Grid (BNG) coordinate system for continuity between climate, species, land cover and any other data included in further analysis. However, climate projections at the 2.2km spatial scale were presented in the rotated grid latitude/longitude (37.5, 177.5) (Fung, 2018) and therefore required re-gridding to BNG. Detail, with code and instructions for use in open-source GIS, on this re-gridding can be found in Appendix 1. Climate projections at the 12km spatial scale did not require re-gridding as they were already available in the BNG coordinate system, with each individual day extracted from the relevant netCDF files and stored as .TIFs. Once individual days of data for both 2.2km and 12km were written, each set of 20-year averages could be computed from these individual days (see Appendix 1 for further detail). There could be potential for faster computation using different temporal scale data, but this was not used in this study. Throughout the three data chapters, climate variables used were: average temperature, average precipitation, maximum temperature, average wind speed, maximum wind gust, eastwards winds, northwards winds and relative humidity. Only one chapter (chapter 3) utilised the lower resolution 12km data, with all chapters using the local 2.2km data.

2.4 The Models

Two established spatial and temporal models which can produce information about the impacts of climate change have been used within this thesis. Subsequent chapters go into great detail about the methods used and how these can inform conservation management in regards to adaptation to climate change. These sections investigate the inputs into the models, the parameters requiring exploration, the formats available and how to analyse outputs. The two models included are Maxent and the Canadian Forest Fire Danger Rating System (CFFDRS).

2.4.1 Maxent

Maxent is a hugely utilised species distribution model (some examples include: Elith *et al.*, 2006; Phillips, Anderson and Schapire, 2006; Barbet-Massin *et al.*, 2012; Farashi and Alizadeh-Noughani, 2018) and works off the theory of maximum entropy. This calculates the distribution of maximum entropy, the closest to uniform distribution, of the study object (e.g. a bird species) when subject to constraints of relevant environmental variables (Elith *et al.*, 2006). The closer to maximum entropy, the better it can be assumed that distributions are being described well by the model in relation to observed data.

In essence, using information about the climate and landscape (if added) alongside data showing where a species is present Maxent identifies the conditions under which a species is likely to thrive, correlating presence in a certain condition with the species' ability to survive. Then, using novel climates or categorical landscape variables, the model is able to predict where in this novel space the same species is likely to be able to inhabit. Maxent provides an idea about a species distribution at a different time or space when compared to known data, and therefore can be used to predict where a species may inhabit under changing climates or land cover. Research has shown that Maxent performs better with continuous data such as climate, compared to categorical data like land cover and altitude (Hof, Jansson and Nilsson, 2012), especially as climate variables such as temperature can be used as a proxy for variables like altitude.

Maxent is available in two different formats. The software is available to download for free at https://biodiversityinformatics.amnh.org/open_source/maxent/, where there are also a number of tutorials and information about the latest updates. Additionally, Maxent can be run in R using the dismo package (Hijmans *et al.*, 2021), where there are also a wide range of help information and tutorials to aid in building the model. Outputs for each model run are presented as .html documents with detailed information as to the importance of variables within the model, how each feature affects the model, maps of predicted suitability and a record of the variables that wrote that specific model. This aids in keeping a record of each model run, and they are easy to understand documents. In this thesis, I used Maxent in R to code a more complex model and to keep track of the model runs I produced.

One benefit of using Maxent is that it is highly customisable to a project, spatial scale or output need (Merow, Smith and Silander, 2013) as there are many input parameters that can be changed from variable types to model fitting values. Below I introduce the parameters that I have used in my research, and the values at which these can be set. Chapter 3 presents the project in which I use Maxent to look at the impact of climate change to five upland bird species in Mid-Wales, with many inputs altered from the default values. The section in this chapter provides an introduction to the inputs that can be changed in Maxent, and provides background to the changes I make throughout my research.

2.4.1.1 Input parameters and model fitting

During my research project, I assessed the impact changing three input parameters had on model performance and outputs. These were: the feature classes used in each run, the number of background points assigned, and, the regularisation multiplier value.

Maxent uses features to produce the model based on the environmental variables used as prediction layers and the functions of these. There are five different feature classes: product, hinge, threshold, linear and quadratic. The model uses all five classes in a default run of Maxent. Below are brief descriptions of what each feature does (Phillips, Anderson and Schapire, 2006; Phillips and Dudík, 2008; Anderson and Gonzalez, 2011).

Linear: this feature uses the variable itself and models the mean value of the variable for locations occupied by the species, to identify the optimum conditions for the study species.

Quadratic: this is the square of the continuous variable used in the modelling process.

Product: this looks at the interactions between variables, and analyses the covariance of two continuous variables.

Threshold: also investigating continuous variables, this feature adds in a threshold to analysis to say for example, that a species is likely to be present when a value is over a certain number.

Hinge: these features model more complex relationships in the training data to provide an estimate of probability of presence.

Changing which features are used in a model run alters outputs, and different features work best with different types and amount of input variables, such as the number of species presence points, or climatic variables included.

In order to understand where a species is, and might be, it also needs to be known where it is not. While Maxent is a presence-only model (Barbet-Massin *et al.*, 2012) the model uses background points as pseudo-absences used to separate out areas in observed and novel space where the study species is not present. This does give the researcher an idea of the sorts of conditions in which a species is unlikely to thrive and gives the model important information about what to assess as suitable space for predictions. The default number of background points in a Maxent model is 10,000, but it has been suggested that this value may not be high enough to correctly represent areas potentially containing conditions that are unlikely to be suitable for a species (Wunderlich *et al.*, 2019).

The regularisation multiplier (RM) parameter affects how focused or closely-fitted the output distribution of the Maxent model is (Phillips, 2017). This is set at a default of 1.0. A RM value smaller than 1.0 will result in a more localised output distribution, closer to the fit of the presence data, but can result in overfitting. On the contrary, a RM value greater than 1.0 results in a more spread out and less localised prediction (Phillips, 2017). As the potential for overfitting increases the more complex the model is, including a higher RM value may reduce the chances of model overfitting, while still providing highly detailed outputs from an intricate model.

2.4.2 Canadian Forest Fire Danger Rating System

The Canadian Forest Fire Danger Rating System (CFFDRS) is a framework that was developed on the back of nearly 100 years of research into wildland fire ignition and behaviour in North America to inform wildfire operations planning of the current and upcoming risk of fires (Wang *et al.*, 2017). This model uses a variety of weather and fuel variables to calculate the inherent risk of fires in terms of strength, likelihood of ignition, spread rate, fuel availability, fire direction and other behaviour indices (Van Wagner, 1987). Daily weather data is required to set up the model, which then calculates the fire weather indices for upcoming hours and days. This has been used to assess the risk of fire across Canada, with some tailoring of the model globally (Dimitrakopoulos, Bemmerzouk and Mitsopoulos, 2011).

This risk assessment system is available in a fairly straightforward R package called cffdrs (Wang *et al.*, 2017), which is accompanied by a number of help and tutorial documents. The base calculations for each inputs are available for editing, but this could greatly increase the complexity of the code, and may end up not representing the system accurately. There is a large amount of information into the calculation of these inputs, called codes, in Van Wagner, (1987), which is easily available online.

While there is potential for analysis of fire risk using this model globally, there are some caveats that must be considered. For one, the model is tailored to upland peatland forests with a high amount of fuel litter. The type of forest can be altered within the model settings to include different types of species, dead or growing wood, or open brush and water. This provides a fair range of conditions experienced in these ecosystems, but may require some further investigation of the study site.

2.5 Conclusions

This section, and the references included, provide some background to the climate data used in the thesis and further information about shared methods in all chapters, with an introduction to the two main models used in analysis. There is a vast amount of information in tutorials and online forums such as stackoverflow.com when learning, analysing and running new models, techniques and when processing data. It cannot be underestimated how useful these online resources, and communication with experts have been to myself as a researcher throughout my PhD studentship. Science is an ongoing learning experience, which is exciting and, occasionally frustrating! Being able to learn from others' mistakes and through (what often feels like) years of testing code and models is such an important experience, and only increases the breadth of knowledge added to the sphere of climate impact modelling and analysis.

Chapter 3: The impact of climate and habitat change to five bird species found in the uplands of Great Britain: Are species-specific model inputs more accurate than default settings?

Abstract

Bird species in the uplands of the UK are vulnerable to climate change, with habitat specialist species most at risk. Projections of climate change are widely used to assess responses of biodiversity to future impacts, at a variety of spatial and temporal scales. The use of local scale climate data and the testing of model settings to predict future species distributions has not been widely explored.

Current and future distributions of five bird species found in the uplands of mainland Britain were modelled using the Maxent model and tailoring important inputs with the ENMEval package in R. These bird species were; golden plover (*Pluvailis apricaria*), meadow pipit (*Anthus pratensis*), skylark (*Alauda arvensis*), wheatear (*Oenanthe oenanthe*) and whinchat (*Saxicola rubetra*). Future climate projections were from the UKCP18 climate change projections at the local 2.2 km and regional 12 km daily scale for comparison in model performance at different spatial scales. Multiple evaluation metrics assessed model performance including, AUC, null models, TSS and SEDI. Habitat layers at the baseline and projected to 2050 were used to investigate the impact of land cover change. Alongside predictions of all species at the Britain scale, a mid-Wales case study at Abergwesyn Common exploring the amount of suitable climate space for the habitat specialist golden plover is presented. This site is an upland peatland and an important site for the golden plover, with monitoring by the National Trust registering declines in species presence and abundance.

Our results show that species-specific local scale species distribution models outperform those at the larger spatial scale. As expected, tailoring inputs to the Maxent model also produces more accurate results compared to default inputs when assessing a variety of model evaluation metrics. There are greater contractions predicted to potential range sizes in the 2030s compared to predictions for the 2070s. Only the specialist golden plover experienced contractions of range size under climate change alone between the 1990s to 2030s. However, all species in this analysis increased their potential distributions by the 2070s when only considering impacts from changes in temperature and precipitation. Land cover is predicted to be more limiting than climate for all species, with specialist species impacted the most. Centroids of species distributions are likely to shift northwards, but with little contraction of southern ranges.

Previous studies that have suggested that tailoring model inputs, such as background points, could lead to more accurate predictions have been furthered. For background predictions, this research suggests that the default 10,000 points is unsuitable for many species, and that a greater number of pseudoabsences are required to increase predictive accuracy of models. Multiple model evaluation metrics need to be utilised to assess both model performance compared to other inputs and goodness-of-fit when examining results.

Local-scale climate data provides detailed information at the site level, and when used alongside other site data can be a valuable addition when undertaking nature conservation. Although it may appear that climate change could be beneficial to the study species, without habitats to support them, the amount of suitable climate and habitat space greatly diminishes. It can be concluded that climate predictions at the 2.2 km scale and tailored model inputs improve the quality of species distribution predictions.

2.1 Introduction

Anthropogenic climate change (Haustein *et al.*, 2019), will be the greatest threat to, and primary driver of, increasing vulnerability and loss to biodiversity by 2100 (Klausmeyer *et al.*, 2011; Pautasso, 2012; Brandt *et al.*, 2017), and will cause disruptions to ecosystems in ways previously unseen (Mooney *et al.*, 2009). Climate change is already affecting the natural world around us as the third highest global impact to biodiversity (Diaz *et al.*, 2019). Most recent climate science warns of unprecedented change within the next 15 years, and a requirement to keep temperature increases below a global average of 2^{o}C if catastrophic thresholds are to be avoided (Masson-Delmotte *et al.*, 2018a).

Severe weather events in the UK over the past 20 years have already been directly attributed to global GHG emissions (Pall *et al.*, 2011; Met Office, 2014; Arnell *et al.*, 2021; Arnell, Freeman and Gazzard, 2021; Clarke, Otto and Jones, 2021), with both humans and the natural world affected. In general, it is projected that UK climate will be warmer and wetter in the winter, with hotter, drier summers (Lowe *et al.*, 2018). However, worst case emissions scenarios predict an increase in average UK temperatures of over 4^{o}C compared to pre-industrial levels (Lowe *et al.*, 2018), far surpassing suggested ‘safe’ levels of warming. Equally, precipitation is expected to change, with on average over 25 % more rain in winter and about 35 % less in summer. This will have profound effects on plant growth, food availability and flooding across the UK. It is these extremes of change that will potentially be the most damaging as species and landscapes are attempting to cope with such a large alteration of expected conditions. So far, mean annual temperatures in Wales have increased by 1.3^{o}C as of 2017 compared to the 1961 to 1998 average, with precipitation also increasing by on average 16 mm (Lowe *et al.*, 2018).

Birds are good indicators of environmental change (Terrigeol *et al.*, 2022) with impacts of climate to birds investigated globally (Huntley *et al.*, 2008; Eyres, Böhning-Gaese and Fritz, 2017; Salas *et al.*, 2017; Liang *et al.*, 2021; Michel *et al.*, 2021; Sierra-Morales *et al.*, 2021). In extreme conditions in central America, species distributions are predicted to decrease by around half under climate scenarios predicting a 3^{o}C increase in average global temperatures (Sierra-Morales *et al.*, 2021). When investigating impacts in Asia, individual species’ distributions shifted northeast and lost some suitable climate space (Liang *et al.*, 2021). Insectivorous bird species in North America are experiencing negative climate impacts, particularly to migratory species (Michel *et al.*, 2021). These impacts are also being recorded in Europe, with increases in hot-dwelling species (Gaüzère *et al.*, 2020), impacts to migrations, egg laying and hatching, spring arrivals and northward and upward range expansion (Pautasso, 2012). Even with some potential range expansions, average numbers of breeding species have been predicted to decrease (Huntley *et al.*, 2008), with over 50 % of internationally important European bird populations are predicted to decline by at least 25 % under high emissions scenarios (Johnston *et al.*, 2013).

Under low emissions scenarios that predict a 2°C global temperature increase by the end of the century (Rogelj, Meinshausen and Knutti, 2012), it has been estimated that 21 % of English species would be at high risk of range loss from changing climates (Pearce-Higgins *et al.*, 2017). Already it has been found that 58 % of all species have decline in the past 50 years in abundance and distribution, with 600 species at risk of extinction in the UK (Hayhow *et al.*, 2019) due to a range of factors from land use change to climate change. Strong decreases to distribution and abundance of species were found to be greater in the short term than those in the long term, but overall impacts are likely to be worse in the long term (Hayhow *et al.*, 2019). Upland species were more at risk than those in other habitats due to altitudinal contractions in range (Pearce-Higgins *et al.*, 2017), with analysis conducted for Great Britain but species data from England. Bird species in the UK are already affected by climate change (Pautasso, 2012; Johnston *et al.*, 2013; Pearce-Higgins *et al.*, 2015; Stralberg *et al.*, 2015; Salas *et al.*, 2017) with cold-associated and habitats specialist species predicted to be the most vulnerable (Pearce-Higgins *et al.*, 2015). However, relatively few predictive models have been applied to this community of rare, narrowly distributed and specialised highly vulnerable bird species, with modelling identified as a priority (Farashi and Alizadeh-Noughani, 2018). Any changes to suitable climate space in summer breeding grounds or wintering sites could change migratory patterns or further affect species' population sizes. Many birds of upland environments, including the golden plover, are habitat specialists, and there is little knowledge as to their vulnerability and predicted habitable range under future climatic change. In England, the golden plover has been recognised as a declining species, with the moorlands of Great Britain of international importance to population survival (Pearce-Higgins and Yalden, 2004). Threats from habitat loss and declining prey abundance are thought to have impacted species numbers, which is likely to have been exacerbated by climate change (Pearce-Higgins and Yalden, 2004). However, some species will benefit from climate change with 44 % of included species predicted to increase their climatic suitability by 2080 (Massimino *et al.*, 2017). Another study assessed that 42 % of included species may expand range extents under future change (Pearce-Higgins *et al.*, 2017) in Great Britain. Climate change could provide opportunities for bird species to increase range and distribution if larger areas of the UK with suitable habitats fall within a species' climate envelope. This may result in improved population abundance and biodiversity of an area due to species movements, with the right management.

Therefore, to understand how best to manage the environment in the future, we must understand how climate change will affect ecosystems at larger scales and at specific sites (Pearce-Higgins *et al.*, 2017). When planning conservation activities, it is valuable to know how any management applied will affect the area and if they are the best actions to take (Han *et al.*, 2018; Bowgen *et al.*, 2022). Often, conservation is limited by time, money and resources so management needs to be efficient and effective (Guisan *et al.*, 2013; Di Febbraro *et al.*, 2018). By planning management based on projected evidence conservation outcomes can be improved (Guisan *et al.*, 2013), and may have a better chance of supporting systems resilient to change and adaptable to the future. For example, creating new habitats adjacent to those already occupied has been shown to increase species' range expansion and occupancy more than conservation actions simply improving existing habitats (Synes *et al.*, 2020). To protect specific species and habitats, and provide accurate predictions of future change, these estimates of change must be tailored for sites and species to implement meaningful adaptive conservation.

Habitat change impacts nature alongside climate change, with intensive management of agricultural land having the largest negative effect on wildlife (Hayhow *et al.*, 2016, 2019). Bird species are influenced by land cover and habitat extent (Pautasso, 2012; Goodenough and Hart, 2013) alongside climate change. Landscape features are an important factor when considering where species will be most vulnerable (Nadeau and Fuller, 2016), as climate may not be the most limiting factor. If current protected areas become outdated through shifts in species distributions, then it becomes even more important to manage at the landscape-scale (Pautasso, 2012). This impacts not only protected areas, but all areas where land is managed even partly for conservation impact or species preservation. It would not be possible to restore habitat in an area that is not currently climatically suitable, but it may be possible to prioritise currently unprotected habitat that is likely to be within climate envelopes for key species in the future. Climate envelopes for some bird species are predicted to potentially increase in the future (Pearce-Higgins *et al.*, 2017), especially in grassland habitats (Vermaat *et al.*, 2017), so conserving these habitats now could result in refuges for wildlife and connect existing areas of suitable habitats (Dormann *et al.*, 2012; Han *et al.*, 2018; McCarthy *et al.*, 2018). Linking and restoring natural areas has already shown successes in both biodiversity improvements and climate resilience (Morecroft *et al.*, 2019). A more diverse landscape is more climate resilient (Pecl *et al.*, 2017; Morecroft *et al.*, 2019; Stafford *et al.*, 2021) and able to support a wider range of species (Smith *et al.*, 2022) and store carbon (Renou-Wilson *et al.*, 2019), thus reducing the impacts on the planet. It is hoped that this research can not only help land managers and conservation teams prioritise where to target conservation activities but contribute to mitigating the effects of and adapting to climate change.

Species distribution models have been widely used to predict the suitable space in both climate and habitats, that species are likely to be able to inhabit (Walker and Cocks, 1991; Guisan and Zimmermann, 2000; Kubisch *et al.*, 2003; Pearson and Dawson, 2003; Elith *et al.*, 2006; Elith and Leathwick, 2009; Gallego-Sala *et al.*, 2010; Hof, Jansson and Nilsson, 2012). These models have a wide variety of uses. They are useful to drive conservation practice at specific sites (Pearson *et al.*, 2007; Guisan *et al.*, 2013), to hypothesis testing of novel methods (Dormann *et al.*, 2012) and even using virtual species (Liu *et al.*, 2013; Qiao *et al.*, 2019; Synes *et al.*, 2020) to evaluate model methods. Models including Maxent, boosted regression trees (BRT) and random forests (RF) are often cited as the highest performing models in a number of reviews (Elith *et al.*, 2006; Bucklin *et al.*, 2015; Salas *et al.*, 2017), with Maxent consistently outperforming other models based of predictive accuracy (Elith *et al.*, 2006; Rebelo and Jones, 2010; Aguirre-Gutiérrez *et al.*, 2013; Merow, Smith and Silander, 2013; Tessarolo *et al.*, 2014; Farashi and Alizadeh-Noughani, 2018; Feldmeier *et al.*, 2018). Maxent was chosen to calculate outputs for this study due to its performance and functionality at multiple temporal and spatial scales (Phillips, Anderson and Schapire, 2006). Many studies using Maxent employ all default input values (Giovanelli *et al.*, 2010; Kearney, Wintle and Porter, 2010; Fourcade *et al.*, 2014; Paquit and Rama, 2018; Liang *et al.*, 2021), with some changing the default background point, features and regularisation multiplier values (Pearson *et al.*, 2007; Warren and Seifert, 2011). It has been suggested that the default inputs to Maxent do not produce the best results (Warren and Seifert, 2011; Merow, Smith and Silander, 2013; Feldmeier *et al.*, 2016) and that only a handful of studies analysed had evaluated multiple input values to their models (Morales, Fernández and Baca-González, 2017). The R package ENMEval (Muscarella *et al.*, 2014; Kass *et al.*, 2021) provides testing for optimum input values for Maxent and other algorithms. Studies (e.g. Bao, Li and Zheng, 2022) have begun to implement this to choose input values that are more likely to produce robust results, but this is not yet the norm and has not been explored to test input values for investigating species distributions of UK birds.

Many species distribution studies have been conducted at low spatial and climatic resolutions, often at the continent (Hof, Jansson and Nilsson, 2012; Johnston *et al.*, 2013) or country (Eglington and Pearce-Higgins, 2012; Pearce-Higgins *et al.*, 2017) scale. Models are at a variety of spatial scales from 50 X 50 km (Huntley *et al.*, 2008), 40 X 40 km (Heikkinen *et al.*, 2007), 25 km grid (Pearce-Higgins *et al.*, 2017) down to 10 X 10 km (Heikkinen *et al.*, 2007). However, studies investigating the local 2.2 km grids of predicted climates have not yet been explored. Finer scale studies are often developed from the collection and modelling of primary data (Pearce-Higgins, 2011), which are highly time and data intensive. Often, climate data is downscaled from global projections to pull out local scale data (Baker *et al.*, 2017). The most recent climate data for the United Kingdom are the Met Office UKCP18 projections released in late 2018 (Lowe *et al.*, 2018). These provide information for a wide range of future conditions under climatic change until 2080. Projections are at a variety of spatial scales from 80 km to 2.2 km, downscaled from HADGEM global models. Predictions of species distributions at the local daily scale, then averaged into larger (e.g. decadal) time frames, have not been widely evaluated, with some doubts as to the accuracy of these predictions due to high levels of uncertainty (Heikkinen *et al.*, 2006; Graham *et al.*, 2008; Oppel *et al.*, 2012; Gottwald *et al.*, 2017). There are some uncertainties as to how well these local scale climate projections can predict future suitable climate space, and whether uncertainties are too high. Daily UKCP18 climate projections at the local 2.2 km scale at the Representative Concentration Pathway (RCP) 8.5 which predicts an average global temperature increase of over 4^{o}C by 2100. These have the potential to produce site level information about the impacts of climate change that could be instrumental in influencing nature conservation actions for adaptation.

Research aims

In this study the value of using local climate data to predict future species distributions to aid in conservation planning for specific species is explored. With reliable predictions at a high spatial resolution, conservation actions tailored to specific areas and species could be much improved. Additionally, the impact to model performance is investigated through the changing of default inputs in Maxent, namely background points, feature classes and the regularisation multiplier. Models are run at the Great Britain scale, with a case study in mid-Wales exploring how site-level predictions of change impact an iconic endangered bird species. Overall, I hypothesis that high spatial resolution species-specific models with tailored inputs will predict more realistic and useful projections of suitable climate space. Additionally, under high emissions scenario climate projections, suitable climate space for five bird species found in the uplands of Great Britain will experience range contractions due to climate change and these will also be negatively affected by habitat and land cover change.

3.2 Methods

3.2.1 Study site

Abergwesyn Common (52.2°N, 3.7°W) is an upland common in Mid-Wales, UK (figure 3.1). It is owned and managed by the National Trust, a UK conservation non-governmental organisation (NGO) alongside local graziers who stock the common with sheep and cattle. Part of the Common is within the Elenydd Site of Special Scientific Interest (SSSI) with other areas designated as a Special Protection Area (SPA) due to containing a core population and breeding sites for golden plovers.

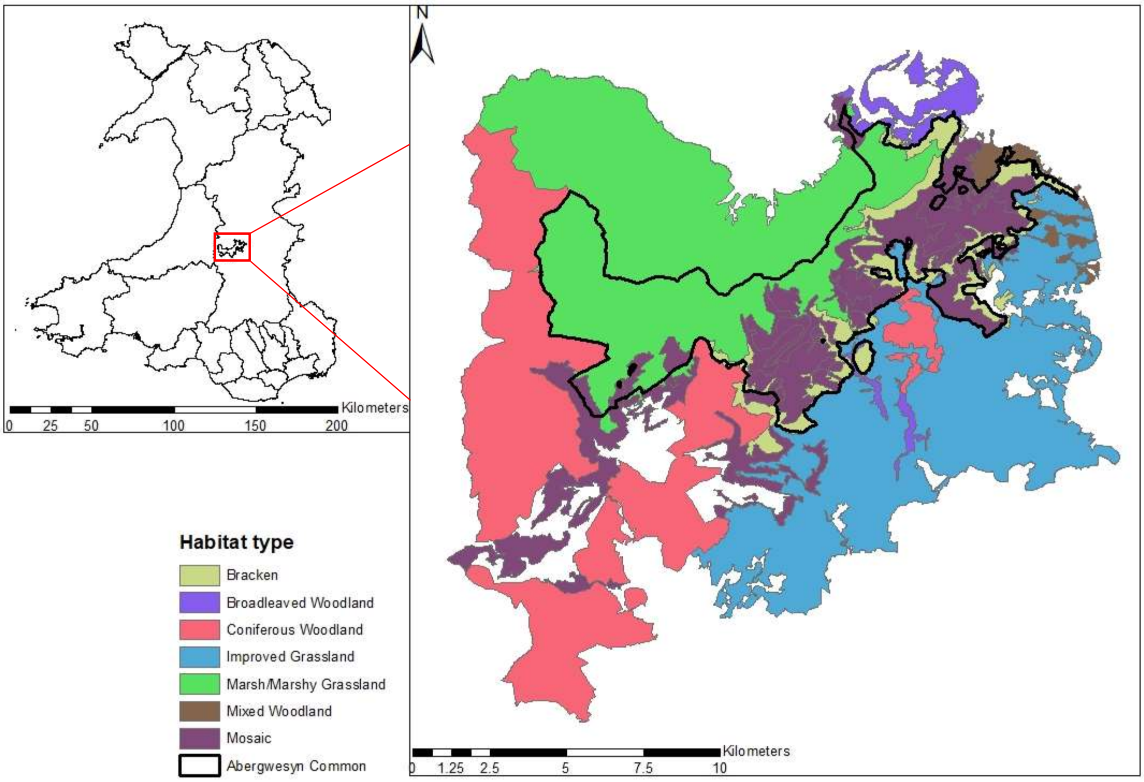


Figure 3.1: The location within Wales and the habitats of Abergwesyn Common in Mid-Wales, UK.

The Common mainly comprises of marshy grassland with areas of bracken and some mosaic habitats (figure 3.1). There are some small areas of improved grassland that cover less than 5% of the site, but most of the upland area is degraded due to historic peatland drainage, with a small area of the Common designated as a Special Area of Conservation (SAC) for blanket bog. The site is covered extensively by *Molinia caerulea*, impacting habitat diversity. Numbers of many bird species, including the Golden plover, have been declining across the Common since 2011 as recorded by the National Trust and RSPB.
Current climates are temperate and often wet, with warm summers and cooler, wet winters. For Wales, the current average climate, sees precipitation rates from 6 mm per day in the winter fall to 3.6 mm per day in the summer. Temperatures are cool, with an average of 4.4^{o}C in the winter increasing to 13.5^{o}C in summer. Future impacts of climate to Wales are similar UK averages, although summers could become over 50% drier and nearly 6^{o}C warmer compared to the 1990s baseline (Lowe *et al.*, 2018).

3.2.2 Bird species

Using National Trust surveys from 2011 to 2018, five bird species found in the uplands of Wales and at Abergwesyn Common were selected for analysis. These study species are; golden plover (*Pluvailis apricaria*), meadow pipit (*Anthus pratensis*), skylark (*Alauda arvensis*), wheatear (*Oenanthe oenanthe*) and whinchat (*Saxicola rubetra*). Species were selected due to their range of life histories and vulnerability to climate change and habitat loss. Iconic species such as *P. apricaria* are declining due to habitat losses while migrants like red-listed *S. rubetra* could see range increases.

Data were obtained from the British Trust for Ornithology (BTO) for all five species at the 2 km tetrad scale for the United Kingdom. Bird species data were included for March to September to fit with the breeding seasons of all target species and presence at Abergwesyn Common to prevent double counting. Data from two BTO surveys were used, the Breeding Bird Survey with data from 1994 to 2000 and BirdTrack data from 1980 to 2000. Species data is included from 1980 to 2000 to fit with the baseline climate data from the UKCP18 projections. Any data points that did not contain one or more of the following were removed; species name, date species recorded, latitude and longitude coordinates, reducing the chance that the data used in the study was not within the species date or location range required. Additionally, duplicate occurrences with the same coordinates were removed to avoid pseudoreplication. To avoid spatial autocorrelation, cell duplicate coordinates were removed, that is that they share a grid cell in the predictor variable data. This method removed more occurrence data when writing models with the 12 km climate data compared to the 2.2 km spatial scale data.

Other available bird occurrence data such as BTO Atlas data and that from the Global Biodiversity Information Facility was not used because the spatial scale of the records are recorded at different or lower resolution than the climate data. Additionally, due to the large uncertainty in data collection methods and potential accuracy, models containing these data may not represent current and future distributions to a high enough precision. The data used in this study was not significantly different ($p > 0.05$) to the data that was excluded. This may be because some of the data contained duplicates, and there were data in many of the same areas as used. Many studies have used the BTO datasets used in this study (Pearce-Higgins, 2011; Renwick *et al.*, 2012; Malm *et al.*, 2020), potentially aiding in some comparisons between research.

3.2.3 Climate data

Climate projections were from the Met Office UKCP18 data set (Lowe *et al.*, 2018; Kendon *et al.*, 2019), released in 2018 as an update to the UKCP09 projections of future climate change in the UK. In this study, the highest spatial scale data were used, the Convection Permitting Model (CPM) at 2.2 km and a comparison scale using the regional 12 km model for the UK. The 2.2 km projections are downscaled from global CMIP5 climate models at 60 km using the Met Office HadGEM3 model. Both the 2.2 km and 12 km projections were run for 12 members. The first model member (model 01) based on the HadGEM3-0.5 model without perturbed physics has been used in this analysis. These 2.2 km and 12 km data are both at the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathway (RCP) 8.5, which estimates a global average temperature increase of approximately 4.5^{o}C by 2100. This is the most extreme climate scenario modelled by the IPCC, and is so far the only available projection for the 2.2 km spatial data.

Baseline data for the study was the 20-year daily average between 1980 and 2000 (1990s), with two 20-year daily average future time frames between 2020 and 2040 (2030s), and 2060 and 2080 (2070s). Hereafter, the time periods will be referred to as the 1990s, 2030s and 2070s. Data from the 2.2 km CPM were re-gridded from the rotated grid latitude/longitude (37.5, 177.5) (Fung, 2018) to British National Grid.

Data processing were done using R 4.0.2 (R Core Team, 2020), the sf (v0.9-8; Pebesma, 2018), ncdf4 (v1.17; Pierce, 2019), raster (v3.4-10; Hijmans, 2021), rgdal (v1.5-23; Bivand *et al.*, 2021) and PCICt (v0.5-4.1; Bronaugh and Drepper, 2018) packages. Data at 12 km were already available at the British National Grid, with daily data averaged into the 20-year projections. Full reproducible code is available in on request. Mean temperature and mean precipitation were used to predict future suitable climate space for the five bird species, as reflected in a number of previous studies (Renwick *et al.*, 2012; Pearce-Higgins *et al.*, 2015; Massimino *et al.*, 2017; Pearce-Higgins and Crick, 2019). Many studies use different amalgamations of seasonal and monthly climate data in models (Eglington and Pearce-Higgins, 2012; Renwick *et al.*, 2012; Johnston *et al.*, 2013; Pearce-Higgins *et al.*, 2015; Massimino *et al.*, 2017; Pearce-Higgins and Crick, 2019). The majority of the studies investigated used data from both the breeding season and winter, either as these two distinct time frames (Eglington and Pearce-Higgins, 2012; Renwick *et al.*, 2012; Johnston *et al.*, 2013), or seasonally (Pearce-Higgins *et al.*, 2015; Massimino *et al.*, 2017; Pearce-Higgins and Crick, 2019). Seasonal conditions have been recognised as strong influences of bird populations (Pearce-Higgins *et al.*, 2015; Massimino *et al.*, 2017). Due to this, the minimum average temperature of the coldest month alongside mean temperature and precipitation for each month between and including March to September was included. This gave a measure of winter severity and annual variation in breeding conditions and covered all seasons. The minimum average temperature for all three time periods at the baseline and two future projections was the month of February.

3.2.4 Species modelling

To assess the potential impact of climate change to the five bird species, the Maxent species distribution model (Phillips, Anderson and Schapire, 2006; Phillips and Dudík, 2008) has been used to identify future areas of likely suitable climate space. This applies the theory of maximum entropy to identify suitable space for a species bases on species occurrence data and historical variables (Elith *et al.*, 2006; Phillips, Anderson and Schapire, 2006; Phillips and Dudík, 2008; Elith, Kearney and Phillips, 2010; Phillips *et al.*, 2017). These are then run with future predictions of climate and categorical data, such as elevation or land use, (Elith *et al.*, 2006; Phillips, Anderson and Schapire, 2006; Norberg *et al.*, 2019) to write spatial estimates of conditions suitable for habitation by the specific species. Predictions of suitable climate space are based on the relationship between the species and climatic variables that determine where the species' climatic niche is (Heikkinen *et al.*, 2006). Maxent is robust to spatial errors in occurrence data (Phillips, Anderson and Schapire, 2006; Graham *et al.*, 2008; Kass *et al.*, 2021), which is important when using secondary species data, as done in this study. Many species distribution models require both presence and absence data to make informed predictions about changes to occurrences, with Maxent using pseudoabsences from the study area. These pseudoabsences are a randomly selected sample of pixels from the study area where the study species are not present and represent areas that are more likely to be climatically or physically unsuitable for that species (Phillips, Anderson and Schapire, 2006).

To choose optimum settings for the Maxent model, species-specific approach to model tuning was utilised. Using the R ENMEval package (2.0, Kass *et al.*, 2021) optimum model settings were selected through automated model evaluation and tuning that the package provides. There was focus on three input parameters that are often overlooked in Maxent modelling; the number of background points, regularisation multiplier value (beta multiplier) (RM) and the feature classes (FC) used. For more information on these input parameters, see chapter 2.

While allowing for quantitative assessment into model inputs, ENMEval also provides a range of model evaluation metrics including the area under the curve of the receiver operating characteristic plot (AUC), Continuous Boyce Index (CBI) and null models. Null models account for features of the system that often lead to incorrect statistical conclusions (Kass *et al.*, 2021), especially when using background data as absences. The null models in ENMEval use withheld data to evaluate both these and empirical models which lead to more statistically reliable results (Kass *et al.*, 2021). Models were built with RM values ranging from 0.5 to 6, in increments of 0.5, and with six different FC combinations (L, LQ, H, LQH, LQHP, LQHPT), similar to Muscarella *et al.* (2014). The corrected Akaike information criterion (AICc), AUC, Continuous Boyce Index, and null model values were tested to assess model suitability metrics and statistical significance.

Occurrence data was partitioned using the block method which increases the independence of validation data and forces models to extrapolate more environmentally, evaluating better the transferability of a model to new conditions (Kass *et al.*, 2021). Each model was run five times to assess the effect five different numbers of background points had on model accuracy. Models were run with 5000, 10,000, 15,000, 20,000 and 25,000 background points.

To reduce sampling bias, the kernel density function was applied, which is a statistical way to estimate densities of data, to write a bias layer which transferred to background points. The two-dimensional kernel density estimator approximates a raster that represents the sampling bias, this is used to estimate where background points would more likely occur based on the occurrences. Sampling bias was run using unfiltered species occurrences to rule out the chance of additional bias from filtering the presence data, with random background points probabilistically generated from this output. Sampling bias background points were used to run the final Maxent models to prevent any possible biases and represent true absences as best as possible, but used completely random background points for the ENMEval optimum input runs. There was very little difference between the AUC score and visual outputs when comparing models run with sampling bias accounted for and those without.

Optimal models, to potentially demonstrate the more accurate and reliable model inputs, were chosen using two methods. The first was based on ΔAICc (optimum AICc) without considering cross-validation results which has been found to be a good method at predicting the occurrence of individual species (Warren and Seifert, 2011). The second model choice method (optimum sequence) was based on cross-validation and used sequential criteria that selected the lowest average test omission rate and highest average validation AUC (Radosavljevic and Anderson, 2014; Kass *et al.*, 2021). To select the best background point value for each optimal model, the background point value for the model with the lowest ΔAICc was used for the first selection method. For the sequential criteria method, the lowest omission rate and highest validation AUC out of all background point models was chosen. These two 'optimal' models for each species at each spatial scale of climate data resulted in four models for each species, at 2.2 km and 12 km spatial resolutions for both the optimum AICc and optimum sequence tests, and 20 models overall. In the results, optimum AICc models are referred to as 'OA' with optimum sequence models as 'OS'.

To add further model inputs, baseline Maxent models were run using the dismo package (Hijmans *et al.*, 2021) in R for these 20 models. These models estimated suitable climate space for the five bird species for the 1990s time period between 1980 and 2000, which was the baseline and 'current' time period from which projections were predicted. Occurrence and environmental layers were the same as inputted to the ENMEval models, while background layers, feature classes, and regularisation multiplier (beta multiplier) were used from the optimal models. Also added were, fade by clamping and Multivariate Environmental Similarity Surface (MESS) analysis and 10 replicates using the replicated bootstrap cloglog method with 40% of the data withheld for testing.

The fade by clamping input parameter reduces the suitability value of model to that between a model only run within the limits of the training data, and with a completely open-ended model response (Webber *et al.*, 2011). This produces a model output that is not completely constrained by training data, which may not be a complete reflection of the entire data set, but one that is not completely beyond the bounds of possibility. MESS analysis evaluates the differences between the reference layer of bioclimatic variables and those under different climatic conditions (Zhang *et al.*, 2021), here the different temporal steps of UKCP18 data. The model was run 10 times (replicates) for each set of input variables to understand the variability within the model results. An average of these models was computed and used in final analysis to control for this variability.

The bootstrap method is a resampling method in which the number of presence points in each training data set equals the total number of presence points in the study, so training data sets have duplicate records (Phillips, 2017). This training data is selected by sampling with replacement from the presence points (Phillips, 2017), so is a more thorough examination of the whole dataset. In this method, 40% of the dataset was withheld in a testing set, with 60% of the data used to train the model. This ensures that the model is tested using data that actually represents the study system and species being investigated, and a higher testing set, such as this 40%, often leads to better model results.

Cloglog results were produced as these provide a probability of suitability between 0 and 1 which aids in clearer analysis (Phillips *et al.*, 2017). Again, as with the ENMEval models, all maxent models were evaluated using AUC and the True Skill Statistic (TSS) and Symmetric External Dependence Index (SEDI) (Wunderlich *et al.*, 2019) were included in evaluation (further information in supplementary material, appendix 2) to estimate the accuracy of predictions between optimal model runs and between species. TSS is an alternative metric to AUC (Allouche, Tsoar and Kadmon, 2006), with sensitivity and specificity values derived from the testing dataset of the model. The threshold dependent TSS calculation is defined as sensitivity + specificity – 1, with ranges from -1 to +1. Values below zero indicate a model performance no better than random, with a score of 1 depicting perfect agreement (Allouche, Tsoar and Kadmon, 2006; Ruete and Leynaud, 2015). Maximum TSS was calculated, which uses a threshold very similar to that calculated by Maxent in the maximum test sensitivity plus specificity threshold also used in analysis. SEDI is an evaluation metric previously used in the field of meteorology and is thought to be an optimal metric for presence-background SDMs (Wunderlich *et al.*, 2019). A similar approach was taken to TSS that any SEDI value above zero is better than random, and any SEDI or TSS value above 0.4 is considered a 'good' model. These Maxent models were projected to the two future climates (2030s and 2070s) each with the same inputs as the original baseline Maxent models. The averaged model across all replicates for the three time periods was calculated and analysed the estimated amount of suitable space for each species. The averaged model across all 10 replicates was calculated and analysed the estimated suitable space for each species. To calculate model fit analysis of the area under the receiving curve (AUC) and TSS values was completed, a 'good' model was produced if AUC > 0.7 and TSS > 0. Models were evaluated using both AUC and TSS to test whether modelled occurrence data was able to accurately distinguish between presences and absences (Merow *et al.*, 2013). AUC is a common and easy way to evaluate the goodness-of-fit of Maxent models, but has been criticised as it is too correlated to the size of the study area and number of records (Aguirre-Gutiérrez *et al.*, 2013). However, this is a good method to use as a threshold-independent measure of model performance (Allouche, Tsoar and Kadmon, 2006). In addition to these two metrics, the Symmetric Extremal Dependence Index (SEDI) (Wunderlich *et al.*, 2019) was calculated. This is thought to be a better measure of a model for presence-background SDMs, such as Maxent, as it is able to distinguish random and skilled predictions (Stephenson *et al.*, 2008; Hogan, O'Connor and Illingworth, 2009; Wunderlich *et al.*, 2019), while also able to interpret overfitted or mis-specified models (Wunderlich *et al.*, 2019). Additionally, using multiple evaluation metrics including null models (Beale, Lennon and Gimona, 2008; Hijmans, 2012; Radosavljevic and Anderson, 2014), narrows down the number of optimum models available and provides more information that aids in choosing the model settings that represent accurate current and future distributions. This reduces the reliance on one model metric, such as AUC, which can result in un-realistic, overfitted models (Lobo, Jiménez-Valverde and Real, 2008). A variety of model evaluation metrics and techniques were used, both to choose model inputs and identify optimum models. AUC is useful when comparing between different model runs (Wisz *et al.*, 2008), but not when examining how good the model actually is at predicting future occurrences and suitability of future climates. However, a low AUC with presence-only data may represent a good model of a species niche if that species is limited by dispersal or low numbers (Yackulic *et al.*, 2013).

Model results were written as two different outputs, as a probability scale measuring a range of how suitable the climate space is likely to be, and as an output with a threshold applied. Thresholds are often used in conservation models (Allouche, Tsoar and Kadmon, 2006; Liu *et al.*, 2013), with a probability of suitable space or presence is translated into a more definite presence or absence. The *maximum test sensitivity plus specificity* cloglog threshold was used. The average for each optimal model was calculated from the 10 model runs. While this threshold may overpredict the amount of space suitable with a slightly higher threshold of presence, it reduces the risk of missing out suitable space for a species (Liu *et al.*, 2013; Liu, Newell and White, 2015).

3.2.5 Land cover data

Land cover was included in these analyses to identify where suitable land cover occurred within modelled suitable climate space. A collaboration between ESRI and Clark University produced predicted land cover data in 300m-pixels for 2050 based on 2018 observations of global land cover and future change (Esri, 2021). Past land cover data from 2010 to 2018 was used to produce a land cover vulnerability model which includes data such as bioclimatic variables, population counts and infrastructure to better understand the global pressures of land development (Esri, 2021). There are 10 classes of land cover predicted for 2050 from the 2018 observations. Of this land cover data, five land cover classes were chosen for the analysis which coincide with suitable habitats for the five study species (table 3.1A).

Observational land cover classifications for the UK are available for each year between and including 1992 and 2000, within the baseline climate data period. There is a less than 5% difference between the percentage of both total land area and the land cover layer that contain both suitable climate and land cover between the 1992 and 2000 layers. For the baseline land cover data, the 2000 observational data were used. This provides a 50-year change in land cover area when comparing to the projected land cover for 2050. The 2000 data consisted of 20 land cover types similar to those used in the 2050 projections. 12 of these classes were selected to write five land cover classes to match with those in the 2050 layer (table 3.1B) which would contain potentially suitable habitats for the study species. Both the 2050 and 2000 land cover layers were used to clip areas of the climate projections to identify suitable climate and potentially suitable habitats. Centroids of potential species distributions containing suitable climate and habitat were calculated to investigate geographical shifts.

Table 3.1: The land cover classes from 2000 observational dataset used to write five land cover classes that were similar to those used in the 2050 projections found at: https://datastore.copernicus-climate.eu/documents/satellite-land-cover/D5.3.1_PUGS_ICDR_LC_v2.x_P

A) 2050 projection layer		B) 2000 layers used to write similar layers	
Value		Value	Land cover type
LC1	Mostly cropland	10 (11,12)	Cropland, rainfed
		30	Mosaic cropland (>50%), natural vegetation (<50%)
LC2	Grassland, scrub, or shrub	40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%), cropland (<50%)
		100	Mosaic tree and shrub (>50%), herbaceous cover (<50%)
		110	Mosaic herbaceous cover (>50%), tree and shrub (<50%)
		120	Shrubland
		130	Grassland
LC5	Sparse vegetation	150	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
LC6	Bare area	200	Bare areas
LC7	Swampy or often flooded vegetation	180	Shrub or herbaceous cover, flooded, fresh/saline/brackish water

3.3 Results

When investigating different data inputs, the higher spatial scale climate data produced the most accurate model results, when comparing all model evaluation metrics, for all species in comparison to coarser scales. Additionally, the default 10,000 background points for Maxent models was often found to be insufficient. This varied with species, with optimum values of background points between 5,000 and 25,000 random points. Models for specialist species had higher evaluation metric values compared to other studied species, suggesting models were of a greater predictive accuracy. Amounts of suitable climate space are expected to increase across Britain under climate change, albeit with northward shifts. Many areas predicted to be suitable under future climates alone, were unsuitable when habitat requirements were considered. This suggests that habitats are a more limiting factor to species distributions than climate alone.

3.3.1 ENMEval and optimum model inputs

Overall, optimum model inputs for the higher spatial scale models (2.2 km) resulted in more complex models that required a greater number of features and background points when compared to the lower spatial scale climate data (table 3.2). This is likely to be expected as the greater level of information within higher resolution data requires a greater level of evaluation. Most models' optimum settings met or exceeded the default 10,000 background point value (table 3.2), with species-specific results. Out of all models at both 2.2 km and 12 km spatial scales, 85% of optimum models required the number of background points that represent pseudoabsences to meet or exceed 10,000.

A greater number of features were selected for the best performing models at 2.2 km compared to those at 12 km (table 3.2), with more features required in optimum AICc methods compared to optimum sequence models. When investigating the regularisation multiplier (RM) value (beta multiplier), 2.2 km scale optimum AICc models computed lower values than for optimum sequence inputs, but with less difference for the 12 km models of both input methods. The smaller the RM value the closer the projected distribution will fit to the training data (Gottwald *et al.*, 2017), suggesting that the 2.2 km results using the optimum AICc input method are likely to be models with greater prediction accuracy.

On average, results at the 2.2 km resolution performed better than those at 12 km for both optimum AICc and optimum sequence inputs, with a higher AUC_{TRAIN} (2.2 km = 0.670, 12 km = 0.566), and lower AUC_{DIFF} (2.2 km = 0.129, 12 km = 0.204) (table 2.2), suggesting that results were more accurate and less overfitted at the higher spatial scale. Additionally, most AUC values ($_{TRAIN}$ and $_{VAL}$) were higher for optimum AICc (table 2.2; OA) inputs when compared with optimum sequence (table 2.2; OS). These patterns were observed for both 2.2 km and 12 km results, apart from Meadow Pipit and Wheatear predictions. In general, optimum AICc results displayed a greater predictive accuracy, with higher AUC_{TRAIN} and AUC_{VAL} metrics compared to optimum sequence. These trends were only not experienced when comparing the 2.2 km resolution AUC_{VAL} results, although with very similar values (OA = 0.626, OS = 0.660) there are likely to be marginal differences. Omission rates are lowest for 2.2 km resolution optimum sequence results (table 2.2: mean = 0.0482), with these inputs outperforming one metric (OR_{10p}) and optimum AICc inputs outperforming for AUC. When comparing null and empirical model results for both spatial resolutions, the null models predicted distributions with less accuracy than empirical models with lower AUC_{TRAIN} and AUC_{VAL} results, and higher AUC_{DIFF} values. Most null and empirical models at 2.2 km resolution are statistically different ($p < 0.05$) for AUC_{TRAIN}, AUC_{VAL} and AUC_{DIFF} metrics (table 3.2). This suggests that empirical models are more realistic than the null models and therefore are better at predicting species distributions when compared to those models with random input data. A greater number of results at 12 km spatial resolution are not significant when examining the relationship between empirical and null models (table 3.2). However, statistical differences for OR_{10} metric are less clear, with most null and empirical models not significantly different (table 3.2). The only exceptions were the Meadow pipit and Wheatear 2.2 km predictions with optimum AICc inputs and Meadow pipit predictions with optimum sequence inputs at 12 km resolution (table 3.2). When investigating further metrics of the Continuous Boyce Index (CBI) and minimum training presence omission rates (OR_{MTP}), trends were very similar to AUC and omission rates at 10%, with empirical models positively correlated with the true probability of presence. These CBI and OR_{MTP} results are available in supplementary material (appendix 2, table A2.1).

It has been proven through analysis of multiple model evaluation metrics that models developed at the 2.2 km spatial scale are generally better predictors of distributions compared to 12 km resolutions and null models when investigating AUC. However, these trends are not ubiquitous, and switch when looking into omission rates. This suggests that the model inputs selected by ENMEval analysis predict more realistic results of species distributions than those with random data from the null models. As models run at the 2.2 km scale consistently outperformed those at the 12 km scale, only results at the higher 2.2 km spatial resolution will be presented in subsequent results.

3.3.2 Maxent model results

Results computed with Maxent at the 2.2 km resolution using the optimum inputs values for both optimum AIC and optimum sequence results are presented in table 3, with those at the 12 km resolution in supplementary material (appendix 2, table A2.2). All model evaluation metrics indicated that results at 2.2 km spatial resolution had greater prediction accuracy when compared to those at 12 km. Every model had AUC values above 0.5 and TSS and SEDI values greater than 0 which are considered thresholds at which models are better than random. AUC_{TRAIN} was greater than AUC_{TEST} for all species and scales, which is expected and suggest that models are not overfitted. Models written with optimum AICc inputs computed higher values of AUC, TSS and SEDI metrics compared to optimum sequence results (table 3.3) indicating models with optimum AICc inputs have a greater predictive accuracy than those with optimum sequence inputs (table 3.3). This differs slightly to the original selection of these optimum inputs (table 3.2), with changes to model performance when modifying replicates and outputs.

When investigating species results, those species that are more specialised with smaller numbers of presence data resulted in the best models (table 3.3). The predictive models for golden plover and whinchat had the highest test AUC and TSS scores (table 3.3), with the only SEDI scores over 0.4, indicating a good model. While no models exceeded a score of 0.4 in the TSS evaluation, they were over zero. One of the most ubiquitous species, the meadow pipit, resulted in the model with the lowest predictive accuracy when investigating the 2.2 km optimum AICc results.

The models represented in table 3.3 are generated with random background points as pseudoabsences. I compared 2.2 km optimum AICc models run with random background points and background points selected through a bias layer. Evaluation matrices showed little difference between biased and random background points, so the random point models were chosen as the final outputs. This matches with the ENMEval input model outputs and allows for comparisons with other studies, as many use random background points in presence-background modelling. The BTO Breeding Bird Survey, one of the data sets used in the models, does account for sampling bias, and therefore there is unlikely to be overwhelming bias in the outputs.

The models built with optimum AICc inputs at the 2.2 km scale UKCP18 climate data were chosen to examine how suitable climate space is likely to change with climate for the five bird species in the analysis.

3.3.3 Suitable climate space

Results in figure 3.2 use the cloglog predictive scale which gives a proportion of overall space that is likely to be suitable climatically from 0 to 1, with the higher the value, the higher the amount of area likely containing suitable climates. All species showed similar trends when investigating suitable climate space for both 2030s and 2070s futures from the 1990s baseline (figure 3.2). The generalist species of meadow pipit (figure 3.2B) and skylark (figure 3.2C) gained more suitable space in the future when compared to specialist species such as the golden plover (figure 3.2A). Any increases in future suitable climate space under future climate change show shifts mainly in areas of higher latitude and altitude (figure 3.2). Greater changes to suitable climate space are expected between 1990s and 2030s rather than between 2030s and 2070s. Out of all five species in the analysis, the golden plover was the only species that saw a predicted reduction in suitable space across mainland Britain (figure 3.2A; 3.3A).

Spatial results show the meadow pipit and skylark with the greatest amount of predicted suitable climate space increasing in the future under climate change (figure 3.2). These results show the areas of mainland Britain that are likely to be suitable when only considering climate, regardless of habitat cover, anthropogenic influence, or accessibility by the species.

Results are presented from the *maximum test sensitivity and specificity cloglog threshold* within Maxent, which coordinated with the threshold used to calculate maximum TSS (figure 3.3).

All species increase in suitable climate space from the 1990s to 2030s and 2070s (figure 3.3) for the threshold results. Again, as with the scaled results (figure 3.2) the generalist meadow pipit and skylark species see the largest increase in suitable space. The golden plover models show the greatest different to the other species (figure 3.3). All species except the golden plover have the potential to expand distributions into eastern and southern Britain (figure 3.3), with all species shifting ranges to the north and increasing these extents.

Table 3.2: Optimum inputs for Maxent models as computed by ENMEval models investigating different background point (BP), feature class (F) and regularization multiplier (RM) inputs. Results are presented from empirical and null models with area under the operating curve (AUC) and omission rates at 10 % (OR_{10p}) explored. Optimum model inputs are reflected in high AUC_{TRAIN} and AUC_{VAL} scores and low AUC_{DIFF} and OR_{10p} values. A significant difference between empirical and null models (pAUC_{TRAIN}, pAUC_{VAL}, pAUC_{DIFF} and pOR_{10p}) indicate models that are more likely to accurately predict species distributions than random. OA = optimum AICc, OS = optimum sequence.

2.2 km																	
Species	Model	BP	F	RM	ΔAICc	AUC_{TRAIN}	$AUC_{VAL-AVG}$	AUC_{-DIFF}	$AUC_{NULL-TRAIN}$	$AUC_{NULL-VAL-AVG}$	$AUC_{NULL-DIFF}$	$pAUC_{TRAIN}$	$pAUC_{VAL}$	$pAUC_{DIFF}$	OR_{10p}	$OR_{10p-NULL}$	pOR_{10p}
Golden plover	OA	25,000	LQHPT	0.5	0	0.772	0.611	0.173	0.663	0.512	0.178	<0.001	0.017	0.468	0.310	0.339	0.324
	OS	15,000	L	1	173.029	0.680	0.674	0.111	0.547	0.541	0.255	<0.001	0.003	<0.001	0.112	0.172	0.172
Meadow pipit	OA	25,000	LQHPT	0.5	0	0.655	0.666	0.054	0.598	0.569	0.093	<0.001	0.002	0.095	0.124	0.197	0.034
	OS	5,000	LQH	1	143.523	0.615	0.688	0.076	0.553	0.692	0.168	<0.001	0.546	<0.001	0.034	0.036	0.473
Skylark	OA	25,000	LQHPT	0.5	0	0.678	0.605	0.154	0.628	0.611	0.114	<0.001	0.603	0.938	0.208	0.117	0.999
	OS	15,000	H	5.5	359.446	0.623	0.653	0.218	0.596	0.632	0.223	<0.001	<0.001	0.232	0.019	0.019	0.503
Wheatear	OA	25,000	LQHPT	0.5	0	0.689	0.672	0.081	0.614	0.560	0.097	<0.001	<0.001	0.298	0.128	0.221	0.015
	OS	15,000	LQHP	6	403.498	0.630	0.681	0.095	0.512	0.615	0.209	<0.001	0.016	0.002	0.048	0.067	0.317
Whinchat	OA	25,000	LQHPT	0.5	0	0.723	0.578	0.215	0.664	0.528	0.153	<0.001	0.076	0.936	0.294	0.294	0.505
	OS	5,000	H	6	196.205	0.636	0.605	0.112	0.508	0.567	0.100	<0.001	0.175	0.584	0.028	0.009	0.873
12 km																	
Species	Model	BP	F	RM	ΔAICc	AUC_{TRAIN}	$AUC_{VAL-AVG}$	AUC_{-DIFF}	$AUC_{NULL-TRAIN}$	$AUC_{NULL-VAL-AVG}$	$AUC_{NULL-DIFF}$	$pAUC_{TRAIN}$	$pAUC_{VAL}$	$pAUC_{DIFF}$	OR_{10p}	$OR_{10p-NULL}$	pOR_{10p}
Golden plover	OA	10,000	LQ	0.5	0	0.610	0.566	0.153	0.558	0.526	0.235	<0.001	0.247	0.063	0.190	0.205	0.435
	OS	20,000	L	0.5	12.534	0.601	0.613	0.267	0.555	0.528	0.258	<0.001	0.051	0.568	0.138	0.202	0.177
Meadow pipit	OA	10,000	LQH	6	0	0.525	0.551	0.233	0.516	0.501	0.197	0.075	0.163	0.687	0.127	0.159	0.360
	OS	20,000	LQHPT	1	83.990	0.554	0.614	0.153	0.584	0.502	0.135	0.999	0.010	0.647	0.053	0.254	0.002
Skylark	OA	5,000	LQ	0.5	0	0.612	0.594	0.111	0.556	0.521	0.245	<0.001	0.097	0.005	0.172	0.211	0.316
	OS	20,000	H	5	22.723	0.545	0.543	0.268	0.532	0.552	0.152	0.001	0.579	0.943	0.016	0.050	0.302
Wheatear	OA	10,000	H	6	0	0.552	0.562	0.232	0.511	0.516	0.042	0.001	0.070	0.999	0.206	0.027	0.999
	OS	10,000	LQ	0.5	19.896	0.557	0.580	0.212	0.532	0.525	0.166	<0.001	0.154	0.773	0.097	0.157	0.214
Whinchat	OA	10,000	LQHPT	5	0	0.549	0.560	0.222	0.525	0.552	0.160	0.009	0.426	0.903	0.149	0.106	0.767
	OS	25,000	L	3.5	0.840	0.548	0.578	0.185	0.519	0.569	0.194	<0.001	0.424	0.433	0.063	0.095	0.313

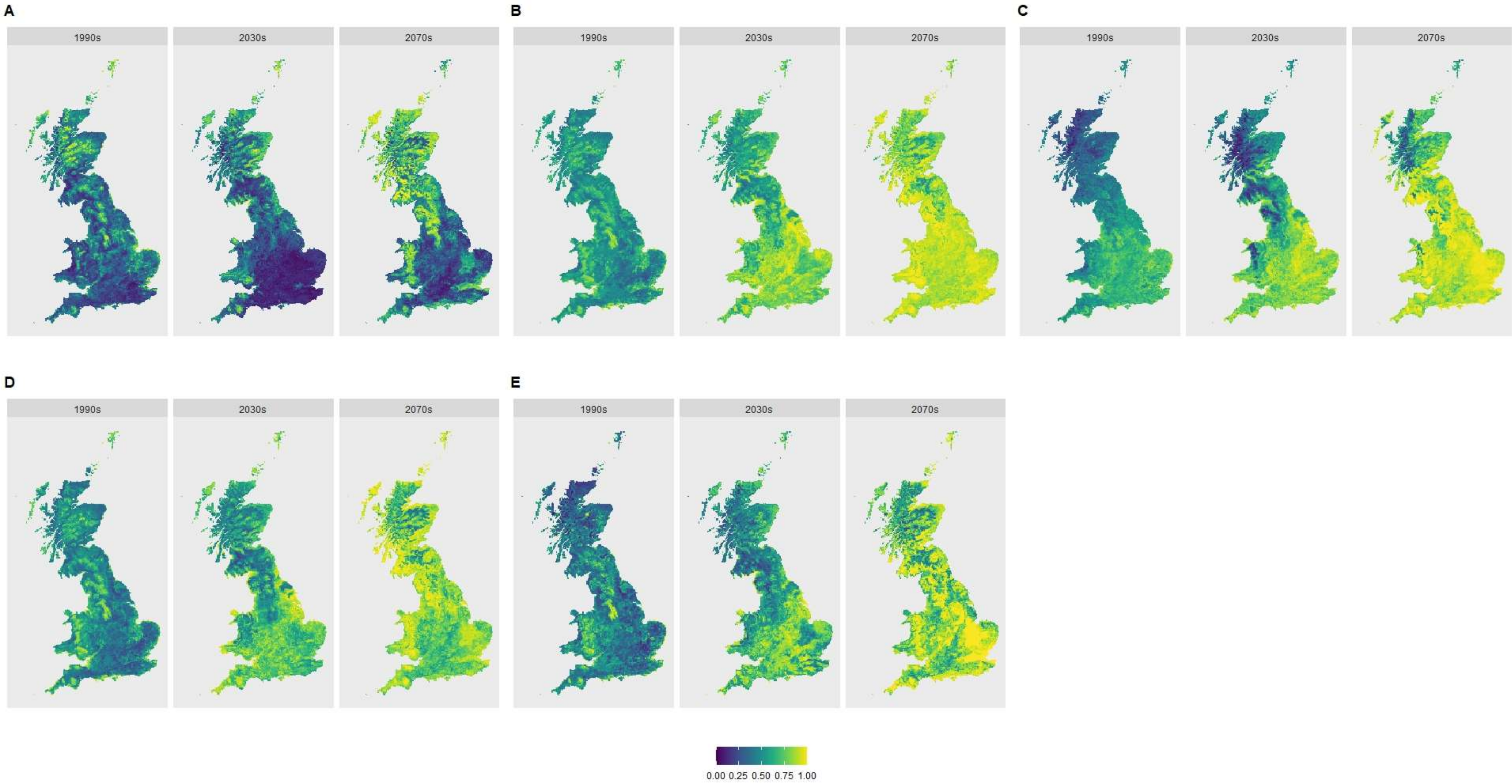


Figure 3.2: The change in suitable climate space for five bird species found in the uplands of Great Britain under climate change. Results are at the 2.2 km spatial resolution with model inputs as indicated by ENMEval optimum AICc results. A) Golden plover, B) Meadow pipit, C) Skylark, D) Wheatear, E) Whinchat.

Figure 3.3: The change in suitable climate space when constrained by maximum test sensitivity and specificity cloglog threshold. Values of 1 indicate geographical space more likely to contain suitable climate space for the species, with values of 0 indicating geographic space unlikely to contain suitable climate space for that species. A) Golden plover, B) Meadow pipit, C) Skylark, D) Wheatear and E) Whinchat.

Table 3.3: Maxent model results using optimum settings from ENMEval (see table 2.1). n = number of presence points for each species.

2.2 km						
Species	*n*	Model	AUC_{TEST}	AUC_{TRAIN}	TSS	SEDI
Golden plover	1441	OA	0.732	0.809	0.348	0.461
		OS	0.643	0.651	0.237	0.355
Meadow pipit	3996	OA	0.624	0.688	0.188	0.289
		OS	0.576	0.587	0.127	0.263
Skylark	4889	OA	0.651	0.703	0.233	0.354
		OS	0.611	0.612	0.179	0.289
Wheatear	3001	OA	0.659	0.727	0.245	0.363
		OS	0.619	0.620	0.188	0.289
Whinchat	1488	OA	0.685	0.789	0.287	0.414
		OS	0.587	0.604	0.150	0.253

The 1990s model estimated 52 % to 74 % of mainland Britain as unsuitable climatically for the five target species, with the least available space for the whinchat (74.8 %) (table 3.4). By 2070s, only one species, the golden plover, has the majority space being climatically unsuitable (51.19 %), with an increase of 21.17 % in suitable climate space from the 1990s (table 3.4). In contrast, the meadow pipit is likely to see the greatest increase of suitable climate space (table 3.4) with the amount of predicted suitable space increasing by 67 % over the study period from the 1990s to 2070s. Both the whinchat and wheatear increase in suitable space by approximately 64 %, and the skylark sees the second smallest increase of 43.87 % (table 3.4).

Table 3.4: Amount of and percentage change in suitable space for threshold Maxent results between the baseline and two climate futures. + or – indicate increases or decreases in the amount of suitable climate space predicted to occur for each species between baseline and future projections.

	Amount of suitable space (%)			Percentage change between years (%)		
Species	1990s	2030s	2070s	1990s to 2030s	2030s to 2070s	1990s to 2070s
Golden plover	27.6	23.8	48.8	- 3.8	+ 25.2	+ 21.2
Meadow pipit	31.6	79.4	97.5	+ 47.8	+ 18.2	+ 67
Skylark	47.9	66.6	91.8	+ 18.6	+ 25.2	+ 43.9
Wheatear	30.1	71.5	94.2	+ 41.4	+ 22.7	+ 64.1
Whinchat	25.2	64.4	89.8	+ 39.2	+ 25.5	+ 64.6
Averages	32.5	61.1	80.4	+ 28.6	+ 23.4	+ 52.2

3.3.4 Suitable climate and land cover

Areas of grassland, scrub and shrub, and cropland are predicted to increase over mainland Britain, however, land cover of sparse vegetation, bare ground and swampy vegetation will potentially reduce in size. The greatest increases in the amount of suitable space within potentially suitable land cover are found in the mostly crops (LC1) and grassland, scrub, or shrub (LC2) habitats. See supplementary material, appendix 2, table A2.3 for percentages and percentages of change of suitable habitat within suitable climate space for every species. The meadow pipit (appendix 2, table A2.3) has the largest increase of suitable space also containing potentially suitable habitat, with a 375 % increase in the amount of LC1 from the 1990s to the 2030s average. The greatest change from the 1990s to 2070s and between 2030s and 2070s was for the skylark within sparse vegetation (LC5) with an increase of 1073 % and 346 % respectively (appendix 2, table A2.3).

Some species see a decline in the amount of suitable climatic space also containing potential suitable habitat (appendix 2, table A2.3) from the 1990s to the 2030s. These are seen in all land cover types for the golden plover (appendix 2, table A2.3) and with less pronounced declines for other species, mainly seen in the bare vegetation (LC5) and swampy or often flooded vegetation (LC7). By the 2070s, all land cover types exceed the amount of suitable space within the habitat layers predicted for the 1990s (appendix 2, table A2.3). For some land covers, more than 90% of suitable climatic space is also likely to contain habitat that may be suitable (appendix 2, table A2.3).

However, when examining this within mainland Britain, there are still increases in suitable climatic and habitat space, but these areas are much smaller. For all percentages and percentage change of suitable climate and habitat within mainland Britain see supplementary material (appendix 2, table A2.4). This may lead to more fragmented, small habitats that species are less likely to be able to inhabit. For all species, the amount of suitable climate space in LC5 and bare area (LC6) land cover types only increase incrementally (appendix 2, table A2.4). This could be an issue for species that rely on bare ground and sparse vegetation in their life cycles. In alignment with appendix 2, table A1.3, LC1 and LC2 are predicted to have the largest increases in amount of suitable space in mainland Britain (appendix 2, table A2.4). However, LC2 has the largest percentage of suitable land cover for all species, in contrast to LC1 in table A2.3 (appendix 2). The golden plover is the only species that is expected to experience a decline of approximately 24 % on average in the amount of suitable climate and habitat space within all habitat types from the 1990s to 2030s (appendix 2, table A2.4). Future projections in the 2070s predict, on average 2.4 % to 8.6 % of mainland Britain within suitable climates and habitats for these five species. For habitats both within climate space and mainland Britain, the highest percentage of suitable space are within cropland (LC1) and grassland, scrub, or shrub (LC2).

Table 3.5: The distance in kilometres, and direction in which the centroid of each species' range is predicted to change from the 1990s baseline to 2030s and 2070s future. The average is of absolute values, disregarding direction.

Species	1990s to 2030s	2030s to 2070s	1990s to 2070s
Golden plover	78 km northwards	59 km southwards	28 km westwards
Meadow pipit	54 km southwards	54 km northwards	12 km northwards
Skylark	66 km northwards	107 km northwards	173 km northwards
Wheatear	84 km southwards	56 km northwards	36 km eastwards
Whinchat	33 km eastwards	54 km westwards	64 km northwards
Average	63 km	66 km	63 km

Figure 3.4 shows potentially suitable habitats that are also within potentially suitable climate space for all five bird species and the centroid of these distributions. On average, species distributions shift the greatest distance between 2030s and 2070s (table 3.5), with the skylark predicted to have the greatest shift of over 100 km north (figure 3.3C; table 3.5). All species shift distributions northwards over time, with the skylark with the greatest potential movement, but also retaining the most southerly centroid of range (figure 3.3C). The golden plover is predicted to be the most northerly distributed species (figure 3.3A), and the only species whose distribution centroid is likely to move southwards in the 2070s. All species' distribution centroids are predicted to shift on average approximately 64 km (table 3.5) with greater amounts of potential suitable cropland in the east of Britain and grasslands in the west (figure 3.3). While croplands may be suitable for species such as the skylark (figure 3.3C) and meadow pipit (figure 3.3B), they may not suit the life histories of more specialist golden plover (figure 3.3A). Species with very similar life histories like the wheatear (figure 3.3D) and whinchat (figure 3.3E) are predicted to have similar potential future ranges, despite their differing migratory habits.

3.3.5 Abergwesyn Common case study: the golden plover

Investigating the site level results show us how results could influence future conservation management. Climatically suitable space does appear to increase across Abergwesyn Common in the future (figure 3.5A, B) for the golden plover. It is predicted that by the 2070s, most of the common land is likely to be suitable climatically for the specialist species (figure 3.5B). There is a slight decline in the amount of suitable space between the 1990s and 2030s (figure 3.5B), but only by about 2 %. However, the climatic space that is suitable does become slightly fragmented across the Common. Only two land cover types are predicted to occur there in the future (figure 3.5C). Areas of grassland, scrub, and shrub (figure 3.5C, LC2) and swampy or flooded vegetation (figure 3.5C, LC7) are predicted to increase between 1990s (figure 3.5Ci) and 2070s (figure 3.5Ciii), with a decline in LC7 in the 2030s (figure 3.5Cii). While the majority of the Common appears to contain suitable habitats and climate

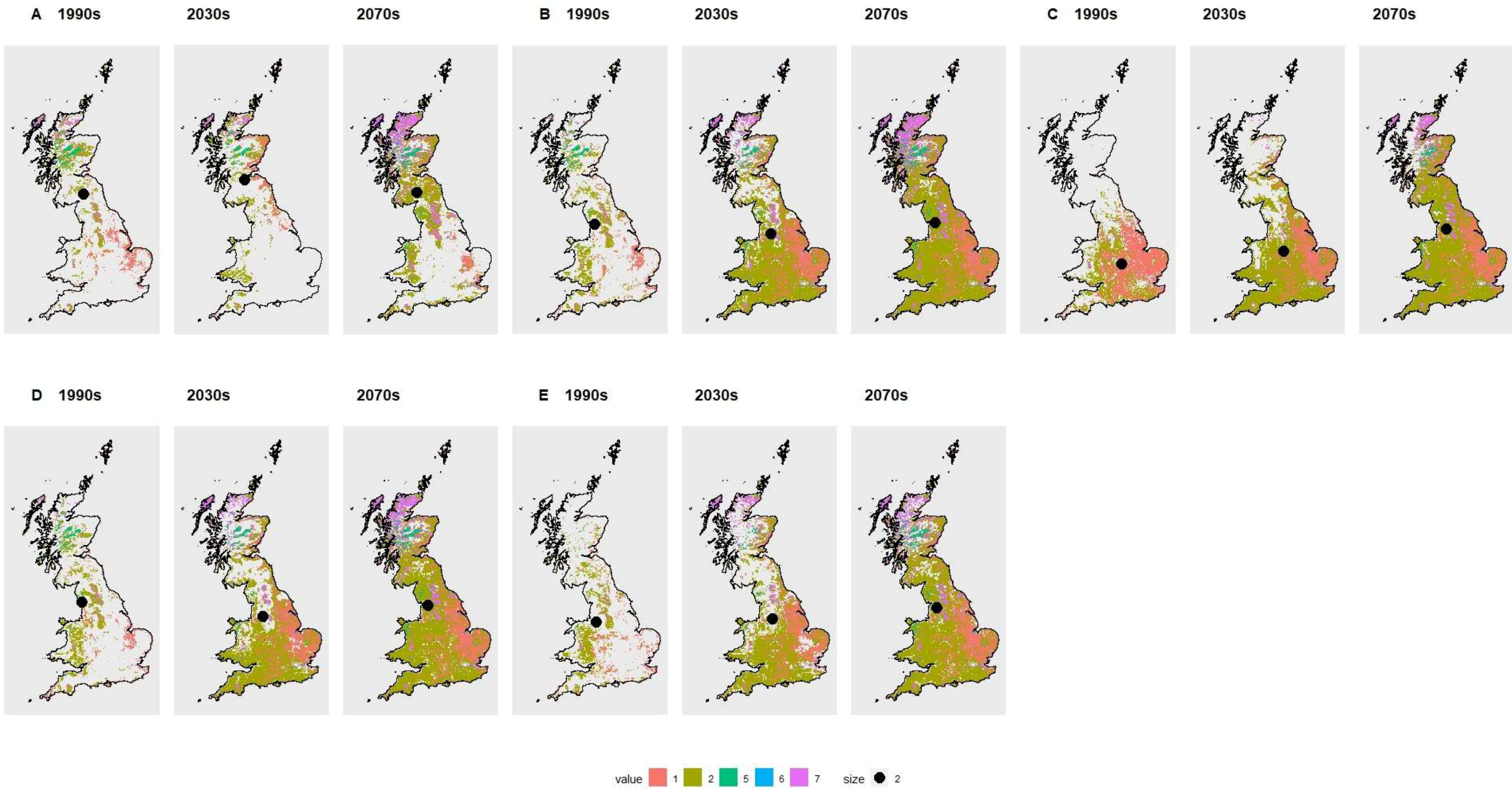


Figure 3.4: Areas of mainland Great Britain containing suitable climate within five different habitat types for five bird species found in the uplands of Britain. Black points represent the centroid of the potential species distribution and indicate general shifts in potential distributions. Species: A) Golden plover, B) Meadow pipit, C) Skylark, D) Wheatear and E) Whinchat. Land cover types: 1) Mostly cropland, 2) Grassland, scrub, or shrub, 5) Sparse vegetation, 6) Bare ground and 7) Swampy or often flooded vegetation. Baseline land cover from 2000, with predictions of land cover to 2050 as projected by Clark Labs X ESRI (Esri, 2021).

for the golden plover, if these are not in good condition or managed incorrectly, then the species will not be able to thrive.

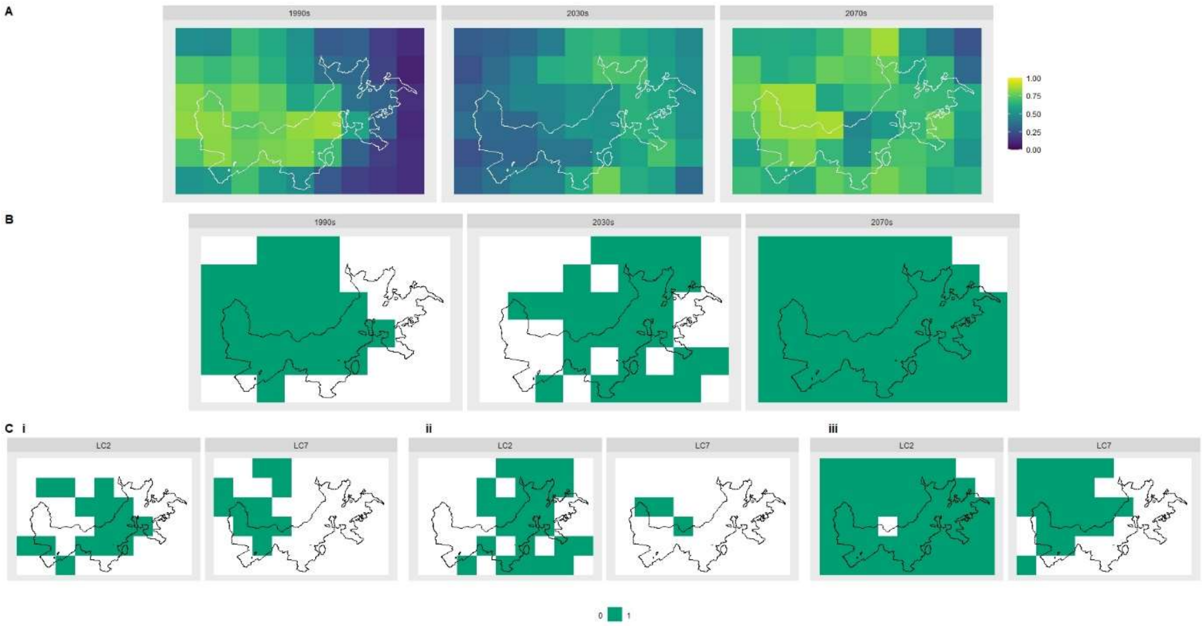


Figure 3.5: Abergwesyn Common case study Maxent model results and land cover estimates. A) Maxent model of climate suitability, the closer the value to 1, the greater likelihood of that area being climatically suitable for the golden plover. B) Threshold Maxent results using 'maximum test sensitivity and specificity cloglog threshold'. C) Areas of Abergwesyn Common likely to contain suitable climate and land cover. i) 1990s, ii) 2030s, iii) 2070s. LC2 = Grassland, scrub or shrub, LC7 = swampy or often flooded vegetation.

3.4 Discussion

3.4.1 Conservation implications

Cold-associated and habitat specialist species are predicted to be the most vulnerable to climate and habitat change. Habitat specialist golden plover and migrant whinchat are predicted to have the least amount of suitable climate and habitat space in the future. This is similar to Pearce-Higgins *et al.*, (2015) who identified that generalist species were less affected than specialists. Even with these vulnerabilities, all species have the potential to expand their ranges, which has been suggested in previous research (Massimino *et al.*, 2017; Pearce-Higgins *et al.*, 2017; Pearce-Higgins and Crick, 2019). It was not found that resident species were affected more than the migrant species (Pearce-Higgins and Crick, 2019), especially when comparing the whinchat and wheatear, with similar life histories. The most abundant species, meadow pipit and skylark, are projected to experience the greatest increases in suitable climate space, potentially due to their generalist traits and current abundance.

Habitat type has a larger impact on potential suitable space than climate change for these five species. This is similar to other studies in the UK and globally, with climate not being the determining factor of species distributions (Beale, Lennon and Gimona, 2008; Rich and Currie, 2017; Vermaat *et al.*, 2017; Liang *et al.*, 2021; Tourinho *et al.*, 2022). Human-influenced croplands and grassland, scrub and shrub habitats provided the most suitable climate space in the 1990s, 2030s and 2070s for all species in this study, with some increases in suitable habitat and climate space over time with climate change. This is similar to Vermaat *et al.*, (2017) where dry grassland habitats saw 50 % bird species increasing. However, distribution increases in these habitats are dependent on human activity alongside climate and land cover availability. It has been established that habitat management can have a greater effect on species distributions and prevalence (Schwartz, 2012; Goodenough and Hart, 2013) regardless of climate, and that habitats in poor condition are likely to be more susceptible to climate change (Segan, Murray and Watson, 2016). Therefore, without some management for wildlife, these habitats will be unable to support the studied bird species even if they are present.

Impacts of climate change are greater in the 2030s than the 2070s, with any contractions of range under climate and/or habitats seen only up to the 2030s. This is unusual as, with global temperatures projected to increase beyond the 2030s (Masson-Delmotte *et al.*, 2018a), it could be hypothesised that the impacts would become more severe. However, there is some evidence to suggest that increasing winter and spring temperatures may result in long-term population increases in some resident UK bird species (Pearce-Higgins *et al.*, 2015), which could be translated to future climates as shown in our research. Additionally, species are predicted to expand distributions northwards without contraction of southern ranges, which has already been observed in the UK (Massimino, Johnston and Pearce-Higgins, 2015). However, these results suggesting population increases only show areas of land where climates are potentially suitable, and not where a species is either currently residing or is able to inhabit. Therefore, these expansions of potential species distributions can be considered a best-case scenario for future distributions when considering conditions under average temperatures and precipitation rates, with consideration of current population sizes, species migration abilities, and other factors such as shelter, food and land cover availability required to provide a more realistic picture of future distributions.

As there are limited negative impacts from climate change for all five species, other factors may have a greater effect on species distributions. Even though habitat did constrain distributions more than climate, each species experiences possible range increases for all habitat types under future conditions. Dispersal could have significant impacts to species' ability to access sites of increasing climatic suitability (Hellmann, Alkemade and Knol, 2016). Fragmented habitats or barriers of unsuitable habitats are likely to significantly impact a species ability to reach suitable space (Segan, Murray and Watson, 2016; Pearce-Higgins *et al.*, 2017), if the area they currently inhabit becomes unsuitable. Creating new habitats adjacent to currently occupied areas (Synes *et al.*, 2020), to create stepping stones (Aben *et al.*, 2016), is one way to reduce these impacts of fragmented habitats, which could occur in future projections. If species, such as the specialist golden plover, are unable to reach the variety of habitats required for their life history then populations will decrease regardless of if they are within suitable climate space. Finally, while distributions have the potential to increase, abundances of species are more vulnerable to change (Renwick *et al.*, 2012; Johnston *et al.*, 2013; Massimino *et al.*, 2017), with impacts from habitat management (Douglas *et al.*, 2017) alongside climate.

The findings presented suggest that species-specific models are required to fully understand how different bird species are likely to react to climate change, especially when suitable habitats are included in analysis. This will result in targeted policies with the potential to improve habitat connection and availability to vulnerable species (Vermaat *et al.*, 2017).

3.4.2 The Case Study – Abergwesyn Common

There are predicted to always be suitable areas of climate space for the golden plover on Abergwesyn Common up to 2080. When investigating the case study results for Abergwesyn Common, two potentially suitable land cover types were observed at the baseline and predicted for the future. The golden plover relies on a variety of habitat types (Whittingham, Percival and Brown, 2001), mostly covered by one of these present (LC2) (Pearce-Higgins and Yalden, 2004). However, these grassland and scrubby habitats require specific plant and prey species to support the plover and without these, the birds are unlikely to thrive due to food availability and shelter requirements (Pearce-Higgins, 2011). Cranefly (*Tipulidae*) larvae and adults are especially important as a food source for young plover chicks, with positive correlations between predation of these insects and plover use of grassland and bare peat areas (Pearce-Higgins and Yalden, 2004). There are areas of grassland (LC2) predicted to be present in the future within areas of suitable climatic space, but bare peat areas are lacking in future projections. However, previously it was mentioned that areas of Abergwesyn Common consist of degraded peatland, with some moves to begin widespread restoration. If small areas of the Common were maintained as bare peat as part of a mosaic of grassland, peat-bog and wetland areas, then the potential for an increase, or at least maintenance, in distribution and abundance of golden plovers is more likely. This suggests that there are climate and land cover conditions suitable for not only species presence, but food availability at Abergwesyn Common currently and in the future, which may require targeted restoration and ongoing conservation actions.

Over half of all ecoregions are predicted to become impacted by habitats loss in this century under RCP8.5 emissions scenarios (Segan, Murray and Watson, 2016), the same extreme scenario used in this study. Wetlands are forecasted to become more vulnerable (Britton *et al.*, 2017) with habitat loss and fragmentation, and climate change decreasing some vulnerability in shrublands (Segan, Murray and Watson, 2016). This contradicts our findings, with scrubland (LC2) and wetlands (LC7) within suitable climate space increasing for every species, although wetlands saw the smallest increases. If habitats become more fragmented, as our results suggest, even increasing the overall amount of these may not benefit the plover, as they require a mosaic of habitats (Whittingham, Percival and Brown, 2001; Pearce-Higgins and Yalden, 2004), confounded by some contraction of ranges under climate change.

Extracting results from country-wide predictions for individual case studies is useful and provides insights into risks at finer scales alongside broader trends. Results at the Abergwesyn Common scale do show spatial and temporal variability, suggesting that there are predicted changes across the site as have been examined. Scaled results in this case are likely to be more useful than those identified through the threshold as threshold results predict the majority of the site to be suitable climatically for the plover, which may not aid in making conservation decisions.

3.4.3 Model choice and input selection

This study suggests that UKCP18 daily climate data from the CPM at the local 2.2 km spatial scale are likely to produce the most accurate models of future distributions for the species studied when compared to the larger scale 12 km data. The higher spatial resolution climate data allows the use of higher spatial resolution bird data for presence modelling, with less data excluded when controlling for pseudoreplication and autocorrelation. Additionally, the 2.2 km data has more information about detailed local climate than the 12 km layers, and provides useful ideas about site level impacts, along with country-wide trends about how climate may affect species distributions. While such local data has not been used extensively (Coll *et al.*, 2010; Feldmeier *et al.*, 2018) in species distribution models, this study shows that these can produce robust future projections. This supports previous findings that showed Maxent performance declining at resolutions greater than 4 km (Farashi and Alizadeh-Noughani, 2018). Additionally, without use of the 2.2 km data, any site level case study would be unlikely to produce detailed results able to make informed decisions about site or regional conservation, although this does depend on the scale of the site in question. Although only one member of the UKCP18 model was utilised due to data processing time constraints, this study provides good information about the useability of the data and incorporating further members will only improve predictions. Local adaptation to climate impacts can deliver biodiversity benefits

(Smith *et al.*, 2022), which could be targeted using the 2.2 km data proven to be useful in this study. Our research highlights the importance of using data at scales that are appropriate for the topic in question (Feng *et al.*, 2019), which could enable scales of conservation to be aligned with scales of climate change projections (Wiens and Bachelet, 2010).

Writing species-specific models improves predictions (Radosavljevic and Anderson, 2014; Aben *et al.*, 2016; Brandt *et al.*, 2017) through tailoring of inputs both in data and models. The use of ENMEval (Kass *et al.*, 2021) to select the best model inputs suggest that the default inputs of features, background points and the regularisation multiplier are not always optimal. Similar studies have also explored this and have suggested that default numbers of background points are not suitable (Feldmeier *et al.*, 2016), but little exploration into values of the other inputs has been noted (Morales, Fernández and Baca-González, 2017; Feng *et al.*, 2019). The models in our study suggest that the default background point number of 10,000 is inadequate for most scenarios, and that testing a wide range of point numbers is required to find the optimum number to use. That the optimum models use a greater number of feature classes suggests that the model is more complex. This could indicate model results explaining better the changes in the study area, but could also suggest overfitting. Therefore, as with all model results, they must be examined carefully, with the remembrance that they do not represent true locations, but a suggested future distribution location. The low regularisation multiplier value in the optimum models (0.5) suggests that the model is more closely fitted to the presence dataset with a more localised output (Phillips, 2017), but the values are not so low to indicate a great level of overfitting.

Using both threshold dependent (TSS and SEDI) and threshold independent (AUC) metrics to evaluate models helps to better identify the best overall results (Merow *et al.*, 2013). However, when investigating the final model results, especially using TSS and SEDI, there is still room for improvement. While all models were better than random, evaluation metrics did not rise above 0.4 for any species. Some observed variability will be due to noise, and variables not included in these models. Other papers analysing model inputs and evaluation criteria also included a range of abiotic and biotic inputs (Aguirre-Gutiérrez *et al.*, 2013; Scherrer and Guisan, 2019), such as soil moisture and nutrients, light, and bioclimatic data exploring seasonality. Changes to management affect bird species abundance (Douglas *et al.*, 2017), which can be controlled to improve prey foraging by chicks (Pearce-Higgins and Yalden, 2004), which the abundance of has a great impact on bird species like the golden plover (Whittingham, Percival and Brown, 2001).

When examining the influence of each climate variable of monthly average temperature and precipitation in the breeding season to the model results, about half had no influence on the results.

However, the minimum temperature from the coldest month (February) had a large contribution to all final Maxent models bar those for the Skylark. This suggests that extremes of conditions have a large impact on species distributions, which may be the case for other variables not studied in this thesis such as extreme storms. All variables were included to aid in comparison with the wider literature, but removing these could produce more accurate results. Overall, using packages such as ENMEval as part of the modelling procedure enables greater certainty that results are robust and fit for purpose. This enables the information used in decision making to be improved and contribute to more useful integrations of scientific predictions into nature conservation.

The choice of threshold is likely to have a large effect on model results (Cao *et al.*, 2013), and potentially future conservation activities. This choice is often largely subjective, but can have a big impact on how results are interpreted and used. Thresholds which maximise the sum of sensitivity and specificity have been found to be the most accurate (Jiménez-Valverde and Lobo, 2007). The *maximum test sensitivity and specificity* threshold used in this study has been utilised in a number of others (Aguirre-Gutiérrez *et al.*, 2013; Liu *et al.*, 2013; Liu, Newell and White, 2015; Feldmeier *et al.*, 2018; Shabani, Kumar and Ahmadi, 2018; Feng *et al.*, 2019) investigating suitable climate space for species, future prevalence and potential spatial shifts. While it may overestimate the amount of space that is likely to be climatically suitable, areas are not missed that may be important. Additionally, presenting larger areas of potentially climatically suitable space at a case study site enables expert local knowledge to pinpoint areas for conservation action.

There is often an emphasis on including estimations of the effect of bias, such as from sampling, in studies (Merow *et al.*, 2013). In our study, models attempting to incorporate bias through background point selection are not significantly different to those run with completely random background points when tested statistically. Results were different, by only > 0.1 % between runs. Keeping models as simple as possible has been found to increase reliability and reproducibility (Bell and Schlaepfer, 2016), with simple ecological niche models providing better results than complex models when exploring climate-driven changes to distribution extents in British breeding birds (Fordham *et al.*, 2018). The BTO data used in this study had already been bias checked and biases accounted for before publishing, suggesting why biases had little effect on the results.

3.5 Conclusions

The use of UKCP18 2.2 km climate data is useful when modelling species shifts in relation to climate change. Results at the finer scale were more statistically accurate than those at the larger 12 km scale in predicting species distributions under baseline and future climates. Additionally, local climate data provides detailed information at the site scale, useful for nature conservation. Tailoring species distribution models to specific species produces more realistic results than using default model inputs. It is demonstrated in this chapter that some default inputs to widely used Maxent models, such as background point number and regularisation multiplier values do not, in this study, produce accurate results.

Overall, climate space is likely to increase for the species analysed over the next century. Specialist species are predicted to see the smallest increases in space, but still potentially benefit from climate change. When incorporating habitat and land cover, the amount of suitable space decreases. Land cover and management is likely to have a greater impact on species than climate change, although both will affect a species individually.

While climate and land cover change will alter natural areas and affect the species in this analysis, there is a chance, due to potentially positive climate-only impacts, that species could thrive with the right management of landscapes and monitoring of populations.

Chapter 4: Assessing the frequency and severity of potential future fires under climate change: A peatland case-study in the Welsh uplands exploring the future of controlled burning.

Abstract

Fire risk in the United Kingdom is increasing, with greater extremes of warm weather and prolonged dry periods expected to occur under climate change. Peatlands, diverse ecosystems storing vital amounts of carbon, are under greater threat from fires than previously. Controlled burning has been used to manage upland areas for conservation and private activities such as grouse rearing, often at the detriment to natural systems. Dedicated projects are currently predicting short-term fire risk in the UK with on-going research to evaluate this risk at larger temporal scales and at greater detail. The UK has committed to net zero emissions by 2050. Peatlands are central to carbon sequestration in the UK, with healthy peatlands locking in the greatest amounts of carbon over time. The Canadian Forest Fire Danger Rating System (CFFDRS) was developed to forecast fire risk to Canadian peat forests. This model has been used and adapted worldwide to calculate short-term risk from fires in a variety of climates.

Estimations of baseline and future fire risk to an upland peatland in Wales on the Ysbyty Ifan Estate using the CFFDRS were tailored to site conditions. Three metrics of fire risk are calculated; fire season length, Fire Weather Index (FWI) and Head Fire Intensity (HFI) for three time periods. Fire season predictions were calculated with default values and values of temperature from known fire days as adjusted methods. Fire risk metrics were validated using data from fires on-site in March 2003, April 2003, and April 2015. Future climate layers were from the UKCP18 daily projections at the 2.2km scale.

Fire seasons are predicted to increase in length under all future scenarios using both default methods, and those adjusted to known fire days. The conditions under which fires may be more likely to occur (FWI) increased under climate change projections. FWI increased the most between the 2030s and 2070s, with a reduced fire risk between the 1990s and 2030s. The largest single percentage change in FWI between the 1990s and 2070s was a 745% increase for the month of October. With similar trends in HFI compared to FWI, decrease in fire strength is predicted from the baseline to the 2030s and an increase to the 2070s. Fires if they do start in the long-term, are likely to become more intense under climate change, as HFI could increase by a maximum of 700 % between the 1990s and 2070s.

Our research suggests that peatlands are likely to become more vulnerable to fires in the future. Additionally, it is indicated that fire risk in frequency and severity of potential fires is likely to increase throughout all months of the year, with some of the biggest increases in risk in months currently considered safe. This study suggests that controlled burning of peatlands is not suitable management for every site when considering carbon sequestration targets and risk to ecosystems. UKCP18 data provides useful insights into these trends, with high validation accuracy for one metric (FWI). Bias correction could improve validation with other fire risk metrics. The results present the first integration of long-term climate change with a tailored version of the CFFDRS to a site in Wales. It is possible to use this model to investigate fire risk under future conditions, but further work needs to be done to improve applicability to landscapes not included in the model.

4.1 Introduction

Peatlands are highly important natural landscapes, providing a range of ecosystem services, perhaps most notably as carbon stores (Lavoie, Paré and Bergeron, 2005; Limpens *et al.*, 2008; Searchinger *et al.*, 2018; Young *et al.*, 2018; Morecroft *et al.*, 2019). These habitats are home to a diversity of birds (Pearce-Higgins and Yalden, 2004), invertebrates (Carroll *et al.*, 2011) and plants, including *Sphagnum* species (Noble *et al.*, 2019) which are vital for peat formation and water quality. Peatlands have the potential to further contribute to nature-based solutions to climate change, acting as a carbon sink, promoted by the UK government and environmental organisations (Stafford *et al.*, 2021). However, many UK peatlands are currently in a degraded state and further at risk from impacts such as fire, while also risking a transition to a source of carbon emissions.

UK peatlands are estimated to occupy approximately 12 % of total UK land area (Evans *et al.*, 2017), containing around 3000 Mt of carbon (Dunn et al., 2021) with about 22% of this remaining in near-natural condition. However, over three quarters of the UK's peatlands are in a modified state, transitioning from a historical greenhouse gas (GHG) sink of approximately 0.25 Mt CO_2e yr^{-1}, to a total source of over 23 Mt CO_2e yr^{-1} (Evans *et al.*, 2017). The UK Climate Change Risk Assessment in 2017 recognised that for Wales, there was more action needed to restore degraded carbon stores, and particularly those in peatlands (ASC, 2017). In this report, over 75 % of Welsh peatlands have been impacted by land-use activities such as drainage, grazing, neglectful management, and conversion to grassland. Due to this, these Welsh peatlands have become a carbon source, currently estimated at 0.7 Mt CO_2e yr^{-1} (ASC, 2017). While this makes up a small proportion of the total UK emissions from peatlands, any emission of GHGs has a negative impact on climate change. Climate modelling of sensitive blanket bog peatlands suggest that under high emissions scenarios, these ecosystems are likely to shrink by 84 % by the end of the century under climate change alone

(Gallego-Sala *et al.*, 2010). This would result in large GHG emissions from these environments, and negatively affect species of conservation and economic importance. Any other impacts are therefore likely to exacerbate this change and further impact peatlands. In 2019, the UK government committed to ‘net zero’ GHG emissions by 2050 under the 2008 Climate Change Act (UK Government, 2008). Large scale of conservation action is required if the aims of net zero as set out by the UK government’s 25 year plan (DEFRA, 2018) are to be met (Field *et al.*, 2020). Restoration of key carbon sequestering habitats is recognised as a critical step towards this target. Over long time periods, peatlands in good condition are able to store far greater quantities of carbon than woodlands of a similar size (Gregg *et al.*, 2021). However, increases of risk in terms of frequency and severity of fires could limit the likelihood of reducing carbon emissions to net zero as peatlands grow as sources of emissions rather than sinks. The UK Government has pledged over £750 million in the next few years to restore peatlands and other carbon storing habitats (BEIS, 2021). Ensuring these peatlands are restored robustly will contribute to aims of reducing emissions from natural resources by up to 50 % by 2035 (BEIS, 2021), but further damaging fire events could reduce these opportunities. Peatlands are central in the move to net zero in the natural world, investigating future trends of risk from fire will aid in understanding how best to maximise these sinks of carbon.
Many areas of moorland in the UK, which often contain peat, are managed by controlled burns (Bedia *et al.*, 2015; Blundell and Holden, 2015; Douglas *et al.*, 2015; Davies, Kettridge, *et al.*, 2016; Morecroft *et al.*, 2019), with implications for future climate. While these burns are generally used to maintain heathland habitats for reared grouse management (Douglas *et al.*, 2015; Davies, Kettridge, *et al.*, 2016; Harper *et al.*, 2018), and are thought to mimic natural fire regimes and reduce wildfire risk (Davies, Kettridge, *et al.*, 2016), greater damage is caused to the natural environment. Controlled burns lead to lower rates of peat accumulation, reduced local water quality (Douglas *et al.*, 2015) and impacts the microbial community, affecting carbon storage (Davies, Kettridge, *et al.*, 2016). Additionally, greater burning to expand the area over which grouse shoots can operate negatively affects the natural ecosystem through losses of habitat for upland bird species (Douglas *et al.*, 2017), and disturbance from human presence. Specialist bird species, like the golden plover, did increase in abundance post-fire, but only during the initial post-burning period (Douglas *et al.*, 2017), with reductions in all other studied species. Low severity fires may or may not have a significant negative impact on peatland structure (Taylor, 2014), with peatland condition a large factor in the potential impact of a fire (Davies, Domènech, *et al.*, 2016). The idea that low severity fires don’t negatively affect peatlands is highly contentious, as even these events lead to decreased water availability (Lukenbach *et al.*, 2015) and *sphagnum* damage (Noble *et al.*, 2019). High severity fires have the largest negative impacts to peatlands (Davies, Kettridge, *et al.*, 2016). These dangerous,

fires cause large emissions of carbon (Davies, Kettridge, *et al.*, 2016), expose peat (Brown *et al.*, 2015), and have been associated with lower rates of peat accumulation (Kuhry, 1994; Blundell and Holden, 2015). These intense fires also cause the greatest damage to important *sphagnum* mosses (Noble *et al.*, 2019), which are vital for peat growth. Controlled burns can spiral into high intensity fires, significantly increasing the risk to ecosystems. Research suggests that these controlled burns should occur on rotation roughly every 10 to 25 years (Davies, Kettridge, *et al.*, 2016), although the number of burns has increased over past years (Douglas *et al.*, 2015) which may compound negative impacts if sites do not recover. It is essential to restore peatlands to a resilient state, and controlled burns, planned in rotation may be part of the toolkit. Understanding the risk from more dangerous potential fires is essential to ensure the sustainable future of peatlands as biodiverse landscapes, and important carbon stores.

Wildfire is a semi-natural hazard, the conditions for which are determined by the surrounding environment, while ignition is often a result of anthropogenic activity (Arnell, Freeman and Gazzard, 2021). There is increasing awareness of the devastating impacts of wildfire, especially in vulnerable areas of the globe including Australia (Wang *et al.*, 2022) and California (Duine, Carvalho and Jones, 2022). Studies have investigated the current risk of wildfire to the UK (Arnell *et al.*, 2021; Perry *et al.*, 2022), North America (Waddington *et al.*, 2012) and the Mediterranean (Bedia *et al.*, 2018), with widespread understanding that wildfire risk will increase with climate change, especially for vulnerable habitats (Fernández-García *et al.*, 2022; Velasco Hererra *et al.*, 2022). Additionally, research has investigated the interactions between fire and peatlands (Benscoter *et al.*, 2011; Nelson *et al.*, 2021), with an understanding that increased fire risk is likely to contribute to the release of carbon from peatlands (Nelson *et al.*, 2021). This will contribute negatively to climate change, and fuelling a feedback loop, increasing the vulnerability of peatlands to extreme weather events.

The vast majority of UK wildfires are on peatlands in lowland and upland heath areas (Benscoter *et al.*, 2011; Santana and Marrs, 2014; Noble *et al.*, 2019; Arnell, Freeman and Gazzard, 2021; Perry *et al.*, 2022), many of which are degraded due to human activity and vulnerable to further change. Future projections of fire danger are predicted to be greatest in late summer under a scenario of 4^{o}C of warming (Perry *et al.*, 2022), with significant increases in risk from wildfires. Much of the UK has not experienced widespread impacts from fire, with this potentially likely to change in the future (Perry *et al.*, 2022). The 2017 UK Climate Change Risk Assessment (CCRA) recognised fire risk as a serious, although uncommon risk to natural landscapes in Wales (ASC, 2017). Current modelling incorporating climate change suggests an increase of 30 to 40 % in wildfire risk in Welsh National

Parks by the 2080s (ASC, 2017). This does not include risk from human activity, accidental or intentional, yet this still indicates a substantial increase in risk in the future.

There are a number of metrics used to calculate the potential risk for fire conditions, many developed from the Canadian Forest Fire Danger Rating System (CFFDRS) (Waddington *et al.*, 2012; Wang *et al.*, 2017; Nelson *et al.*, 2021). These were mostly developed to predict potential fire events in boreal forests. Using a variety of weather and habitat metrics, CFFDRS predicts daily fire risk, fire behaviour and indices about length of fire season (Wotton, 2009; Wang *et al.*, 2017). The model has been in development since the 1970s (Turner and Lawson, 1978; Lawson and Armitage, 2008) and is used extensively in Canada and internationally. The model appears to be relatively easily edited in an attempt to make daily site specific predictions (Waddington *et al.*, 2012; Tsinko *et al.*, 2018) using local weather and climate inputs. However, the main calculations for the System relate to a forested ecosystem (Turner and Lawson, 1978; Lawson and Armitage, 2008), often in commercial plantation and on peat soils. Calculating fire behaviour metrics using local data but keeping to default inputs in CFFDRS may be more likely to result in unrealistic fire behaviour patterns and risk indices for different habitats, such as upland peatlands. This is due to the difference in above ground combustible material in a North Wales upland peatland featured in this chapter, and the forested peatlands in Canada that the model was developed for.

Despite many publications exploring the future likelihood of fires on peatlands due to climate change (Nelson *et al.*, 2021; Rein and Huang, 2021), estimating how fire risk could change spatially is covered less. Studies have investigated fire in forestry (Turner and Lawson, 1978; Wotton and Flannigan, 1993; Gazzard, McMorrow and Aylen, 2016), the impacts of fire to peatland soil content and health (Rein *et al.*, 2008; Magnan, Lavoie and Payette, 2012; Noble *et al.*, 2019), vegetation recovery post-fire events (Lukenbach *et al.*, 2015; Lees *et al.*, 2021), and vegetation responses to rewetting (Renou-Wilson *et al.*, 2019) and climate change (Basińska *et al.*, 2020; Ziegler *et al.*, 2021).

Research aims

This chapter tailors the CFFDRS model to a partly restored upland peatland in North Wales, UK and evaluate the ability to use this tool to predict how fire risk and behaviour is likely to change in the future under climate change. A popularly used metric of the CFFDRS in the FWI is evaluated, with consideration of different ways to examine fire risk through HFI and potential fire season length. Additionally, weather data from the Climate, Hydrological and Ecological Research Support System (CHESS) dataset was used to validate the CFFDRS model with known dates of fires at the case study site, and predict these fire risk variables into the future using Met Office UKCP18 climate projections for the 2030s and 2070s. Reports have outlined a need for empirical research into the risk of wildfires to Wales (Jollands, Morris and Moffat, 2011) and this study contributes to this need through evaluating these CFFDRS metrics and projecting risk spatially and temporally.

This chapter examines if and when there are likely to be changes to fire risk and evaluate whether the high resolution UKCP18 scenarios can be used to make fire risk predictions for a partially restored peatland site of historic and conservation value in the uplands of North Wales. There has not been, to our knowledge, research in the UK which examines these site level changes in peatland risk to sites in this geographical area. Peatlands are an important part of the net zero strategy and assessing the risk of increased fire is crucial to their longevity for biodiversity and contribution to solving the climate crisis.

4.2 Methods

4.2.1 Study site

The Migneint peatland is part of the Ysbyty Ifan Estate in North Wales (figure 4.1), which is the largest single estate cared for by the National Trust. The Estate comprises of 51 farms situated on open moorland, peatland, and river valleys. Designated as a SSSI, the Migneint is a large stretch of moorland and blanket bog on the south of the Estate. Peatland restoration over the past decade has rewetted the site through a change in farming practices and grip blocking. There has been a good uptake of sphagnum mosses, with a greater amount of water now held on the peatland. Restoration work is ongoing in close collaboration with the National Trust, local farmers, and other conservation organisations.

There have been a number of fire events at the Ysbyty Ifan Estate on the Migneint peatland over the past decade. I collated fire data from 1st November 2000 to 8th April 2022 from the Moderate Resolution Imaging Spectroradiometer (MODIS) (C6.1) and Visible Infrared Imaging Radiometer Suite (VIIRS) (SUOMI C2 and J1 C1) databases. Data is available from November 2000 and analysis started in April 2022, hence the date range for data collation. These comprised of five data sets of archive and Near Real-Time (NRT) data. There were 54 fire events on the estate since 2000 (figure 3.1) over seven individual days within the study area. There was also evidence of a fire in March 2003 from personal communications, but no corresponding data or dates. While there are no records of managed burning on site the evidence for known fires on site are during seasons when these burns can be undertaken. Four known fire days (KFDs) are used in this study, 17th, 18th and 19th April 2003 and 22nd April 2015.

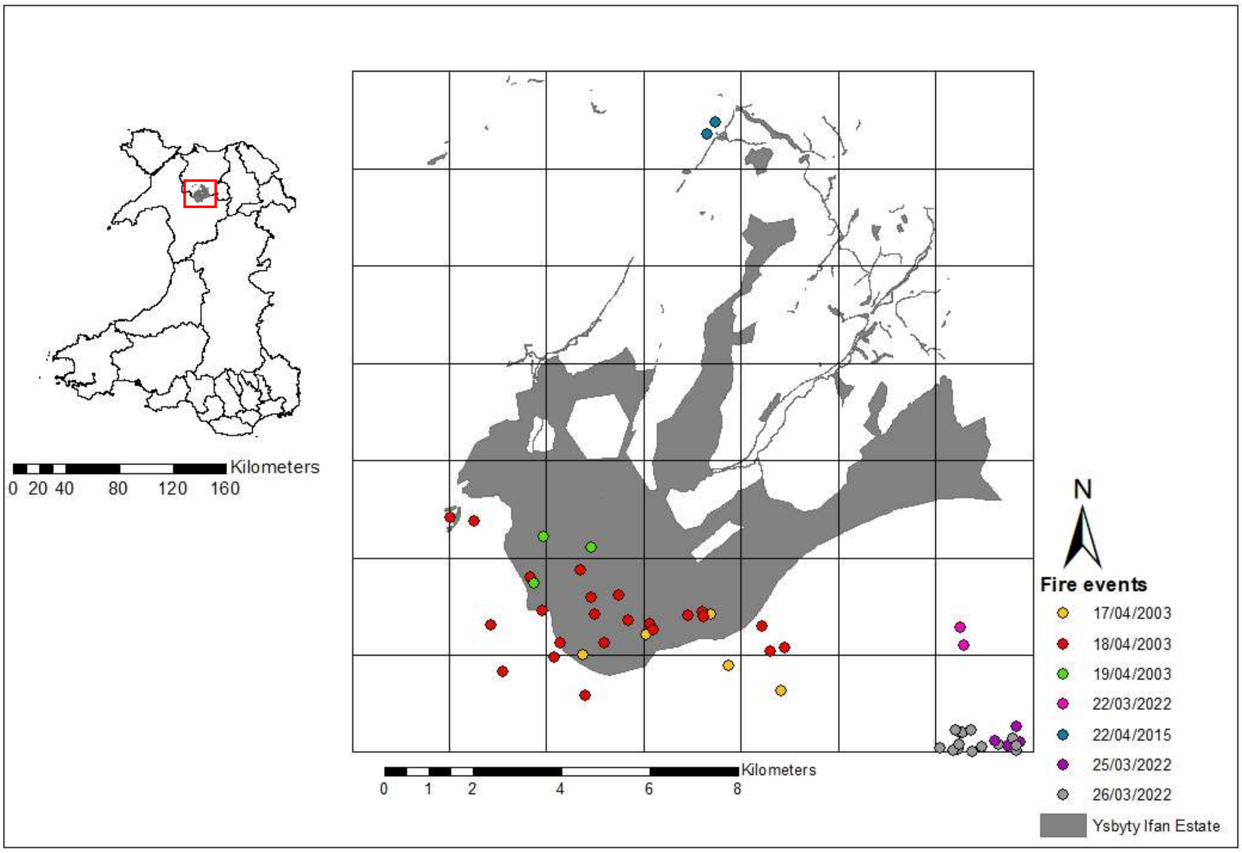


Figure 4.1: The location of the Ysbyty Ifan Estate within Wales, UK, and locations of known fire days (KFDs) at the case study site.

4.2.2 Climate data

The Met Office have developed the UKCP18 climate predictions (Lowe *et al.*, 2018; Kendon *et al.*, 2019) as an update to the UKCP09 projections of future climate change in the UK. Here the Convection Permitting Model (CPM) 2.2km local projections downscaled from the 60 km global CMIP5 climate models using the Met Office HadGEM3 model are used. These projections were run for 12 members to explore the range of futures expressed in the model. The first model member (model 01) based on the HadGEM3-0.5 model without perturbed physics has been used in this analysis.

Five climate variables were used in analysis, mean temperature (^{o}C) (tas), mean relative humidity (%) (rh), mean wind speed (m s^{-1}) (sfcWind), mean precipitation (mm day^{-1}) (prec) and maximum temperature (^{o}C) (tmax) All variables were at the 2.2 km spatial scale and for RCP 8.5 which predicts global average temperatures increasing by over 4^{o}C by the end of the century. These data layers were re-gridded from the rotated grid latitude / longitude (37.5, 117.5) (Fung, 2018) to British National Grid. Data processing were done using R 4.0.2 (R Core Team, 2020), the sf (v0.9-8; Pebesma, 2018), ncdf (v1.17; Pierce, 2019), raster (v3.4-10; Hijmans, 2021), rgdal (v1.5-23; Bivand *et* *al.*, 2021), and PCICt (v0.5-4.1; Bronaugh and Drepper, 2018) packages. This data was averaged into three 20-year predictions of climate for five variables: average temperature, average relative humidity, average wind speed, average precipitation, and maximum temperature. Full reproducible code detailing re-gridding and averaging of climate data available on request. Baseline data was between 1980 to 2000 (1990s), with two future projections between 2020 and 2040 (2030s), and 2060 to 2080 (2070s). Hereafter, the time periods will be referred to as the 1990s, 2030s and 2070s. These spatial data for the UK were cropped to the Ysbyty Ifan Estate (figure 4.1) for ease in data processing time during analysis. This resulted in 49 grid squares of data across the case study site (figure 4.1).

4.2.3 Weather data

The Climate, Hydrological and Ecological research Support System (CHESS) dataset (Robinson *et al.*, 2020a, 2020b) comprises of daily mean meteorological variables largely drawn from the Meteorological Office Rainfall and Evaporation Calculation System (MORECS) data downscaled to a 1 km resolution using information about the impact of topography. MORECS calculates the evapotranspiration and soil moisture deficit from daily values of five weather variables: hours of sunshine, air temperature, vapor pressure, wind speed and rainfall (Hough and Jones, 1997). This data is available via the Centre for Ecology and Hydrology (CEH). Metrics of near surface air temperature at 1.2 m (K), daily temperature range (K), precipitation from the Gridded Estimates of Areal Rainfall (GEAR) (kg m^{-2} s^{-1}) dataset, near-surface wind speed at 10 m (m s^{-1}), near surface specific humidity at 10 m (kg kg^{-1}) and surface air pressure (Pa) are included to calculate the same variables used in predictions (see 4.2.2). All variables were converted to the same metric as the UKCP18 data (see 4.2.2) e.g., specific humidity, atmospheric pressure and mean temperature were used to calculate relative humidity. Data was extracted for two years of KFDs at the case study site, resulting in 49 grid squares of five variables of weather data for 2003 and 2015. Data for 2022 was not available and therefore these KFDs were excluded from further analysis. R code for all weather data processing is available on request.

4.2.4 Canadian Forest Fire Danger Rating System (CFFDRS)

Three metrics of fire risk from the CFFDRS were calculated to estimate risk at the baseline and future at the case study site. First, UKCP18 and CHESS data were converted into the units required for the CFFDRS. Then, fire season, Fire Weather Index (FWI) and Fire Behaviour Prediction (FBP) calculations were run. From these, results are explored relating to fire season, FWI and Head Fire Intensity (HFI). Additionally, the Fine Fuel Moisture Code (FFMC) was investigated using thresholds as described in (Davies and Legg, 2016a; De Jong *et al.*, 2016) and Initial Spread Index (ISI) (Davies and Legg, 2016a).

Hereafter, fire risk refers to the overall risk from fire at the site based on multiple metrics, fire danger refers to results of FWI with fire strength referring to HFI.

4.2.4.1 Fire season

Fire season length was estimated using default and tailored settings for baseline and future climate scenarios. There are multiple thresholds that trigger organisations to begin the weather recording season to identify a potential fire season. In Canada, the CFFDRS model begins this *'after three consecutive days of noon temperatures greater than 12^{o}C for areas with no snow cover'* (Turner and Lawson, 1978). The National Fire Danger Rating System (NFDRS) in the USA starts their weather recording season *'four weeks before the first fire season is to start'*, with each region deciding when this is (Wotton and Flannigan, 1993). There is little information as to how the end of a fire season is calculated. A study by Wotton and Flannigan (1993) developed thresholds based on the previous methods, with fire seasons starting after three consecutive days of maximum temperatures greater than 12^{o}C and ending after three consecutive days of maximum temperatures below 7.2^{o}C. These thresholds are useful, although there is little justification for their use. Thresholds were developed for the case study using local temperature and records of fire occurrence.

Temperature was used as an indicator of the start and end of fire seasons, to fit with previous research and due to its strong annual cycle (Wotton and Flannigan, 1993). Additionally, temperature data is an accessible metric being readily available across the UK at multiple different scales. Using CHESS data (see 3.2.3) highest maximum temperature at the case study site for the three days preceding and the lowest maximum temperature following each fire event in 2003 and 2015 were calculated. These methods were developed to be similar to those used in Wotton and Flannigan (1993), but with maximum temperature thresholds taken from the study site to give a more accurate representation of temperatures under which fires were more likely to ignite. Maximum temperature data for the 2022 fires was not available in the CHESS database. This resulted in an overall maximum temperature before a known fire event of 18.5^{o}C and after a fire event of 12^{o}C and was taken from the 2003 fire event between the 17th and 19th April.

Two thresholds of fire season length at the case study site were tested –

1. CFFDRS default settings
2. Highest maximum temperature in the three days before a known fire event (18.5^{o}C) and lowest maximum temperature in the three days after a known fire event (12^{o}C). Hereafter, these are referred to as '2003 adjusted'.

4.2.4.2 Fire Weather Index (FWI)

The Fire Weather Index (FWI) is a commonly used metric which establishes the daily fire danger level for an area. While this is often used and updated in real time, here I am assessing whether these metrics can be used in long-term predictions of future fire danger, and how this danger may change spatially and temporally. FWI has a dimensionless scale, so results are presented as the percentage change of FWI to give an idea of change in risk. FWI calculations were run in the CFFDRS package using Met Office UKCP18 20-year averages of mean temperature, humidity, wind speed and precipitation. Default settings were used as Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC) and Drought Code (DC) values are calculated for each consecutive day using previous inputs and therefore viable values of these metrics are used after the first day's calculations. These three input values relate to different fuel moistures of: forest litter fuels under the shade of the forest canopy (FFMC), decomposed organic material underneath litter (DMC) and moisture content deep in the soil (DC). High values of all these codes indicate drier fuels and potentially higher fire risk (Wotton, 2009). A previous study (De Jong *et al.*, 2016) suggested calibration percentiles for FWI. These thresholds were investigated by calculating the 99th and 75th percentiles of the FWI results calculated for the case study area, as these are expected to contain over 50% of all potential wildfires (De Jong *et al.*, 2016).

Additionally, metrics of FFMC and the Initial Spread Index (ISI) which estimates a spread potential of fire based on fuel moisture and windspeed, were calculated and analysed based on thresholds from Davies and Legg (2016) and De Jong *et al.* (2016). Thresholds were: those exceeding 75 for FFMC and 2 for ISI (Davies and Legg, 2016), and those exceeding 72 in spring, 74 in summer and 69 in autumn for FFMC (De Jong *et al.*, 2016). These thresholds, when exceeded, indicate conditions in which managed burning should be avoided due to the risk of development into dangerous wildfires. Scales for both metrics are dimensionless and FWI results for the Migneint which included these two metrics were analysed.

4.2.4.3 Head Fire Intensity (HFI)

The final metric calculated from CFFDRS and tailored to the case study site was Head Fire Intensity (HFI) (kw m^{-1}) which measures the potential intensity of any fire if one were to ignite. Input settings were tailored to the Ysbyty Ifan Estate, most notably the *FuelType* input. Using land cover data from the ESA CCI (Climate Change Initiative) global land cover maps the most common land cover type in each of the 49 grid-squares across the peatland was identified. Baseline land cover data was from 2000, with future land cover from predictions of 2050 developed by ESRI X Clark Labs (Esri, 2021). The closest *FuelType* in the Fire Behaviour Prediction (FBP) model was matched to the most prevalent land cover type at Ysbyty Ifan and selected as the input (table 4.1), with HFI an output from the FBP.

Table 4.1: The land cover types present (2000) and predicted to occur (2050) at the Ysbyty Ifan Estate on the Migneint peatland, and the FuelType they correspond to for the Fire Behaviour Prediction (FBP) calculations in the CFFDRS package.

2000	FuelType input	2050	FuelType input
Grassland	O1B	Grassland, scrub, or shrub	O1B
Tree cover, needleleaf, evergreen, closed to open (>15%)	C7	Mostly needleleaf/evergreen forest	C7
Mosaic tree and shrub (>50%)/herbaceous cover (<50%)	M2		
Mosaic tree and shrub (<50%)/herbaceous cover (>50%)	M2		
Water bodies	WA		

Lidar data for the area was used to compute group slope percentage and slope aspect for each grid-square. Julian Day, FFMC and Buildup Index (BUI) were taken from previous FWI calculations. In order to understand risk from fire intensity, raw values and the change in kW m^{-1} are presented as results.

4.2.5 Model validation

In order to understand the accuracy of the outputs of FWI and HFI at the baseline and future scenarios, models were validated using weather data from fire data at the case study site. FWI and HFI metrics were calculated for 2003 and 2015 at the case study site using CHESS data (Robinson *et al.*, 2020a, 2020b), which resulted in four validation data points. KFD data from 2022 was not used in model validation as CHESS data for the 2022 dates was not available. To assess risk over time and the applicability of FWI and HFI predictions, with comparisons of KFD dates to values of FWI and HFI calculated for 2003 and 2015. These values were used as thresholds of known risk and used to evaluate predictions of projected risk under future climates. While these data points for validation are not extensive, it does provide a very general idea as to whether these metrics of fire risk are, to an extent, an accurate representation of the impacts possible to an upland Welsh peatland.

4.3 Results

4.3.1 FFMC and ISI

Mean FFMC exceeds both proposed thresholds (Davies and Legg, 2016a; De Jong *et al.*, 2016) for all individual months and seasons at all years. Maximum FFMC exceeds all seasonal thresholds at all years as stated by De Jong *et al.*, (2016), and exceeds the threshold set by Davies and Legg, (2016) for 94 % of grid-squares for all years (table 4.2). Maximum ISI exceeds the threshold set by Davies and Legg, (2016) for 81 % of grid-squares for all years (table 4.2). There are reductions in grid-squares experiencing conditions above these thresholds in the 2030s for ISI (table 4.2). However, these reductions are not predicted to also occur for FFMC (table 4.2), suggesting overall risk is continuing in the future.

Table 4.2: The percentage (%) of days in each grid-square over each month that exceed the threshold set by Davies and Legg (2016) for A) Initial Spread Index (ISI) (2) and B) Fine Fuel Moisture Code (FFMC) (75) as to conditions in which managed burning should be avoided.

Month	Threshold	1990s	2030s	2070s
January	ISI > 2	90	0	100
	FFMC > 75	100	98	98
February	ISI > 2	100	0	100
	FFMC > 75	100	100	76
March	ISI > 2	100	0	100
	FFMC > 75	100	100	100
April	ISI > 2	100	61	100
	FFMC > 75	100	100	100
May	ISI > 2	100	100	100
	FFMC > 75	100	100	100
June	ISI > 2	100	100	100
	FFMC > 75	100	100	100
July	ISI > 2	100	100	100
	FFMC > 75	100	100	100
August	ISI > 2	100	100	100
	FFMC > 75	100	100	100
September	ISI > 2	100	100	100
	FFMC > 75	100	100	100
October	ISI > 2	100	12	100
	FFMC > 75	100	100	100
November	ISI > 2	100	0	100
	FFMC > 75	100	100	100
December	ISI > 2	63	0	100
	FFMC > 75	16	12	100

4.3.2 Fire season

Fire seasons are predicted to increase in length under both default and CHESS adjusted inputs in the future under climate change (table 4.3). Greatest increases and amount of time within fire season conditions are seen under the default inputs, with the maximum length of a fire season lasting nearly three years (table 4.3, 2070s). This is fairly implausible, especially within climate conditions in North Wales, even under climate change. The adjusted inputs appear more likely, with a maximum potential increase between 1990s and 2070s of 23% (table 4.3). Other differences between default and adjusted inputs are the total number of fire seasons present in a 20-year period. The adjusted inputs predict a higher number of fire seasons per 20 years, with 1.15 fire seasons per year by the

2070s (table 4.3). However, this is a slight decrease from the baseline (1990s) with a predicted 1.25 fire seasons per year. The default input results suggest that there is likely to be only one fire season per year, so negligible differences between these methods for this metric.

Table 4.3: The estimated mean and maximum total number of fire season in a 20-year period (mean total start, mean total end), length of fire season (days) and length between fire seasons (days) at the Ysbyty Ifan Estate on the Migneint peatland at the baseline (2030s), short-term future (2030s) and long-term future (2070s). Comparing the CFFDRS default inputs (default) and adjusted inputs using temperatures around the 2003 known fires (2003 adjusted) using temperature data for the case study site from the CHESS dataset.

Year	Input	Mean total start	Mean total end	Mean length	Mean length between	Maximum total start	Maximum total end	Maximum length	Maximum length between
1990s	Default	20	20	192	147	21	21	573	227
	2003 Adjusted	25	25	79	256	27	27	169	668
2030s	Default	20	19	208	122	21	20	586	211
	2003 Adjusted	21	21	109	229	22	22	175	626
2070s	Default	21	20	235	88	23	22	1047	167
	2003 Adjusted	23	23	143	192	25	25	208	261

The greatest change in fire season length across the case study site is between the 1990s and 2070s (figure 4.2). Some areas in the south and south-west areas of the Estate could see an increase of up to over three months extra in a fire season during the 2070s compared to the 1990s baseline (figure 4.2, change 1990s to 2070s). This area is where the majority of known fires were seen (figure 4.1), indicating that this area of the site could remain susceptible to fire.

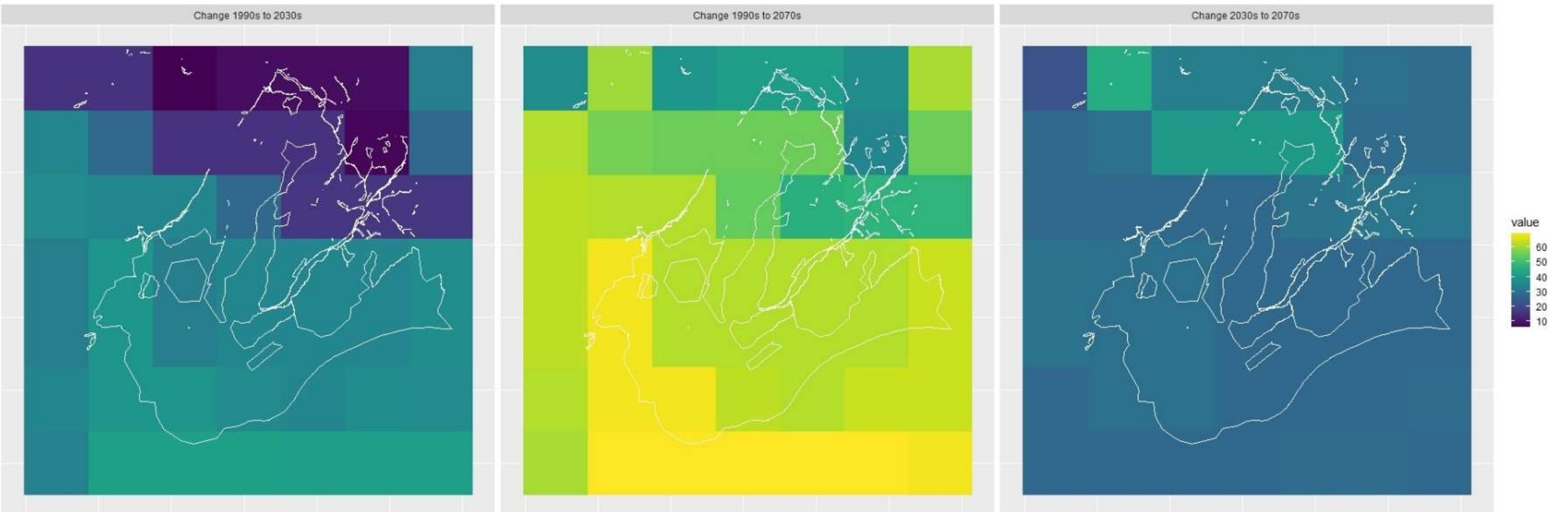


Figure 4.2: Change in the predicted maximum length (days) of a fire season between the baseline (1990s), a short-term (2030s) and long-term (2070s) future and between these futures using inputs adjusted with CHESS data on-site. Value = number of days within a fire season.

4.3.3 FWI and HFI

There are similar patterns in FWI and HFI predictions (figure 4.3). Overall, it is predicted that danger from potential fire ignition and strength from burning fires is likely to increase in the future (table 4.4, 3.5; figure 4.3). On average, FWI is predicted to increase by 143 % and HFI by 21 % across all time periods and grid-squares, with maximum increases of 131 % and 467 % respectively. Greatest change for both metrics is estimated by the 2070s, with average and maximum change in FWI between 2030s and 2070s of 355 % and 334 % and between 1990s and 2070s of 36 % and 716 % for HFI. Mean change of FWI is greatest over time (table 4.4), with maximum change having the largest impact for HFI (table 4.5). Change in FWI and HFI is predicted to decrease between the 1990s and 2030s (figure 4.3, table 4.4 & 3.5), before experiencing large long-term increases far greater than those experienced at the baseline in 1990s.

Peaks of fire risk are predicted to occur in summer months (table 4.4 & 3.5; figure 4.3), under both metrics and for both mean and maximum conditions. Fire risk is likely to be much greater in the 2070s when compared to the 1990s and 2030s in all months other than winter (figure 4.3), although 20-year averages follow similar trends between metric and condition. Predictions for the 2030s suggest two peaks of fire danger for both metrics (figure 4.3), with these potentially less severe than the baseline in mean conditions, with average FWI (figure 4.3A) likely to decrease more than average HFI (figure 4.3C). Even with decreases at the short term (-4.2 % average), mean HFI of a fire igniting in the 2030s is still likely to exceed 10 kW m^{-1} (table 4.5). FWI between the baseline and 2030s is also predicted to decrease by almost half (table 4.4), but it can be estimated that even with a reduction over the short term, danger from fires does not disappear (figure 4.3A & B). Both metrics predict a slight shift later in the year in the peak of maximum fire risk, compared to the mean, in the 2070s (figure 4.3B & D), suggesting a longer fire risk period, as echoed by fire season length predictions (table 4.3).

Percentage change of risk and strength of potential future fires is more varied, with greatest changes between then 2030s and 2070s (figure 4.3E, F & H). However, percentage change for mean HFI (figure 4.3G) follows the same trends between 1990s and 2070s and 2030s and 2070s. Both FWI and HFI are predicted to experience decreases in percentage change between 1990s and 2030s. Only FWI in November (table 4.4), and HFI in June, July, September, and November (table 4.5) are predicted to increase between the 1990s and 2030s. Greatest maximum percentage change of FWI and HFI are likely to occur in March and November (figure 4.3 G & H), suggesting that out of season fires could become more frequent and stronger. There is a large change in the strength of potential fire over time, with maximum fire strength far greater in the 2070s than in the 2030s or 1990s (table 4.5).

On average over all years and grid squares average fire strength is predicted at 24 kW m^{-1}, but with a maximum strength of over 500 kW m^{-1}. However, as seen for all values of FWI (table 4.4), average raw HFI remains fairly low, even at extremes (164 kW m^{-1} in August 2070 (table 4.5)).

These results suggest that severity and frequency of fires are likely to increase across the case study site in the 2070s, but that future conditions in the 2030s average are not predicted to exceed 1990s values, and only slightly exceed 1990s frequency. Maximum HFI has a larger impact than maximum FWI, which suggests that maximum fire strength is likely to increase more than maximum fire danger. However, the reverse is true for average conditions, which may be more likely, with average fire danger (FWI) is predicted to increase more than average fire strength (HFI).

Table 4.4: Mean and maximum percentage (%) change of monthly Fire Weather Index (FWI) between each time period. Mean average = 143.4 %, maximum average = 130.8 %.

Month	Year	Mean	Maximum	Month	Year	Mean	Maximum
January	1990s to 2030s	-74.0	-72.1	July	1990s to 2030s	-17.2	8.5
	1990s to 2070s	-25.1	63.2		1990s to 2070s	147.7	33.2
	2030s to 2070s	118.4	485.2		2030s to 2070s	199.3	22.8
February	1990s to 2030s	-55.0	-63.2	August	1990s to 2030s	-52.3	-44.2
	1990s to 2070s	-12.8	5.8		1990s to 2070s	221.7	123.0
	2030s to 2070s	93.9	187.3		2030s to 2070s	573.9	299.3
March	1990s to 2030s	-75.6	-77.0	September	1990s to 2030s	-24.5	65.9
	1990s to 2070s	1.9	81.6		1990s to 2070s	233.7	189.8
	2030s to 2070s	318.0	691.2		2030s to 2070s	341.8	74.6
April	1990s to 2030s	-56.2	-63.9	October	1990s to 2030s	-64.0	-59.8
	1990s to 2070s	65.3	46.1		1990s to 2070s	203.9	170.7
	2030s to 2070s	277.6	304.4		2030s to 2070s	744.5	572.7
May	1990s to 2030s	-47.5	-49.0	November	1990s to 2030s	22.5	-58.9
	1990s to 2070s	127.8	64.2		1990s to 2070s	290.9	207.7
	2030s to 2070s	334.3	221.7		2030s to 2070s	219.1	649.1
June	1990s to 2030s	-37.8	-18.3	December	1990s to 2030s	-77.6	-56.0
	1990s to 2070s	132.6	99.6		1990s to 2070s	78.2	101.0
	2030s to 2070s	274.0	144.3		2030s to 2070s	694.1	356.4

Table 4.5 The change in Head Fire Intensity (HFI) over time from the 1990s to the 2030s and 2070s. A) Raw HFI (kW m^{-1}) for each time period. B) Change (%) in HFI (kW^{-1}) between each time period.

	A) Raw Head Fire Intensity (HFI) (kW / m^{-1})					
	1990s		2030s		2070s	
	Mean	Maximum	Mean	Maximum	Mean	Maximum
January	2.8	60.7	0.6	11.9	2.1	102.9
February	3.3	81.3	1.2	20.8	2.6	75.1
March	5.7	128.3	1.2	28.8	5.0	152.2
April	10.3	197.1	4.1	65.5	14.3	324.5
May	15.3	299.6	9.6	126.0	35.4	490.3
June	24.4	341.0	18.8	367.7	68.3	1194.2
July	32.1	610.1	31.6	768.4	85.1	1069.6
August	38.1	716.1	20.0	324.8	164.4	3265.5
September	31.9	524.0	34.1	1271.7	134.2	3579.0
October	11.8	323.2	4.7	116.1	36.0	1219.9
November	2.0	80.3	2.1	32.2	6.8	194.6
December	1.2	38.5	0.2	11.4	1.9	63.6
	B) Difference in Head Fire Intensity (HFI) (%)					
	1990s – 2030s		2030s – 2070s		1990s – 2070s	
	Mean	Maximum	Mean	Maximum	Mean	Maximum
January	-2.2	-48.8	1.5	91.0	-0.7	42.2
February	-2.0	-60.5	1.3	54.4	-0.7	-6.1
March	-4.6	-99.5	3.8	123.5	-0.8	24.0
April	-6.2	-131.6	10.2	259.0	4.0	127.4
May	-5.6	-105.6	25.7	364.3	20.1	260.7
June	-5.6	26.7	49.5	826.5	43.9	853.2
July	-0.4	158.4	53.5	301.2	53.0	459.5
August	-18.1	-391.3	145.4	2940.7	127.3	2549.4
September	2.2	747.8	100.1	2307.2	102.4	3055.0
October	-7.1	-207.1	31.3	1103.9	24.2	896.7
November	0.1	-48.1	4.6	162.4	4.7	114.2
December	-1.0	-27.1	1.7	52.2	0.6	25.1

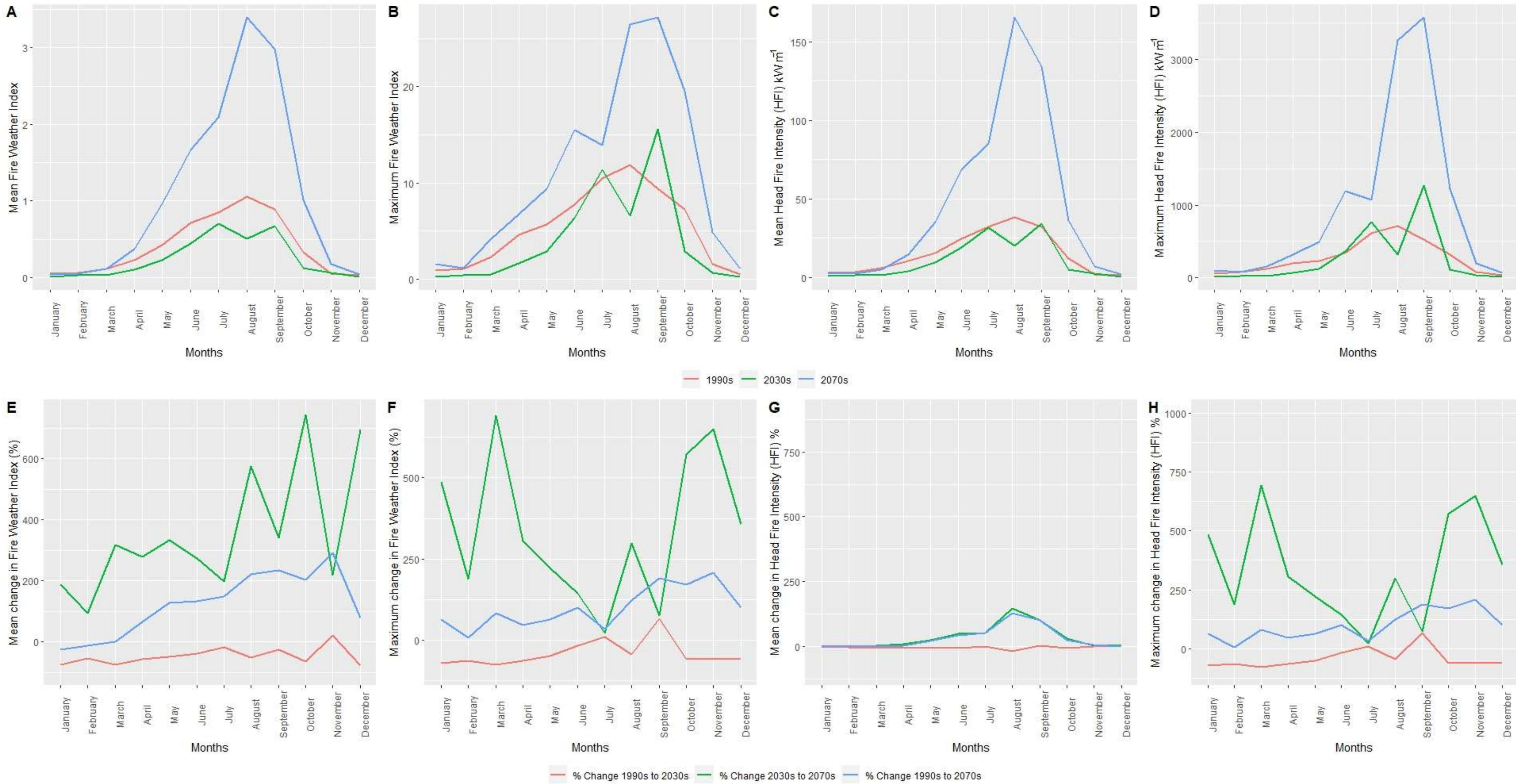


Figure 4.3: Raw values and percentage change of mean and maximum Fire Weather Index (FWI) and Head Fire Intensity (HFI) for the case study site at the baseline and in the future. A) Mean FWI, B) Maximum FWI, C) Mean HFI (kW m^{-1}), D) Maximum HFI (kW m^{-1}), E) Percentage change of mean FWI, F) Percentage change of maximum FWI, G) Percentage change of mean HFI, H) Percentage change of maximum HFI.

4.3.4 Validation with CHESS

Both models of FWI and HFI using CHESS data identify a KFD (see supplementary material, appendix 3; figure A3.1), with greater success in identifying KFD's in 2003 using FWI. All three days of known fire in 2003 are greater than the average values of mean (appendix 3; figure A3.1(A)) and maximum (appendix 3; figure A3.1(C)) FWI and are prominent in results. Additionally, it is likely that the 2003 data is a better indicator of extreme conditions than that from 2015, as peaks in 2015 results (appendix 3; figure A3.1B & D) are larger than those calculated for KFDs. However, there are further peaks of fire risk, particularly of maximum HFI (appendix 3; figure A3.1(D)) that are not recognised as a KFD. This suggests that there could be a risk of higher intensity fires, but the weather conditions to cause a fire are less common. It also could indicate that fires are not igniting naturally and the results could show that there is a greater risk from future anthropogenic ignition as any fires that do start are likely to be more intense in strength. There are no peaks of FWI greater than that for the 2003 fire, suggesting it is a reliable threshold of risk. FWI predicts what actually happened more accurately than HFI, but both models identify a KFD.

4.3.5 Future risk

There are a number of days for both FWI and HFI that are likely to see risk above that calculated for the KFDs using CHESS data (table 4.6, figure 4.4). Conditions modelled to have occurred during the April 2015 fire are predicted to be exceeded the most often for both FWI and HFI (table 4.6, figure 4.4). Peaks of FWI exceeding all KFD thresholds are predicted during each summer season (figure 4.4), with duration of the peak remaining fairly narrow. These FWI peaks above all KFD thresholds are predicted to occur for over half of years during the 2070s (figure 4.4A), which is the greatest when comparing to the baseline and 2030s. HFI risk is likely to be greater and more frequently exceed all thresholds of risk compared to FWI (figure 4.4B). All predictions exceed the conditions identified during KFDs (table 4.6), with the 2070s exceeding these the most. Predictions of maximum FWI and HFI exceed the KFD thresholds more often than mean values. Both metrics see similar percentages of projected days which exceed threshold values of mean and maximum FWI and HFI. For example, mean FWI and HFI exceeds the KFD threshold for 6 % of days in the 2070s, with 50% and 44 % of days exceeding the maximum prediction values for FWI and HFI respectively. As with FWI and HFI estimations, there is a decrease in the number of days predicted to be over the KFD threshold in the 2030s compared to the 1990s and 2070s. Mean values of FWI and HFI fall by about half between 1990s and 2030s, with maximum predictions decreasing between 3 and 4 %.

Table 4.6: The percentage of projected days when mean and maximum Fire Weather Index (FW)I and Head Fire Intensity (HFI) are likely to exceed thresholds set by four Known Fire Days (KFDs) at the case study site in 2003 and 2015.

	Mean FWI			Max FWI			Mean HFI			Max HFI		
KFD	1990s	2030s	2070s	1990s	2030s	2070s	1990s	2030s	2070s	1990s	2030s	2070s
17^{th} April 2003	0.24	0.22	3.63	0.31	0.15	3.59	0.68	0.99	8.68	0.21	0.96	6.56
18^{th} April 2003	0.14	0.18	3.08	0.21	0.13	2.89	60.24	56.66	69.93	59.73	55.33	70.04
19^{th} April 2003	0.03	0.11	2.02	0.07	0.08	1.88	31.33	21.80	47.99	10.95	5.37	30.21
22^{nd} April 2015	4.40	2.26	13.6	4.14	2.00	14.28	61.65	61.78	71.14	57.17	51.81	68.24

On average, there is more time during the 2070s when the case study site is likely to experience predicted conditions that are above the values calculated for KFDs. If FWI and HFI conditions are at their maximum predicted strength, nearly half of all days in the 2070s could experience these conditions.

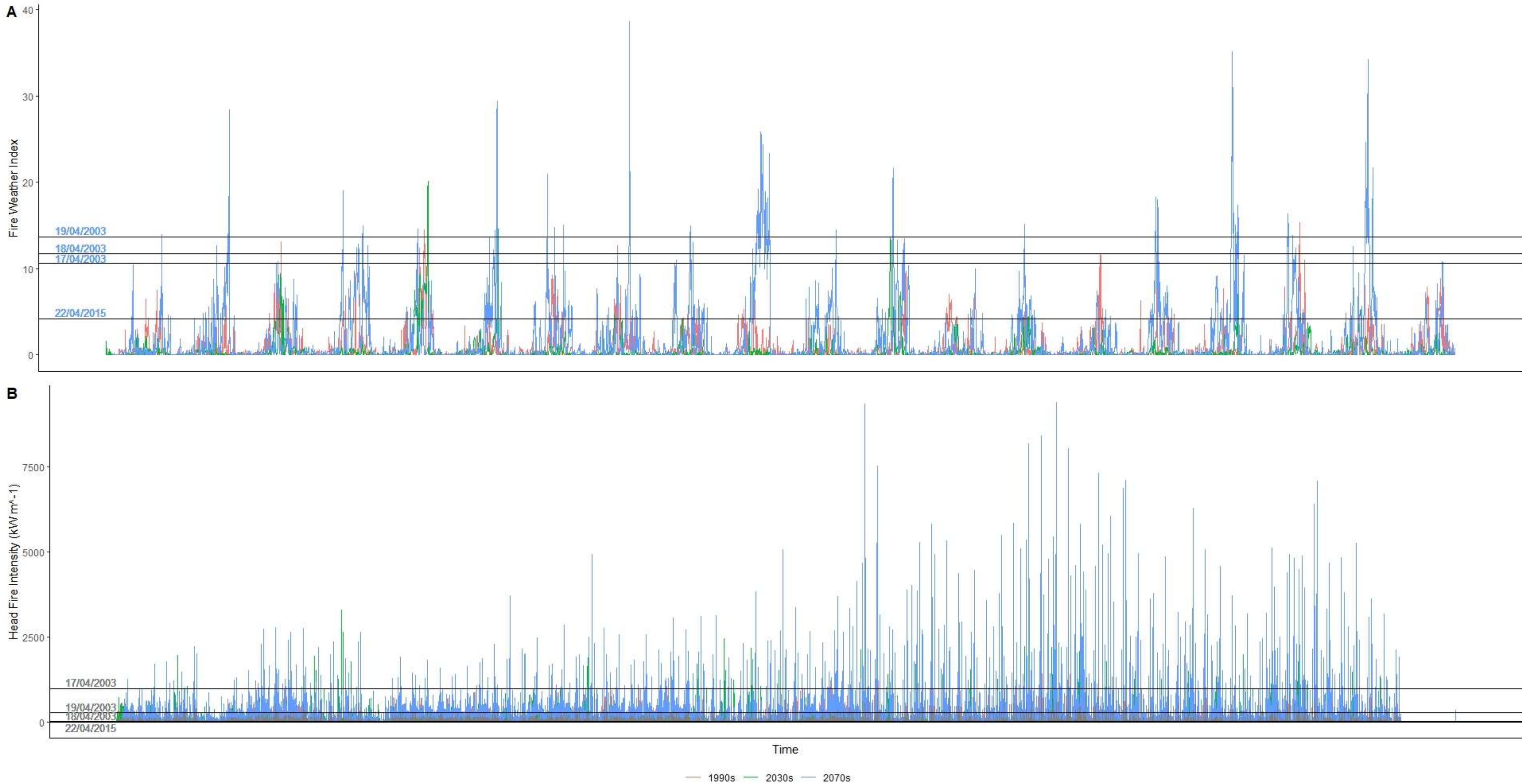


Figure 4.4:Predictions of Fire Weather Index (FWI) and Head Fire Intensity (HFI) with thresholds of Known Fire Days (KFDs) at the case study site. A) Maximum predicted FWI and maximum FWI of KFDs, B) Maximum predicted HFI and maximum HFI of KFDs.

4.4 Discussion

This study presents the applicability of using the CFFDRS to investigate long term risk of fire for multiple metrics at a case study site for two futures. This study builds on previous research through extending the timeframes of prediction and testing the HFI metric not often explored in the literature. Using data from KFDs the reliability of these metrics is further proven, especially FWI, at accurately predicting fire risk. Using CFFDRS as a projection tool rather than forecasting has not been widely explored, especially not in a UK setting, or at the small site scale. Dual peaks of fire risk in the spring and the summer have been identified in the UK (Perry *et al.*, 2022). Our research also identifies two peaks of risk, especially in the 2030s. However, these appear to potentially occur in summer and autumn, suggesting a shift in risk over time. The peatland in the case study is likely to experience increased fire risk in the future, in particular in areas that have previously experienced fire which could have implications for managed burning and the recovery of these landscapes and habitats.

4.4.1 Using CFFDRS in a UK setting

Thresholds for FFMC and ISI (table 4.7) are used in the UK to identify risk of sustained fires (De Jong *et al.*, 2016) over which controlled burns are not advised (Davies and Legg, 2016a). Our results exceed at least one threshold at every season, month, and year for the majority, or all, grid-squares at the case study site. Using these metrics alone, it can be concluded that the risk of sustained fires is extremely high throughout most of the year, but especially in summer months, and that controlled burns at any month would be dangerous. However, these could indicate that country-wide thresholds as determined by De Jong *et al.*, (2016) and Davies and Legg, (2016) are inappropriate for North Wales (table 4.7) due to predicting very high risk with few fires experienced. This could suggest that further development of regional thresholds would produce more accurate results as suggested for other metrics (Davies and Legg, 2016a; De Jong *et al.*, 2016; Arnell, Freeman and Gazzard, 2021).

Predictions of fire season have not been examined extensively in the literature for the UK (Davies and Legg, 2016a; Perry *et al.*, 2022), but this chapter shows that it is likely to be a useful metric of change. Fire season calculations adjusted to local temperatures predict a greater number of fire seasons in a 20-year period, and with these increasing in length over time. Tailoring calculations of fire season to local weather data appears to produce predictions of fire seasons that are more realistic than those from default CFFDRS settings. While fire season length is not recorded or investigated on the case study site currently, the default settings predicted maximum fire season lengths of over 500 days for all time frames, which is highly implausible. Adjusted settings (table 4.7) predicted maximum lengths of between 170 and 210 days per year, which is still high, but potentially more likely. Investigating spatial risk from fire seasons, areas previously burnt appear to remain at risk. This could target patrols or conservation activities to these areas of the site. A maximum potential increase in fire season length with the 2003 adjusted inputs of 23% is predicted. This is similar to, but slightly greater than the average increase in fire season length as calculated by Wotton and Flannigan, (1993). This is likely to be expected with updates in climate change projections, and estimations of increasing average temperatures growing. Considering fire season length in the future could encourage occasional monitoring around temperatures used in calculations when conditions could be thought to be optimum for a fire season. Recognising that a site is within a fire season may raise further awareness of risk outside those living and working within the site and provide more impetus to restrict some activities on the site.

Table 4.7: A summary of all thresholds used for multiple metrics in assessing fire risk to the upland Migneint peatland in North Wales

Metric/Variable measured	Threshold used	Origin of threshold
Initial Spread Index (ISI)	> 2	(Davies and Legg, 2016)
Fine Fuel Moisture Code (FFMC)	> 75	(Davies and Legg, 2016)
	> 72 in spring, > 74 in summer and > 69 in autumn	(De Jong *et al.*, 2016)
Fire season length	CFFDRS default settings = after three consecutive days of noon temperatures greater than 12^{o}C for areas with no snow cover	(Turner and Lawson, 1978)
	2003 adjusted settings using KFD data = three consecutive days of 18.5^{o}C to start a fire season and three consecutive days of 12^{o}C to end a fire season (maximum temperatures)	Based on Wotton and Flannigan (1993) but values calculated from Known Fire Day data from 2003
Fire Weather Index (FWI)	Maximum 10.6 = 17/04/2003 11.7 = 18/04/2003 13.7 = 19/04/2003 4.2 = 22/04/2015 Average 7.2 = 17/04/2003 8 = 18/04/2003 9.6 = 19/04/2003 0.1 = 22/04/2015	Extracted from calculations of FWI using CHESS data for the years 2003 and 2015 to correspond with Known Fire Days (KFDs).
Head Fire Intensity (HFI)	Maximum 977.8 = 17/04/2003 6.2 = 18/04/2003 267.5 = 19/04/2003 10.3 = 22/04/2015 Average 140.7 = 17/04/2003	Extracted from calculations of HFI using CHESS data for the years 2003 and 2015 to correspond with Known Fire Days (KFDs).

	0.3 = 18/04/2003 10.7 = 19/04/2003 0.2 = 22/04/2015	

Fire Weather Index (FWI) is a metric of the CFFDRS most used outside Canada (Davies and Legg, 2016a; Bedia *et al.*, 2018; Tsinko *et al.*, 2018). This study has proven the use and applicability of FWI as it best explains future fire risk at the case study site. Research shows that an increase of 20 % in an individual FWI value is the smallest change that can be associated with recognisable differences in fire behaviour (Turner and Lawson, 1978). Most of the FWI results presented in our study are above this 20 % change threshold and could lead to a recognisable difference in fire behaviour at the Ysbyty Ifan Estate.

Head Fire Intensity (HFI) required the most inputs to be tailored and relied on vegetation inputs specific to those found in the Canadian Peatlands (Turner and Lawson, 1978). This is likely the reason why HFI was not as good a predictor of KFDs compared to FWI, as even though a fuel type input was chosen as close to the case study site as possible, this is still unlikely to represent the Estate exactly. Fire intensity is predicted between a class 1 to 4 (Lawson and Armitage, 2008), indicating a wide range of likely conditions. Classes 4 and above specify the transition from a surface fire to intermittent and continuous crown fires (Lawson and Armitage, 2008). These are unlikely to occur at the Ysbyty Ifan Estate due to the more open peatland, but also a positive that these high intensity fires are only occasionally predicted and more unlikely to occur. Important *Sphagnum* mosses are most damaged by fires at high temperatures (Noble *et al.*, 2019), with preventing these high intensity fires a priority.

4.4.2 Implications for peatland conservation

Current risk of fire is during the spring, with all KFDs during March and April, matching country-wide trends (Perry *et al.*, 2022). However, out of season fires are potentially becoming far stronger, potentially due to warmer, drier summers. These fires could become more damaging due to a greater availability of fuel (Benscoter *et al.*, 2011; De Jong *et al.*, 2016; Arnell, Freeman and Gazzard, 2021), and suitable weather conditions over previous months. Some research suggests that controlled burns can reduce the amount of fuel that then would be available to a severe wildfire (Davies, Kettridge, *et al.*, 2016). While this could be an option in the short term, as their risk is predicted to be reduced in the 2030s from the 1990s, long term plans such as burning rotations, may require adapting. Yet, there is a stronger imperative for changing management, ideally to re-wetting peatland or replacing burning with cutting (Douglas *et al.*, 2017), the latter which has been associated with increases in some bird species abundances. Wet peatlands lower fire risk and potential intensity compared to drained peatlands (Loisel and Gallego-Sala, 2022), and early re-wetting puts peatlands in better condition to resist degradation from climate change with a wet peatland body likely to withstand drier summers in the future. These risks combined with a longer potential fire season may require further monitoring and awareness to the general public of risk. When examining predicted changes, and comparing results in the 2030s to 2070s, it must be taken into consideration how natural processes can adapt to change. Peat has been found to be resilient to gradual, long-term changes in climate and hydrology, but responds rapidly to short-term high intensity anthropogenic disturbance (Page and Baird, 2016). Natural changes in fire risk may be tolerable by peatlands at the case study site, especially as greater risk is predicted into the 2070s. However, greater risk coupled with short-term anthropogenic disturbance from controlled burns could compound risk of severe fires further. Additionally, fire-return intervals have been identified over a number of spatial and temporal scales, ranging from yearly to thousands of years (Davies, Adam Smith, *et al.*, 2010; Turetsky *et al.*, 2015; Bona *et al.*, 2020; Wang *et al.*, 2022) and vary significantly regionally and locally (Davies, Adam Smith, *et al.*, 2010). Shorter fire-return intervals are often associated with relatively low intensity fires and vice versa for fires over longer time frames (Davies, Kettridge, *et al.*, 2016; Wang *et al.*, 2022), with management fires in the UK recommended on a 10 to 20 year cycle (Davies, Gray, *et al.*, 2010). However, our research predicts both increases in frequency and severity, suggesting that shorter fire-return intervals could become more damaging. Considering the results from this chapter, it can be hypothesised that with fire risk metrics predicting values similar to those seen in KFDs without fire present suggests that many fires at the case study site are not igniting naturally. Controlled, or otherwise, burning has been used historically for land management. This negatively affects the flora and fauna on site, particularly ground nesting birds at the beginning of the breeding season. This increase, or continued presence, of fire risk indicates that there is no good time in the year to deliberately burn an upland peatland.

Taking a whole system approach to understanding fire risk and utilising a variety of metrics alongside current monitoring is likely to have the greatest positive impact on the environment (Rowland *et al.*, 2021b). This research has started this by examining multiple metrics of fire danger to understand length, strength, and severity of risk. Even with reductions in potential fire risk between the 1990s and 2030s, the overall danger is still present, especially when considering predictions for FFMC and ISI. Further understanding the system through peat health (Davies *et al.*, 2013) and site biodiversity could improve these predictions of risk further.

4.4.3 The future and net zero in the UK

In vulnerable areas, higher temperatures and drier summers, as predicted in UKCP18 projections (Lowe *et al.*, 2018), are likely to contribute to increases in emissions of carbon (ASC, 2017). A greater frequency of conditions likely to initiate wildfires are also predicted, which could lead to more frequent emissions of GHG and damage to the case study site peatland. These emissions could be linked to the increased likelihood of fire events on peatlands, as shown in this study, strengthening the positive feedback cycle of increasing GHG concentrations and fire risk. Climate change may increase wildfire frequency, extent and amount of high-severity fire (Dillon *et al.*, 2011; Sommers, Loehman and Hardy, 2014), with peat fires potentially able to contribute significantly to global emissions of GHGs (Turetsky *et al.*, 2015).

Estimates of fire carbon emissions appear to depend on indications of fire frequencies, that is, the more fires, the more emissions (Turetsky *et al.*, 2015). However, low-severity fires typically release less carbon per fire event (Sommers, Loehman and Hardy, 2014), suggesting that controlled burns are not as damaging compared to wildfires in terms of emissions. Yet impacts to soil structure (Thompson *et al.*, 2016; Loisel and Gallego-Sala, 2022) and biodiversity (Douglas *et al.*, 2015, 2017) may be nearly as bad. Fire severity is likely to increase, through investigation of HFI results. This could suggest that any fire at the case study site may release more emissions in the future, and that even with reductions in risk in the 2030s, any fire will release carbon, which will not help meet net zero targets by 2050. Additionally, even with reduced frequency of fires in the 2030s, severity is likely to increase in some months. This could see controlled burns developing into dangerous wildfires, with serious consequences for both carbon and ecosystems.

This study adds to the growing evidence base of the vulnerability of modified ecosystems and habitats to climate change (Dodd *et al.*, 2020). It highlights the importance of evidence-based research in developing strategies and management tailored to the specific threat and location, and provides a development of methodology specific to UK peatlands and future climate change (Dodd *et al.*, 2020; Stafford *et al.*, 2021). Tackling the climate crisis takes concerted effort from every facet of society, with land use choices on individual sites able to contribute a positive impact. Rewetted peatlands show reductions in GHG emissions (Evans *et al.*, 2017; Renou-Wilson *et al.*, 2019), and these restored peatlands are also more resilient to fire (Rowland *et al.*, 2021b). Peatland restoration and wetland plant community which drives peat formation and carbon sequestration will have a smaller short term influence on GHG management than avoiding high severity fires (Renou-Wilson *et al.*, 2019) which, as well as releasing significant amounts of carbon, also damage the *Sphagnum* species, soil structure and the water table which are vital in peat formation (Noble *et al.*, 2019). It is important to build peat resilience, biodiversity and fire resistance through rewetting and restoring upland peatlands creating a stronger ecosystem that addresses both the climate and nature crises at site, Wales, and UK scales.

Some alternative management practices on peatlands, such as paludiculture (Ziegler *et al.*, 2021) which is the practice of wet agriculture and forestry on peatlands, have the potential to reduce GHG emissions while keeping these landscapes in agriculture (Lahtinen *et al.*, 2022), Land uses such as paludiculture require peat to be wet, potentially bringing together restoration, maintenance of livelihoods and contributions to net zero. Paludiculture is however in its very early stages of development in the UK, and currently focused more on lowland peatland areas. The idea of carbon farming however is growing apace for all peatlands, and providing revenue through carbon markets such as the IUCN Peatland Code.

While fire has formed part of the management toolbox for upland areas in the UK for many years, change in approach is now well underway, with early stage and prospects of wider bans in England and Scotland. Welsh Government launched the National Peatlands Action Programme in 2020 to manage and restore existing peatlands. There is a large increase in fire risk predicted for the 2070s, for when any planned fire would be at a greater risk of becoming difficult to control, and therefore a high severity fire. With the UK's commitment to net zero by 2050, and a continued commitment to the environment, is it recommended that controlled burning will not be a suitable management tool in many cases as the likelihood of development into an out-of-control fire is too great. Alternative management practices including grazing and cutting of vegetation to control plant matter are likely to be more appropriate. Additionally, removing fire from management plans will benefit species such as ground nesting birds, and allow plant species requiring longer timeframes to establish the chance to thrive.

4.4.4 Limitations and future research

Work is needed to increase the accuracy of vegetation type habitat factors to reflect UK vegetation types. This is particularly so for peatlands, with different factors likely to be relevant for drained and re-wetted peatlands as fire risk is markedly lower for wetland peatlands supporting typical bog vegetation. For example, the Marsden Moor fire of 2019 stopped largely at re-wetted areas, with extensive damage caused to other areas Updating these habitat types and integrating into models like the CFFDRS would provide a prediction of risk within sites based on habitat quality and type alongside climate and weather variables.

Ongoing tailoring of fire risk metrics will increase the reliability and accuracy of models. Addition of fire monitoring and data collection to validate models of risk would improve site level understanding of risk and potentially guide future management plans. The application of more realistic input variables, such as fuel types to calculate HFI, would greatly improve these outputs and further inclusion of peat health could identify areas most at risk from carbon loss. Additionally, the data processing of climate projections could be developed further. Bias correction of projections and including further model members in analysis would provide a more accurate representations of local climate and risk. Further understanding the climatic reasons why these fires are likely to be stronger and more frequent could help to guide management and improve model accuracy. Unpicking the relationships between management activities, site diversity and climate are more likely to reveal drivers of change and further understanding of the requirements for a healthy, resilient ecosystem.

4.5 Conclusions

This study has shown applicability of CFFDRS at the local scale and for long term predictions. Using local validation data highlights strength of FWI at predicting fire risk, and greater risk is likely in 2070s from fires in frequency and severity when compared to the 2030s and baseline 1990s. The UKCP18 data provides a good basis for tailoring of the CFFDRS, although further tailoring could be improved through further data manipulation such as bias correcting. This greater fire risk over multiple metrics including fire season indicates dangers of burning for management control, especially when considering impacts of regular fires to peatland biology and hydrology. However, with potential shifts of severity predicted to occur later in the year, the winter burning season is unlikely to be viable and this research supports the growing call to ban burning on peatlands. Burns are especially not advised in the long-term with far greater severity and frequency of fires predicted to increase from the end of the 2030s. While, under historic management and climate, burning regimes may have been a key part of a land-management toolkit, this may not be the norm for the future. Resilient, healthy, carbon sequestering peatlands must be the goal for biodiversity and climate, considering commitments to net zero targets, global agreements, nature-based solutions, and the intrinsic need to protect the natural world.

Chapter 5: The impact of current and future wind speeds and direction to historic parkland trees: using low-cost methods to inform long-term conservation plans

Abstract

Wind impacting woodlands and individual trees has a negative impact on tree health and lifespan. Additionally, in public nature areas, such as National Trust properties, high wind speeds impact health and safety, and access to and within sites. Conservation charities like the National Trust, and other bodies with public access responsibility around trees, are keen to understand potential future risk from wind to parkland trees. Trees are important for biodiversity, leisure, and heritage, with these anthropogenic and biological aspects going hand in hand. Climate change is likely to have larger impacts to wind speed over direction, although small changes in these metrics can result in large changes to wind power. Higher latitude trees are at a greater risk from changing wind speeds influenced by changing climates which could result in greater windthrow and damage.

Tatter flags have been used to assess the impact of strong winds to conifer plantations over the past 30 years, but they have not been utilised for measuring the impacts to individual trees, or to guide conservation work. This research builds on the low-tech tatter flag methods to assess wind speed to quantify exposure to individual trees under climate change assessing two wind metrics, maximum average wind speed and maximum wind gusts. Future climate projections were from the UKCP18 climate change projections at the local 2.2km daily scale. A year-long fieldwork study at Chirk Castle National Trust property assessed the impacts of wind speed and direction to 21 parkland trees using tatter flags. This site contains historic parkland trees as part of a parkland plan unchanged for hundreds of years. Spatial and temporal exposure to wind was calculated for the fieldwork period and two future projections. Additionally, the number of days wind speeds were likely to exceed a threshold leading to the closure of the property were calculated to assess impacts to the running of a site from high winds. Finally, the most common wind direction at the current baseline and two future climate projections were estimated. If directions change to those not commonly currently experienced, trees could be more vulnerable to a range of wind speeds.

This study shows that it is possible to use the tatter flag method for individual trees, and that local scale climate data provides a picture of future exposure. There are both temporal and spatial differences in exposure, with autumn and winter seasons likely to be the most exposed to high winds. Maximum gust exposure is predicted to be greater than the 1990s baseline at more times and sites in the 2070s compared to the 1990s and the 2030s. There is likely to be a higher percentage of

days in the year when wind speeds could exceed the closure thresholds in winter and spring months in future years. With however, an overall reduction in closure days to approximately 3 weeks a year in the 2070s. Wind directions are not predicted to change dramatically, with a continuing prevailing south-westerly wind, yet Chirk is likely to experience more winds from the north-west. Understanding where on site and when during the year wind exposure is likely to be greater is useful for conservation planning and visitor management. Future wind exposure is not predicted to exceed the baseline average during all months of the year, aligning with current research which indicates the higher impact from storms in winter months. The case study property at Chirk Castle will be more impacted from wind speeds at the Christmas and Easter holidays which are important events for visitors. Particular areas of the site will be more exposed to wind speeds in the future, influencing both site biodiversity and public access. UKCP18 data allows for future predictions of risk, although at a coarser resolution than fieldwork. This study highlights the usefulness of low-cost fieldwork methods of tatter flags to gain an understanding of a site's exposure to wind speeds both currently and into the future, and the importance of integrating these predicted impacts into conservation and visitor management planning.

5.1 Introduction

Negative impacts from wind often arise from extreme events, such as storms, which are likely to intensify in the future (Masson-Delmotte *et al.*, 2018b; Arnell *et al.*, 2021; Forzieri *et al.*, 2021). Impacts from extreme winds are increasing (Forzieri *et al.*, 2021), and being identified in areas previously unaffected (Gardiner, 2021), suggesting climate change is already having an effect. Wind speeds and direction have large impacts on tree growth and morphology, with changes to winds likely to have negative effects and increase tree wind damage (Zhu *et al.*, 2004; Ciftci *et al.*, 2014; Dupont, 2016; Gardiner, 2021). Damage to forests by wind has significant impacts and is responsible for over 50% of tree damage in Europe (Hart *et al.*, 2019), leading to tree loss and disturbance to the surrounding ecosystem (Zhu *et al.*, 2004). This could be especially damaging in these areas as trees are unlikely to be acclimated to strong winds (Gardiner, 2021) due to the protection from surrounding trees.

There have been efforts to understand how wind influences trees in the forest ecosystem, and in commercial plantations (Suárez, Gardiner and Quine, 1999; Schelhaas *et al.*, 2007; Kamimura *et al.*, 2008; Blennow, Andersson, Bergh, *et al.*, 2010; Gardiner, 2021). Trees are vulnerable to sudden changes due to their long life-spans, limiting their ability to rapidly adapt (Seidl *et al.*, 2017; Forzieri *et al.*, 2021) to extreme events and sustained increases in wind speeds. Larger trees grow to buffer to prevailing wind directions, and if these change, they are at a higher risk from windthrow. Current research about forest vulnerability to windthrow in European forests has found no significant trend, and dynamics appear to be largely dominated by interannual variability in climate (Blennow, Andersson, Sallnä, *et al.*, 2010; Forzieri *et al.*, 2021). However, nearly 60% of European forests' biomass was found to be vulnerable to windthrow between 2009 and 2018, which appear to correlate to increases in precipitation and wind speed (Forzieri *et al.*, 2021).

A greater proportion of potential changes in future wind damage are likely to be due to changes in wind climate rather than changes within the forest (Blennow, Andersson, Bergh, *et al.*, 2010), suggesting that climate change could have a larger impact on forests in the future. Colder forests, and those at higher latitudes including the British Isles, were found to be the most vulnerable to disturbance due to current environmental conditions and intensified warming over recent decades (Forzieri *et al.*, 2021), which is likely be exacerbated in the future. Currently cooler areas projected to experience warmer, wetter conditions may become more vulnerable to wind disturbances in forests in the future (Seidl *et al.*, 2017) due to cascading effects from interacting disturbances (Stadelmann *et al.*, 2014; Forzieri *et al.*, 2021).

There has been extensive research investigating how turbulent winds impact forest stands (Schindler, Bauhus and Mayer, 2012), aerodynamic interactions between trees and tree features (Schindler, Bauhus and Mayer, 2012), the impacts of wind to trees in urban environments (Giachetti, Ferrini and Bartoli, 2021; Gu *et al.*, 2021), wind damage at forest margins (Talkkari *et al.*, 2000) and in trees stands (Dupont, 2016). All this research investigates impacts to trees as one of a stand or forest, but with useful information about wind flows, turbulence and interactions causing disturbance. Additionally these wind events causing windthrow and damage can be positive for a forest to kickstart changes in structure, composition and landscape patterns (Schindler, Bauhus and Mayer, 2012). The centre of forests are considerably more sheltered than the edges and therefore less prone to windfall. Investigating effects on forest edges could also serve as a general indicator of how individual trees are likely to react to changes to wind disturbances. Some models (Peltola *et al.*, 1999; Gardiner, Peltola and Kellomäki, 2000; Talkkari *et al.*, 2000) were developed to analyse critical wind speeds at the forest stand edge.

There have been some attempts to model wind risk to individual trees within the stand level for commercial forestry (Ancelin, Courbaud and Fourcaud, 2004; Hale *et al.*, 2012; Seidl, Rammer and Blennow, 2014; Kamimura *et al.*, 2019). While this is suitable in a uniform forest, it is not applicable to individual parkland broadleaf trees of differing ages and at different distances to other vegetation. Some models at the individual scale identify those trees which could impact infrastructure (Gullick *et al.*, 2019) and urban environments (Ciftci *et al.*, 2014; Gu *et al.*, 2021).

However, all these methods are highly specific and require large amounts of complex data, which are above many projects' scope and budget.

Wind speeds resulting in damage and disturbance are often very localised. While country-wide forecasts are useful, detailed local information is vital to understand wind patterns and the impacts from these. Vulnerability to wind speed varies over geographical regions, with changing magnitudes of local sensitivity (Forzieri *et al.*, 2021), highlighting the added value of high resolution data and simulations (Outten and Sobolowski, 2021).

Research into calculating threshold wind speeds and other vulnerability metrics to quantify risk to windthrow has utilised a range of wind and tree variables to make these predictions. These often aim to use or estimate local wind speed values using a variety of methods. Using regional wind data, and information about topography of the site and geographical elements, local spatial wind speeds can be interpolated, as in Suárez, Gardiner and Quine (1999) who used anemometer data alongside terrain and landscape roughness metrics. To ascertain high resolution temporal data, they calculated mean wind speeds from half-hour frequency distributions to predict wind speeds in forests (Suárez, Gardiner and Quine, 1999). Some papers have utilised remote sensing techniques to identify wind impacts to specific areas post-storm damage (Rich *et al.*, 2010; Forzieri *et al.*, 2021). Combining wind speed data with knowledge of a specific site through imagery (Rich *et al.*, 2010), tree measurements (Rich *et al.*, 2010; Ciftci *et al.*, 2014) and field results produces a detailed picture of how wind is likely to affect an area. Higher resolution data and simulations of wind impacts are more useful than those at coarser resolutions (Outten and Sobolowski, 2021), so integrating these with site information will provide further useful evidence of the impacts of damaging wind to trees. However, often these methods utilise high levels of technology and data in statistical models that may exceed the scope of time, data inputs and workforce present in conservation organisations.

Long-term fieldwork studies using low cost tatter flags to estimate the effects of wind to conifer stands were developed and assessed in a number of publications (Rutter, 1966; Miller, Quine and Hunt, 1987; Mackie and Gough, 1994; Quine and White, 1994; Quine, 2000). In these, the amount of flag lost to the wind over time is calculated, the rate of tatter, to equate to scores predicting windthrow hazard, exposure and other metrics of risk to trees (Miller, 1985; Quine and White, 1994). When combined with topographical variables, these metrics have proven useful to forestry and forest conservation in the UK in previous years. There is a proven relationship between estimates of windiness derived from tatter flag experiments and observations of wind speeds (Quine, 2000), and the methods ability to predict risk using a variety of models (Suárez, Gardiner and Quine, 1999). Tatter flags are a simple, robust and inexpensive method to measure wind exposure (Willoughby, Stokes and Kerr, 2009) and can be employed in all conditions and landscapes.

While there is a research interest in examining the impacts of climate change to historically important structures (Sabbioni *et al.*, 2009; Lankester and Brimblecombe, 2012; Leissner *et al.*, 2015), there is little to no research investigating these impacts to parkland landscapes in the UK. These landscapes, often managed by grazing and home to veteran native trees, are historically and biologically important to the area and wider environment. There has been the debate around environmental conservation versus preservation over recent decades. Preservation can be thought of as preventing resource production through an intrinsic need to protect nature (Minteer and Corley, 2007), and conservation taking a more malleable approach to land management through, what should be, the use of natural resources sustainably (Minteer and Corley, 2007). There is recognition that culture and conservation can be on opposite sides, and that integrating cultural desire into conservation practices is important (Shen and Tan, 2012), which can also relate to the history of a site. In this study, preservation is recognised as the maintenance of landscapes without change to original plans, and conservation as adapting to change, whether reactive or proactive, while protecting biodiversity and heritage priorities. It is recognised that often both preservation and conservation require anthropogenic intervention to maintain and protect the site for future generations and from natural and anthropogenic change.

Conservation organisations, like the National Trust in England and Wales, are noticing increasing impacts of wind to sites, from extreme events and sustained high winds, which are affecting the environments looked after and access to sites by staff and visitors. There is a need to understand the changes to wind speeds and direction in relation to tourism, heritage and recreation at these sites, alongside biological implications. Some affected areas are historic parklands, with trees often planted according to plans spanning back centuries. Generally, estates have been managed with an emphasis on preservation for local and national heritage, but this is unlikely under climate change. Due to increasing wind speeds and changes to wind direction with climate change (Lowe *et al.*, 2018), the chance of exceeding critical wind speeds that impacts both the trees themselves and site closures could be increased. When investigating whether a site is focusing on preservation alongside or instead of conservation, it is important to assess whether this will be sustainable for the future. This includes thinking about the work required to maintain a site as well as how the site could be impacted by these disturbance conditions. Minimising health and safety risks to the public is just as important an aspect to a property as is preserving the heritage and conserving biodiversity. Finding the balance in these needs is likely to prove difficult, with this study aiming to provide another level of information to help in decision making around this historic and biologically important parkland.

Research aims

In this paper, novel analysis of current and future wind exposure to wind speeds and directions at the individual tree level in parkland is presented using the case study of Chirk Castle in North Wales. There is assessment of tatter flag methods, and if these can be used as a low-cost method for quantifying individual tree exposure in a parkland setting in comparison with already established tatter flag experiments on single trees in commercial forestry stands. Field spatial measures of tree exposure derived from the tatter flags are integrated with Met Office UKCP18 projections of future climate to estimate spatial and temporal trends in exposure from mean wind speeds, maximum gust speeds and wind direction in a parkland context. This tests whether it is realistic to preserve existing landscapes under climate change and if visitor safety will be affected by future conditions.

5.2 Methods

5.2.1 Study site

Chirk Castle is on the border between Wales and England (figure 5.1) and is a popular National Trust property with over 170,000 visitors in 2019. The parkland trees at Chirk Castle host internationally important groups of invertebrates and fungi, and are historically important as they are part of the original plans of the parkland. Chirk Castle is one of the best examples of ancient wood pasture and parkland in Wales and holds a Site of Special Scientific Interest (SSSI) designation. Over 700 trees are identified on the oak dominated castle site as being of mature parkland tree status. These trees are at risk from increasing wind speeds and changes in wind directions which are predicted to change in the future under climate change (Lowe *et al.*, 2018). Storms cause significant damage on site due to the high number of mature trees and the wooded, narrow driveway is easily blocked. When speeds and gusts over 40mph and 50mph respectively are recorded, the site is closed due to safety concerns. Sites for wind exposure measurement were chosen randomly across the site based on the location of surveyed broadleaf trees identified in a 2017/18 survey.

Wind speeds are monitored daily on site using a Skylink-Pro weather station which is situated at the top of Adams Tower in the south-west corner of the castle. The weather station has been active since February 2016 and records 33 metrics of weather relating to temperature, wind, humidity, and precipitation at five-minute intervals. Chirk Castle is often closed during times of high wind, using the data from the weather station alongside weather forecasts. The dates of closure were extracted from social media postings and correlated against the wind speed data for those days over the past six years.

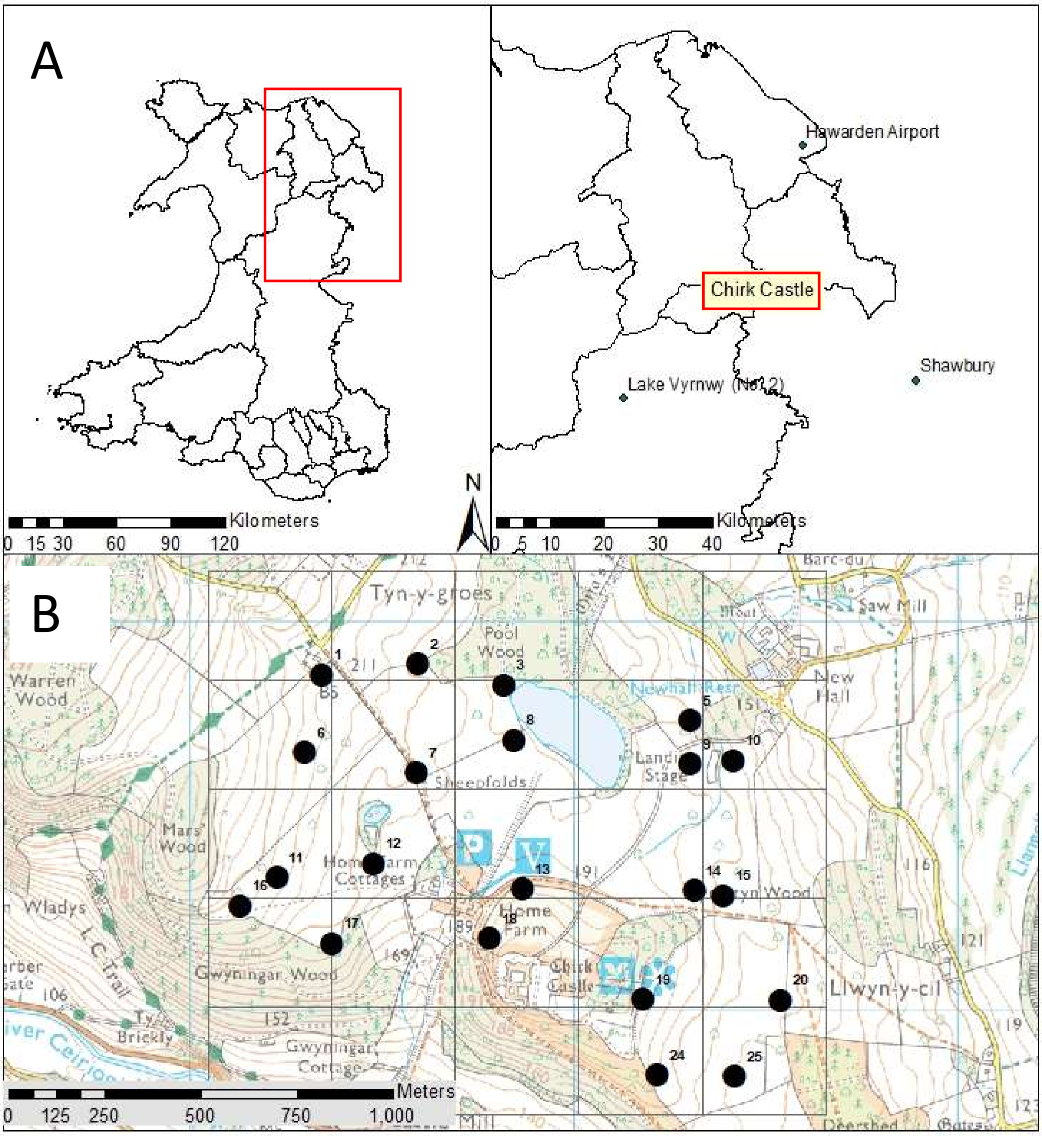


Figure 5.1: A) The location of Chirk Castle and the three closest MIDAS weather stations with available data (Hawarden Airport, Shawbury and Lake Vyrnwy No. 2) within Wales. B) The location of 21 study trees across the Chirk Castle parkland case study site.

5.2.2 Measurements of wind and exposure

5.2.2.1 Tatter flags

Tatter flags were installed at Chirk Castle between November 2019 and November 2020 with five data collection periods. May to July were excluded due to COVID-19 restrictions. The five fieldwork periods were between November and January, January and March, March and May, July and September, and September and November. Subsequently, these periods will be referred to as NDJ, JFM, MAM, JAS, and SOC respectively throughout this chapter.

The Chirk Castle site was stratified into a 5 X 5 grid of 9-hectare squares (figure 5.1). 711 parkland trees with GPS locations and known species were included in the study. One tree was chosen in each square using stratified random sampling and allocated as the study tree for that area. Three squares did not contain a tree so 22 trees were selected in total. 22 more trees were allocated as back-ups in case the original study tree was unable to be reached on site. Species, topographic exposure (topex) and altitude were recorded for each tree location. Access restrictions meant that 21 of the planned 22 trees were used for the fieldwork.

Flags were made by hand from 100% muslin, as the closest match to Madapollam cotton (Mackie and Gough, 1994) available. Each flag was 420 mm X 305 mm, which is slightly larger than recommended for standard practice (Mackie and Gough, 1994), to accommodate overlap with 50 mm X 32 mm 1.8 m stakes the flags were attached to. Four flags were installed at each study tree at the north, south, east, and west sides to gather data on the effect of wind direction and overall tree exposure to wind. Each stake was placed at least one metre from the edge of the visible root system of the tree to try and reduce the impact of shelter from branches. 85 flags were put out at Chirk Castle for each fieldwork period; 4 X 21 (84) at each tree (figure 5.1B), plus one flag at the weather station.

Tatter flags were placed at 1.8 m on stakes at the foot of each study tree and changed every two months (table 5.1), or between 55 and 67 days (Mackie and Gough, 1994). Flags were checked in the intervening month. Each flag was placed one meter away from the root system of the tree to attempt to reduce the impact of the shelter effect of each tree. Two fieldwork periods, three and five (table 5.1), exceeded the maximum 67-day length. This was due to COVID-19 restrictions which meant that the researcher was unable to get into the field any sooner. An increase of one to two days extra on site is unlikely to have a significant impact on results.

Table 5.1: The start and end date of each fieldwork period at Chirk Castle and the number of days each set of flags was out for. Dates in italics saw no data collection due to COVID-19 restrictions.

Number	**Start date**	**End date**	**Number of days**	**Fieldwork period code**
1	6th November 2019	6th January 2020	62	NDJ
2	6th January 2020	6th March 2020	61	JFM
3	6th March 2020	12th May 2020	68	MAM
4	*12th May 2020*	*15th July 2020*	*65*	MJJ
5	15th July 2020	21st September 2020	69	JAS
6	21st September 2020	20th November 2020	61	SON

Post-fieldwork, all flags were soaked for minimum 52 hours to remove dirt collected throughout the fieldwork months. Flags were separated into two containers, keeping the dirtiest flags together to prevent dirt transfer to cleaner flags. Warm water was added to each container until just covering the flags, and approximately 20 ml of 20% Deacon 90 detergent mixed into the water. After all flags were soaked, they were rinsed in clean, warm water with any residue gently washed off by hand with a sponge. Flags were left to air dry overnight, as machine washing and drying caused damage to the material.

Two metrics were used to calculate how the flags changed over time. Both methods were used to ensure accurate results and to assess which metric is more useful to measure change. In previous studies (Jack and Savill, 1973; Miller, Quine and Hunt, 1987; Mackie and Gough, 1994; Quine and White, 1994; Quine and Bell, 1998; Quine, 2000), tatter rate is expressed in units of $cm^2\ day^{-1}$. Change was estimated with similar methods, through weight change and area loss. Both methods were undertaken prior to, and after fieldwork for each two-monthly periods. All flags were weighed using laboratory balances to four decimal places. Weights were taken the first time the balance settled for reproducibility.

The second flag analysis method consisted of photographing each flag to calculate change in area by calculating the amount of white space (the flag) before and after fieldwork. Weights of flags were found to be more reliable and consistent than the photography and coding method and therefore, the below methods and results relate only to the change in weight of flags before and after fieldwork. For full photography methods, see supplementary material in appendix 4.1 and table A4.1.1.

Livestock disturbance was a significant problem throughout the fieldwork study. Visual analysis combined with records of livestock presence were used to score flags on a rating system. All flags were given a score from zero to two. Flags with a score of one were present and not impacted by livestock, and it is these flags that were analysed. Additionally, any flags that were found on the ground in the in-between month (e.g., December in the NDJ fieldwork period) were disregarded from analysis. Any flags that scored either zero (flag not present) or two (flag present but impacted by livestock) were also disregarded from analysis.

5.2.2.2 Meteorological data

A combination of weather observations from the Skylink-Pro and MIDAS weather stations and future climate projections from Met Office UKCP18 predictions were used in analysis.

When analysing weather data from the Skylink-Pro station, some records for Chirk Castle were missing. The weather station automatically uploads data to the Skylink database via a solar panel. However, some of the data did not upload for a number of days over the fieldwork period. Therefore, methods were tested to interpolate this data and get an estimate of wind speeds and temperature for the Chirk Castle site on days that did not upload data. Hourly wind speed, gust, and direction data were obtained from the nearest Met Office Integrated Data Archive System (MIDAS) stations and further Skylink weather data from National Trust Erddig to interpolate missing data at Chirk Castle. These were all averaged to daily data. The three MIDAS stations closest to Chirk Castle are Shawbury, Hawarden Airport and Lake Vyrnwy (No.2) (Figure 5.1A).

Both deterministic and stochastic regression methods were tested to interpolate missing weather station data for the fieldwork study period. The true and predicted correlations were compared and used the regression method that most closely predicted the true correlation, without overestimation. The closer to the true correlation, the more it can be assumed that wind speeds, and other missing weather data, predicted using these regression methods are accurate estimations of past conditions. Future wind exposure was calculated based on average daily wind speed and maximum daily wind gusts, and therefore only these values were interpolated. All imputations were run using the mice (v 2.9, Van Buuren and Groothuis-Oudshoorn, 2011) package in RStudio. Weather station data for Chirk Castle between 1st November 2019 and 30th November 2020 is missing 146 days of data, which is a 36.9% loss, compared to the full dataset of 365 days. 37 interpolations of a multiple regression were run, as as many imputations should be run as the percentage of missing data (Bodner, 2008; White, Royston and Wood, 2011). The multiple regression was run using data from all four of the closest weather stations. For results, see supplementary material in appendix 4 3.2 and table A4.2.1. Interpolated wind speed results are shown in figure A4.2.1.

5.2.3 Climate data

The Met Office have developed the UKCP18 climate projections, the most up to date predictions for how climate is likely to change in the future in the UK. Here the Convection Permitting Model 2.2km local projections were used, downscaled from the 60km global CMIP5 climate models using the Met Office HadGEM3 model. These projections were run for 12 members. The first model member (model 01) based on the HadGEM3-GC3.05 model without perturbed physics has been used in this analysis.

Four climate variables were used for analysis, mean daily wind speed (m s^{-1}) (sfcWind), maximum daily wind gusts (wsgmax10m), eastwards wind (uas) and northwards wind (vas). All variables were at the 2.2km spatial scale and for RCP 8.5 which predicts global average temperatures rising by over 4^{o}C before the end of the century. This data was averaged into three 20-year predictions of climate for mean wind speed, maximum gust speeds, mean eastwards wind and mean northwards wind. Baseline data was between 1980 to 2000 (1990s) with two future projections between 2020 and 2040 (2030s), and 2060 and 2080 (2070s). These spatial data for the UK were cropped to Chirk Castle for ease in data processing times during analysis.

Daily mean and maximum wind speeds and gust speeds, and daily mean eastward and northward wind directions were produced for Chirk Castle from the UKCP18 (model 01) scenarios and averaged to three 20-year time frames. These consisted of; the baseline 1980 to 2000 (1990s), a present future of 2020 to 2040 (2030s) and the long-term future between 2060 and 2080 (2070s). Hereafter, the time periods will be referred to as the 1990s, 2030s and 2070s.

5.2.4 Data analysis

5.2.4.1 Closure analysis

National Trust staff are required to close the site when maximum gust speeds exceed 50 miles per hour (mph) due to danger to staff and visitors from falling trees and debris preventing access to the property, with interest as to how frequently this threshold may be exceeded in the future under projected climate change. Three time periods of 20-year daily data, 1990s, 2030s and 2070s (see chapter 2, section 2.3.5 for detailed information about data processing) were investigated. All wind speeds from the UKCP18 data are in metres per second (m s^{-1}). The threshold of 50 mph was converted to m s^{-1} which equals 22.4 m s^{-1}. This threshold was added to the UKCP18 max gust data for each day to identify the number of days in both the baseline and future scenarios exceed(ed) 22.4 m s^{-1}.

5.2.4.2 Flag analysis

The difference between weights before and after fieldwork exposure were calculated as a percentage loss

$$((\text{after weight} - \text{before weight}) / \text{before weight}) * 100$$

Proportions of flags and potential future exposure using UKCP18 wind speed and direction data were calculated. As all flags were handmade, there were slight discrepancies across flag size, and therefore, weight. Using proportions of flag weight change made for a comparable and repeatable method to assess the level and change in wind exposure across the Chirk Castle site. To do this, fc was calculated, the flag weight change where fa is the weight after fieldwork and fb is the weight before fieldwork,

$$fc = fa - fb.$$

The proportion of the weight change for each flag is fp and calculated by

$$fp = fc / fb$$

where the flag weight change is divided by the flag weight before to give a calculation of the proportion of flag lost due to wind tattering. The relative difference in proportion of flags was then calculated, that is, how the proportion of weight loss of each flag differs compared to the average of all flag weight loss proportions across all fieldwork periods. The average of all flag weight change proportions (fp) given as fav to calculate the relative difference of all proportions by

$$frd = fp / fav$$

where the flag proportion (fp) is divided by fav to give the relative difference of proportion of weight change (frd). Values of frd > 1 represent flag proportions higher than the average and therefore more exposed than the average due to more flag weight lost. Values of *frd* < 1 represent the opposite.

To then assess the change in exposure across the site under climate change conditions, change in four wind climate variables (wind speed, wind gusts, eastwards, and northwards wind directions) was measured from the 1990s to the short term 2030s and long term 2070s. This change in wind metrics is calculated by

$$w1 = wf1 - wb$$

$$w2 = wf2 - wb$$

where *w1* is the change in the wind climate variable between the 1990s baseline *wb* and the 2030s projections (*wf1*) and *w2* is the change in the wind climate variable between *wb* and the 2070s projections (*wf2*). The value of wind speed (from *w1* and *w2*), was extracted for each flag location. To calculate the impact of future climate at each flag location,

$$rel.exp = frd * fw$$

where *fw* is the wind climate variable from the difference between baseline and future climate (*w1* or *w2*). The *rel.exp* therefore is the potential future exposure at each flag.

The *rel.exp* value for each flag was calculated using both the averages and maximum of the four wind metrics, wind speed, gusts, and northward and eastward directions. All further analysis is conducted using the exposure results calculate with the maximum values of wind metrics as the averages did not have a great impact on results.

To assess whether there is an effect of seasonality across the fieldwork study, statistical tests were run to determine differences between each fieldwork period. To test for normality, Shapiro-Wilk's test was run for both ANOVA model residuals across all fieldwork periods and each fieldwork period separately. A log-transformed data set was analysed and found to be normally distributed. For full results see supplementary material in appendix A4.3 and figure A4.3.1.

5.2.4.5 Direction analysis

Wind direction data is presented as eastwards and northwards metrics of wind speed, with negative values of that direction representing the opposite direction e.g., positive eastwards wind values indicate a wind going towards the east, negative eastwards wind values indicate a wind going towards the west. The most likely prevailing wind direction for each UKCP18 grid square within the study site were calculated with values at the baseline (1990s), short-term future (2030s) and long-term future (2070s) 20-year averages of daily direction data. Wind direction data was split into negative and positive values, with the most common (negative or positive) indicating the prevailing wind direction. By combining these prevailing directions for each grid square from the eastwards and northwards direction data, baseline and future prevailing wind directions could be predicted.

For example, if both positive eastwards and northwards directions were the most common, this would predict a south westerly prevailing wind.

5.3 Results

5.3.1 Castle closures

Since February 2016, the Chirk Castle estate was closed 63 times due to high wind speeds, and 14 times due to other adverse weather such as snow and ice. Highest wind speeds on closure days were around 70 mph with these winds from a West/North-West direction. The days of closure during this period were mainly in December, February, and March.

Through analysis of UKCP18 climate data, baseline years were predicted to have the highest number of days exceeding the closure threshold of 22.4 m s^{-1} with 559 days over the 1990s experiencing a maximum gust speed above the threshold (figure 5.2). This decreases under future predicted climate change (figure 5.2), with little change between the 2030s and 2070s when considering count of days (figure 5.2). In the long-term future predictions, the least days when wind speeds are projected to exceed the closure threshold are in August, with the most days predicted during January.

Additionally, the percentage of days when maximum wind gusts are predicted to exceed the closure threshold were examined seasonally (table 5.2). Winter has historically been the time of year with the highest instances of gust speeds over the threshold, and this is predicted to be the same in the future (table 5.2). There are slight increases in the percentage of days exceeding the closure threshold in winter and spring in the future under climate change. By the 2070s, half of the days when wind gusts could exceed the threshold are likely to be in winter (table 5.2). However, percentages of high wind gusts in summer and autumn are predicted to decrease (table 5.2). This could be positive as a reduction in high wind gust events when trees are in full leaf may reduce windfall in these months.

Table 5.2: The percentage (%) of days maximum wind gusts are predicted to exceed the closure threshold of wind gusts over 50 mph (22.4 m s-1)

	1990s	2030s	2070s
NDJ	26.5	30.2	30.0
JFM	31.4	28	32.1
MAM	15.3	17.3	17.1
MJJ (No fieldwork)	6.7	5.4	4.6
JAS	6.5	4.8	3.5
SON	13.5	14.2	12.7

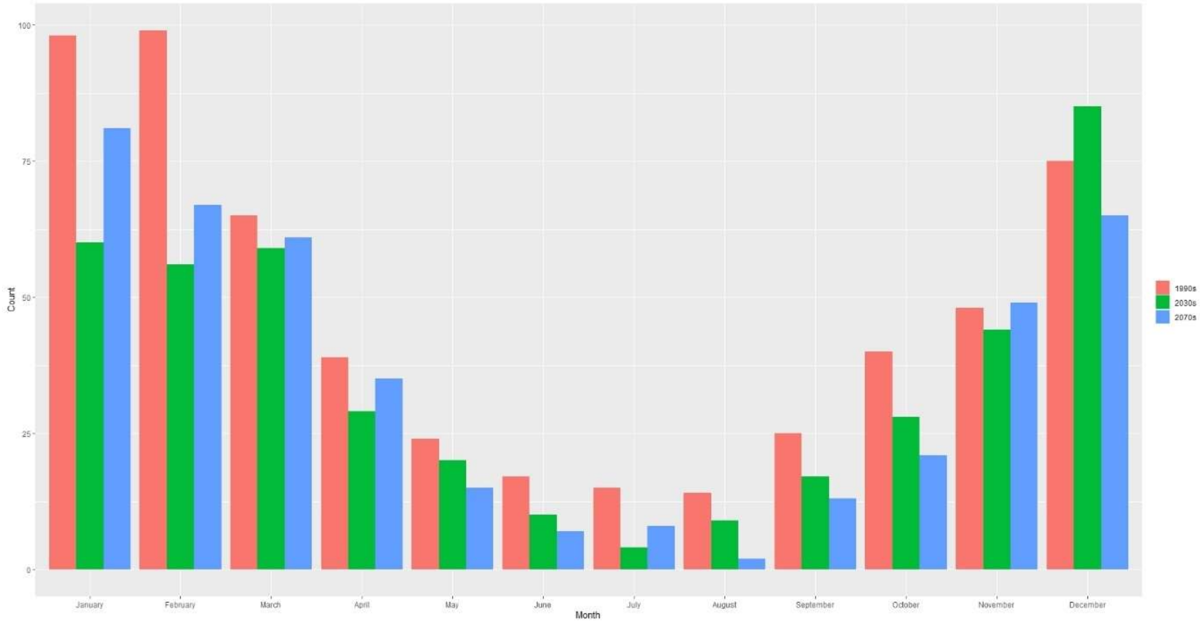


Figure 5.2: The number of days (count) per month in each 20-year period when wind speeds are predicted to exceed the closure threshold of 50 mph (22.4 m s^{-1}).

Overall, this amounts to approximately a month per year of closures predicted at the baseline, in comparison to about three weeks a year in the future. For both projected 20-year climate future averages, Chirk Castle is predicted to close for 22 days per year. Winter months are likely to have the highest number of windy days with summer the least affected (table 5.2). Spring wind gusts are likely to be more prevalent than at the baseline for both scenarios (figure 5.2, table 5.2). Seasonal events at Christmas and Easter could be more affected by wind gust speeds in the future, but popular summer holiday seasons are unlikely to be greatly impacted.

5.3.2 Flag change analysis and exposure

When comparing results using weight and size change for flag analysis, weight changes were the most accurate way to measure exposure to wind. Analysis of size did not show patterns similar to weight change for all months, but some were correlated. Subsequent analysis was conducted using the weight change results only. For size change results, see supplementary material in appendix 4 (table A4.3.1).

All flags lost weight over each two-month fieldwork period, showing evidence of tattering. Wind exposure varied spatially and temporally across the Chirk Castle property, with some areas of the site more exposed throughout the year than others. Figure 5.3 shows the average percentage of weight lost by the four flags at each tree during each fieldwork period. Flags in the north-western and eastern areas of the parkland lost the most weight throughout the year (figure 5.3), with greatest average weight lost during the SON fieldwork period (figure 5.3, SON). Flags at trees 14, 15, 19, 20, 24 and 25 were the most impacted by livestock (figure 5.3), resulting in less analysis on winds from a south-easterly direction.

When comparing observed and interpolated wind speeds (appendix 4.2, figure A4.2.1) with average weight loss for each tree (figure 5.3) across the study year, there are patterns between wind speeds and tattering. Spring and summer months (March to August; figure 5.3, MAM, JAS) see predicted and observed wind speeds lower than the average (3 m s^{-1}), which also saw lowest amounts of tattering and less weight lost (figure 5.3). Highest wind speeds in JFM and SON fieldwork periods (appendix 4.2, figure A4.2.1) correlate with highest average percentages of flag weight lost at each tree (figure 5.3).

Relative exposure for the baseline and future periods was calculated relative to the overall average exposure at the time period in question. This assumes that a relative exposure score of one is equal to the overall mean flag weight loss. Any data below one was less exposed than the average and vice versa. Higher values indicated greater exposure spatially and temporally. For baseline exposure values, see appendix 4, table A4.3.2.

Exposure of flags was greatest during winter and spring months of the fieldwork period, with the least exposed fieldwork periods during the summer (table 5.3C). Additionally, there are changes throughout the site regardless of fieldwork period with some areas of the parkland being more exposed than others (table 5.3A). Flags to the north and edges of the parkland were more exposed than those in other areas (table 5.3A, B). About half of trees were more exposed than the average (table 5.3A), with flags at one tree providing no data due to the impact of livestock. Livestock affected flags at study trees across the estate, but especially those between 19 and 25 (see appendix 4.3, table A4.3.2), with a loss of data for the majority of the year. The fieldwork period between July and September (JAS, table 5.3C) was most affected by livestock, with 64% of data missing.

Table 5.3: A) The average relative difference in the proportion of flag weight lost compared to the average for every tree. B) The average relative difference in the proportion of flag weight lost as an average of each compass direction. C) The average relative difference in the proportion of flag weigh tlost as an average of each fieldwork period. NDJ – November to January, JFM – January to March, MAM – March to May, JAS – July to September, SON – September to November. Values > 1 represent flags, directions and fieldwork periods that lost more weight than the average and values < 1 represent flags, directions and fieldwork periods that lost less weight than the average.

A	Tree	Average relative difference	Tree	Average relative difference	
	1	1.300	13	0.997	
	2	1.036	14	0.949	
	3	0.943	15	1.027	
	4	1.018	16	0.814	
	6	1.035	17	0.926	
	7	1.197	18	0.846	
	8	1.149	19	0.854	
	9	0.980	20	0.729	
	10	1.034	24	NA	
	11	1.098	25	0.863	
	12	1.024			
B	Direction	Average relative difference	C	Fieldwork period	Average relative difference
	North	1.001		NDJ	1.038
	South	0.990		JFM	1.054
	East	1.007		MAM	0.862
	West	1.002		JAS	0.915
				SON	1.072

Figure 5.3: Average flag weight loss (%) for each study tree site in the Chirk Castle parkland over the fieldwork period between November 2019 and November 2020. Black points represent the site of the study tree. The more weight lost by the four flags on average at that tree, the darker the larger point. Any black points without a larger point represent a tree without data collected due to livestock or wind disturbance to those flags. NDJ) November – December – January 2019-2020 (62 days), JFM) January – February – March 2020 (61 days), MAM) March – April – May 2020 (68 days), JAS) July – August – September 2020 (69 days), SON) September – October – November 2020 (61 days).

Figure 5.4 shows the relative exposure of each flag during the fieldwork study between November 2019 and November 2020. The warmer months (figure 5.4C, D) were the least exposed and the colder months (figure 5.4A, B, E) were more exposed. Areas of the site to the north-west were more exposed than those in the south-west or south-east. Between tree exposure varied seasonally, with the majority of trees having greater than the average exposure at some point during the year (figure 5.4). More flags were more exposed than the average between the NDJ (figure 5.4A) and JFM (figure 5.4B) fieldwork periods than at other times of year. Flags between MAM (figure 5.4C) and JAS (figure 5.4D) had the least number of flags more exposed than the average, although both these fieldwork periods saw the highest amount of livestock disturbance. Some flags were consistently more exposed than the average during the entire fieldwork study (figure 5.4). These were flags at trees one and two in the north-west area of the property, flags at tree seven in the centre north-west area and flags at tree 13 in the centre of the parkland close to the castle, which had one or more flags exposed more than the average for every fieldwork period (figure 5.4). Log-transformed Welch-one way ANOVA results indicated that the exposure of trees to wind was statistically different between NDJ and MAM (-0.21, 95% CI (-0.33 to -0.09), $p < .001$), NDJ and JAS (-0.16, 95% CI (-0.32 to -0.01), $p < 0.05$), JFM and MAM (-0.21, 95% CI (-0.35 to -0.07), $p < .001$) and MAM to SON (0.22, 95% CI (0.06 to 0.37), $p < 0.05$), but no other combination of fieldwork periods were statistically different. There is some evidence of seasonality affecting wind exposure, most notably in fieldwork periods that were in different seasons. Those fieldwork periods that were concurrent, with the exception of JFM to MAM were not statistically difference from one another.

Results calculating future predicted exposure with average wind speed and average maximum gust speeds showed very little change from zero (appendix 4, table A4.3.3). Therefore, all results presented are future exposure of trees to maximum average wind speeds and maximum gust speeds. Raw results for each flag can be found as supplementary material in appendix 4 (table A4.3.3 and table A4.3.4).

Future predicted exposure from maximum average wind speeds (figure 5.5), and maximum wind gusts (figure 5.6), vary spatially within and between future climate averages. In the 2030s (figure 5.5A-E), more areas on the property are predicted to experience maximum average wind speeds that could increase the exposure risk to the individual trees. This can be seen clearly in the JFM fieldwork period (figure 5.5B) with the whole site being more exposed to maximum average wind speeds than the average. Where just a few flag sites are more exposed, these are all to the north side of a tree (figure 5.5A, D) in the SON and JAS fieldwork periods, suggesting these sides of those individual trees could be more at risk. When investigating potential risk in the 2070s (figure 5.5F-J), the risk of exposure from maximum average wind speed is only above the average for the NDJ fieldwork period (figure 5.5E). All other fieldwork periods in this projection are predicted to see a smaller risk of exposure from maximum average wind speeds. This suggests a greater risk in the short term, with some temporal shifts in exposure.

Maximum gust speeds (figure 5.6) have a greater impact on exposure than maximum average wind speeds (figure 5.5). There are some changes between both future climate periods, but in this case predictions for exposure in the 2070s (figure 5.6F-J) are greater than those in the 2030s (figure 5.6A-E). Similar to figure 5.5, the JFM fieldwork periods (figure 5.6B, G) predict that trees could be more exposed than the average to maximum gust speeds, with less impact on other fieldwork periods. There are predicted to be a greater number of trees in the 2070s (figure 5.6F-J) that are likely to be more exposed than the average, with the majority of trees in the MAM fieldwork periods (figure 5.6H) to be at a greater risk of exposure. This is a large change from the fieldwork period baseline (figure 5.4C), when the MAM fieldwork period is observed to have the least impact from wind exposure. There are some similarities to the maximum average wind speed predictions, with trees along the north side of the parkland being most exposed to maximum wind gusts when other trees are not affected (figure 5.6I, J).

When investigating the impacts of wind direction, there was minimal change between the baseline and both future projections (figure 5.7). Winds from the south-west are predicted to be the most common over all time periods (figure 5.7), in line with current prevailing winds. Largest changes in predicted wind direction were between the 1990s and 2030s, with south-easterly winds becoming more prevalent (figure 5.7B). North-westerly winds were predicted to become more widespread in the 2070s, with no prevailing winds from the east (figure 5.7C). Despite some predicted changes to wind directions, a south-westerly prevailing wind is likely to remain the most common over the next 80 years at the case study site. Spatial changes to prevailing wind direction are most common in the summer months (see supplementary material, appendix 4.3 table A3.3.5), when there are greater changes for prevailing winds to occur from a north-westerly direction. However, during winter periods when exposure is greatest, prevailing wind direction is not predicted to change (appendix 4.3, table A4.3.5).

Overall, the largest impacts from wind temporally, observed and predicted, are during winter months, with the JFM fieldwork period most affected in the future in all years and metrics (figure 5.5B, figure 5.6B, G). Maximum gust speeds are likely to have a greater negative impact on tree exposure than maximum average wind speeds, with the risk of exposure in the latter staying roughly the same temporally and only shifting spatially (figure 5.5). The risk of exposure from maximum gust speeds is likely to double across the Chirk Castle parkland with more flag sites becoming exposed spatially and temporally (figure 5.6). The most affected flag sites from wind exposure are to the north of the study trees in all time periods and wind metrics.

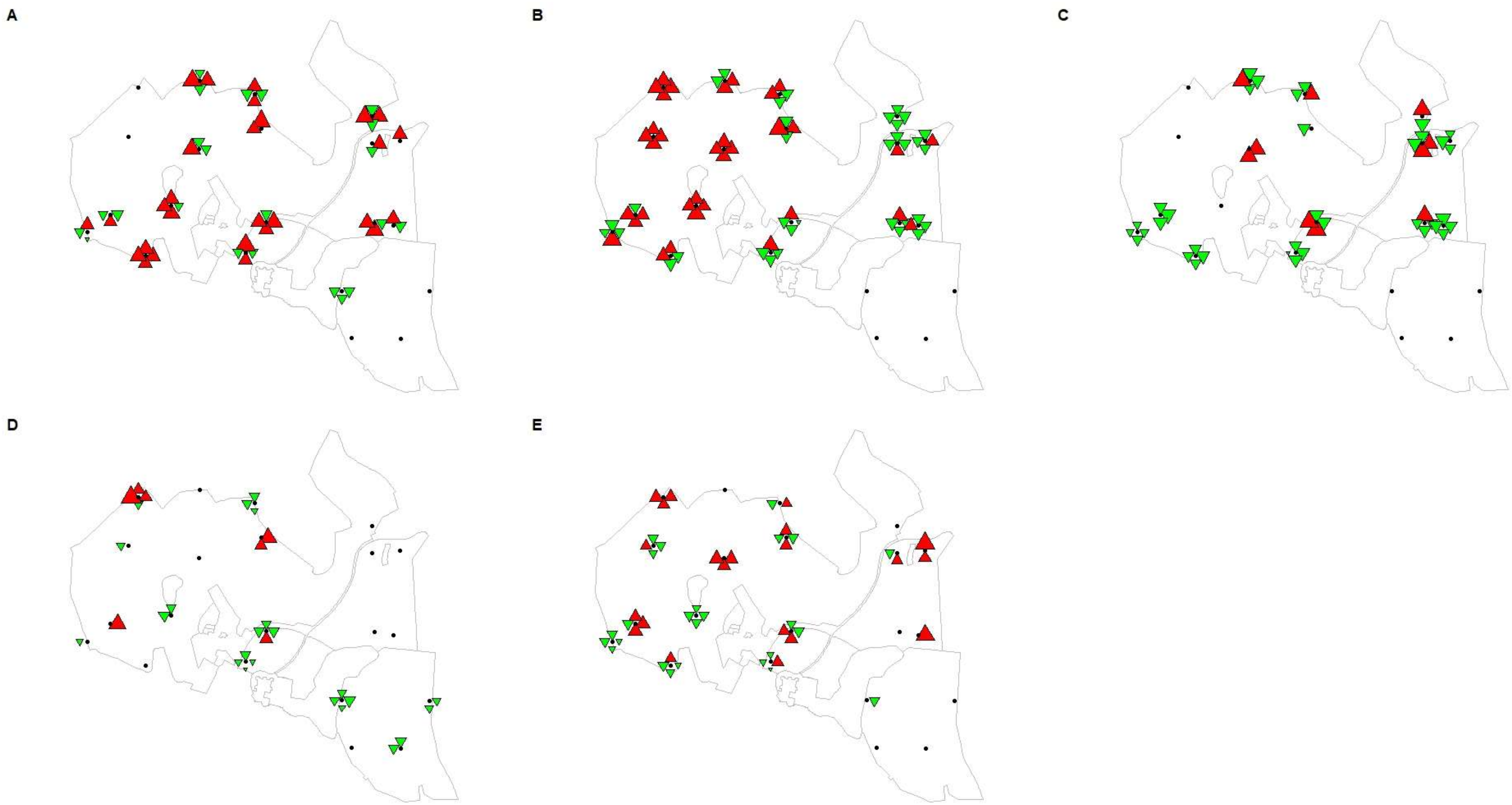


Figure 5.4: Relative exposure of each study tree in the Chirk Castle parkland to wind speeds and direction during the fieldwork period between November 2019 and November 2020. Exposure calculated from the relative proportion of flag weight loss over time. Red, upward arrows represent flags that lost more than the average weight and are therefore more exposed to wind speeds. Green, downward arrows represent flags that lost less weight than the average and are therefore less exposed to wind speeds. A) November – December – January (NDJ), B) January – February – March (JFM), C) March – April – May (MAM), D) July – August – September (JAS), E) September – October – November (SON).

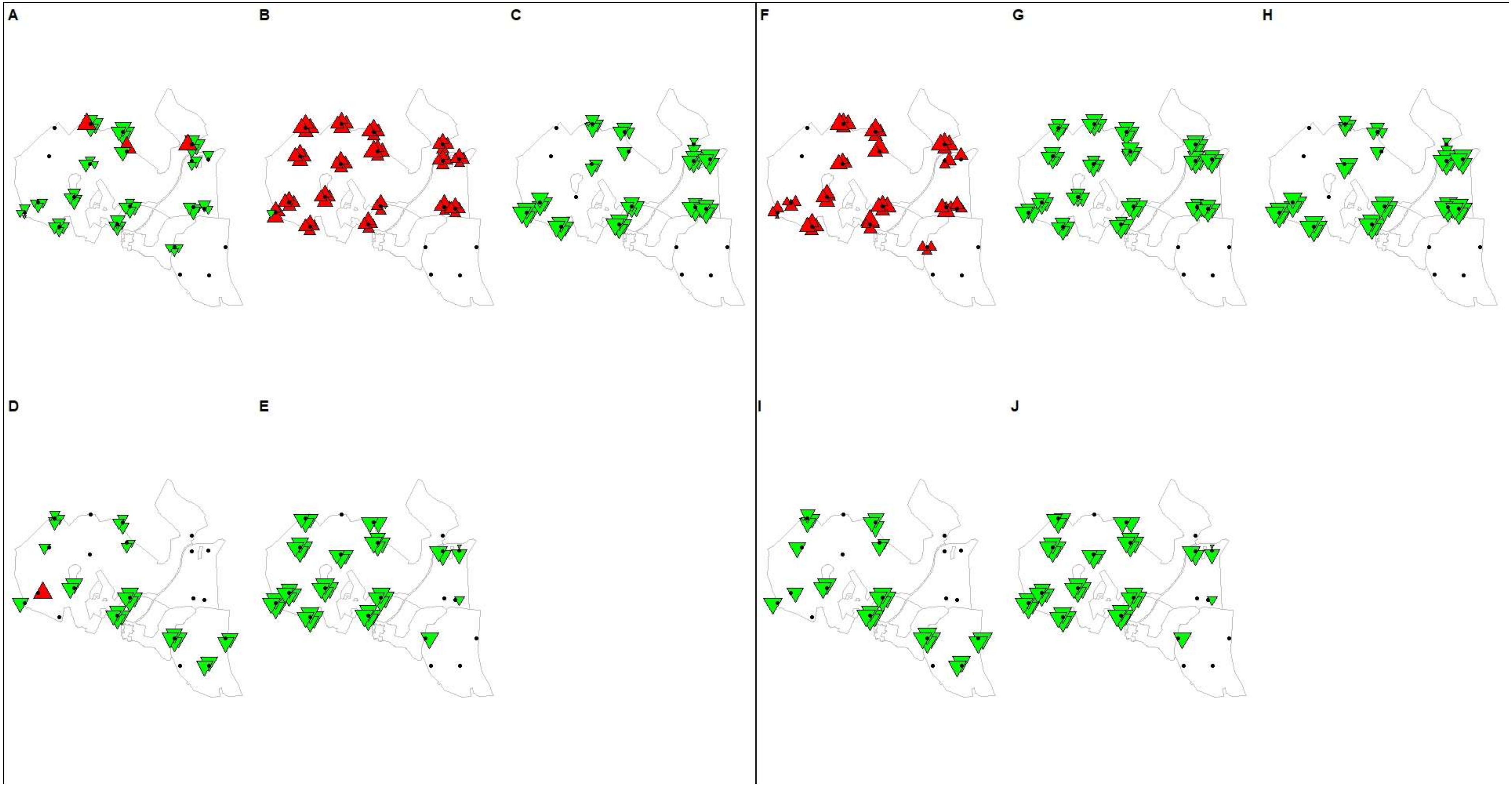


Figure 5.5: Estimated future relative exposure for study trees from maximum average wind speeds. Red, upwards arrows represent flags that are predicted to lose more weight than the average and therefore would be more exposed to future maximum average wind speeds. Green, downward arrows represent flags that are predicted to lose less weight than the average and therefore would be less exposed to future maximum average wind speeds. Panels A to E show predictions for the 20-year average between 2020 and 2040. Panels F to J show predictions for the 20-year average between 2060 and 2080. A/F) November – December – January (NDJ), B/G) January – February – March (JFM), C/H) March – April – May (MAM), D/I) July – August – September (JAS), E/J) September – October – November (SON).

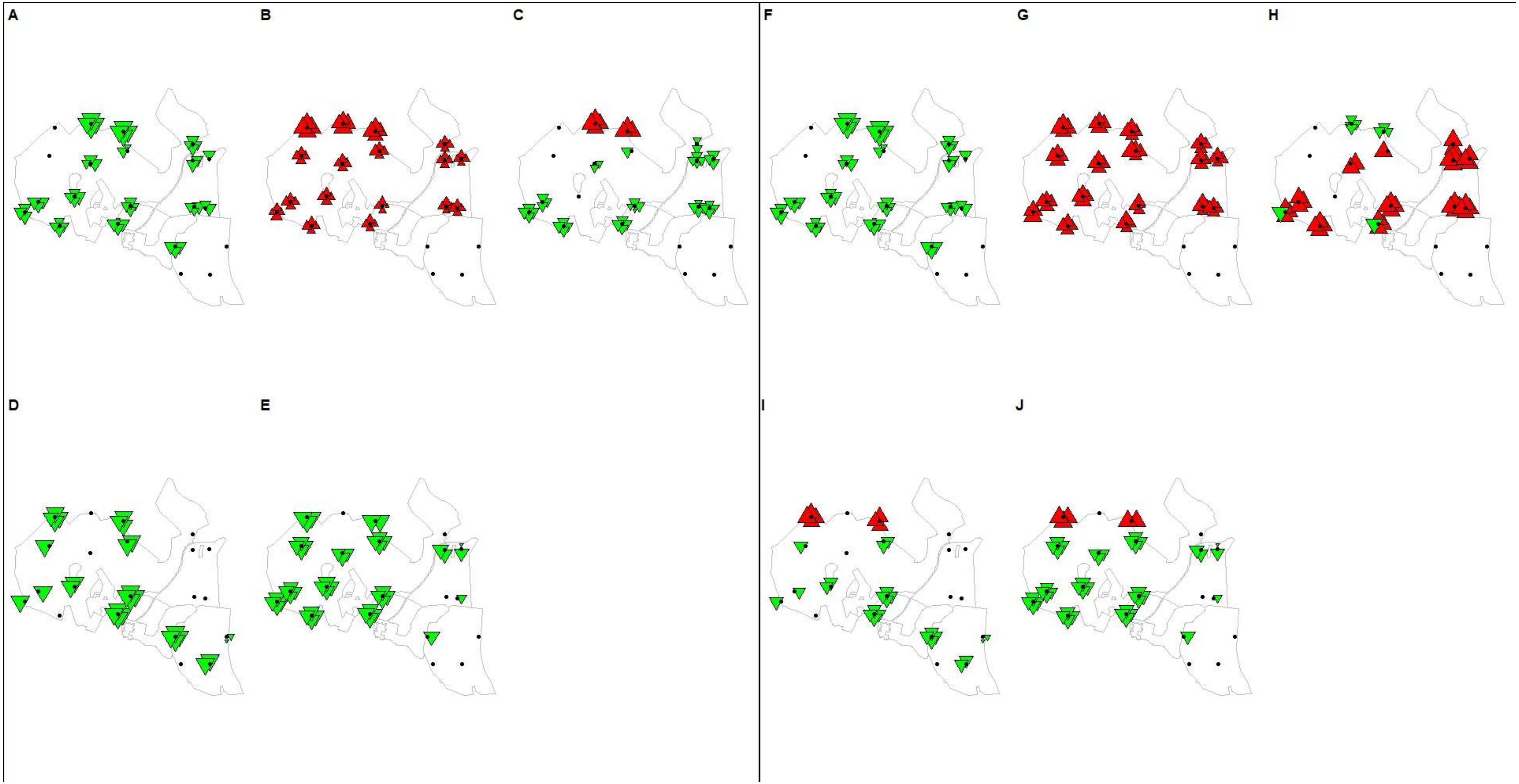


Figure 5.6: Estimated future relative exposure for study trees from maximum gust speeds. Red, upwards arrows represent flags that are predicted to lose more weight than the average and therefore would be more exposed to future maximum wind gust speeds. Green, downward arrows represent flags that are predicted to lose less weight than the average and therefore would be less exposed to future maximum wind gust speeds. Panels A to E show predictions for the 20-year average between 2020 and 2040. Panels F to J show predictions for the 20-year average between 2060 and 2080. A/F) November – December – January (NDJ), B/G) January – February – March (JFM), C/H) March – April – May (MAM), D/I) July – August – September (JAS), E/J) September – October – November (SON).

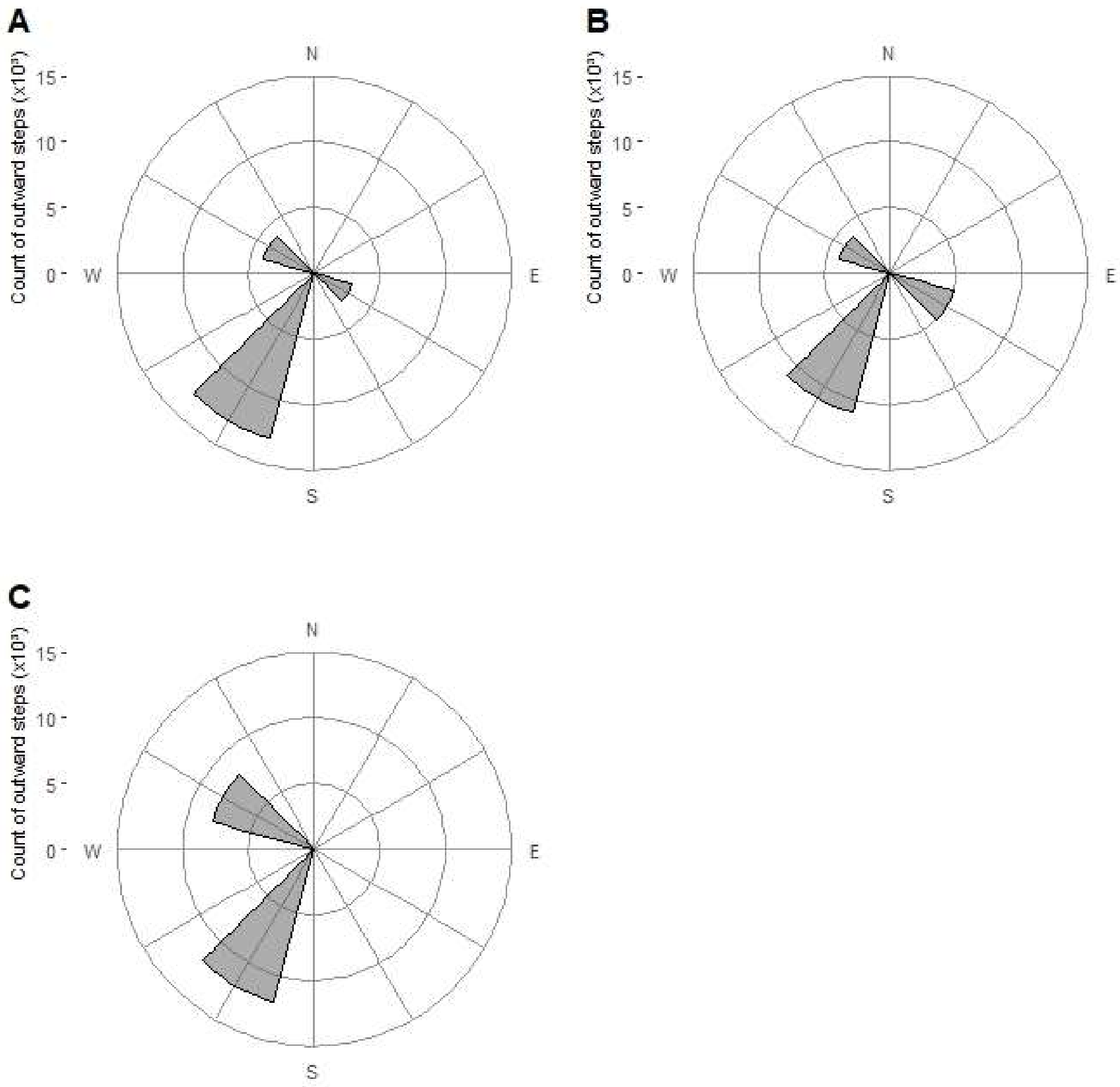


Figure 5.7: The most common wind direction at Chirk Castle from the baseline (A) 1980 to 2000), to the short-term future (B) 2020 to 2040) and long-term future (C) 2060 to 2080. The direction indicated shows the wind azimuth direction. E.g., the most common wind direction at the baseline is south-westerly.

5.4 Discussion

5.4.1 Fieldwork use of tatter flags

This study has demonstrated that tatter flags can be used to identify areas of exposure to individual trees at a broadleaf parkland scale and that these methods are not restricted to commercial forestry. Deploying multiple flags at each site has shown that direction influences wind exposure to trees, something that is often not explored with tatter flag studies in commercial forestry as only one flag is stationed at a site (Quine and White, 1994; Quine, 2000). Direction impacts wind exposure to trees, with winds from the north the most likely to cause a larger impact to an individual tree under future conditions.

There were some limitations to stationing multiple flags at multiple trees over a fieldwork period. All flags were handmade to reduce monetary cost, which added significant time to the study through marking out, cutting and labelling each flag before weighing before and after the flag was in the field. Additional time was required to soak, hand wash and air dry all the flags to prevent unwanted damage in machine washing and drying. Another consideration is to the type of cotton used in flag making. Madapollam cotton is stated in Mackie and Gough, (1994), although this is difficult to acquire. The closest available muslin cotton was used, which may also affect comparisons between this study and those before. Although methods were not directly replicated, this chapter presents an alternative way to calculate exposure using tatter flags regardless of flag size or material, relying on proportion of loss rather than cm^2, which is likely to be more accessible.

Unforeseen impacts are present in many experimental studies, and in this case, livestock on the Chirk Castle estate caused significant damage and data loss throughout the study period. Results may therefore be skewed to tree sites that did not experience data loss, and these affected study trees and subsequent flags may have provided a different story to tell. However, from the little data collected from the most affected field (trees 19, 20, 24 and 25), wind exposure is below the average and these trees are not expected to be those most at risk from wind speeds on the estate. However, this could be due to cattle favouring these areas on the site.

Another unforeseen impact was the COVID-19 pandemic and the subsequent lockdowns, which prevented travel to and from the study site for three months of the fieldwork period. This meant that three months of fieldwork between May, June and July were not undertaken which may skew results as the impacts of wind speed and direction to the site during these times could not be assessed. However, subsequent months of fieldwork yielded the lowest wind exposure values of the whole year, with wind conditions not dissimilar to those during the months of missing data. This could suggest that even though three months of data is missing due to the pandemic, exposure values for these times are likely not to be the greatest for the year and as such, at risk times are not underestimated.

5.4.2 Weight vs. size

There is little information in the literature regarding the analysis of tatter flags post-fieldwork with methods on tatter rate calculation from Forest Research (Mackie and Gough, 1994) stating that '*the amount of tatter is measured and the actual tatter rate ($cm^2 day^{-1}$) is calculated*'. From this, two methods were developed to calculate tatter rate, although this was done over each two month fieldwork period rather than per day due to the amount of data collected. In past studies, fewer flags were deployed at each site, often just a handful rather than over 400 in this experiment. Therefore, measuring change by hand, as was done in the past, was simply not feasible. Weighing and photographing each flag before and after fieldwork was completed to calculate weight and area lost from each respective method. Only the weight change results produced a repeatable outcome, with too many variables from the photography method being difficult to control. This could be due to issues with how flags were photographed and analysed, as laboratory conditions for photographing were unavailable. Estimating size loss using photographs and robust analysis of size change using R coding is potentially a very useful method, but more analysis and tests need to be done before this is a reliable method of estimating tatter rate. Other studies investigating tatter rate to measure tree exposure have not been forthcoming on the methods used in analysis (e.g. Willoughby, Stokes and Kerr, 2009), often simply citing Mackie and Gough (1994) without further information.

5.4.3 Exposure, wind data and scale

For most of the fieldwork periods and wind metrics (figures 4.4 to 4.6), flags at each tree experience similar exposure, which is consistent across site. This suggests a greater temporal effect than spatial, and highlights the potential importance for fine scale wind data. Maximum wind gusts are found to have a greater impact on exposure than maximum average wind speed, which is expected as gusts are always higher than average speeds. The study period between and including January to March (JFM) is predicted to experience the highest exposure from average wind at the short term and wind gusts for both future periods. Winter storms in the past 20 years have been concentrated in these months, so current trends are expected to continue, although potentially worsen.

Some recent evidence (Gardiner, 2021) suggests that damage is likely to occur when canopy top hourly wind speeds exceed 8.5 m s^{-1}. Wind speeds are likely to exceed a higher threshold of 22 m s^{-1} more often in the future in winter and spring, increasing the potential for damaging conditions. The lower damage thresholds are likely to be exceeded much more often, posing a far greater risk than currently expected, at least in the study site presented here.

Additionally, it has been suggested that in colder climates, there is increased forest vulnerability to windthrow due to shallower rooting systems and lower stem resistance of trees in these regions (Forzieri *et al.*, 2021). This, coupled with an increase in wind exposure, especially when trees are coming into leaf earlier across the UK and worldwide (Parmesan and Yohe, 2003; Walther, 2010; Polgar and Primack, 2011; Primack *et al.*, 2015; Reeves *et al.*, 2022) exacerbated by climate change, could have significant impacts on tree damage and windthrow. Furthermore, a warming-induced reduction in plant defence mechanisms is increasing forest vulnerability to insect outbreaks, especially in higher latitudes (Forzieri *et al.*, 2021). These could increase vulnerability of trees to windthrow due to damage from insects even in wind events that are not significantly more extreme than the average.

This study also predicts that there may be fewer prevailing easterly winds, with no easterly prevailing winds predicted to occur in the 2070s. This could mean that storms such as the 'Beast from the East' which caused country-wide damage due to colder, more intense conditions could become less prevalent. Easterly winds have brought the most severe spells of winter weather over recent years (Kendon *et al.*, 2022), and these incidences may remain few and far between in the future at the very localised study site. Increases in wind speeds from the north-west are predicted, and, although an isolated event, the strongest wind speeds from the damaging Storm Arwen in November 2021 were from the north (Kendon *et al.*, 2022). This could suggest that storms with strong wind speeds could become more common bringing together our predictions of increased winter wind exposure, more winds from northerly directions and observations of previous damaging storms. These however, are predictions of wind speeds rather than extreme events, with other variables factoring into the occurrence of a winter storm that must be taken into consideration alongside wind direction predictions.

There are other impacts that are likely to affect established broadleaf trees, exacerbating or overwhelming the impacts of wind. Fire and insect outbreaks were found to have greater impacts in some locations compared to wind (Forzieri *et al.*, 2021). The impacts of fire at the case study site are unlikely due to the site use and wetter Welsh climate (Lowe *et al.*, 2018). However, incidences of hotter, drier summers are increasing and could increase the likelihood of a fire event. The Chirk Castle estate is internationally recognised for saproxylic invertebrates which feed on decaying wood. These species rely on old-growth structures (Bouget and Parmain, 2016), which may be at risk from increased exposure, and could lead to clearing by staff for health and safety. Wind-thrown trees have been found to promote biodiversity and restoration within forests (Thorn *et al.*, 2014), and are likely to do the same in a mature parkland. Removing these downed trees reduced biodiversity and removed habitat for saproxylic species (Thorn *et al.*, 2014). Additionally, tree-level parameters including size and species were more important than landscape-level predictors (Buse, Schröder and Assmann, 2007) on the occurrence probability of an endangered saproxylic beetle. Ensuring that suitable trees are maintained and that some wood remains on-site when limbs or the tree are lost, could bolster populations of these internationally important invertebrates. Increased windthrow could improve distributions of saproxylic invertebrates, but large-scale loss of trees is not sustainable for the long-term support of these species.

There are some limitations to this work. Previous studies using tatter flags deployed flags for a minimum of three years (Jack and Savill, 1973; Willoughby, Stokes and Kerr, 2009) to gather longer-term patterns and extremes. This length of time was not possible during this study, and there were further time constraints due to the COVID-19 pandemic. A full year of data collection was not possible under pandemic restrictions, and further long-term data collection could reveal trends that do not present themselves under this short time scale. Due to the highly localised nature of wind trajectories and speeds, the use of multiple climate models investigating these trends is important (Forzieri *et al.*, 2021). However, due to the limitations of this study only one model member was used, which may significantly alter the results presented. This study does provide a very useful analysis of wind exposure to a specific site, yet incorporating a greater range of model members would provide a more robust assessment of potential future risk. Additionally, methods and analyses were tested at a local scale, focusing on one case study site. Analysis of multiple sites over a wide range of landscapes would display meaningful trends, although the time and labour costs in employing our methods may be significant.

5.4.4 Impacts of results to conservation organisations and the National Trust

Results from this study have shown that times of greatest wind exposure may change but are predicted to be focused into specific times of year and in specific areas of the site. Conservation and site management can be targeted to these areas and these results used to influence current and future conservation and visitor management plans. Areas of the site more exposed by a change in prevailing wind direction could be targeted to protect trees which could become more vulnerable to winds from another direction. Exposure from wind gusts in the JFM time period could increase by over 16 times that of the baseline at the short-term future between 2020 to 2040. This is likely to have significant impacts to trees and other landscape features especially as prevailing wind directions on the Chirk Castle estate are predicted to switch from south-west to north-west, potentially bringing in colder weather. It has been estimated that small changes to wind speeds and directions can have a large impact on wind strength (Fung *et al.*, 2018), which could impact trees greatly, especially if they are not acclimated to wind from an unfamiliar direction.

Spatial maps are useful in estimating site vulnerability to wind exposure alongside values of exposure. Other studies have simply used numeric valuations of risk and exposure (Miller, Quine and Hunt, 1987; Quine and White, 1994; Quine, 2000; Mylona, 2012; Kamimura *et al.*, 2019; Valta *et al.*, 2019), but developing these spatial maps increases the chance these results will be put into place by experts on the ground.

There are useful implications for the National Trust in further exploring these results, and to other conservation and nature organisations utilising the methodology that has been developed. Wind exposure is likely to increase at certain times of year at the Chirk Castle estate, with health and safety measures impacted in response to this. Understanding where and when risk to staff and visitors is more likely to occur is useful in updating operational procedures including risk assessments and site access. Our research has highlighted that high wind speeds are expected to become more common around busy Christmas and Easter periods at Chirk Castle.

There are likely to be significant changes to landscape features that the National Trust are working to preserve on-site. While management considers tree health and mitigates tree loss and damage, trees are currently replaced like for like. This push to keep landscapes the same, due to original plans and heritage need, may not be feasible in the future. There is a wealth of literature examining how to preserve culturally important structures from climate change (Sabbioni *et al.*, 2009; Lankester and Brimblecombe, 2012; Leissner *et al.*, 2015), with less research into protecting culturally important natural landscapes. At this case study site, the historic parkland may need to evolve in terms of the individual trees and species. While it is understandable that the preservation of a historical parkland is likely to be an important consideration when planning site work, it is unclear if preservation will be sustainable in the long-term viability of such a site. The parkland at Chirk Castle follows the original plans of tree species and placement, and has not been changed since the 1300s. Everything from global climate, local weather, land management practices and site use have changed drastically since the original plans were devised, which may not suit current circumstances. Conservation, including adaptation to change, would lead to a more sustainable future for the parkland, while also preserving the heritage background of the site. Becoming responsible stewards of these environments through adaptation, sustainability, transformation and reform (Mathevet, Bousquet and Raymond, 2018) is vital to bring together humans and the environment to support landscapes that will both thrive in the future and also represent past heritage. While negative impacts in the 2070s may seem like a lifetime away, the long-term nature of tree management and planning requires these conditions to be included in consideration. Not considering the impact felt by relatively young 50-year-old trees planted today, could spell disaster for future biodiversity and heritage in a parkland that has been around for many centuries longer than the scales of these projections. There is a delicate balance between conserving the environment and preserving heritage, which need to be taken forward hand in hand through compassionate records and forecasts of change and evidence-based decisions about how these changes should occur.

There could be some physical measures put in place to conserve trees of high heritage value. These could include hedges made up of hardier trees such as hawthorn or alder, or tiered screens of more wind-resistant trees especially coniferous species in a 3-row structure which was found to reduce wind speeds by 75 % at a height of 1.5 metres (Jeong and Lee, 2020). Methods such as these are likely to have a large, and potentially negative, visual impact to a historic site, but could increase site biodiversity and provide shelter for a range of species, alongside the benefit of heritage tree protection.

While the effect of climate change will be site specific, it is likely that other historic sites will be similarly affected, and management will require similar considerations. Further work to understand regional or country-wide trends may be useful to pinpoint areas of vulnerability. One way this was estimated previously was through the Windthrow Hazard Classification (Miller, 1985; Quine and White, 1994). These methods could be brought up to date using remote sensing and currently available data to highlight areas potentially requiring more detailed investigations.

5.5 Conclusions

Tatter flags are useful to assess impacts from future wind exposure and direction to individual parkland trees. In flag analysis, using high resolution weight change data is more useful than change in size from photograph analysis. Through successful integration of tatter flag results and climate projections, fieldwork results can be used to predict future exposure. This study shows that exposure to wind does change spatially and temporally, with greater short-term impacts from maximum average wind speed and greater long-term impacts from maximum gust speeds, both in winter months. Wind direction is expected to change, with the greatest impacts to winter months at the short-term and summer months in the long term. Higher wind speeds from northerly directions are expected to bring more damaging conditions. The current preservation and/or hold-the-line conservation approach and techniques are unlikely to maintain biodiversity and heritage value in the future at the case study site. Our study combines established tatter flag methods with climate change projections to present a novel and low-tech way of quantifying exposure to individual parkland trees.

Chapter 6: Working with end users through iterative feedback improves the outcomes of climate impact models for nature conservation

Abstract

There is a recognised gap between science and practice, with few research outputs translating into conservation management decisions due to lack of time, access, or resources as issues commonly cited. This includes future impacts of risk and often practical conservation at local sites is based on experience, historic knowledge and business-as-usual, with a core team of dedicated staff sharing information about a site they know very well. To adapt to climate change, conservation decision-makers will need to understand the impacts of change in order to protect species and habitats. Studies have shown that integrating stakeholders and decision-makers in research projects at all stages increases usefulness and likelihood of use of outputs. This study explores how the projects and results were developed with case study site staff, and how this influenced the results presented in this thesis.

Studies investigating suitable climate space for birds in the uplands (chapter 3), the variation of fire risk to an upland peatland (chapter 4), and the impact of wind speed and direction to individual parkland trees (chapter 5), were developed with case study partners. An online feedback questionnaire was shared, sent to each case study site to gather opinions and information about the chapter results and current site management. The questionnaire was sent out alongside site-specific results with explanations of these results and details on the study rationale and methods used. Responses from staff at every site were welcomed and from any area within their site. Responses were collated and used to guide the next iteration of results.

Repeated sharing of study results and information leads to information that is more useful to staff on site, which is more likely to be used in conservation planning. Understanding management need was a common response in regards to the usefulness of the results presented, as often work is required regardless of climate impact. This study shows that involvement with site-specific staff is essential when investigating the impacts of climate to a site. Not only were results improved following feedback with staff, but that through the building of relationships and sharing of knowledge, that these results are more likely to be used on site in the future.

As with other studies, including site staff in research from the outset lead to study results of greater use and significance. Understanding, through iterative feedback, how results are, and are not, useful and the needs and requirements of information needed to make conservation management

decisions, is important in the development of sound science and nature conservation actions. Integrating research and pure science with actual conservation work will lead to more resilient, healthy ecosystems and evidence-based decisions for future plans which are vital in the work against the climate crisis.

6.1 Introduction

Both scientists and conservation professionals have voiced long-standing concerns about the lack of exchange between science and practice (Pullin and Knight, 2005; Cook, Hockings and Carter, 2010; Anderson, 2014; Fabian *et al.*, 2019). From limited access to journal articles (Anderson, 2014), language barriers (Fabian *et al.*, 2019), lack of time for rigorous research (Cook, Hockings and Carter, 2010; Anderson, 2014; Fabian *et al.*, 2019), and overall inaccessibility and overcomplication of published research (Pullin and Knight, 2005; Ainsworth *et al.*, 2020). This could lead to useful research not being implemented, or conservation issues left unchecked, causing potential negative impacts to the natural world. One study found that around 60 % of conservation management decisions relied on experience-based information, with a lack of useful evidence-based research (Cook, Hockings and Carter, 2010). Practitioners have to make judgements and give advice based on the available evidence at the time, often for multiple activities, in response to ongoing impacts and keeping in mind budgets and implementation time. These professionals are under increasing pressure to drive positive change, despite increasing time and resources pressures (Jones, Turvey and Papworth, 2021). Many models investigating the links and drivers between climate change and biodiversity are often highly complex and difficult to understand outside of research circles (and for some of us currently in those circles!). However, ecological models could be useful to professionals through analysis of different interventions and future impacts (Parrott *et al.*, 2012). Making 'pure science' accessible to conservation professionals is vital to meeting global targets, boosting biodiversity, and tackling the climate crisis. All which local sites and experts on the ground can have a significant positive impact to, but only if the information they require is accessible and relevant. Management decisions for local sites, from nature reserves to National Trust properties are often made by staff on-site. These sites often have a dedicated, long-term staff base who have a deep understanding of these areas, the pressures to the systems and how to alleviate these. This provides invaluable local knowledge, and the ability for conservation work to maintain the status quo of a site, often to a high standard, especially if following guidance to preserve the status of protected sites such as SSSIs. That experience-based information rather than evidence-based through published material has been found to be commonly used in nature conservation (Fabian *et al.*, 2019). Staff in practice on-site are often those making decisions about current and future management. For example, site managers at each National Nature Reserve (NNR) in England write management plans every 5 to 10 years in response to site observations and information provided by outside bodies (Duffield, Le Bas and Morecroft, 2021). However, consideration of climate impacts is not as well understood or included extensively in management plans, with further considerations to conserve and improve biodiversity required in the long term (Duffield, Le Bas and Morecroft, 2021). Additionally, future conditions are likely to be significantly different to those currently experienced (Lowe *et al.*, 2018; Masson-Delmotte *et al.*, 2018a), and the experience and practices currently in use to manage and protect natural spaces could be less effective in the future.

Integrating local knowledge with scientific research can significantly improve environmental decision making (Ainsworth *et al.*, 2020), although often there are many competing views and agendas. This implementation of research, and communication with professionals through discussion and field-trips builds these important relationships (Fabian *et al.*, 2019). Bottom-up modelling, incorporating the views and expertise of on-site practitioners, can contribute to new landscape science based on scenario building (Parrott *et al.*, 2012). Through these practices, all views can be heard and discussed, although care must be taken to ensure diversity of attendees and methods of knowledge transfer (Fabian *et al.*, 2019). Visualisation of results can be a good tool in understanding climate change impacts (Shaw *et al.*, 2009; Palacios-Agundez *et al.*, 2013). Discussing a figure or graph is likely to provide more meaningful discourse than a statistic or number, especially if relevant sites and recognisable places are highlighted. These highly participatory methods are more successful at engaging practitioners and implementing research (Palacios-Agundez *et al.*, 2013). Additionally, studies on the science-policy interface that engage non-academic stakeholders throughout the research processes creates ownership, accountability and a willingness to act (Shaw *et al.*, 2009). Early involvement of stakeholders in the transparent development of projects and improvement of methods has shown increased chance of success of subsequent management efforts (Guisan *et al.*, 2013; Seidl *et al.*, 2013; Samson *et al.*, 2017).

Climate change presents us with an opportunity to make new plans for future conservation management which put resilience and flexibility at the heart of natural systems, to adapt and mitigate to future change. Stakeholders, conservation professionals and local people need to be at the centre of these plans from first development, contributing to science and practice as experts in their local area. Local climate change is likely to impact species and habitats in a variety of ways. Some species are likely to thrive (chapter 3), with habitats (chapter 5), and extreme events (chapter 4) more at risk from negative impacts in the long term. Additionally, national Non-Governmental Organisations (NGOs) and charities in the UK driven by public membership such as the National Trust and RSPB have a need to protect local natural and built environments to provide places for people to interact with nature alongside biodiversity benefits. Local nature has a large impact on peoples wellbeing (Buijs *et al.*, 2022) alongside important contributions to ecosystem services in an area such as flood prevention (Dolan *et al.*, 2021). Diversification of environmental governance, as seen in the inclusion of natural capital and green economy discussions in EU policy, can bring more stakeholders to the table when discussing environmental management (Buijs *et al.*, 2022). Although these policies do not affect the UK post EU exit, they should not be dismissed or forgotten. The UK's commitment to net zero by 2050 (BEIS, 2021) should include multiple stakeholders in the reduction of GHG emissions, and discussions around local environmental management could provide a strong basis to these plans. Integrating these ideas with sound, evidence-based research presented in an accessible manner increases the likelihood of implementation and strong relationships between researchers and professionals. There are a strong diversity of experts in nature conservation in the UK, from complex statistical modellers to those with an intimate knowledge of local natural processes. This presents an exciting chance to bring together conceptual ideas with what actually happens on the ground to make positive steps in adaptation and mitigation to climate change.

Research aims

This study aims to bring together climate impact modelling with non-academic experts at contrasting case study sites. Through in-person meetings, ongoing communication, and questionnaire feedback we, as the researcher and collaborative partners from all case study sites, aim to improve predictions of change and the ways these are presented. Questionnaire feedback was iterative, with subsequent results developed with previous feedback answers. Results post-iterations are hypothesised to become more useful to site practitioners, and through their involvement a greater ownership and desire to integrate results into conservation management planning is achieved. Research is only useful if it is implemented, either into further research or practical application. I, as the researcher, hope that the results presented in this thesis are more likely to be implemented into conservation practices due to the inclusion of experts from project conception to thesis completion. Through investigation of quantitative and qualitative data exploring the results and scope of project, ways to integrate site-based staff and their expert knowledge into scenarios of future change and risk under climate change have been identified. This chapter also provides a reflection on the survey development and application, and what could be improved in similar future projects.

6.2 Methods

6.2.1 The case studies

In previous chapters, three impacts to National Trust Wales properties likely to be exacerbated by climate change were explored using climate projections to make predictions of future risk. The studies at:

1. Abergwesyn Common explored if and when there is likely to be suitable climate and habitat space for a suite of birds found in the uplands of Great Britain (chapter 3),
2. The Migneint Peatland on the Ysbyty Ifan Estate quantified the fire risk impact and intensity of future fires (chapter 4), and
3. Chirk Castle investigated the impacts of wind exposure and direction to individual parkland trees (chapter 5).

These studies were all developed from day one with staff at each case study site, through regular email communication and at least one in-person visit to each field site. These visits consisted of site tours, discussion of site history, current management, and future perceptions of risk. The impacts staff are most worried about were discussed, and through further research narrowed down research questions for each chapter. These questions were confirmed with staff at each site prior to the projects beginning, with regular updates and sharing of information between the research student and site professionals.

6.2.2 The questionnaire

A questionnaire exploring quantitative and qualitative aspects of the studies and National Trust requirements for conservation was developed (see supplementary information in appendix 5). Research was reviewed and approved by the College of Natural Sciences ethics committee at Bangor University prior to undertaking the study. This questionnaire was sent out online using Microsoft Forms (https://forms.office.com) to conservation professionals at all three case study sites alongside current results for that site, with some explanations of rationale, methods, and results. 19 questions explored current information and time frames used to plan conservation management, how staff felt results were useful or not, and gave staff a chance to add comments for future improvements of the questionnaire and research. Ongoing recruitment of professionals through word of mouth and direct communication occurred throughout the study period. The questionnaire was sent out three times each to Abergwesyn Common and the Ysbyty Ifan Estate teams, and twice to Chirk Castle. Disruption due to Covid-19 limited the number of iterations of the questionnaire and resulted in a fairly low sample size.

6.2.3 Data analysis

6.2.3.1 Qualitative questions

Taguette (Rampin and Rampin, 2021), a free and open-source qualitative data analysis software was used to analyse thematic trends in questionnaire responses (appendix 5, table A5.1), with *highlights* for each theme identified in question answers. Every part of an answer could relate to one or multiple highlights. If an answer clearly repeats itself, this was included as one highlight to avoid double counting. These themes were analysed across all case study site responses, with the total number of times each theme was mentioned summed and ranks assigned. From this common themes were identified in answers relating to current management, time frames, usefulness of research results and how these results were not useful to on-site nature conservation. Themes were summarised into main categories for ease in analysis.

6.2.3.2 Quantitative questions

Quantitative questions were analysed through summation of all answers in each question to identify trends. Change over time was examined between result iterations and between different sites. Additionally, the most common responses in likert-scale type questions were identified for each iteration and site, to recognise any change over time.

6.3 Results

The questionnaire survey was live for over 18 months between October 2020 and May 2022 in which time 14 responses from 12 different staff members over the three case study sites were gathered.

6.3.1 Current users of results and overall questionnaire results

Responses were gathered from staff at every case study site, with one response from a member of staff working across all Wales sites. The respondents held a range of jobs, from more senior Head Ranger positions to wider scale Countryside Manager roles and specialist roles around Archaeology and Nature Conservation. The range of respondents gave a good idea as to the structure of teams and those who are involved in making conservation management planning decisions. Staff at Abergwesyn Common completed the greatest number of responses. This site was also used to pilot the questionnaire, which may have influenced the total number of answers. Most members of staff responses to the questionnaire once, but three positions responded twice, a Countryside Manager, Project Manager and Ranger. The Countryside Manager and Project Manager respondents provided two replies each from different case study sites, Abergwesyn Common and Ysbyty Ifan Estate respectively, with Rangers from two different properties (Abergwesyn Common and Chirk Castle). This suggests that mangers may have a greater interest in the impact of results to conservation planning and may have a greater amount of time, and potentially feeling of responsibility, to give to these questions.

Quantitative questions investigated how useful respondents though results were on scale, how likely they were to use them and how they would like to receive the information (supplementary material, appendix 5, questions 9, 13, 16 and 17). Overall, staff at all the case study sites through that the information they currently use on site is extremely or somewhat useful when planning and undertaking conservation work. This suggests that while many respondents are happy with the information they have at their availability, there is room for improvement. All responses about the results and information from how the three studies were perceived to be mostly ‘moderately clear and sufficient’. It is good to see that all responses regarding the results are positive and that staff appear to have been engaged with the study overall. One respondent indicated that they would be unlikely to use the results, but the majority indicated that they would ‘definitely’ or ‘likely’ use the results to support conservation or site management planning and decision making. Most staff would prefer to have maps and analysis already completed, but two members of staff were keen to conduct analyses themselves.

6.3.2 Current conservation management planning and time frames

Six themes from survey responses were identified regarding current site management (table 6.1). Themes around National Trust data use, the role of external organisations and local information were most commonly mentioned when considering information used in current conservation management planning. Collaborations with external organisations were the second highest ranked theme for planning conservation work (table 6.1). Natural Resources Wales input around protected area guidance was commonly mentioned, alongside Welsh Government policy and priorities information.

Table 6.1: Themes relating to current site management at three National Trust Wales properties. Questionnaire question 7 (supplementary material, appendix 5.1).

Theme	Explanation	Rank
Data from National Trust	From a wide variety of sources and scales to direct future work	1
	Historic data provides the background to future work	
	Continuous observations and surveys update plans for future years	
	There is a wealth of information within the National Trust used for planning	
	Estate Management Plans are driven by National Trust strategies	
External organisations	Site designation guidance from SSI and SAC data	2
	Collaboration with organisations including NRW, RSPB, county councils, ecologists, government grants e.g., Glastir	
Local people and knowledge	People and information at the local scale often know the most about properties and sites	3
	Decisions for conservation actions are made at the site-specific local scale	
Priorities and responses	The Covid-19 pandemic has shifted priorities and halted work and planning	4
	These often relate to funding, visitor pressure, tenants, current risk, and previous Estate Management Plans	
Teamwork	For surveys and data collection on-site	5
	Decisions and work plans are made within site teams through discussion	
Engagement	Activities with visitors and volunteers to promote work at specific sites	6
	Disruptive works are planned around busy visitor times	

Data from within the National Trust was ranked first (table 6.1), with evidence from surveys, ecologist reports and archaeological records used to make decisions. Inputs and knowledge from local people was in the top three important themes when considering current conservation management planning (table 6.1). Those involved at the local scale often hold the greatest amount of knowledge about the site or area with their input highly valuable. Estate Management Plans were mentioned by all case study sites as documents which guide future planning at the properties. On-site knowledge is integral to the sites (table 6.1), with one respondent commenting that

"local knowledge is a big element … farmers and ranger team who know [the] location[s] of specific features and structures".

This local information, combined with teamwork for planning works ensures each property runs as an independent unit. Unfortunately, conservation priorities can often change in response to unforeseen impacts. For example, the Covid-19 pandemic had a large impact on conservation work and funding for the National Trust,

"Covid has prevented work planned for this year on Abergwesyn [Common] and as such we have missed out on SMS funding which would [have] been used to help fund works".

These outside, uncontrollable impacts can have large impacts to conservation planning, which is reactive to continuous observations, data collection and current events.

Three planning time frames were identified, with most responses detailing short-term planning for site and conservation works (table 6.2). Planning in the short term is more common than planning in the long or medium term, but these longer time scales are still considered when planning conservation management. These short-term time frames between one and three years, related to ongoing yearly work and reactive measures to impacts,

"project delivery is generally over a 1 – 3 year cycle (depending on funding)".

Table 6.2: The time periods in which planning, and conservation works are undertaken within National Trust Wales sites included in this study. Relating to question 8 of the online questionnaire (appendix 5).

Theme	Explanation	Rank
Short term	Project delivery and funding are generally on a one to three year cycle	1
	Yearly surveys and monitoring keep track of site indicators such as tree health and species numbers	
Long term	Long term management categorised as 10 years plus	2
	Correct management continues in perpetuity post-intervention	
Medium term	Three to 10 years of work and planning	3
	Some restoration e.g., blanket bog, takes a number of years to complete	

Site Management Plans and funding within the National Trust run on these short-term cycles (table 6.2), influencing the type of conservation planning that is undertaken. Other themes, including more general aspects of planning have a large influence on the time frames, such as the financial year, with flexibility brought up as an important consideration when dealing with natural processes. Often, longest-term plans are made with ongoing management in mind (table 2), for example, one respondent mentioned,

" [For] Fridd (hill edge land) expected management timescales would be in decades".

Project timescales and Site Management Plans do consider medium- and long-term time scales, with generic climate change resilience built in in the form of nature conservation, and carbon and water management. However, limitations from weather, funding and biological constraints were highlighted as important themes when considering time scales of planning and undertaking nature conservation,

"Conservation/mitigation work would all ideally be during better weather but is often when it can be fitted into the schedule or when the money comes through".

6.3.3 Usefulness of results presented to case study sites

Results presented in this section relate to answers gathered from questionnaire questions 10 and 11 (supplementary material, appendix 5). Respondents did find results presented to them to be useful to make some management decisions over a range of themes (table 6.3). The greatest use was found to be in the visualisation of results (table 6.3) with respondents understanding climate impacts through maps and figures of spatial change.

Table 6.3: The reasons staff from each case study site found results presented to be useful.

Theme	Explanation	Rank
Visualisation of results	To show spatial changes to sites due to climate change impacts	1
	The data provided could help to plan better in the future	
Site-specificity	Results can steer management for specific restoration and management	2
	On-site policies and documents for specific actions	
Understanding of impact	Including narrative alongside visual results	3
	Presentation and targeting the correct individuals for the information	
Testing	To use the data and results to test scenarios	4

Some ways in which the results were useful were site-specific (table 6.3), to steer management around individual issues. Respondents at Abergwesyn Common mentioned,

"As a general guide, it is helpful to understand predicted change in future climate space for species",

and that,

"The specific maps relating to Abergwesyn Common are the most useful".

At this case study site, spatial, local scale maps are the most useful in planning conservation management. The Chirk Castle study focuses more on visitor health and safety and the impacts to the parkland trees. Respondents thought,

"The tools and data provided could help us to plan for closure due to wind better",

and,

"[The results could] help us plan new walking routes … away from most 'vulnerable' trees".

Again, it was visualisation of results and their fit to the specific site making them most useful at the castle. Respondents from the Ysbyty Ifan Estate noted that,

"[The results are] very useful, as [they] confirm the benefits of key interventions",

and that,

"The maps are useful in providing broad view risks".

Understanding how a site is likely to be impacted by climate change through site specific analysis could prove most useful in future conservation planning. Overall, each case study site found the results useful for different reasons, but they all either found that the results justified the use of conservation interventions or could be used directly to positively impact both natural processes and visitor experience.

6.3.4 How results presented were not useful

There were some ways in which results presented were thought to not be useful to the staff at case study sites that were identified through four main themes (table 6.4). The most common themes identified were around management need at a site (table 6.4). Respondents from Abergwesyn Common and the Ysbyty Ifan Estate mentioned that many other factors go into how management decisions are made, and that sites often require work regardless of the impact from future climatic conditions. When considering the impact of future climate change in relation to fire risk on the upland peatland, one respondent at Ysbyty Ifan stated that,

"[Maps are useful] but only form part of a wider context of things that happen on land".

Additionally, results that are site-specific are limited to the scale they cover, acting as a positive (table 6.3) and negative (table 6.4) impact of this work, depending on the use of the results. One respondent mentioned that,

"Localised/micro-scale circumstances and nuances may be missed".

Further clarification of materials was suggested to make results more useful, as some of the results were found to be misleading. Staff at two sites said that some information was hard to understand, and that a better understanding of what the results mean in different scenarios (table 6.4, 'testing') would be useful.

Table 6.4: The reasons why results presented for each case study site were thought to not be useful to site professionals.

Theme	Explanation	Rank
Management need	Not useful if an area required work was in opposition to results of models	1
	Management is sometimes required for other reasons	
Clarification	Need to develop a better understanding of the results	= 2
	Interpretation of results could be misleading without clarification	
Scale	The results are only useful at the scale they cover	= 2
	Levels of detail change depending on the scale of work planned	
Testing	Need to use the data to test scenarios, not useful if taken at face value	4
	Inclusion of new data important otherwise not useful in the long term	

6.3.5 Improvement suggestions from feedback

Finally, the questionnaire explored how staff felt overall about the results presented, and if there was any further information, figures or questions which were required or needed answering (supplementary material, appendix 5, questions 15, 18, and 19). These, and answers from previous questions outside the main scope, were compiled as improvement suggestions (table 6.5). Overall, most respondents felt that the amount, content, and quality of information was sufficient and said that they did not require further information or had further questions. Those that did have comments were mainly around ideas for further research and development of the results (table 6.5). These centred around understanding current threats, and the links and drivers between species populations, land management and climate change. Additionally, accessibility of results was commonly mentioned,

"[If] models can be incorporated into existing systems [NT GIS]. If so, that would help make the information more accessible / useful".

It is very important that results generated can actually be used by staff on site, and it was encouraging that staff are keen for this to be included, with one respondent asking,

"Before you complete your project are you planning to undertake training on the use of the tool with NT staff?".

Communication of results is important for a successful project, with a respondent from the Ysbyty Ifan Estate commenting that,

"For communication with tenants and other key stakeholders … useful to distil findings into a synopsis of risks".

More help was requested around the understanding of the materials (table 6.5), which led to developing the narrative presented with results at each iteration of the research. Finally, respondents mentioned that it would be useful to include further species, landscapes, or scales in future results, even if they were not at risk,

"… use this data to work out what the current species most at threat from climate change is, including those currently abundant".

This suggests a move to proactive conservation management to prevent future losses of species and / or suitable habitats and vital natural processes.

Table 6.5: Improvement suggestions mentioned by staff at each case study site in the online questionnaire regarding feedback around the site-specific research. These themes relate to answers mainly from questions 15, 18 and 19 (supplementary material, appendix 5).

Theme	Explanation	Rank
Further research	Which species are currently most at threat	1
	The relationships between land management / species / climate change	
	Investigating scenarios where landscapes in favourable condition are affected by climate change – resilience	
	Using the climate / other data to look at different impacts / consider more factors at the same time	
	Different scenarios and other groups of species	
Explanation and understanding	Further explanation around site variations	2
	Need more help to understand results	
Accessibility of results	Incorporating results into National Trust GIS	=3
	Results available as a dataset	
Communication	Further presentation and communication ideas	=3
	Training on using a tool with National Trust staff	
	Communication with tenants and stakeholders	
Scale	Site scale alongside wider scale maps	5
	More detailed spatial scale of results	

6.3.6 The impact of iterative feedback

For responses from both from Abergwesyn Common and the Ysbyty Ifan Estate, one staff member completed the questionnaire twice, providing some insight into the impact of iterative communication and feedback throughout the project. Responses from the Countryside Manager at Abergwesyn Common were relating to the same modelling project, with results updated over iterations. Estate Manager responses from the Ysbyty Ifan Estate related to two different research projects. For both sites, the responses relating to likelihood of using the results increased from 'likely' to 'definitely', suggesting that the iterative nature of the research was improving the results. Additionally, responses from the staff at the Ysbyty Ifan Estate relating to other results, developed the scope of the research into the chapter presented here (chapter 4). Fire risk was suggested by staff as an impact to focus on,

"[It could be] useful to model a scenario where peatland is in favourable conditions … and the corresponding risks associated with each scenario in a future fire risk sense".

This showed the importance of continued communication with all study sites during the research period to share ideas and allow for further development of research scope.

6.4 Discussion

This study has shown through qualitative analysis that the results presented to each case study site are likely to provide a useful addition of data in conservation management planning. Uptake of results was positive among all questionnaire respondents, and through iterations, although brief, results became more useful over time.

6.4.1 Integration of results with stakeholders

Even though numbers of respondents and iterations were low, the usefulness of developing climate impact models alongside conservation professionals is demonstrated. To make evidence-based decisions so important in the fight against the climate crisis (Stafford *et al.*, 2021), meaningful science needs to fit with organisational frameworks (Meakin and O'Connell, 2018). Making decisions for a site at a conservation NGO level is dependent on such a wide variety of reasons that presenting useful, tailored information can help to streamline resources and time. So much practical conservation has been, and is, performed by small organisations, and at a local level (Garrod and Willis, 1994; Duffield, Le Bas and Morecroft, 2021), although often supported by larger bodies. There is recognition that the need to make trade-offs with resources and priorities in management is important and is a large factor in conservation decision-making. This is why this researcher thinks that working in collaboration with researchers and on-site professionals is likely to produce most meaningful results, as explored in this chapter. Additionally, the importance of evidence and guidance provided by external organisations is already recognised, suggesting teams are receptive to collaborations or outside information. Frameworks from reports (e.g. Stafford *et al.*, 2021) and journal articles (e.g. Pearce-Higgins *et al.*, 2022) could aid in putting modelling results in the greater context of adaptation responses to climate change impacts. Staff on-site are acutely aware of day-to-day changes, but may not notice wider changes over time, which could lead to underestimation of the magnitude of long-term environmental change and damage. Thankfully, these impacts have not yet been found to be significant (Jones, Turvey and Papworth, 2021), but outside perspectives to a site or impact were recognised as being useful in presenting a more un-biased view.

There are some challenges in developing results with stakeholders. Interpretation of methodologies and results, and communication of model caveats and uncertainties was often difficult to pick up, and also something that staff on-site should not necessarily have to do. However, monitoring developed from these more refined methodologies has been found to be relatively simple and inexpensive (Meakin and O'Connell, 2018), suggesting that after successful integration, methodologies developed with researchers could be useful in the long term. Additionally, as respondents knew the researcher asking the questions, there is a likelihood of tailoring of answers to what they think they wanted to hear. Completely unbiased qualitative data collection in a small study is difficult, and unlikely to occur when the respondents and researchers already have a working relationship. This could be overcome through greater numbers of in-person meetings and structured group feedback as these can be more informal. A repeated question around methods, involved how land management and land cover could be likely to affect species and fire risk alongside climate change. These interactions are complex and were outside of the scope of this research. It is reiterated that these outputs are designed to form one part of the information used in planning conservation management over specific sites and are not intended to be a one-stop-shop in planning. Further research and integration of data will improve these results and their utilisation, but care must be taken in the reporting of further complexities that could increase uncertainty of modelling and interpretation.

Additionally, even though this thesis attempts to make some steps towards bridging the gap between science and practice, this work cannot be considered over and complete until results are implemented or at least considered. This requires ongoing communication and collaboration with the case study sites to monitor uptake and satisfaction of the projects, and to introduce updates or changes to the results.

6.4.2 Reflections on a questionnaire

6.4.2.1 What went well

Communication and visits to each case study site were ongoing from the start of the project, with at least one in person meeting and tour of the sites occurring within the first year of research. This was invaluable in building personal connections with the researcher and staff on-site which benefited the studies going forward. All chapter hypotheses were developed in response to finding out what staff on-site had noticed change, or were most concerned about in the face of climate change. This gave staff some ownership to the projects, and understanding why they were being undertaken, rather than just being presented with results from someone unknown. This could have led to the high number of questionnaire respondents recording that they would be likely to use the results in conservation planning, because it is something they are actually keen to understand about and monitor on site. The Abergwesyn Common site team provided the greatest number of responses and discussion surrounding the species distribution modelling of birds in the uplands. This is likely due to greater involvement on site with researcher involvement in two field visits, and down to questionnaire piloting at this property. However, this does not compare to the amount of time spent at Chirk Castle during fieldwork, so could be down to time availability of staff or individual interest around the project.

6.4.2.2 What went less well

The Covid-19 pandemic was an unforeseen and significant roadblock in the overall research project and questionnaire element. Without site visits, or even sites being open, getting in touch with staff became increasingly more difficult, with some restructures in teams exacerbating this. This is potentially why there were fewer responses throughout later months, and without this, overall engagement with staff could have been greater. Additionally, site visits in later months were confined to those that were essential for the project. This meant that further development of projects may have been slowed, and further discussion with staff on-site not possible. Focus group-style feedback was planned for within the project, which is likely to have improved results, and future uptake further. Unfortunately, with pandemic restrictions and further time constraints this was not possible.

6.4.2.3 For next time

Although the researcher is happy with the results presented and the feedback study completed, future research bridging the gap between science and practice can always improve. Further research into needs on site and working with staff from conception of projects will always be important. This includes ongoing and regular meetings with stakeholders including interactive feedback with interviews, open meetings and focus groups. Engaging with the local community alongside site professionals is likely to bring another level of knowledge and expertise about an area. This is especially important in close knit communities, such as those on the Ysbyty Ifan Estate to build important relationships which are often vital in ensuring work is received positively and implemented.

Following this research, it can be reflected that a questionnaire cannot be sent out too often. This not only increases the number of potential responses and iterations of results, but maintains stakeholder awareness and engagement. Conservation staff are contending with many needs and wants for their sites and are constantly juggling projects and budgets. Keeping them in the loop regularly about research not only ensures the work is not forgotten, but lessens the responsibility of professionals to remember many details about a project. It also means that we as researchers are constantly improve our skills to learn what is actually needed on the ground, and how to make results more useful for an applied setting. Implementation of science is just as important as the researching of it all in order to have a positive impact on the environment.

6.5 Conclusions

Through a detailed online questionnaire, the importance of scientific data in conservation planning has been proven at the case study sites explored in this thesis. Iterative discussions and sharing of results improved these outputs and ensured they were more useful for inclusion in conservation planning. Although the project was limited in responses, the more iterations presented, the more likely respondents were to use results in their work on-site. Bridging the gap between science and practice is an ongoing journey, and one that is strengthened through human connection and shared goals.

Chapter 7: General discussion

7.1 Key findings

Our modelling showed that, although climate change does have some negative impacts to species distributions of a suite of birds in the uplands of Great Britain (chapter 2), habitat is more limiting than climate. Habitat specialist species exhibited the greatest decline in suitable space under tow climate projection periods, whilst more generalist species gain suitable climate space. Species distributions are predicted to shift northwards in mainland Great Britain, whilst southern ranges for these species were found to be unlikely to contract. High spatial resolution models are more accurate at predicting potentially suitable climate space compared to lower resolution data, yet models still do not meet some of the thresholds considered to be ‘good’ models for more than one evaluation metric. This may reflect higher levels of uncertainty, with general trends useful in exploring future species distributions.

Fire risk and severity of fires is predicted to increase substantially in the future at the Ysbyty Ifan Estate (chapter 3), advising that management by controlled burning is overly dangerous with the potential to develop into more damaging wildfires. Further monitoring onsite to investigate peat health and depth would shed more light about the damage from fires, and where peatland site fires may be at greater risk of ignition. Fire risk should be considered more in the future by staff on peat sites and by farmers managing hefts. UKCP18 was useful in the prediction of fire risk, with higher accuracy for one metric (Fire Weather Index) over others (Head Fire Intensity). Further tailoring of models to local climate data will increase predictive accuracy and usefulness of results.

The risk from high winds at Chirk Castle is predicted to increase, especially at more popular Easter and Christmas visitor periods (chapter 4). Future risk from high winds is likely to be greatest from maximum wind gusts compared to maximum average wind speeds, suggesting that intense periods of high winds may be the most damaging. Fieldwork to identify areas more exposed to wind is useful, and provides spatial and temporal information about future risk. Longer-term study periods may provide better insights into wind trends and risks. Methods used were fairly labour and time intensive which may influence uptake for future research. These could be addressed through weather station technology, which could automate some data collection.

Implementing research with potential users is vital (chapter 5), and the more iterations of results to practitioners, the more useful our results were for management. This aspect of the research was hindered by the Covid-19 pandemic, preventing a lack of face-to-face meetings, feedback, and discussion to develop ideas and adaptation responses, and to further improve both content and presentation of the outputs. Further use of the outputs and ongoing communication with study sites is required to ensure understanding of results, developing site management, and tailoring the models to increase their accuracy.

7.2 Are local scale UKCP18 projections useful in and able to identify and quantify climate risks?

A range of approaches have been explored for the integration of local scale climate projections for analysis of future impacts with the direct use of UKCP18 data (chapter 4), to use in distribution models (chapter 3), and to supplementing with secondary landscape data and using to model future risk (chapters 3 and 5). There are advantages and disadvantages to each approach, which leads to discussion around which models are the most useful to explore impacts of climate change to species and sites.

Direct use of UKCP18 projections is highly accessible post-data processing and is relatively easy to undertake. However, this approach, and further use of average climate layers in models, can expose biases in the climate data (Ahmed *et al.*, 2013), which could skew results and lead to unreliable predictions. Collection of primary baseline data and bias correcting (Ahmed *et al.*, 2013; Fourcade *et al.*, 2014) can help to reduce these uncertainties. Climate-only gridded inputs to species distribution models are more straightforward in producing predictions but can form more of a 'black box' approach (Morales, Fernández and Baca-González, 2017), with little understanding as to the model workings. This can encourage a high use of default inputs (Cao *et al.*, 2013; Merow *et al.*, 2013), whereas our study indicates that user-led inputs at the local climate scale are likely to produce more reliable results, as also found in other studies (Shcheglovitova and Anderson, 2013; Bao, Li and Zheng, 2022). In risk modelling, again, it was useful to include straightforward gridded climate inputs, and tailor other geographical inputs, to provide good indications of future risk. However, there was difficulty when other inputs do not fit the system completely due to biological differences between our study site and the ecosystems for which the model was built (Davies and Legg, 2016a; Taylor *et al.*, 2021).

The usefulness of data available from UCKP18 were explored when considering the conservation of an ecosystem. The 20-year averages of climate data utilised are useful in examining long-term species distribution trends, or impacts to tree growth, and have proved useful in examining the likelihood and frequency of extreme events in this thesis. However, some shorter-scale impacts could be missed and data averages used may not fit within conservation management or funding time frames, or those required to enact policy (Pearce-Higgins *et al.*, 2022). Data interpolation could fill in gaps between the 2040 and 2060 periods, although this could generate predictions with a higher uncertainty (Baker *et al.*, 2017).

The 2.2 km local projections more accurately predicted species distributions than projections at 12 km, and were also able to clearly identify some metrics of fire risk. One advantage of using 2.2 km data is that resolution better matches the scale at which conservation data is collected (Wiens and Bachelet, 2010), such as 2 km spatial resolution Breeding Bird Survey data, and 1 km meteorology datasets (Robinson *et al.*, 2020a) or that existing models use. This increase the likelihood that results are useful at scales considered in management and conservation of species and habitats. Another is simply that there is a greater amount of climate information available for a site. For example, 2.2 km resolution data for Chirk Castle allowed modelling of some spatial change across the site, whereas any data at a coarser resolution would not show spatial changes at the scale of this site. Further work to assess the usefulness and accuracy of this additional resolution is required at the site scale, as there are inherent uncertainties from downscaled data. Without this increase in spatial resolution, predictions would not have been able to be made around spatial changes at the site, which is vital for management intervention and decision-making. Yet, there are some difficulties in utilising the 2.2 km data, namely through greater technical skill required in data processing, large amounts of data and longer model run times, exacerbated by the high spatial resolution. The data is only available at the worst-case climate scenario of RCP8.5 (Met Office, 2019), which does not aid comparison between scenarios.

More work is required to assess the full use of 2.2 km data, especially for example in the ability of modelling small scale, variable impacts such as site level wind speed exposure. Additionally, predictions at the site scale exclude transboundary impacts so pulling out site results from larger scale models (e.g., chapter 2), may be more useful than those only modelled for a site (e.g., chapter 3 & 4). Methods developed for each site are unlikely to be transferable between the studies in this thesis, due to scale (table 7.1). For example, bird species distribution modelling and fire risk at the Chirk Castle site would lead to greater uncertainties in results due to low spatial scale at the site (table 7.1), although results obtained from larger scale models could explore general trends. Overall, the 2.2 km UKCP18 climate projections provide huge steps forward in the spatial resolution of climate models, and enables more identification of the spread of risks at the site scale. Further work to understand predictive power compared to other spatial resolutions is ongoing, but the presentation of general climate risk trends at the site scale is useful for conservation organisations (McLaughlin *et al.*, 2022) like the National Trust.

Table 7.1: Comparing and contrasting the potential for direct translation of chapter modelling between case study sites exploring the scales required to produce robust results. Scales are represented as the number of grid-squares of UKCP18 2.2 km data included at each case study site.

	Abergwesyn Common (9 X 6)	Ysbyty Ifan Estate (7 X 7)	Chirk Castle (2 X 2)
Species	Yes (chapter 2)	Yes, but only if results are identified from wider scale modelling. If modelling at site scale, uncertainties are too great due to less available climate data.	No, there is not enough data to properly represent species, climate impacts and potential future distributions.
Fire	Yes, as site scales are similar to the Ysbyty Ifan Estate and data would be readily available online.	Yes (chapter 3)	Yes, but only as broad risks to the site. Coarser scale results may limit within site comparisons.
Wind	No, due to too high labour and time costs in making of tatter flags and accessing sites. Scale of site is too large to be fully explored using tatter flags.		Yes (chapter 4)

7.3 How accessible is UKCP18? A reflection on (nearly!) 4 years of data use.

There are a large range of useful written publications explaining the overall climate science, projections and specific variables of the UKCP18 projections (e.g. Fung *et al.*, 2018; Lowe *et al.*, 2018; Kendon *et al.*, 2019; Met Office, 2019), yet these appear aimed at technical modellers and not potentially conservation practitioners who may still want to access predictions. Issues were recognised for applied modellers (like me, the researcher) and on-site practitioners.

It is difficult and time consuming for non-climate, but applied, modellers to understand and access products of raw, daily climate projections from UKCP18. Data processing of UKCP18 data is not straightforward and required significant learning around coding and projection grids which was time consuming. The 2.2 km resolution data was presented in a rotated pole projection grid which did not align with the British National Grid, and significant time and effort went into learning about these rotated poles and also rotating the data. Additionally, UKCP18 climate projections are presented as a 360-day year, rather than the standard 365 with 12 months of 30 days. While this is standard format for climate modellers, this was another thing to contend with as an applied modeller, requiring more research and testing into producing averaged outputs. 12 km climate data was presented in a non-rotated pole format which enabled more simple data processing, but further work to make sure projections between resolutions were identical for further comparison. Additionally, all UKCP18 raw climate data is presented in netcdf files, which are not commonly used in nature conservation. These file types are useful due to their ability to hold vast quantities of data, but can be tricky to access. Writing reproducible R code to pull out daily projections of climate in order to write 20-year climate averages took considerable time and ongoing learning, but resulted in files which can, and were, shared among other applied modellers. Only then could data be inputted into models, and is likely not a step practitioners would be able to contend with. PhD studies provide valuable time for the learning of new techniques supported by experts in the field. Practitioners are unlikely to have access to this wealth of support, which would make accessing the data even more difficult. Therefore, without this time or previous knowledge, calculating data required for model inputs would be impractical for a NT site staff member. There is an understanding that the climate models were not necessarily designed to be utilised by site practitioners, but these data should still be accessible to those who want to access them.

Further use of the UKCP18 portfolio to explore probabilistic projections and standalone products can be accessed without in-depth knowledge of climate projections, and while these may be at a coarser resolution and some outputs unable to be incorporated into models, they do provide good ideas about broad trends on sites. Guidance within the UKCP User Interface aids in the production of standalone summaries of climate risks for sites and variables. Increasing access for all to the UCKP18 detailed projections could include more detailed instructions in extracting data from files, and / or providing further information written for the non-expert to guide practitioners through the different projections and which one could be the most useful for their project. For example, in 2020 I wrote a blog (Watts, 2020) detailing methods to extract and average UKCP18 2.2 km data for use in models, or simply visualisation of projections. At the time of writing, this blog has been accessed over 590 times since publication, suggesting that similar step-by-step explanations could be useful in data accessibility. These publications could enhance useability of data and allow practitioners the chance to investigate the climate trends at their sites themselves.

Research has shown that engagement between applied modellers and practitioners increases positive outcomes of both predictive science and implementation of results (Parrott *et al.*, 2012; Fabian *et al.*, 2019; Ainsworth *et al.*, 2020). These methods could be applied further up the modelling scale, with engagement between climate and applied modellers potentially increasing uptake of projections. This could take the form of workshops at universities with aspiring modellers, more detailed help guides or surveys from climate modellers to understand uptake and barriers of the data. Over the course of this PhD, I have become comfortable with using the raw UKCP18 data and associated documentation in models and have momentously improved my coding skills and knowledge. From starting with only a very basic knowledge in R, I am now comfortable conducting data processing, running models and analysing results in the language and this PhD study has provided the necessary time for this professional growth. While this is not possible for those within practitioner roles, any sharing of knowledge and information is important for steps forward in our ability to protect the natural world.

7.4 Can we produce useful models of climate risk at the local scale for conservation adaptation?

NGOs are recognising the enormous impact climate change is likely to have on the areas they manage (National Trust, 2015; Hayhow *et al.*, 2016, 2019), and are keen to understand these further to be able to take appropriate action. The literature (Pearce-Higgins, 2011; Thomas *et al.*, 2011; Johnston *et al.*, 2013; Han *et al.*, 2018; Hayhow *et al.*, 2019; Netherwood, 2022), three site studies in this thesis and questionnaire study (chapter 5) shows that there is a clear need for including information about risks from climate change in developing ideas in conservation management planning and delivery. There has been consideration of current climate risk to UK landscapes (Hayhow *et al.*, 2019; Kendon *et al.*, 2022), but less information about how ongoing climate change could impact these in the future . Even with caveats identified in the thesis chapters, from variability and uncertainty in modelling, this thesis nevertheless provides useful information for site management to incorporate future impacts. Categorising impacts into those more likely to happen, these findings add to the current literature (Morecroft *et al.*, 2019; Duffield, Le Bas and Morecroft, 2021) contributing to site-based conservation and visitor management.

For all three data chapters, it has been predicted that climate is likely to have a smaller negative, or overall positive, effect at the short-term up to the 2030s, with greater negative impacts up to the 2070s. Greatest negative impacts are likely to occur in risk from fires (chapter 3), with the least risk to species distributions of a small suite of birds in mainland Britain (chapter 2). Management needs to identify areas of high wind speed risk (chapter 4) may be met more effectively than those at the other case studies as primary data collection of wind exposure to trees provides a potentially more accurate baseline than those developed from secondary data. There has been some shift from conservation prioritising rare species to protecting common species and ecosystem functions (McLaughlin *et al.*, 2022), which may also translate to habitats currently, or predicted to be less at risk. Yet it is shown that climate change has greater impact on rarer species, even common species that may be 'fine' in models may still require conservation for maintaining distributions and abundance, especially if climate change requires range shifts.

Results from each chapter can be applicable to the other chapters, for example by guiding future monitoring in another case study site. Higher fire risk quantified on the Ysbyty Ifan Estate is likely to be similar at other upland peatlands such as Abergwesyn Common. This higher fire risk is likely to have direct implications to bird species on site, especially ground nesting species like the golden plover. Fires affect the habitats suitable for bird species, for example increasing areas of bare ground, affecting hunting areas and vulnerability to predation (Pearce-Higgins, 2011); and habitat at a greater risk of loss from fires will exacerbate the impacts of climate change to both flora and fauna

(Arnell, Freeman and Gazzard, 2021), particularly to vulnerable species. The results of these studies may not be useful for the wider National Trust (NT) site portfolio if they are not transferable: however, the modelling approaches used are transferable. Species distribution model results are already potentially available for all NT sites in England and Wales, following on from modelling at the Great Britain scale. At smaller sites, a reduced number of gridsquares were included, and while this may limit the fine details across the site, this is still a far more detailed resolution than previous studies exploring predictions at sites across the UK (Pearce-Higgins *et al.*, 2017; Fordham *et al.*, 2018).

Alongside investigating the impacts of climate change at the site level, which is useful for those managing the specific sites, there is also a need to look at vulnerability and risk across the wider portfolio of National Trust sites, and indeed other natural spaces. Some chapter methods such as species distribution modelling (chapter 2) and fire risk (chapter 3) could be developed at the wider scale fairly easily. Data requirements are greater for calculating fire risk (chapter 3), and both models could be improved with on-site data collection. Transferring wind exposure methods (chapter 4) would be more difficult due to time and labour intensive baseline data collection. Wind speeds are highly localised and variable and depend on topography as well as weather (Kamimura *et al.*, 2019), so simply taking trends from Chirk Castle and applying them elsewhere would be unlikely to provide useful insight. Yet, as similar temporal trends in risk across all three case studies are suggested, there may be potential for wider trends in wind exposure to be similar, and therefore useful, although lacking site-specific detail.

7.5 How best can we communicate these climate risks and are there ways to bridge the science – practice gap?

While feedback from National Trust site staff has been positive, and there have been proposals about the implementation of these results, their long term usefulness of these results remains speculative, and indeed their inclusion in management planning is not yet known. Implementation and guidance about results ideally should be ongoing in order for a project to be as successful as possible (Anderson, 2014; Jarvis *et al.*, 2020), with further feedback about future outputs. Monitoring the uptake and success of research results, as well as further testing the ideas and the modelling itself, will be future indicators of the value of the findings. For example, ongoing wind speed monitoring at Chirk Castle (chapter 4) to assess longer-term trends of wind exposure could highlight corridors of more, or less, exposed areas of the site. This could help to improve future models while providing information for short-term management. More regular monitoring of daily temperature and peatland quality, particularly wetness, could aid in developing more accurate thresholds of risk for fire seasons, streamlining the time and effort needed to check for fires on the Ysbyty Ifan Estate (chapter 3). Finally, ongoing species monitoring alongside habitat surveys and restoration would provide further information about bird species assemblages on Abergwesyn Common (chapter 2) and their needs and requirements. These, combined with climate change predictions, should enable practitioners to develop a range of management decisions for different time scales and conditions. Understanding how the results become used will doubtless highlight further gaps in knowledge which could improve the development of the models and implementation of results still further.

Presentation of results through visual aids (Shaw *et al.*, 2009; Pettit *et al.*, 2011; Palacios-Agundez *et al.*, 2013) have proved useful in understanding impacts to a site, which was also identified through the presentation of climate risks. Some stakeholders showed interest in using results as a layer in GIS programs for a more interactive assessment of risk. This could be a useful way to build understanding of risk and use of results within the organisation, although there would be need for training and ongoing communication with users. Finally, extending these models to the wider NT would enable wider implementation of results in pro-active adaptation management, building on the experience from pilot users in the case studies in this thesis. A few respondents of the questionnaire have expressed an interest in conducting modelling themselves and developing their knowledge of modelled impacts and how these are generated. Responding to this demand would increase the usefulness of this study and its results, enable focusing on particular needs and giving users full ownership of outputs: a likely valuable investment from the training and resources required.

7.6 Study limitations

The case studies are representative of sites and risks across the Welsh NT portfolio, with important species and priority habitats included in assessments. Additionally, these sites are representative of other nature conservation organisations in Wales, such as the Lake Vyrnwy RSPB Nature Reserve, at which blanket bog restoration and whinchat distribution and abundance research is ongoing. However, all three case study sites are inland, and within Wales. There have been significant impacts of climate change identified in coastal habitats (Nicholls *et al.*, 2013; Bennett, Kadfak and Dearden, 2016) and to the built heritage environment (Sabbioni *et al.*, 2006; Lankester and Brimblecombe, 2012; Leissner *et al.*, 2015), which have not been explored in this thesis. Nonetheless, these methodologies have the potential to be extended and developed to cover a much wider range of NT property interests and features.

The Covid-19 pandemic limited fieldwork and questionnaire research with valuable time missed on site and fewer questionnaire responses received. A full data collection year at Chirk Castle would have been likely to provide a better picture of trends. Small numbers of survey responses may have skewed the results, and expanding the survey to the wider NT to explore general opinions and action about climate change management could have been used to investigate wider trends and gain more responses. Finally, the researcher had aimed to conduct face-to-face interviews and discussion groups surrounding model results and project progress with NT stakeholders. These experiences and data could have provided further discussion around model results and potential adaptation management ideas.

A further limitation in this thesis is the use of a single model member of future climate change from the UKCP18 projections. These were not explored due to high data processing costs and ongoing coding education by the researcher. Further data processing to calculate an average of multiple members would be likely to reduce uncertainties in the future climate as a greater number of variations of potential trends would be included. Understanding the differences in predictions these futures provide would be likely to provide greater insight into presented trends. Yet, ever finer modelling resolution may not result in markedly different user information.

Additionally, some models, especially for wind exposure (chapter 4) could be improved through the bias correction of climate projections in order to write more realistic projections of climate by comparing predictions to observations (Fourcade *et al.*, 2014; Bedia *et al.*, 2018). Again, this was not undertaken due to computational costs and there is recognition that some time series of raw wind speed predictions used in chapter 4 are unlikely to be as accurate as possible. To mitigate for this, only maximum averages of time series were used to show longer-term, more extreme trends which could be thought of as a worst case scenario.

The habitat data used forms another limitation. This layer of future projected habitats is not yet peer-reviewed, and provides only one time stamp of potential future habitats. While this is useful as a general picture, the fewer number of habitat types available in the future projection produced broad habitats at the site level which may be unclear if used for management. This provides scope for further development of habitat layers, and potentially integration of site-level habitat surveys that may be able to include temporal changes throughout a calendar year.

Only one model for each study site project was explored. Comparing multiple models could increase certainty in trends and investigate if certain models provide more accurate results at local scales than others. Finally, there could have been greater exploration of model inputs and evaluation matrices to further understand the accuracy of models and the level of uncertainty they show.

7.7 Conclusions

'All models are wrong but some are useful' the statistician George Box once said, and it is concluded that the models presented in this thesis provide useful information about the different site-level impacts of climate change at three National Trust sites in Wales.

Throughout this thesis, the needs of site staff have been considered through the development of projects in collaboration with the case studies to explore risks that are less understood and yet which need to be included in future conservation and visitor management planning and decision-making. Climate change affects each of the National Trust sites in this study, with some increases in species' potential ranges (chapter 2) and risk of damage (chapters 3 & 4) from a range of impacts. Local scale UKCP18 data has proven to be useful in identifying and quantifying climate risks when compared to coarser resolution climate data, and although there are large data processing requirements, data is easily manipulated once processed. The scales at which results are useful differ between chapters, with 2.2 km data not able to provide some direct translation of modelling. High spatial scale data is useful to represent the scale more closely at which conservation data is collected, and provides a greater idea about local trends, although with resolution accuracy yet to be fully explored. Methods used for each model are likely to be transferable to similar sites, with some on-site data collection required to tailor predictions.

Communication of the risks is vital for successful implementation of this research. Including stakeholders in the project from day one helped to develop the project, increased the usefulness of the findings, and developed some strong working relationships. Bridging the gap between science and practice and developing accessible and useful local scale models of climate risk, will aid in the development of better adaptation decision-making and management to increase resilient ecosystems in the face of climate change. Climate projection data accessibility is lacking for non-experts, with high processing and modelling time costs. Further development of accessible information could make this data more useful to a wide range of people in the nature conservation sector.

Future research is broad with opportunities to further explore scale and accuracy of local scale climate data, the impacts multi-member models and bias correction have on results, implementation of modelling results with practitioners and ongoing relationships with nature conservation organisations and sites to build a larger picture of the likely risks to the natural world. This thesis has provided a strong basis for many of these opportunities, but continuing partnerships, development of models and integration of evidence-based science into nature conservation adaptation is likely to positively contribute to the protection of species and habitats that are essential to us and the natural world.

Appendix 1: Supplementary material for chapter 2 – Data and data use in environmental modelling: what do we need and how do we need it?

How to: using Met Office UKCP18 2.2km climate projections

My last How to: blog was about sea turtles. This one is a little different… I am using the UKCP18 climate change projections developed by the Met Office in my PhD research. Here is my blog in two parts about how to read in and visualise this data for two spatial resolutions – 5km and 2.2km. This blog looks at the 2.2km data, see the previous post for my blog about the 5km data. The data was released in November 2018 to provide further insight into the climate change impact to the UK at a range of temporal and spatial scales.

Here I provide some information and code to help with downloading and visualising UKCP18 projections at 5km resolution as part of the Convection Permitting Model.

Downloading UKCP18 data

All the raw UKCP18 data is freely available via the CEDA Archive although there is a requirement to sign up for an account to be able to access the data.

Navigating through the data portal is relatively simple as seen below, these are the steps I have take to get to the full set of UKCP18 2.2km data.

1. badc
2. ukcp18
3. data
4. land-cpm
5. uk
6. 2.2km
7. rcp85
8. 01

Step 7 relates to the model run chosen for analysis. There are model runs between 01, 04-15 which correspond to the members in the data detailed in the .csv outputs available from the user interface (https://ukclimateprojections-ui.metoffice.gov.uk/products). I have chosen to use model 01 in this case, but the other model runs are useful.

When downloading the raw data file you want, right click on the link and save the .nc file to your workspace. There is a lot of useful information on the internet about NetCDF (.nc) files, I found this link and also this link especially helpful!

2.2km data

Reading in NetCDF files

There has been some difficulty in preparing the highest resolution 2.2km climate data for use in geographical information systems (GIS), computer modelling and general visualisation due to the unusual coordinate reference system the files were produced in. The files are in the rotated pole coordinate system in which the north pole is rotated to 37.5° N. 177.5° E so that the equator runs through the centre of the modelled area. For more information, see section 2.3 here. The files in rotated pole coordinates cannot be combined with other data sets without some pre-processing to change the coordinate system in the open source GIS QGIS and/or R. This can be done completely in R, but I will demonstrate both methods.

To read in the NetCDF file:

netcdf_data <- nc_open("tas_rcp85_land-cpm_uk_2.2km_01_mon_19801201-19811130.nc")

To explain what the file name means: **tas** (average temperature at 1.5m), **rcp85** (the representative concentration pathway, **land-cpm** (the UKCP18 model, **uk** (where the model is run for), **2.2km** (spatial resolution of the model), **01** (model run), **mon** (temporal resolution of the model – here = month), **19801201-19811130** (the start and end dates of the layer – this file has data between 1st December 1980 to 30th November 1981.

Some differences you might see in file names:

Spatial resolution – could also be 60km, 25km, 12km or 5km (check out my other blog here for the 5km information)

Temporal resolution – could also be at ann, seas, mon, day, 1hr – corresponding to annual, seasonal, monthly, daily and hourly scales (in this blog I use data at daily spatial scales, check out my other blog which looks at 5km data at a monthly scale).

However, when you run;

print(netcdf_data)

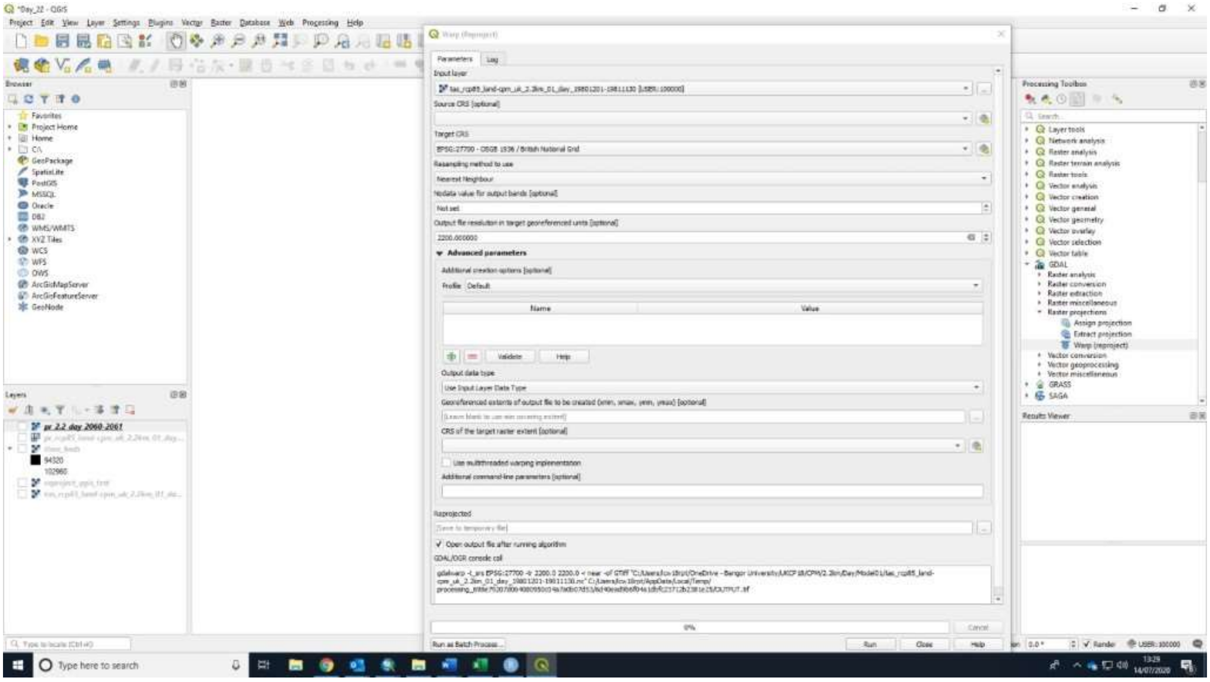
and

plot(netcdf_data)

there is a huge amount of information from the print() function, and the plot() function doesn't run as the layer is in the rotated pole coordinate. The steps below (either in QGIS or R) rotate the pole to the OSGB/British National Grid coordinate system so we can export and visualise the layers.

QGIS

1. Use the Warp (reproject) tool in the Raster Projections section of the GDAL toolbox to read in the rotated grid. Remember to have the output file resolution as 2200.00 to keep the 2.2km spatial resolution of the layers.
2. Export the file as a GeoTIFF which still contains all the individual layers corresponding to each day. This GeoTIFF can now be read into R and run through a loop that pulls out each day similar to that for the 5km data.



Input layer – the file you want to rotate
Target CRS – EPSG:27700 – OSGB 1936/British National Grid
Resampling method to use – Nearest Neighbor
Output file resolution in target georeferenced units – 2200.00

If you are running this for multiple files, running the tool as a batch process speeds everything up a bit!

R

1. Make sure you are using the latest version of R and RStudio (4.0.2).
2. If not using the above QGIS method, the sf package has the gdal_utils tool which, when using with the correct coordinate system changes, this will have the same effect as using QGIS.

library(sf)
library(ncdf4)

setwd("where the 2.2 NetCDF files are stored")

#to rotate the pole to British National Grid – new file written as a .tif file
#when run, use the new .tif file in the extraction code on page 4
gdal_utils(util = "warp", source = "original 2.2km file.nc", destination = "tas_2.2_day_1980-1981.tif",

```
    options = c("-tr", "2200",  "2200", "-t_srs", "EPSG:27700", "-r", "near", "-overwrite"))

## if you want to write the new file as a .nc
gdal_utils(util = "warp", source = "original 2.2km file.nc", destination = "new 2.2 file rotated to BNG.nc",
    options = c("-tr", "2200",  "2200", "-t_srs", "EPSG:27700", "-r", "near", "-overwrite"))

##this will give you a stack with all the bands
all.bands <- paste0("Band", 1:360)
raster.list <- lapply(1:360, function(x) raster("new 2.2 file rotated to BNG.nc", varname=all.bands[x]))
test <- stack(raster.list)
nlayer(raster.list)
```

When you've got your rotated files in TIF format, the code below will pull out each day individually and save them as a new TIF file. While you can save the rotated file as a NetCDF file (see code above), I would suggest saving the rotated files as .tif files to streamline the amount of code that needs to be run.

Whether you choose to rotate the files using QGIS or R, both methods use the gdal warp utility.

I (along with my supervisors) have developed a code that pulls out each layer individually and saves this layer as a .tif file. This TIF file has each date the layer corresponds to as it's name. TIFs are rasters that can be used in R and GIS software and are much easier to analyse and map than having all the layers within a netCDF file.

A word about calendars
It is generally recognised that the Western calendar comprises of 365 days. However, the UKCP18 data is in a 360 day calendar – 12 months of 30 days (yes, even February!). Additionally, time of the layers is recorded in the number of hours since 1st January 1970. To deal with this, install the R package PCICt, which sorts out years when they're not the year length you're expecting.

Warning This code does generate a LOT of files (360 for each .nc or .tif file). I save all my files to OneDrive as I have the extra space. Make sure you're not about to fill up your computer with many files!!

For 2.2km data

```
install.packages("rgdal")

install.packages("ncdf4")

install.packages("PCICt")

library(rgdal)
library(ncdf4)
```

```
library(PCICt)

#open rotated raster
r<-stack('where the rotated file is saved/tas_2.2_day_1980-1981.tif')



#Plot it just to see if everything is ok
plot(r)

#Check the number of bands
nlayers(r)

#to add dates
netcdf_data <- nc_open("where the netCDF file is saved/tas_rcp85_land-
cpm_uk_2.2km_01_day_198012-200011.nc")

# the initial date as indicated in NetCDF file
initial_date <- as.Date("01-01-1970", "%m-%d-%Y")
initial_date

# hours from initial date to real date
time_hours <- ncvar_get(netcdf_data,"time")
time_hours

#calculate date based on 360 day calendar
date_list <- as.PCICt(time_hours*3600, cal="360_day", origin="1970-01-01")
date_list

#date list to nearest day – rounds up, so gets rid of hours but not the correct day
x.day <- round(date_list, "days")

#take off number of seconds in a day (seconds in an hour*hours) to get it back to the correct day
days <- c(x.day – 3600*24)
head(days)

#wales as extent
wales <- readOGR("where the shapefile to be cropped to is saved/wales2001.shp")

#CRSuk
ukgrid = "+init=epsg:27700"

#pull out each day, crop to Wales and save as individual raster with date in title
for(i in 1:nlayers(r)){
  l1<-r[[i]]

  proj4string(l1) <- CRS(ukgrid)

  cr <- crop(l1, extent(wales), snap="out")

  fr <- rasterize(wales, cr)
```

```
  lr <- mask(x=cr, mask=fr)

  # export each layer as a numbered .tif
  writeRaster(lr, paste0("where you want to save the new files/tas_",
                days[i],".tif", sep=""))
}
```

Note: in this code for the 2.2km data I have cropped the files to Wales, so that I don't get the whole of the UK as I only want to use Wales in my analysis. The 5km example (here) doesn't include this crop.

Next steps

Now you have many many files depicting daily (2.2km) projections for the UKCP18 data it's time to get them into a format that can be used in many different ways e.g. modelling, presentations, infographics.

What I did:

My modelling uses averages of these data of average temperature and precipitation for Wales.

In Arc (and R if you use the raster package) I used the cell statistics tool to run averages of this data and then converted them to ascii files using raster to ascii tool.

BUT: the individual files can now be identified by themselves as they are labelled with their date and can be pulled into GIS software or straight into a word/powerpoint document.

Happy data-ing!

Please leave any comments at the bottom of the page.
This blog could not have been written without the huge amounts of help from Dr James Gibbons, Bangor University.

Appendix 2: Supplementary material for chapter 3 – The impact of climate and habitat change to bird species found in the uplands of Great Britain: Are species-specific model inputs more accurate than default settings?

Table A2.1: Optimum inputs for Maxent models as computed by ENMEval models investigating different background point (BP), feature class (F) and regularization multiplier (RM) inputs. Results are presented from empirical and null models with Continuous Boycce Index (CBI) and minimum training presence omission rates (OR_{MTP}) explored. Optimum model inputs are relefcted in high CBI_{TRAIN} and CBI_{VAL} scores and low OR_{MTP} values. A significant difference between empirical and null models ($pCBI_{TRAIN}$, $pCBI_{VAL}$, and pOR_{MTP}) indicate models that are more likely to accurately predict species distributions than random.

2.2 km														
Species	Model	BP	F	RM	Coeff.	CBI_{VAL}	CBI_{TRAIN}	$CBI_{NULL-VAL}$	$CBI_{NULL-TRAIN}$	$pCBI_{TRAIN}$	$pCBI_{VAL}$	OR_{MTP}	$OR_{MTP-NULL}$	pOR_{MTP}
GP	OA	25,000	LQHPT	0.5	261	0.522	1	-0.04	0.991	0.234	0.005	0.076	0.089	0.387
	OS	15,000	L	1	13	0.811	0.985	0.105	0.874	0.147	<0.001	0	0.014	0.247
MP	OA	25,000	LQHPT	0.5	253	0.627	0.997	0.569	0.991	0.318	0.016	0.002	0.022	0.121
	OS	5,000	LQH	1	107	0.752	0.991	0.626	0.943	0.167	0.175	0	0.003	0.399
S	OA	25,000	LQHPT	0.5	275	0.468	1	0.394	0.999	0.252	0.288	0.008	0.012	0.355
	OS	15,000	H	5.5	35	0.453	0.996	0.218	0.993	0.286	<0.001	0	<0.001	0.431
WHE	OA	25,000	LQHPT	0.5	248	0.731	0.997	0.116	0.989	0.280	0.003	0.004	0.032	0.081
	OS	15,000	LQHP	6	63	0.694	0.993	0.245	0.730	0.081	0.011	0	0.004	0.267
WHI	OA	25,000	LQHPT	0.5	267	0.137	0.998	0.041	0.664	0.301	0.084	0.045	0.066	0.265
	OS	5,000	H	6	33	0.269	0.984	0.487	0.459	0.022	0.694	0	<0.001	0.453
12 km														
Species	Model	BP	F	RM	Coeff.	CBI_{VAL}	CBI_{TRAIN}	$CBI_{NULL-VAL}$	$CBI_{NULL-TRAIN}$	$pCBI_{TRAIN}$	$pCBI_{VAL}$	OR_{MTP}	$OR_{MTP-NULL}$	pOR_{MTP}
GP	OA	10,000	LQ	0.5	13	0.032	0.973	0.027	0.880	0.173	0.491	0.028	0.043	0.374
	OS	20,000	L	0.5	11	0.257	0.979	0.001	0.856	0.099	0.128	0	0.043	0.157
MP	OA	10,000	LQH	6	1	-0.260	0.543	0.506	0.555	0.522	0.798	0.001	0.019	0.259
	OS	20,000	LQHPT	1	40	0.397	0.988	0.011	0.960	0.197	0.067	0	0.042	0.121
S	OA	5,000	LQ	0.5	15	0.071	0.952	0.020	0.880	0.215	0.405	0.019	0.043	0.316
	OS	20,000	H	5	9	0.090	0.990	0.132	0.191	0.058	0.559	0	0.003	0.343
WHE	OA	10,000	H	6	5	0.343	0.923	0.323	0.230	0.028	0.476	0.003	0.004	0.469
	OS	10,000	LQ	0.5	13	0.441	0.972	0.049	0.789	0.110	0.077	0	0.025	0.231
WHI	OA	10,000	LQHPT	5	2	0.058	0.788	0.130	0.616	0.248	0.621	0.007	0.011	0.400
	OS	25,000	L	3.5	3	0.139	0.846	0.163	0.467	0.060	0.542	0.001	0.009	0.297

Table A2.2: Maxent model results at 12 km spatial scale with additional model inputs (see methods 2.2.4) and evaluation matrices (TSS and SEDI).

12 km						
Species	*n*	Model	AUC_{TEST}	AUC_{TRAIN}	TSS	SEDI
Golden plover	639	Opt AICc	0.603	0.636	0.178	0.262
		Opt seq	0.593	0.606	0.161	0.237
Meadow pipit	1240	Opt AICc	0.519	0.531	0.057	0.086
		Opt seq	0.540	0.646	0.021	0.112
Skylark	1132	Opt AICc	0.538	0.544	0.072	0.110
		Opt seq	0.532	0.543	0.062	0.100
Wheatear	1073	Opt AICc	0.526	0.545	0.058	0.103
		Opt seq	0.547	0.564	0.090	0.138
Whinchat	705	Opt AICc	0.540	0.563	0.097	0.138
		Opt seq	0.527	0.558	0.071	0.108

Table A2.3: The percentage of (1990s, 2030s, 2070s) and difference between (1990s to 2030s, 1990s to 2070s, 2030s to 2070s) of the amount of suitable habitats also containing suitable climate space. Negative values indicate a reduction in suitable habitat space also containing suitable climate space, and vice versa for positive values. The average of the total amount of suitable habitat space also containing suitable climate space for each habitat type is presented (average 1990s, average 2030s, average 2070s).

<table>
<tr><th></th><th></th><th>1990s</th><th>2030s</th><th>2070s</th><th>1990s to 2030s</th><th>1990s to 2070s</th><th>2030s to 2070s</th><th>Average 1900s</th><th>Average 2030s</th><th>Average 2070s</th></tr>
<tr><td rowspan="5">Golden plover</td><td>LC1 – mostly crops</td><td>19.3</td><td>15.6</td><td>29.0</td><td>-19.4</td><td>49.7</td><td>85.6</td><td rowspan="5">47.7</td><td rowspan="5">35.3</td><td rowspan="5">60.0</td></tr>
<tr><td>LC2 – grassland, scrub or shrub</td><td>24.7</td><td>24.9</td><td>51.5</td><td>0.73</td><td>108.5</td><td>106.9</td></tr>
<tr><td>LC5 – sparse vegetation</td><td>78.7</td><td>53.8</td><td>73.6</td><td>-31.7</td><td>-6.5</td><td>36.8</td></tr>
<tr><td>LC6 – bare area</td><td>52.3</td><td>33.3</td><td>64.5</td><td>-36.2</td><td>23.4</td><td>93.5</td></tr>
<tr><td>LC7 – swampy or often flooded vegetation</td><td>63.2</td><td>48.7</td><td>81.1</td><td>-23.0</td><td>28.3</td><td>66.6</td></tr>
<tr><td rowspan="5">Meadow pipit</td><td>LC1 – mostly crops</td><td>20.0</td><td>95.3</td><td>99.5</td><td>375.7</td><td>396.9</td><td>4.4</td><td rowspan="5">45.7</td><td rowspan="5">73.2</td><td rowspan="5">97.1</td></tr>
<tr><td>LC2 – grassland, scrub or shrub</td><td>32.8</td><td>75.1</td><td>96.9</td><td>129.4</td><td>196.0</td><td>29.0</td></tr>
<tr><td>LC5 – sparse vegetation</td><td>71.2</td><td>53.7</td><td>96.3</td><td>-24.5</td><td>35.3</td><td>79.3</td></tr>
<tr><td>LC6 – bare area</td><td>61.3</td><td>83.4</td><td>98.5</td><td>36.1</td><td>60.7</td><td>18.1</td></tr>
<tr><td>LC7 – swampy or often flooded vegetation</td><td>43.5</td><td>58.2</td><td>94.2</td><td>34.0</td><td>116.8</td><td>61.8</td></tr>
<tr><td rowspan="5">Skylark</td><td>LC1 – mostly crops</td><td>77.1</td><td>93.0</td><td>99.6</td><td>20.7</td><td>29.2</td><td>7.0</td><td rowspan="5">36.9</td><td rowspan="5">50.3</td><td rowspan="5">78.0</td></tr>
<tr><td>LC2 – grassland, scrub or shrub</td><td>35.1</td><td>61.2</td><td>90.8</td><td>74.3</td><td>158.9</td><td>48.5</td></tr>
<tr><td>LC5 – sparse vegetation</td><td>3.8</td><td>9.9</td><td>44.3</td><td>163.0</td><td>1073.6</td><td>346.2</td></tr>
<tr><td>LC6 – bare area</td><td>54.8</td><td>67.3</td><td>83.9</td><td>22.8</td><td>53.1</td><td>24.7</td></tr>
<tr><td>LC7 – swampy or often flooded vegetation</td><td>13.7</td><td>19.9</td><td>71.5</td><td>44.6</td><td>421.4</td><td>260.5</td></tr>
<tr><td rowspan="5">Wheatear</td><td>LC1 – mostly crops</td><td>16.7</td><td>90.8</td><td>97.5</td><td>445.1</td><td>485.1</td><td>7.3</td><td rowspan="5">46.3</td><td rowspan="5">71.6</td><td rowspan="5">92.2</td></tr>
<tr><td>LC2 – grassland, scrub or shrub</td><td>32.6</td><td>66.1</td><td>93.1</td><td>103.2</td><td>186.1</td><td>40.8</td></tr>
<tr><td>LC5 – sparse vegetation</td><td>66.2</td><td>66.4</td><td>87.4</td><td>0.3</td><td>31.9</td><td>31.6</td></tr>
<tr><td>LC6 – bare area</td><td>71.0</td><td>85.0</td><td>96.2</td><td>19.8</td><td>35.6</td><td>13.2</td></tr>
<tr><td>LC7 – swampy or often flooded vegetation</td><td>44.5</td><td>49.6</td><td>86.7</td><td>10.6</td><td>93.4</td><td>74.8</td></tr>
<tr><td rowspan="5">Whinchat</td><td>LC1 – mostly crops</td><td>18.5</td><td>82.0</td><td>95.4</td><td>343.0</td><td>415.7</td><td>16.4</td><td rowspan="5">24.5</td><td rowspan="5">58.0</td><td rowspan="5">85.8</td></tr>
<tr><td>LC2 – grassland, scrub or shrub</td><td>28.6</td><td>60.3</td><td>88.8</td><td>110.9</td><td>210.6</td><td>47.2</td></tr>
<tr><td>LC5 – sparse vegetation</td><td>7.1</td><td>36.1</td><td>77.5</td><td>410.7</td><td>997.6</td><td>114.9</td></tr>
<tr><td>LC6 – bare area</td><td>45.2</td><td>66.9</td><td>91.5</td><td>48.2</td><td>102.6</td><td>36.7</td></tr>
<tr><td>LC7 – swampy or often flooded vegetation</td><td>23.2</td><td>44.9</td><td>76.0</td><td>93.4</td><td>227.0</td><td>69.1</td></tr>
</table>

Table A2.4: The total percentage of mainland Great Britain that contains suitable climate and habitat space for the five bird species (1990s, 2030s, 2070s) and difference between (1990s to 2030s, 1990s to 2070s, 2030s to 2070s) of the amount of mainland Great Britain containing suitable habitat and climate space. Negative values indicate a reduction in the area of mainland Britain (%) containing suitable climate and habitat space, and vice versa for positive values. The average of the total amount of mainland Great Britain containing suitable climate and habitat space for each habitat type is presented (average 1990s, average 2030s, average 2070s).

		1990s	2030s	2070s	1990s to 2030s	1990s to 2070s	2030s to 2070s	Average 1990s	Average 2030s	Average 2070s
Golden plover	Lc1 – mostly crops	1.8	1.4	4.1	-21.8	131.5	196.0	1.4	1.2	4.2
	Lc2 – grassland, scrub or shrub	3.6	3.6	11.9	-0.08	230.3	230.6			
	Lc5 – sparse vegetation	0.5	0.3	1.1	-31.4	116.8	216.1			
	Lc6 – bare area	0.05	0.03	0.3	-40	494	890			
	Lc7 – swampy or often flooded vegetation	1.0	0.8	3.7	-25.2	254.8	374.1			
Meadow pipit	Lc1 – mostly crops	1.8	13.5	14.1	635.9	668.8	4.5	1.6	7.0	8.6
	Lc2 – grassland, scrub or shrub	4.8	17.5	22.5	263.5	369.0	29.0			
	Lc5 – sparse vegetation	0.5	0.8	1.4	75.3	214.2	79.3			
	Lc6 – bare area	0.06	0.4	0.5	550.8	667.8	18.0			
	Lc7 – swampy or often flooded vegetation	0.7	2.7	4.3	270.6	449.6	61.8			
Skylark	Lc1 – mostly crops	7.0	13.1	14.1	86.7	99.8	7.0	2.5	5.7	7.9
	Lc2 – grassland, scrub or shrub	5.1	14.2	21.1	176.2	310.2	48.5			
	Lc5 – sparse vegetation	0.02	0.1	0.7	516.7	2650	345.9			
	Lc6 – bare area	0.05	0.3	0.4	484.9	628.3	24.5			
	Lc7 – swampy or often flooded vegetation	0.02	0.9	3.3	300.9	1345.4	260.5			
Wheatear	Lc1 – mostly crops	1.5	12.8	13.8	743.0	804.8	7.3	1.5	6.4	8.2
	Lc2 – grassland, scrub or shrub	4.8	15.4	21.6	221.9	353.4	40.8			
	Lc5 – sparse vegetation	0.4	1.4	1.3	219.5	205.6	-4.3			
	Lc6 – bare area	0.07	0.4	0.4	475.0	551.5	13.3			
	Lc7 – swampy or often flooded vegetation	0.7	2.3	4.0	206.0	434.9	74.8			
Whinchat	Lc1 – mostly crops	1.7	11.6	13.5	585.1	697.6	16.4	1.3	5.7	7.8
	Lc2 – grassland, scrub or shrub	4.2	14.0	20.6	234.3	392.2	47.2			
	Lc5 – sparse vegetation	0.05	0.5	1.2	1093.3	2466.7	115.1			
	Lc6 – bare area	0.04	0.3	0.4	616.3	879.1	36.7			
	Lc7 – swampy or often flooded vegetation	0.4	2.1	3.5	435.3	805.2	69.1			

Appendix 3: Supplementary material for chapter 4 – Assessing the frequency and severity of potential future fires under climate change: A peatland case study in the Welsh uplands exploring the future of controlled burning.

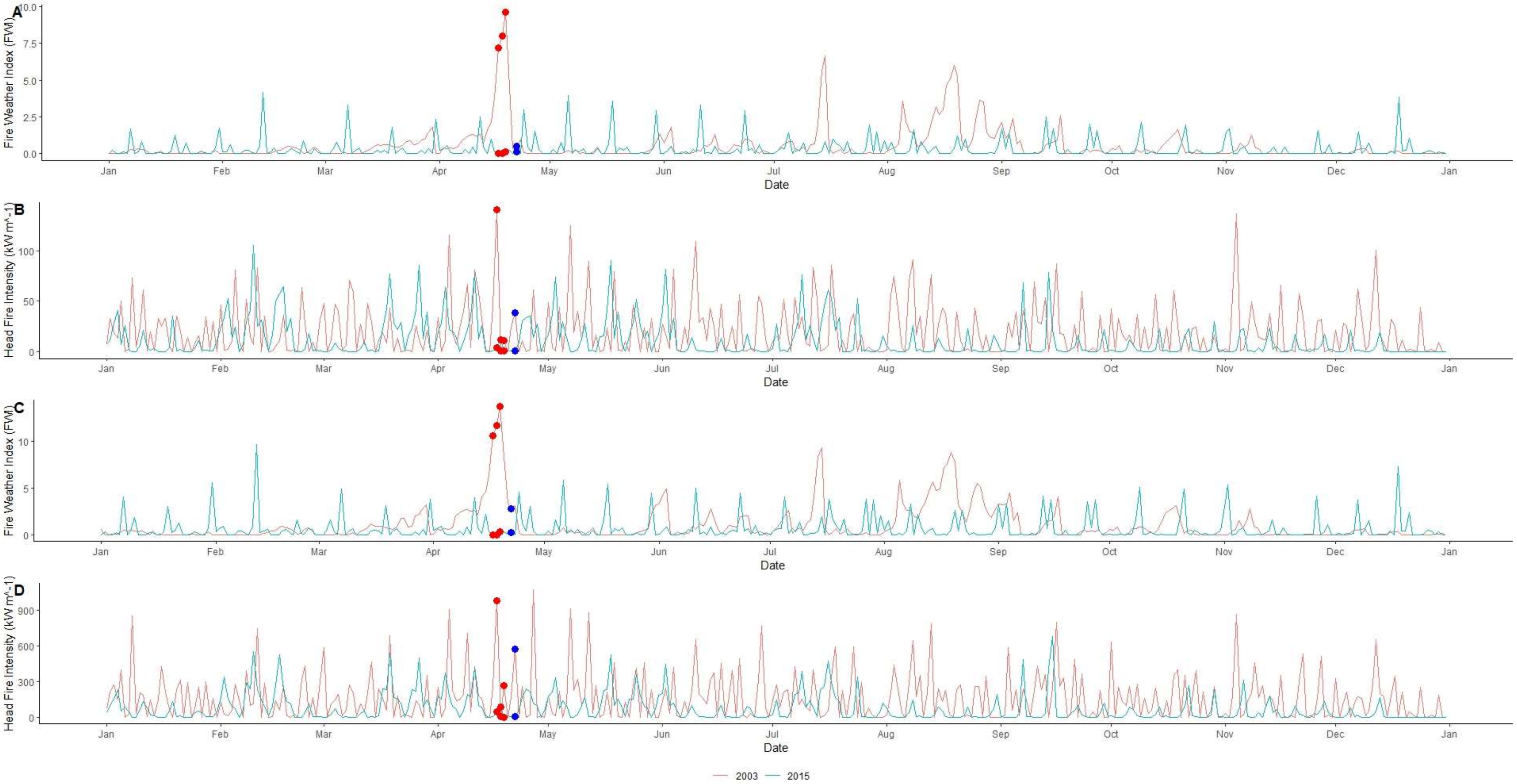


Figure A3.1: Mean (A & B) and maximum (C & D) FWI and HFI calculated for 2003 and 2015 using CHESS data. Red points indicate known fires in 2003, blue points indicate known fires in 2015. A) Mean FWI, B) Mean HFI, C) Maximum FWI, D) Maximum HFI.

Appendix 4: Supplementary material for chapter 5 – The impact of current and future wind speeds and direction to historic parkland trees: Using low-cost methods to inform long-term conservation plans.

A4.1

All flags were photographed against a black background from a height of approximately 70 cm before and after fieldwork. Light around the camera set-up was limited to reduce the amount of glare in the photographs. Each photograph was taken and edited in Adobe Lightroom according to the same settings (see appendix 4.1, table A4.1.1). All photos were converted to 72 dpi for consistency. Three presets were made in Adobe Lightroom to make sure photos were edited using the same methods and to create similar final results. These presets enhanced the contrast between the black background and white flag. Additionally, any light spots and stray fabric fibres were removed in Adobe Lightroom editing. Using R 4.0.2 (R Core Team, 2020) and the magick package (v2.7.3, Ooms, 2021), each flag photograph was converted to black and white and the white pixels were counted. Difference in white pixels in before and after flag installation quantified the amount of flag lost and therefore the level of wind exposure. The difference was calculated the same way as the weight data using

((after size – before size) / before size) * 100.

Table A4.1.1 Camera and Adobe Lightroom settings for flag photography and analysis.

Photograph settings (editing)		**Camera information**	
Dimensions	7952 X 5304 pixels	Make	Sony ILCE-7RM3
Horizontal and vertical resolution	300 dpi reduced to 72 dpi	F-stop	f/4.5
Bit depth	24	Exposure time	2 seconds
Resolution unit	2	ISO speed	ISO-100
Colour representation	sRGB	Exposure bias	0 step
		Focal length	24mm
		Max aperture	0.96875
		Metering mode	Pattern
		Flash mode	No flash
		35mm focal length	24

A4.2

Stochastic regression correlations were closest to the true correlation when comparing to deterministic regression results (table A4.2.1). A stochastic regression was used to interpolate all wind speed data. This method also accounts for random error, resulting in a more realistic and accurate correlation between target and explanatory variables. There are strong positive correlations between the Chirk Castle wind speed and gust data and those from the four stations used in the multiple regression interpolations (table A4.2.2). True correlations were strongest between Chirk Castle and the MIDAS weather station at Lake Vyrnwy (No. 2) (table A4.2.1) for both wind speed and gusts. The interpolated time series data (figure A4.2.1) show the same trends for wind speeds and gusts, which would be expected from a full data set. There are peaks of wind speed and gusts during the winter months, especially in February 2020. This may correlate with the high winds recorded during Storm Ciara, which hit the UK at the beginning of February 2020. Mean wind speed for the interpolated data across the year was 3.9 m s^{-1} for average wind speeds and 13.4 m s^{-1} for maximum gust speeds (figure A4.2.1).

Table A4.2.1: Comparing deterministic and stochastic multiple regression models to impute two metrics of historic weather data (A) Mean daily wind speed, B) Maximum daily wind gust) for Chirk Castle using the nearest MIDAS and National Trust weather stations. The weather stations: X1 = National Trust Erddig, X2 = MIDAS Shawbury, X3 = MIDAS Hawarden Airport, X4 = MIDAS Lake Vyrnwy No. 2.

Correlation type	X1	X2	X3	X4	Average
A)					
True	0.908	0.885	0.894	0.927	0.904
Deterministic	0.916	0.858	0.899	0.931	0.901
Stochastic	0.903	0.848	0.884	0.920	0.889
B)					
True	0.921	0.910	0.656	0.927	0.854
Deterministic	0.933	0.922	0.634	0.938	0.857
Stochastic	0.915	0.904	0.628	0.923	0.843

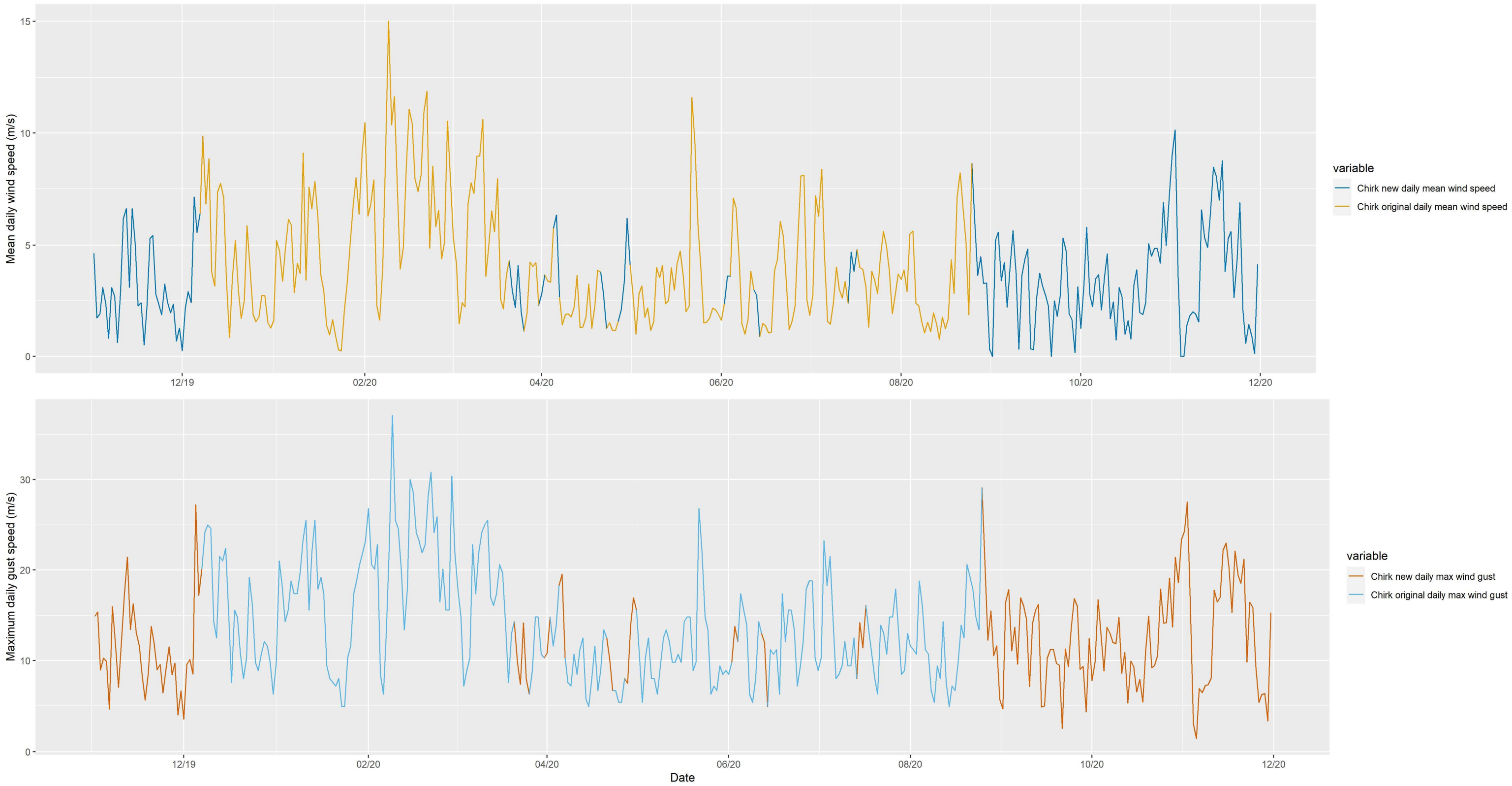


Figure A4.2.1: Interpolated wind speed results for Chirk Castle November 2019 to November 2020.

A4.3

When analysing proportion data (*frd*), the full data set was found to be not normally distributed ($p < .001$). Additionally, the score were not normally distributed for 60% fieldwork periods ($p < 0.05$) as assessed by Shaprio-Wilk's test of normality. Therefore, normality for the raw proportion data can not be assumed. When data was transformed to a logarithmic scale, the full data set is still found to be not normally distributed ($p < .001$), but the score were normally distributed when comparing between fieldwork periods for most monthly groups ($p > 0.05$ *NJ, JM and MM*, $p < 0.05$ *JS and SN*). Additionally, when investigating the QQ plot for the logarithmic data (figure A4.2.2), more points fall within the reference when comparing individual fieldwork periods, suggesting they are better to assess separately rather than as a full data set. We assumed normality of the logarithmic-transformed data set, as the Shapiro-Wilk's test is sensitive to minor deviations in normality.

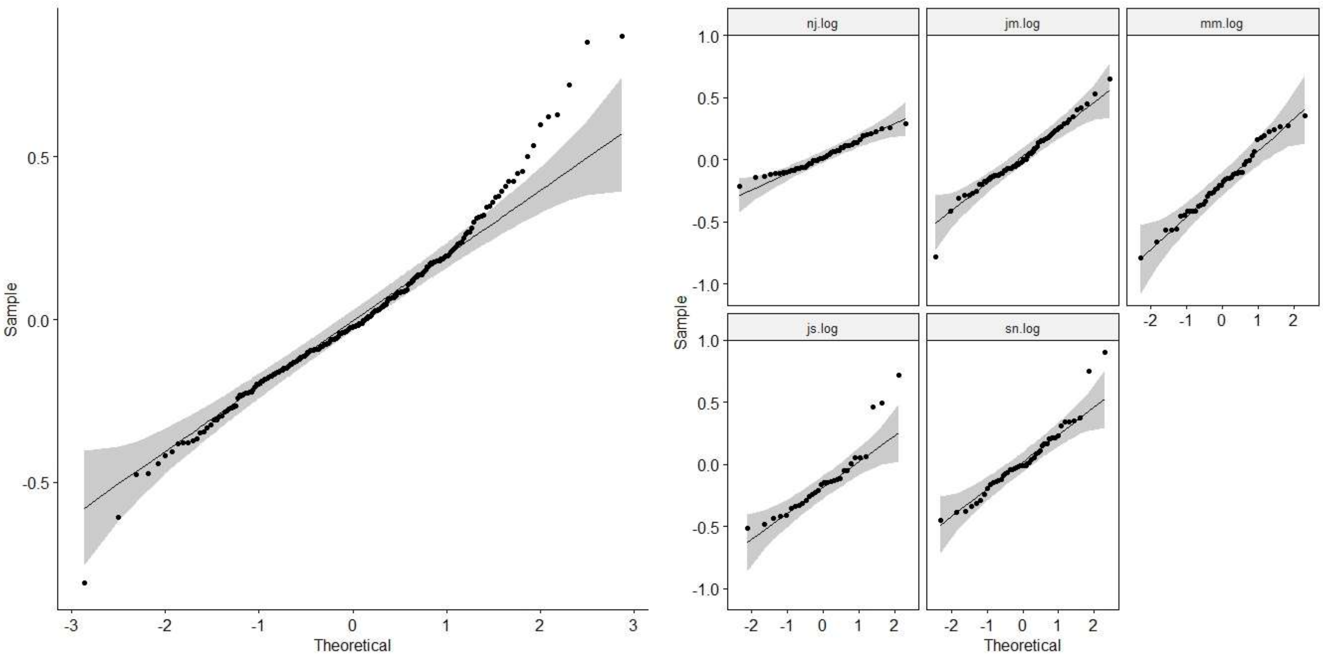


Figure A4.3.1: A) Linear model comparing fieldwork period and theoretical results along the logarithmic scale. The majority of points fall along the reference line suggesting normality. B) Linear model comparing each fieldwork period results along the logarithmic scale. Most points for each month fall along the reference line, suggesting normality.

The Levene's test was used to check the homogeneity of variances between fieldwork periods. The p-value was significant ($p < 0.05$) signifying significant difference between variance across groups. Therefore, we cannot assume homogeneity of variances in the difference fieldwork periods. To test for significant differences between fieldwork periods without assuming homogeneity of variances, we performed the Welch one-way ANOVA test with the Games-Howell post hoc test to compare all possible combinations of fieldwork periods.

Table A4.3.1 The average (%) size change of flags for each tree at the case study site, averaged from four wind directions (north, south, east, west). Flags are separated into fieldwork periods: NDJ) November-December-January, JFM) January-February-March, MAM) March-April-May, JAS) July-August-September, SON) September-October-November

Tree	NDJ	JFM	MAM	JAS	SON
1	-4.150	-13.084	-28.228	-4.829	-29.903
2	1.779	-31.833	-29.920	-1.731	-20.755
3	0.986	-31.582	-29.961	-25.243	-30.503
5	-0.917	-29.998	-29.591	-1.792	-29.688
6	-8.589	-31.687	-29.973	0.214	-32.348
7	0.534	-31.649	-30.357	-2.086	-32.116
8	-0.511	-32.233	-31.170	-5.143	-22.726
9	2.202	-30.570	-32.653	-2.476	-29.689
10	-31.014	-31.597	-27.100	-0.485	-27.643
11	0.284	-30.254	-28.607	0.608	-21.156
12	NA	-30.112	-27.792	NA	-7.160
13	NA	-29.172	-27.568	-0.068	-29.629
14	-20.901	-28.458	-27.004	NA	-27.325
15	-25.265	-29.932	-27.047	1.132	-20.542
16	3.336	-29.899	-28.189	0.430	-7.639
17	5.529	-29.123	-28.225	-15.984	NA
18	5.361	-29.557	-29.132	0.551	NA
19	-2.034	-41.187	-27.920	NA	NA
20	-24.974	-39.233	-28.617	NA	NA
24	-60.030	-36.411	NA	NA	NA
25	-3.612	-39.391	NA	NA	NA

Table A4.3.2: The relative difference of the proportion of flag weight lost compared to the average for the fieldwork period between November 2019 and November 2020. All missing data is represented with NA. Data > 1 indicates flags that lost more weight than the average and data < 1 indicates flags that lost less weight

Tree	NJ				JM				MM				JS				SN			
	N	S	E	W	N	S	E	W	N	S	E	W	N	S	E	W	N	S	E	W
1	NA	NA	NA	NA	1.343	1.299	1.521	1.498	NA	NA	NA	NA	1.053	0.773	1.055	2.049	NA	1.100	1.236	1.368
2	0.874	0.994	1.119	1.289	0.819	1.409	1.155	0.967	0.907	0.700	0.897	1.305	NA	NA	NA	NA	NA	NA	NA	NA
3	1.072	1.028	0.968	0.970	1.073	0.935	0.945	1.195	0.766	NA	1.032	0.749	0.865	0.649	NA	0.876	NA	NA	1.003	0.961
4	0.996	0.998	1.176	1.233	0.841	0.917	0.967	0.885	1.211	0.960	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
6	NA	NA	NA	NA	1.050	1.343	1.149	1.245	NA	NA	NA	NA	NA	NA	NA	0.733	0.971	0.853	0.932	1.042
7	0.940	NA	0.903	1.212	1.301	1.164	1.221	1.098	NA	1.178	1.252	NA	NA	NA	NA	NA	NA	1.233	1.408	1.458
8	1.300	NA	NA	1.041	0.936	0.936	1.205	1.912	NA	NA	NA	0.769	NA	1.003	1.640	NA	1.161	1.183	0.993	0.863
9	NA	0.917	1.078	NA	0.872	1.005	0.879	0.898	0.867	1.313	1.068	0.906	NA	NA	NA	NA	NA	1.090	NA	0.872
10	1.033	NA	NA	NA	0.983	0.754	1.006	0.763	0.573	0.639	NA	0.889	NA	NA	NA	NA	2.464	1.236	NA	NA
11	NA	1.011	0.958	0.888	0.842	1.189	1.031	1.263	0.764	0.859	0.991	NA	NA	NA	1.592	NA	1.258	1.422	1.412	0.990
12	1.102	1.151	0.865	1.060	1.115	1.569	1.002	1.095	NA	NA	NA	NA	0.784	NA	NA	0.953	0.784	0.967	0.913	0.980
13	0.944	1.070	1.253	1.130	1.178	0.855	0.457	0.821	0.895	1.422	0.844	1.273	0.811	1.064	0.883	0.864	0.876	1.184	0.994	1.121
14	NA	1.223	0.941	1.119	1.277	0.774	0.869	0.951	1.194	0.798	0.635	0.659	NA	NA	NA	NA	NA	NA	NA	NA
15	1.079	NA	0.934	NA	0.933	0.917	0.900	1.055	0.992	0.693	0.814	0.858	NA	NA	NA	NA	NA	NA	2.123	NA
16	1.012	0.810	NA	0.907	0.951	1.694	0.737	0.660	0.570	0.662	0.569	0.519	NA	NA	NA	0.666	0.889	0.730	0.687	0.958
17	1.125	1.006	1.102	1.146	1.054	0.985	0.888	1.169	0.688	0.660	0.817	0.664	NA	NA	NA	NA	1.018	0.826	0.678	0.991
18	1.342	1.019	0.899	0.898	1.384	0.879	0.753	0.968	0.719	0.788	0.860	0.454	0.890	0.596	0.618	0.703	0.746	0.640	1.055	0.715
19	NA	0.910	0.932	0.918	NA	NA	NA	NA	NA	NA	NA	NA	0.719	0.659	0.955	0.798	NA	NA	0.939	NA
20	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.746	0.711	NA	NA	NA	NA	NA
24	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
25	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.871	NA	NA	0.854	NA	NA	NA	NA

Table A4.3.3: Average exposure for each flag as calculated from the proportion of the relative difference in weight of each flag against two wind metrics (average wind speed and average maximum gust speed) over two time periods (2020 to 2040 and 2060 to 2080). For baseline results see Appendix 2 Table 1.

			2020 to 2040 - average wind speed					2060 to 2080 average wind speed					2020 to 2040 average maximum wind gust					2060 to 2080 average maximum wind gust				
flag	easting	northing	nj	jm	mm	js	sn	nj	jm	mm	js	sn	nj	jm	mm	js	sn	nj	jm	mm	js	sn
e	326345	338862	NA	-0.28	NA	-0.12	-0.18	NA	-0.07	NA	-0.42	-0.51	NA	-0.36	NA	-0.10	-0.49	NA	0.22	NA	-0.93	-1.33
e	326596	338891	-0.15	-0.21	-0.06	NA	NA	-0.25	-0.05	-0.04	NA	NA	-0.21	-0.27	0.03	NA	NA	-0.42	0.17	0.07	NA	NA
e	326821	338836	-0.13	-0.17	-0.06	NA	-0.14	-0.22	-0.04	-0.04	NA	-0.41	-0.18	-0.22	0.04	NA	-0.40	-0.36	0.14	0.08	NA	-1.08
e	327305	338744	-0.15	-0.18	NA	NA	NA	-0.26	-0.04	NA	NA	NA	-0.25	-0.24	NA	NA	NA	-0.39	0.18	NA	NA	NA
e	326302	338662	NA	-0.21	NA	NA	-0.13	NA	-0.05	NA	NA	-0.39	NA	-0.28	NA	NA	-0.40	NA	0.22	NA	NA	-1.07
e	326592	338610	-0.13	-0.21	-0.08	NA	-0.25	-0.19	-0.03	-0.07	NA	-0.57	-0.19	-0.30	0.03	NA	-0.60	-0.30	0.23	0.06	NA	-1.61
e	326848	338695	NA	-0.22	NA	-0.19	-0.14	NA	-0.06	NA	-0.65	-0.41	NA	-0.30	NA	-0.28	-0.43	NA	0.23	NA	-1.84	-1.14
e	327305	338633	-0.16	-0.15	-0.07	NA	NA	-0.23	-0.02	-0.06	NA	NA	-0.23	-0.22	0.02	NA	NA	-0.36	0.16	0.05	NA	NA
e	327419	338642	NA	-0.17	NA	NA	NA	NA	-0.02	NA	NA	NA	NA	-0.25	NA	NA	NA	NA	0.19	NA	NA	NA
e	326229	338341	-0.14	-0.18	-0.06	-0.23	-0.25	-0.20	-0.03	-0.06	-0.73	-0.57	-0.21	-0.25	0.02	-0.27	-0.60	-0.32	0.19	0.04	-1.79	-1.62
e	326480	338376	-0.13	-0.17	NA	NA	-0.16	-0.18	-0.02	NA	NA	-0.37	-0.19	-0.25	NA	NA	-0.39	-0.29	0.19	NA	NA	-1.05
e	326870	338311	-0.18	-0.08	-0.05	-0.13	-0.17	-0.26	-0.01	-0.05	-0.41	-0.40	-0.27	-0.11	0.02	-0.15	-0.43	-0.42	0.09	0.04	-0.99	-1.14
e	327315	338307	-0.14	-0.15	-0.04	NA	NA	-0.20	-0.02	-0.04	NA	NA	-0.20	-0.21	0.01	NA	NA	-0.31	0.16	0.03	NA	NA
e	327391	338295	-0.14	-0.16	-0.05	NA	-0.37	-0.20	-0.02	-0.05	NA	-0.86	-0.20	-0.22	0.02	NA	-0.91	-0.31	0.17	0.04	NA	-2.43
e	326133	338269	NA	-0.13	-0.04	NA	-0.12	NA	-0.02	-0.03	NA	-0.28	NA	-0.18	0.01	NA	-0.29	NA	0.14	0.03	NA	-0.79
e	326373	338171	-0.16	-0.15	-0.05	NA	-0.12	-0.23	-0.02	-0.05	NA	-0.28	-0.24	-0.22	0.02	NA	-0.29	-0.37	0.17	0.04	NA	-0.78
e	326784	338185	-0.13	-0.13	-0.05	-0.09	-0.18	-0.19	-0.02	-0.05	-0.28	-0.43	-0.19	-0.19	0.02	-0.11	-0.45	-0.30	0.14	0.04	-0.69	-1.21
e	327181	338027	-0.14	NA	NA	-0.14	-0.16	-0.20	NA	NA	-0.44	-0.38	-0.20	NA	NA	-0.16	-0.40	-0.31	NA	NA	-1.07	-1.08
e	327540	338025	NA	NA	NA	-0.09	NA	NA	NA	NA	-0.30	NA	NA	NA	NA	-0.09	NA	NA	NA	NA	-0.74	NA
e	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
e	327423	337830	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
s	326345	338862	NA	-0.24	NA	-0.09	-0.16	NA	-0.06	NA	-0.31	-0.45	NA	-0.31	NA	-0.07	-0.43	NA	0.19	NA	-0.68	-1.18
s	326596	338891	-0.13	-0.26	-0.04	NA	NA	-0.22	-0.07	-0.03	NA	NA	-0.19	-0.33	0.03	NA	NA	-0.37	0.21	0.05	NA	NA
s	326821	338836	-0.14	-0.17	NA	-0.08	NA	-0.23	-0.04	NA	-0.26	NA	-0.19	-0.22	NA	-0.06	NA	-0.39	0.14	NA	-0.57	NA
s	327305	338744	-0.13	-0.17	-0.06	NA	NA	-0.22	-0.04	-0.04	NA	NA	-0.21	-0.23	0.02	NA	NA	-0.33	0.17	0.04	NA	NA
s	326302	338662	NA	-0.24	NA	NA	-0.12	NA	-0.06	NA	NA	-0.35	NA	-0.33	NA	NA	-0.37	NA	0.25	NA	NA	-0.98
s	326592	338610	NA	-0.20	-0.07	NA	-0.22	NA	-0.03	-0.07	NA	-0.50	NA	-0.29	0.02	NA	-0.53	NA	0.22	0.05	NA	-1.41
s	326848	338695	NA	-0.17	NA	-0.12	-0.17	NA	-0.04	NA	-0.40	-0.49	NA	-0.23	NA	-0.17	-0.51	NA	0.18	NA	-1.13	-1.36

s	327305	338633	-0.13	-0.17	-0.08	NA	-0.19	-0.19	-0.02	-0.08	NA	-0.44	-0.20	-0.25	0.03	NA	-0.47	-0.30	0.19	0.06	NA	-1.25
s	327419	338642	NA	-0.13	-0.04	NA	-0.22	NA	-0.02	-0.04	NA	-0.50	NA	-0.19	0.01	NA	-0.53	NA	0.14	0.03	NA	-1.42
s	326229	338341	-0.15	-0.21	-0.05	NA	-0.25	-0.21	-0.03	-0.05	NA	-0.58	-0.22	-0.29	0.02	NA	-0.61	-0.34	0.22	0.04	NA	-1.63
s	326480	338376	-0.17	-0.27	NA	NA	-0.17	-0.24	-0.04	NA	NA	-0.39	-0.25	-0.39	NA	NA	-0.41	-0.38	0.29	NA	NA	-1.11
s	326870	338311	-0.16	-0.15	-0.09	-0.16	-0.21	-0.22	-0.02	-0.08	-0.49	-0.48	-0.23	-0.21	0.03	-0.18	-0.51	-0.36	0.16	0.06	-1.20	-1.36
s	327315	338307	-0.18	-0.13	-0.05	NA	NA	-0.26	-0.02	-0.05	NA	NA	-0.26	-0.19	0.02	NA	NA	-0.41	0.15	0.04	NA	NA
s	327391	338295	NA	-0.16	-0.04	NA	NA	NA	-0.02	-0.04	NA	NA	NA	-0.23	0.01	NA	NA	NA	0.17	0.03	NA	NA
s	326133	338269	-0.12	-0.29	-0.04	NA	-0.13	-0.17	-0.04	-0.04	NA	-0.30	-0.17	-0.42	0.01	NA	-0.31	-0.27	0.32	0.03	NA	-0.84
s	326373	338171	-0.15	-0.17	-0.04	NA	-0.14	-0.21	-0.02	-0.04	NA	-0.34	-0.22	-0.24	0.01	NA	-0.35	-0.33	0.18	0.03	NA	-0.95
s	326784	338185	-0.15	-0.15	-0.05	-0.09	-0.11	-0.21	-0.02	-0.05	-0.27	-0.26	-0.22	-0.22	0.02	-0.10	-0.27	-0.34	0.16	0.03	-0.67	-0.73
s	327181	338027	-0.13	NA	NA	-0.10	NA	-0.19	NA	NA	-0.30	NA	-0.19	NA	NA	-0.11	NA	-0.30	NA	NA	-0.74	NA
s	327540	338025	NA	NA	NA	-0.10	NA	NA	NA	NA	-0.31	NA	NA	NA	NA	-0.09	NA	NA	NA	NA	-0.78	NA
s	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
s	327423	337830	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	326345	338862	NA	-0.24	NA	-0.12	NA	NA	-0.06	NA	-0.42	NA	NA	-0.32	NA	-0.10	NA	NA	0.20	NA	-0.93	NA
n	326596	338891	-0.11	-0.15	-0.06	NA	NA	-0.20	-0.04	-0.04	NA	NA	-0.16	-0.19	0.03	NA	NA	-0.33	0.12	0.07	NA	NA
n	326821	338836	-0.14	-0.19	-0.05	-0.10	NA	-0.24	-0.05	-0.03	-0.34	NA	-0.20	-0.25	0.03	-0.08	NA	-0.40	0.16	0.06	-0.77	NA
n	327305	338744	-0.13	-0.15	-0.07	NA	NA	-0.22	-0.04	-0.05	NA	NA	-0.21	-0.21	0.02	NA	NA	-0.33	0.16	0.05	NA	NA
n	326302	338662	NA	-0.19	NA	NA	-0.14	NA	-0.05	NA	NA	-0.40	NA	-0.26	NA	NA	-0.42	NA	0.20	NA	NA	-1.11
n	326592	338610	-0.14	-0.23	NA	NA	NA	-0.20	-0.03	NA	NA	NA	-0.20	-0.32	NA	NA	NA	-0.31	0.24	NA	NA	NA
n	326848	338695	-0.17	-0.17	NA	NA	-0.17	-0.29	-0.04	NA	NA	-0.48	-0.28	-0.23	NA	NA	-0.50	-0.43	0.18	NA	NA	-1.33
n	327305	338633	NA	-0.15	-0.05	NA	NA	NA	-0.02	-0.05	NA	NA	NA	-0.22	0.02	NA	NA	NA	0.16	0.04	NA	NA
n	327419	338642	-0.15	-0.17	-0.04	NA	-0.43	-0.22	-0.02	-0.03	NA	-1.00	-0.22	-0.24	0.01	NA	-1.06	-0.34	0.18	0.03	NA	-2.82
n	326229	338341	NA	-0.15	-0.05	NA	-0.22	NA	-0.02	-0.04	NA	-0.51	NA	-0.21	0.02	NA	-0.54	NA	0.16	0.03	NA	-1.44
n	326480	338376	-0.16	-0.19	NA	-0.11	-0.14	-0.23	-0.03	NA	-0.36	-0.32	-0.24	-0.28	NA	-0.13	-0.34	-0.37	0.21	NA	-0.88	-0.90
n	326870	338311	-0.14	-0.20	-0.06	-0.12	-0.15	-0.20	-0.03	-0.05	-0.37	-0.36	-0.20	-0.29	0.02	-0.14	-0.38	-0.31	0.22	0.04	-0.91	-1.00
n	327315	338307	NA	-0.22	-0.08	NA	NA	NA	-0.03	-0.07	NA	NA	NA	-0.32	0.02	NA	NA	NA	0.24	0.05	NA	NA
n	327391	338295	-0.16	-0.16	-0.06	NA	NA	-0.23	-0.02	-0.06	NA	NA	-0.23	-0.23	0.02	NA	NA	-0.36	0.18	0.04	NA	NA
n	326133	338269	-0.15	-0.16	-0.04	NA	-0.16	-0.21	-0.02	-0.03	NA	-0.36	-0.22	-0.24	0.01	NA	-0.38	-0.34	0.18	0.03	NA	-1.02
n	326373	338171	-0.17	-0.18	-0.04	NA	-0.18	-0.24	-0.03	-0.04	NA	-0.41	-0.24	-0.26	0.01	NA	-0.44	-0.37	0.20	0.03	NA	-1.17
n	326784	338185	-0.20	-0.24	-0.05	-0.13	-0.13	-0.28	-0.03	-0.04	-0.41	-0.30	-0.29	-0.34	0.01	-0.15	-0.32	-0.45	0.26	0.03	-1.00	-0.85
n	327181	338027	NA	NA	NA	-0.10	NA	NA	NA	NA	-0.33	NA	NA	NA	NA	-0.12	NA	NA	NA	NA	-0.81	NA
n	327540	338025	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	327423	337830	NA	NA	NA	-0.13	NA	NA	NA	NA	-0.40	NA	NA	NA	NA	-0.15	NA	NA	NA	NA	-0.98	NA

w	326345	338862	NA	-0.27	NA	-0.24	-0.20	NA	-0.07	NA	-0.81	-0.57	NA	-0.35	NA	-0.19	-0.54	NA	0.22	NA	-1.81	-1.47
w	326596	338891	-0.17	-0.18	-0.08	NA	NA	-0.29	-0.04	-0.05	NA	NA	-0.24	-0.23	0.05	NA	NA	-0.48	0.14	0.10	NA	NA
w	326821	338836	-0.13	-0.22	-0.05	-0.10	-0.14	-0.22	-0.06	-0.03	-0.35	-0.40	-0.18	-0.28	0.03	-0.08	-0.38	-0.36	0.18	0.06	-0.77	-1.03
w	327305	338744	-0.16	-0.16	NA	NA	NA	-0.28	-0.04	NA	NA	NA	-0.26	-0.22	NA	NA	NA	-0.41	0.17	NA	NA	NA
w	326302	338662	NA	-0.23	NA	-0.09	-0.15	NA	-0.06	NA	-0.29	-0.43	NA	-0.31	NA	-0.13	-0.45	NA	0.23	NA	-0.82	-1.19
w	326592	338610	-0.18	-0.19	NA	NA	-0.25	-0.25	-0.03	NA	NA	-0.59	-0.26	-0.27	NA	NA	-0.62	-0.40	0.21	NA	NA	-1.67
w	326848	338695	-0.14	-0.35	-0.05	NA	-0.12	-0.23	-0.09	-0.03	NA	-0.36	-0.22	-0.47	0.02	NA	-0.37	-0.35	0.36	0.03	NA	-0.99
w	327305	338633	NA	-0.16	-0.06	NA	-0.15	NA	-0.02	-0.05	NA	-0.35	NA	-0.22	0.02	NA	-0.37	NA	0.17	0.04	NA	-1.00
w	327419	338642	NA	-0.13	-0.06	NA	NA	NA	-0.02	-0.05	NA	NA	NA	-0.19	0.02	NA	NA	NA	0.14	0.04	NA	NA
w	326229	338341	-0.13	-0.22	NA	NA	-0.17	-0.19	-0.03	NA	NA	-0.40	-0.19	-0.31	NA	NA	-0.42	-0.30	0.24	NA	NA	-1.13
w	326480	338376	-0.16	-0.19	NA	-0.14	-0.17	-0.22	-0.03	NA	-0.44	-0.40	-0.23	-0.27	NA	-0.16	-0.42	-0.35	0.21	NA	-1.07	-1.12
w	326870	338311	-0.17	-0.14	-0.08	-0.13	-0.20	-0.24	-0.02	-0.07	-0.40	-0.45	-0.24	-0.20	0.03	-0.15	-0.48	-0.38	0.15	0.06	-0.97	-1.28
w	327315	338307	-0.16	-0.16	-0.04	NA	NA	-0.23	-0.02	-0.04	NA	NA	-0.24	-0.24	0.01	NA	NA	-0.37	0.18	0.03	NA	NA
w	327391	338295	NA	-0.18	-0.05	NA	NA	NA	-0.03	-0.05	NA	NA	NA	-0.26	0.02	NA	NA	NA	0.20	0.04	NA	NA
w	326133	338269	-0.13	-0.11	-0.03	-0.10	-0.17	-0.19	-0.02	-0.03	-0.31	-0.39	-0.19	-0.16	0.01	-0.11	-0.41	-0.30	0.12	0.02	-0.75	-1.10
w	326373	338171	-0.17	-0.20	-0.04	NA	-0.17	-0.24	-0.03	-0.04	NA	-0.40	-0.25	-0.29	0.01	NA	-0.42	-0.38	0.22	0.03	NA	-1.14
w	326784	338185	-0.13	-0.17	-0.03	-0.10	-0.12	-0.19	-0.02	-0.03	-0.32	-0.29	-0.19	-0.24	0.01	-0.12	-0.31	-0.30	0.18	0.02	-0.79	-0.82
w	327181	338027	-0.13	NA	NA	-0.12	NA	-0.19	NA	NA	-0.37	NA	-0.20	NA	NA	-0.14	NA	-0.30	NA	NA	-0.90	NA
w	327540	338025	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
w	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
w	327423	337830	NA	NA	NA	-0.12	NA	NA	NA	NA	-0.39	NA	NA	NA	NA	-0.15	NA	NA	NA	NA	-0.96	NA

Table A4.3.4: Maximum exposure for each flag as calculated from the proportion of the relative difference in weight of each flag against two wind metrics (maximum average wind speed and maximum gust speed) over two time periods (2020 to 2040 and 2060 to 2080). For baseline results see Appendix 2, Table 1.

			2020 to 2040 - maximum average wind speed					2060 to 2080 maximum average wind speed					2020 to 2040 maximum wind gust					2060 to 2080 maximum wind gust				
flag	easting	northing	nj	jm	mm	js	sn	nj	jm	mm	js	sn	nj	jm	mm	js	sn	nj	jm	mm	js	sn
e	326345	338862	NA	2.40	NA	-0.52	-2.72	NA	-0.63	NA	-0.46	-3.95	NA	54.67	NA	-13.27	-7.23	NA	5.80	NA	18.41	1
e	326596	338891	0.94	1.82	-0.34	NA	NA	1.94	-0.48	-0.20	NA	NA	-16.76	41.51	28.48	NA	NA	-16.74	4.40	-3.85	NA	NA
e	326821	338836	0.82	1.49	-0.39	NA	-2.21	1.68	-0.39	-0.23	NA	-3.21	-14.51	33.97	32.77	NA	-5.86	-14.49	3.60	-4.43	NA	15.8
e	327305	338744	0.99	1.52	NA	NA	NA	2.04	-0.40	NA	NA	NA	-58.39	10.70	NA	NA	NA	-54.22	3.30	NA	NA	NA
e	326302	338662	NA	1.81	NA	NA	-2.05	NA	-0.48	NA	NA	-2.98	NA	12.70	NA	NA	-34.00	NA	3.92	NA	NA	-42.
e	326592	338610	0.57	1.67	-0.36	NA	-2.91	1.49	-0.61	-0.05	NA	-4.66	-44.82	13.51	-40.23	NA	-51.33	-41.63	4.16	2.40	NA	-64.
e	326848	338695	NA	1.90	NA	-0.81	-2.19	NA	-0.50	NA	-0.72	-3.17	NA	13.32	NA	-7.03	-36.21	NA	4.11	NA	-16.04	-4
e	327305	338633	0.68	1.20	-0.30	NA	NA	1.78	-0.44	-0.05	NA	NA	-53.50	9.72	-34.31	NA	NA	-49.68	3.00	2.05	NA	NA
e	327419	338642	NA	1.37	NA	NA	NA	NA	-0.50	NA	NA	NA	NA	11.12	NA	NA	NA	NA	3.43	NA	NA	NA
e	326229	338341	0.60	1.41	-0.28	1.37	-2.92	1.58	-0.51	-0.04	-0.41	-4.67	-47.53	11.39	-31.83	-6.83	-51.49	-44.14	3.51	1.90	-15.57	-6.
e	326480	338376	0.54	1.37	NA	NA	-1.89	1.43	-0.50	NA	NA	-3.02	-42.96	11.08	NA	NA	-33.29	-39.89	3.42	NA	NA	-42.
e	326870	338311	0.79	0.62	-0.24	0.76	-2.05	2.07	-0.23	-0.04	-0.22	-3.29	-62.22	5.05	-27.11	-3.79	-36.24	-57.78	1.56	1.62	-8.63	-4
e	327315	338307	0.59	1.19	-0.18	NA	NA	1.55	-0.43	-0.03	NA	NA	-46.71	9.61	-20.42	NA	NA	-43.38	2.96	1.22	NA	NA
e	327391	338295	0.59	1.23	-0.23	NA	-4.39	1.54	-0.45	-0.04	NA	-7.02	-46.37	9.95	-26.14	NA	-77.40	-43.06	3.07	1.56	NA	-97.
e	326133	338269	NA	1.01	-0.16	NA	-1.42	NA	-0.37	-0.02	NA	-2.27	NA	8.15	-18.29	NA	-25.04	NA	2.51	1.09	NA	-31.
e	326373	338171	0.69	1.21	-0.23	NA	-1.40	1.82	-0.44	-0.04	NA	-2.24	-54.69	9.82	-26.26	NA	-24.73	-50.79	3.03	1.57	NA	-31.
e	326784	338185	0.56	1.03	-0.24	0.53	-2.18	1.48	-0.37	-0.04	-0.16	-3.49	-44.60	8.33	-27.63	-2.65	-38.47	-41.42	2.57	1.65	-6.04	-4
e	327181	338027	0.58	NA	NA	0.82	-1.94	1.54	NA	NA	-0.24	-3.10	-46.25	NA	NA	-4.10	-34.23	-42.95	NA	NA	-9.34	-4
e	327540	338025	NA	NA	NA	0.60	NA	NA	NA	NA	-0.15	NA	NA	NA	NA	-65.89	NA	NA	NA	NA	-41.54	
e	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
e	327423	337830	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
s	326345	338862	NA	2.05	NA	-0.38	-2.42	NA	-0.54	NA	-0.34	-3.52	NA	46.66	NA	-9.73	-6.44	NA	4.95	NA	13.50	1
s	326596	338891	0.84	2.22	-0.27	NA	NA	1.72	-0.59	-0.15	NA	NA	-14.89	50.64	22.24	NA	NA	-14.87	5.37	-3.01	NA	NA
s	326821	338836	0.87	1.47	NA	-0.32	NA	1.78	-0.39	NA	-0.28	NA	-15.40	33.58	NA	-8.17	NA	-15.38	3.56	NA	11.33	
s	327305	338744	0.84	1.45	-0.37	NA	NA	1.73	-0.38	-0.21	NA	NA	-49.55	10.14	-30.85	NA	NA	-46.02	3.12	1.84	NA	NA
s	326302	338662	NA	2.12	NA	NA	-1.88	NA	-0.56	NA	NA	-2.73	NA	14.85	NA	NA	-31.11	NA	4.58	NA	NA	-39.
s	326592	338610	NA	1.59	-0.33	NA	-2.55	NA	-0.58	-0.05	NA	-4.08	NA	12.87	-37.86	NA	-44.95	NA	3.97	2.26	NA	-56.
s	326848	338695	NA	1.48	NA	-0.50	-2.61	NA	-0.39	NA	-0.44	-3.78	NA	10.35	NA	-4.30	-43.14	NA	3.19	NA	-9.81	-5

s	327305	338633	0.58	1.37	-0.37	NA	-2.25	1.51	-0.50	-0.06	NA	-3.60	-45.50	11.11	-42.19	NA	-39.74	-42.25	3.43	2.52	NA	-50.
s	327419	338642	NA	1.03	-0.18	NA	-2.55	NA	-0.37	-0.03	NA	-4.09	NA	8.34	-20.53	NA	-45.07	NA	2.57	1.23	NA	-56.
s	326229	338341	0.63	1.62	-0.24	NA	-2.94	1.67	-0.59	-0.04	NA	-4.70	-50.18	13.14	-27.62	NA	-51.83	-46.60	4.05	1.65	NA	-65.
s	326480	338376	0.72	2.14	NA	NA	-2.00	1.90	-0.78	NA	NA	-3.20	-57.15	17.35	NA	NA	-35.27	-53.07	5.35	NA	NA	-44.
s	326870	338311	0.67	1.17	-0.40	0.92	-2.45	1.77	-0.42	-0.06	-0.27	-3.92	-53.09	9.45	-45.69	-4.56	-43.18	-49.30	2.91	2.73	-10.41	-5
s	327315	338307	0.77	1.06	-0.23	NA	NA	2.02	-0.38	-0.03	NA	NA	-60.72	8.56	-25.63	NA	NA	-56.38	2.64	1.53	NA	NA
s	327391	338295	NA	1.25	-0.20	NA	NA	NA	-0.45	-0.03	NA	NA	NA	10.14	-22.28	NA	NA	NA	3.12	1.33	NA	NA
s	326133	338269	0.51	2.31	-0.19	NA	-1.51	1.34	-0.84	-0.03	NA	-2.41	-40.23	18.74	-21.29	NA	-26.63	-37.36	5.78	1.27	NA	-33.
s	326373	338171	0.63	1.34	-0.19	NA	-1.71	1.66	-0.49	-0.03	NA	-2.73	-49.91	10.89	-21.22	NA	-30.12	-46.35	3.36	1.27	NA	-38.
s	326784	338185	0.64	1.20	-0.22	0.51	-1.32	1.68	-0.44	-0.03	-0.15	-2.12	-50.59	9.72	-25.31	-2.56	-23.34	-46.98	3.00	1.51	-5.83	-2
s	327181	338027	0.57	NA	NA	0.57	NA	1.50	NA	NA	-0.17	NA	-45.17	NA	NA	-2.83	NA	-41.95	NA	NA	-6.45	
s	327540	338025	NA	NA	NA	0.63	NA	NA	NA	NA	-0.16	NA	NA	NA	NA	-69.14	NA	NA	NA	NA	-43.59	
s	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
s	327423	337830	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	326345	338862	NA	2.12	NA	-0.52	NA	NA	-0.56	NA	-0.46	NA	NA	48.26	NA	-13.25	NA	NA	5.12	NA	18.38	
n	326596	338891	0.74	1.29	-0.35	NA	NA	1.51	-0.34	-0.20	NA	NA	-13.09	29.41	28.82	NA	NA	-13.08	3.12	-3.89	NA	NA
n	326821	338836	0.90	1.69	-0.29	-0.43	NA	1.86	-0.45	-0.17	-0.38	NA	-16.07	38.55	24.34	-10.88	NA	-16.05	4.09	-3.29	15.09	
n	327305	338744	0.84	1.33	-0.46	NA	NA	1.73	-0.35	-0.27	NA	NA	-49.45	9.30	-38.91	NA	NA	-45.92	2.87	2.32	NA	NA
n	326302	338662	NA	1.66	NA	NA	-2.14	NA	-0.44	NA	NA	-3.11	NA	11.61	NA	NA	-35.42	NA	3.58	NA	NA	-44.
n	326592	338610	0.59	1.78	NA	NA	NA	1.55	-0.65	NA	NA	NA	-46.66	14.39	NA	NA	NA	-43.33	4.44	NA	NA	NA
n	326848	338695	1.10	1.48	NA	NA	-2.56	2.25	-0.39	NA	NA	-3.71	-64.53	10.35	NA	NA	-42.34	-59.93	3.19	NA	NA	-53.
n	327305	338633	NA	1.19	-0.25	NA	NA	NA	-0.43	-0.04	NA	NA	NA	9.65	-27.87	NA	NA	NA	2.97	1.66	NA	NA
n	327419	338642	0.65	1.34	-0.16	NA	-5.09	1.71	-0.49	-0.02	NA	-8.15	-51.30	10.87	-18.42	NA	-89.85	-47.64	3.35	1.10	NA	-11
n	326229	338341	NA	1.15	-0.22	NA	-2.60	NA	-0.42	-0.03	NA	-4.16	NA	9.31	-24.56	NA	-45.88	NA	2.87	1.47	NA	-58.
n	326480	338376	0.69	1.52	NA	0.68	-1.62	1.82	-0.55	NA	-0.20	-2.59	-54.68	12.33	NA	-3.36	-28.58	-50.78	3.80	NA	-7.66	-3
n	326870	338311	0.59	1.61	-0.25	0.70	-1.81	1.56	-0.58	-0.04	-0.21	-2.90	-46.87	13.02	-28.77	-3.48	-31.96	-43.53	4.01	1.72	-7.93	-4
n	327315	338307	NA	1.74	-0.34	NA	NA	NA	-0.63	-0.05	NA	NA	NA	14.12	-38.37	NA	NA	NA	4.35	2.29	NA	NA
n	327391	338295	0.68	1.27	-0.28	NA	NA	1.78	-0.46	-0.04	NA	NA	-53.57	10.32	-31.88	NA	NA	-49.74	3.18	1.90	NA	NA
n	326133	338269	0.63	1.30	-0.16	NA	-1.84	1.67	-0.47	-0.02	NA	-2.94	-50.21	10.51	-18.32	NA	-32.41	-46.63	3.24	1.09	NA	-40.
n	326373	338171	0.71	1.44	-0.20	NA	-2.10	1.86	-0.52	-0.03	NA	-3.37	-55.82	11.65	-22.11	NA	-37.13	-51.84	3.59	1.32	NA	-46.
n	326784	338185	0.84	1.89	-0.20	0.77	-1.54	2.22	-0.69	-0.03	-0.23	-2.47	-66.61	15.30	-23.10	-3.82	-27.21	-61.86	4.72	1.38	-8.71	-3
n	327181	338027	NA	NA	NA	0.62	NA	NA	NA	NA	-0.18	NA	NA	NA	NA	-3.08	NA	NA	NA	NA	-7.03	
n	327540	338025	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
n	327423	337830	NA	NA	NA	0.75	NA	NA	NA	NA	-0.22	NA	NA	NA	NA	-3.74	NA	NA	NA	NA	-8.52	

w	326345	338862	NA	2.36	NA	-1.02	-3.01	NA	-0.62	NA	-0.90	-4.37	NA	53.82	NA	-25.79	-8.00	NA	5.71	NA	35.77	2
w	326596	338891	1.09	1.52	-0.50	NA	NA	2.23	-0.40	-0.29	NA	NA	-19.31	34.74	41.44	NA	NA	-19.29	3.68	-5.60	NA	NA
w	326821	338836	0.82	1.88	-0.29	-0.43	-2.12	1.68	-0.50	-0.17	-0.38	-3.07	-14.54	42.95	23.78	-11.02	-5.62	-14.52	4.55	-3.21	15.29	1
w	327305	338744	1.04	1.39	NA	NA	NA	2.14	-0.37	NA	NA	NA	-61.20	9.78	NA	NA	NA	-56.83	3.02	NA	NA	NA
w	326302	338662	NA	1.96	NA	-0.36	-2.29	NA	-0.52	NA	-0.32	-3.33	NA	13.77	NA	-3.14	-37.98	NA	4.24	NA	-7.17	-4
w	326592	338610	0.76	1.50	NA	NA	-3.01	2.00	-0.55	NA	NA	-4.82	-60.14	12.15	NA	NA	-53.15	-55.85	3.74	NA	NA	-67.
w	326848	338695	0.88	3.01	-0.29	NA	-1.90	1.80	-0.80	-0.17	NA	-2.76	-51.67	21.14	-24.70	NA	-31.46	-47.98	6.52	1.48	NA	-39.
w	327305	338633	NA	1.23	-0.26	NA	-1.80	NA	-0.45	-0.04	NA	-2.88	NA	9.93	-29.12	NA	-31.81	NA	3.06	1.74	NA	-40.
w	327419	338642	NA	1.04	-0.25	NA	NA	NA	-0.38	-0.04	NA	NA	NA	8.43	-28.55	NA	NA	NA	2.60	1.71	NA	NA
w	326229	338341	0.56	1.72	NA	NA	-2.05	1.47	-0.63	NA	NA	-3.27	-44.09	13.96	NA	NA	-36.10	-40.94	4.30	NA	NA	-45.
w	326480	338376	0.67	1.49	NA	0.82	-2.03	1.75	-0.54	NA	-0.24	-3.24	-52.60	12.11	NA	-4.09	-35.73	-48.84	3.73	NA	-9.32	-4
w	326870	338311	0.71	1.12	-0.36	0.75	-2.32	1.87	-0.41	-0.06	-0.22	-3.71	-56.10	9.07	-40.91	-3.70	-40.86	-52.09	2.80	2.44	-8.45	-5
w	327315	338307	0.70	1.30	-0.19	NA	NA	1.85	-0.47	-0.03	NA	NA	-55.57	10.52	-21.19	NA	NA	-51.60	3.24	1.27	NA	NA
w	327391	338295	NA	1.44	-0.24	NA	NA	NA	-0.52	-0.04	NA	NA	NA	11.67	-27.57	NA	NA	NA	3.60	1.65	NA	NA
w	326133	338269	0.57	0.90	-0.15	0.57	-1.98	1.50	-0.33	-0.02	-0.17	-3.17	-45.04	7.30	-16.66	-2.86	-34.91	-41.82	2.25	1.00	-6.52	-4
w	326373	338171	0.72	1.60	-0.19	NA	-2.05	1.89	-0.58	-0.03	NA	-3.28	-56.90	12.93	-21.34	NA	-36.14	-52.84	3.99	1.27	NA	-45.
w	326784	338185	0.56	1.32	-0.13	0.61	-1.48	1.48	-0.48	-0.02	-0.18	-2.37	-44.57	10.70	-14.59	-3.01	-26.08	-41.39	3.30	0.87	-6.88	-3
w	327181	338027	0.58	NA	NA	0.69	NA	1.52	NA	NA	-0.20	NA	-45.56	NA	NA	-3.42	NA	-42.31	NA	NA	-7.80	
w	327540	338025	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
w	327220	337833	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
w	327423	337830	NA	NA	NA	0.74	NA	NA	NA	NA	-0.22	NA	NA	NA	NA	-3.66	NA	NA	NA	NA	-8.35	

Table A4.3.5: The most common prevailing wind direction for each grid square and fieldwork period at the baseline (B) 1980 to 2000, short-term future (F1) 2020 to 2040 and long-term future (F2) 2060 to 2080. Changes in prevailing wind direction from the baseline are indicated in italics. Each fieldwork period represented by a three letter code indicated in 3.2.1 table 1. Grid square coordinates as follows; 1) 337547.667925258, 326335.303968053, 2) 337547.667925258, 328535.303968053, 3) 339747.667925258, 328535.303968053 , 4) 339747.667925258, 326335.303968053 .

	N-D-J			J-F-M			M-A-M			J-A-S			S-O-N		
Grid square	B	F1	F2	B	F1	F2	B	F1	F2	B	F1	F2	B	F1	F2
1	SW	SW	SW	SW	*NW*	SW	NW	*SW*	NW	SW	SW	*NW*	SW	*SE*	SW
2	SW	SW	SW	SW	*NW*	SW	NW	*SW*	NW	SE	*SW*	*NW*	SW	SW	SW
3	SW	*SE*	SW	SW	*NW*	SW	NW	*SW*	NW	SE	*SW*	*NW*	SW	SW	SW
4	SW	*SE*	SW	SW	*NW*	SW	NW	*SW*	NW	SE	*SW*	*NW*	SW	SW	SW

Appendix 5: Supplementary material for chapter 6 – Working with end users through iterative feedback improves the outcomes of climate impact models for nature conservation

Participant consent

1. Please indicate your agreement below
    a. I agree with the above statements
    b. I disagree with the above statements
2. Do you consent to your responses to this questionnaire beign used within the project to develop the models/tools?
    a. Yes
    b. No
3. Do you consent to your anonymised responses, including quotes, to be used in my thesis chapter, research presentations and any subsequent journal publications?
    a. Yes
    b. No

About you

4. Which site do you work at?
    a. Abergwesn Common (Brecon Beacons)
    b. Chirk Castle
    c. Migneint (Snowdonia)
    d. Other
5. What is your job title?
    a. General Manager
    b. Head Ranger
    c. Ranger
    d. Gardener
    e. Other
6. Today's date
    a. Date input

National Trust conservation management and decision making activities

7. What do you use currently to plan work on site (e.g. conservation, for visitors, general maintenance) and help make decisions surrounding management. For example, this may

include details of policy, funding reports, reports from outside bodies e.g. Natural Resources Wales, visitor number data etc. that are used to help inform decisions.

    a. Answer input

8. What is the time period planned for when thinking about site/conservation work (e.g. planning horizons)?
    a. Answer input
9. How useful do you find these current methods when planning/undertaking site/conservation work?
    a. Extremely useful
    b. Somewhat useful
    c. Neutral
    d. Not very useful
    e. Not useful at all
    f. No opinion/I don't know

The results – relating to the results for each data chapter

10. If you were to use this map/tool to make management decisions, how would you find it useful? How easy is it to read and understand the information?
    a. Answer input
11. Is you were to use this map/tool to make management decisions, in what ways would you find it to not be useful? What do you dislike about the results?
    a. Answer input
12. Is there anything you were hoping to receive that you did not? If yes, please provide details.
    a. Answer input
13. Is the information attached to the maps/tools regarding methods/background sufficient and clear?
    a. Extremely clear and sufficient
    b. Moderately clear and sufficient
    c. Neutral
    d. Moderately unclear and sufficient
    e. Extremely unclear and sufficient
    f. No opinion/I don't know
14. If the answer to Question 13 was 'unclear' please give details why.
    a. Answer input

15. Would you like any additional information regarding the map/tool you received? If yes, please provide details.
    a. Answer input
16. Do you think you would use maps/tools similar to these/this if provided to you to support conservation/site management planning and decision making?
    a. Definitely
    b. Likely
    c. Natural
    d. Unlikely
    e. Not at all
    f. No opinion/I don't know
17. Would you prefer to be provided with the maps with analysis already completed or conduct the analysis yourself (with training opportunities)?
    a. Maps and analysis already completed
    b. Conduct analysis myself (after/during training)
18. Do you have any further comments? Are there any additional questions we should have asked?
    a. Answer input
19. Do you have any questions regarding anything about the project?
    a. Answer input

Table A5.1: Themes and explanation of these themes identified in qualitative questionnaire responses.

Question	Themes used as 'highlights' in *Taguette*							
Q7: What do you currently use to plan work on site (e.g. conservation, for visitors, general maintenance) and help make decisions surrounding management? For example, this may include detail of policy, funding reports, reports from outside bodies e.g. Natural Resources Wales, visitor number data etc. that are used to help inform decisions.	National Trust (specific information) – *the information used to plan work that is developed by the National Trust within properties and the Trust as a whole.*	Local – *from National Trust staff and local communities/groups, including local involvement and local knowledge.*	Teamwork – *within local and regional National Trust teams*	Priorities – *depending on current need, funding, ongoing management and reacting to events.*	Continuous observations – *working reactively and using ongoing data collection to inform management.*	Engagement – *with volunteers and visitors.*	External organisations – *such as Natural Resources Wales, Welsh Government and local councils.*	Data – *from National Trust work, commissioned work, external surveys, local knowledge, past work. This highlight does overlap some others (National Trust, local knowledge, external organisations), but showcases how important data is in management decision making.*
Q8: What is the time period planned for when thinking about site/conservation work (e.g. planning horizons)? Please provide this information for all activities which are	Short term – *categorised as one to three years (National Trust funding cycles).*	Medium term – *categorised as three to 10 years.*	Long term – *categorised as 10 years plus.*	No time scale stated – *where work is done on an ad-hoc basis.*	Limitations – *such as funding, biological constraints, visitors, access.*	General – *including further information about how time scales are planned and used.*		

applicable to you site/area of work.								
Q10: If you were to use this map/tool to make management decisions, how would you find it useful? How easy is it to read and understand the information?	Useful – *how the results could be useful to National Trust staff for conservation management.*	Unsure – *how recipients are unsure about the results presented.*	Specifics – *how specific results could be useful.*	Understanding – *the level of understanding gained from the results presented.*	Improvement suggestions – *how the results presented could be more useful to National Trust staff.*			
Q11: If you were to use this map/tool to make management decisions, in what ways would you find it to not be useful? What do you dislike about the results?	Scale – *how the scale (temporal, spatial and within management) results are presented at makes them less useful for conservation management decision making.*	Testing – *how to use data to test the results (linked to clarification).*	Clarification – *a need for better understanding of what the results mean, otherwise they are not useful.*	Management need – *results are not useful to sites that need management regardless of future risk.*	Improvement suggestions – *how the results presented could be more useful to National Trust staff.*			
Q12: Is there anything you were hoping to receive that you did not? If yes, please provide details.	No – *recipients received all data they needed.*	Scale – *results showing different spatial scales.*	Data – *further information of local climate data and risks.*	Explanation – *further explanation of results.*				
Q15: Would you like any additional information regarding the maps/tools	No – *recipients received all information they needed.*	Scale – *further detailed scale results.*	Data – *comparisons with other datasets.*	Understanding – *further explanation of results in*				

you have received? If yes, please provide details.				*included narrative to aid understanding.*					
Q18: Do you have any further comments? Are there any additional questions we should have asked?	No – *recipients did not have further comments or examples of additional questions.*	Land management – *the influence of land management on results.*	Biggest threats – *concerns around areas/species at greatest risk.*						
Q19: Do you have any questions regarding anything about the project?	No – *recipients did not have further questions about the project.*	Communication – *how the project will be communicated to stakeholders.*	Accessibility – *how the results/data will be available to stakeholders.*						

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