Master Thesis in Geographical Information Science nr 104

Plant phenology and climate change: possible effect on the onset of various wild plant species first flowering day in the UK.

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Master's Thesis, 30 credits in Geographical Information Sciences

Supervisor: Anna Maria Jönsson

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Abstract

Nigel Fox

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The IPCC states that the planet is significantly warming due to effects of climate change. This warming effect has consequences for phenological events. Many species cannot track rapid climate change, resulting in phenological mismatches. This study looks at an extreme weather event and the longer-term effects of climate change. According to the IPCC, extreme weather is linked to climate change. The study utilises geographical information science (GIS) tools to present the results of the possible relationship between climate change and the first flowering day (FFD) of the 5 species of wild plants. The results show that the UK has significantly warmed by up to 1°C during the period 1984 – 2017 compared to 1950 – 1983, confirming various IPCC reports in the literature that the GMST is warming. Various studies report that the winter of 2007 reflects an *extreme* weather event, where the winter was significantly warm. Regarding the short-term extreme weather events and their effects on FFD, the UK winter temperatures of 2006 were compared against the winter of 2007. The results showed that the winter mean daily temperatures in 2007 were significantly greater by about 2°C compared to 2006 ($p<0.05$), where the 2006 winter temperatures were similar to the 1961 – 1990 baseline average, confirming studies in the literature that 2007 experienced an *extremely* warm winter. The FFD of each species was compared between 2006 and 2007. The results showed that the mean FFD of all species significantly advanced between 13 and 18 days ($p<0.05$) during the *extreme* warmer winter of 2007 compared to the cooler (average) 2006 winter, confirming that FFD is affected by temperature. Regarding the longer-term climate change effects on FFD, this study looked at the spatial distribution of FFD based on simple linear regression using temporal data of time series with at least 15-years of FFD records at the same location. This provided a measure of the FFD response to temperature, with the notion that the strongest negative responses are linked to the warmest regions. The results from a total of 351 simple linear regressions showed that 74.6% were significant *negative* response rates ($p<0.05$) (FFD advancement ranging from -3.5 to -6.7 days $°C^{-1}$), 1.7% were non-significant *positive* response rates ($p\geq0.05$), the rest were non-significant *negative* response rates ($p\geq0.05$). Spearman rank correlations were conducted on the 74.6% of significant negative response rates in relation to latitude, longitude and elevation to determine if there was a spatial element that influenced the FFD temperature response rates. There was only one positive significant correlation and this was in respect of coltsfoot ($p<0.05$), where its response rate became increasingly more negative with decreasing latitudes, showing that this species' FFD becomes more sensitive to temperature in the warmer regions of the UK, regarding a north to south distribution. Since no FFD temperature was recorded at the time of FFD data collection (this site-specific variable was required for the FFD/temperature response rates), temperatures were approximated from calculations using the *Environmental Lapse Rate* and 0.25° (WGS84) mean gridded temperature/elevation data supplied by European Climate Assessment & Dataset (ECA&D). Error induced, from using such coarse mean gridded data, may lead to less precision regarding temperatures at each FFD location. So, other methods may be required to reduce these possible errors by using finer resolutions, which provide more detailed information on localised terrain, such as those produced from LiDAR images, leading to greater accuracy in FFD location temperatures. Given that all species in the study significantly respond to increased ambient temperatures, where they advance their FFD, then, it is suggested, that they can act as climate change indicators, which can be included in earth system and ecosystem models as simple phenological variables. The use of GIS provides maps that are easy to interpret and provide relevant climatic information in relation to its impacts on the natural world (through phenology). Governments and non-experts can benefit from the visually appealing results, so that appropriate actions can be taken in possible mitigations to reduce the effects of climate change.

Keywords: Geography, GIS, Plants, Phenology, Climate-change, Global-warming, FFD, IPCC, Bluebell, Garlic mustard, Coltsfoot, Cuckooflower, Woodland Trust, United Kingdom, UK

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Glossary

ArcGis®	Software geographic information system produced by ESRI for working with maps and geographic information.
Biodiversity	The variety of plants and animals in the world, usually in a particular habitat
ELR	Environmental Lapse Rate: used to calculate location specific temperature
FFD	First Flowering Day
Feb – Apr	The period of: February, March and April
GIS	Geographical Information System/Science
GMST	Global Mean Surface Temperature
IPCC	Intergovernmental Panel on Climate Change
Jan - Mar	The period of: January, February and March
LiDAR	Light Detection and Ranging
MATLAB®	Desktop tool for iterative analysis that expresses matrix and array mathematics
Phenology	Timing of biological life-cycle events
UNFCC	United Nations Framework Convention on Climate Change

1. Introduction

1.1 Global climate change

1.1.1 The international stage

It is well documented that human induced climate change is occurring (The Royal Society, 2014; IPCC, 2014). The issue of climate change has gained impetus over the years and the Intergovernmental Panel on Climate Change (IPCC) has stated that the climate is unequivocally warming and that the climate is changing (IPCC, 2014). In their report, the IPCC states that the atmosphere and oceans have warmed, snow and ice have reduced, sea levels have risen and greenhouse gas concentrations have increased, all from observed changes in the climate system, since the 1950s (IPCC, 2014). Climate change negatively impacts, for example, human health, ecosystems, food security, socio-economics and water supply (IPCC, 2014). Factors that drive climate change include global warming, which can be defined as "*...recent observed increase in global mean surface temperature…*" (Peake and Smith, 2009).

Agreement of countries to UN climate change treaties, through the United Nations Framework Convention on Climate Change (UNFCCC), has been problematic. In the recent 2015 Paris Agreement on climate change, there was international agreement on a number of effective measures at reducing atmospheric CO_2 emissions (UNFCCC, 2015). However, through the last change in US government, this agreement currently appears to be in jeopardy, with the USA purporting to withdraw its obligations under the treaty (Milman et al., 2017).

1.1.2 Policy development

Scientific investigations may assist governmental policy makers with making effective decisions, particularly, on the protection of useful and endangered species that may struggle with climate change. Further, policy makers may need such studies to assist them in the eradication of invasive pest species that are more adaptable to a warming climate, while outcompeting useful native ecosystem service species.

Geographical Information Science (GIS) can provide information on the changes to the spatial distribution of various factors driving climate change over a number of years. These factors include climate variables such as greenhouse gas emissions, temperature and precipitation. Scientific

research into climate change, augmented by GIS, may inform national governments and possibly improve emissions reduction reporting, to which many countries subscribe.

Phenology may help provide further evidence that climate change is occurring. Phenology can be defined as the timing of biological events and recurring plant and animal life cycle stages (USA National Phenology Network, 2011). Phenology, as a proxy for climate change, may inform national governments on the urgency to take a more proactive approach in emission reduction targets or subscribe to such targets; the UK seeks to cut greenhouse gas emissions by at least 80% (UK Parliament, 2008).

Many natural cycles, such as plant phenology, are particularly affected by climate change. Consequently, these cycles, for some species, may become unsynchronized with a warming climate, which may have a negative effect on ecosystem services and, subsequently, affect human society. Other species may have a better adaptation to climate change and this could cause problems for interspecific species associations (Both et al., 2006; McKinnon et al., 2012).

1.1.3 Knowledge gap

There are a number of factors that may influence plant phenology such as pollinators, seed dispersal mechanisms, nitrogen deposition, photoperiod, variations in precipitation and temperature. Much work and analysis on phenology seems to point towards the climatic variables such as temperature and precipitation as the principle factors that affect many phenotypical characteristics (Rehfeldt, 1995; Rehfeldt et al., 2002; Aitken et al., 2008; Alberto et al., 2013; Münzbergová et al., 2017; Petrie et al., 2017). Temperature is considered the most important factor controlling plant phenology (Peñuelas and Filella, 2001; Menzel et al., 2006). Precipitation has not been included in this study, since, in mesic temperate regions, such as the UK, temperature data is regarded as an adequate variable in early spring plant phenological modelling studies (Jochner et al., 2016). This study will proceed with investigating the temperature variable to see if there is an association between this climatic variable and changes to a particular phenological event, the First Flowering Day (FFD) of various UK wild plants species. A plant's FFD can be described as the first day of the year that flowers begin to emerge and this day may vary from year-to-year, affected by factors such as temperature, location and elevation.

Investigations that utilize GIS will present visually appealing data, which can straightforwardly contextualize results (e.g. in the form of maps) to a non-expert audience, for example, interested

stakeholders and possibly to people who do not have specialized knowledge, but are interested in the effects of climate change. Thus, further studies on plant flowering phenology, that utilize GIS in relation to climate change, may provide a more informative picture to relevant stakeholders, enhancing their knowledge on the climatic factors that affect ecosystems.

Having searched the literature it transpires that there are a limited number of peer-reviewed studies that use GIS regarding plant phenology, which help highlight the problem of human-induced climate change (Cope et al., 2017; Kroschel et al., 2013; Cheng et al., 2018). Specific to flowering phenology, Cope et al (2017) undertook an investigation into the effects of extreme spring temperatures on flowering events for a number of species. They used location data gleaned from a global positioning system (GPS) and a LiDAR digital elevation model. This research showed that warmer spring temperatures advanced flowering in the calendar and precipitation extremes in the summer delayed flowering (Cope et al., 2017). There are a number of studies that investigate climate variables in relation to phenology, but many do not utilize GIS as a tool (Tooke and Battey, 2010; Burger et al., 2012; Visser et al., 2006; McEwan et al., 2011; Molau et al., 2005).

1.2 Aim, objectives and research questions

1.2.1 Aim

This investigation aims to enhance climate change studies by contributing to a broader knowledge of how climate change affects plants. Its scope is limited to a time series study on the FFD of five wild plant species, distributed throughout the UK, in relation to climate change and associated extreme weather events (e.g. unusually warm and mild winters). The FFD of plants are useful in climate change studies, because this variable (FFD) is sensitive to climatic factors such as temperature (Fitter and Fitter, 2002) and, consequently, may act as an indicator of human-induced climate change through global warming. In order to use FFD, as a proxy for climate change, indicator plant species need to be identified first. Therefore, this study will specifically investigate whether or not temperature has an effect on the FFD of various UK wild plant species. The use of GIS tools will help produce spatial distribution maps of climate change on the wild plant species' FFD and on climate change variables, such as temperature (Perry and Hollis, 2005). Overall, the aim incorporates the motivation to produce a project that enhances knowledge on the effects of climate change.

1.2.2 Research objective and questions

The general objective of the investigation is to quantify and explain the effect of temperature on the onset of various wild plant species' FFD. In order to meet this objective, the following research questions (RQ) will be addressed:

1. What are the trends and variations in atmospheric surface temperature from 1950 to 2017?;
2. What is the association between atmospheric surface temperature and FFD variation?;
3. What spatial atmospheric surface temperature variations can explain the FFD observational differences in time and space?

1.2.3 Hypothesis

The hypothesis is that variations in the FFD between 1950 – 2017, of various plant species, is caused by changes in atmospheric surface temperature.

2. Background

2.1.1 Phenology

Phenological events are linked to abiotic environmental factors such as photoperiod, temperature (Wolkovich et al., 2014) and adiabatic air pressure differences (the effect of cooling air with altitude as pressure reduces) (Colling, 2001). Examples of biotic factors are the timing of: pollination; flowering; leaf senescence; egg laying; and reproduction. Various studies have been conducted in this area of science, for example: bird migratory patterns linked to temperature (Bauer et al., 2008); genetic responsiveness linked to changing day length (photoperiod) (Van Dijk and Hautekèete, 2007); and the timing of germination linked to rainfall (precipitation) (Kimball et al., 2010). Much work has been widely reported that allows a better understanding of the drivers of phenology for both fauna and flora (Fitter and Fitter, 2002; Forrest and Miller, 2010; Denny et al., 2014; Menzel et al., 2006). Climate change and associated extreme weather events may be responsible for the observed changes to various species' phenology.

2.1.2 Climate and weather extremes

Climate can be described as the long-term weather averages (IPCC, 2013), while weather is "*The state of the atmosphere with respect to wind, temperature, cloudiness, moisture, pressure, etc. Weather refers to these conditions at a given point in time (e.g., today's high temperature)*" (NOAA, 2009).

According to the IPCC (2012) *"…A changing climate leads to changes in the frequency, intensity, spatial extent, duration and timing of extreme weather and climate events, and can result in unprecedented extreme weather and climate events…*" (IPCC, 2012), one such example is an extremely warm winter.

With the above in mind, there is plenty of motivation for scientists to produce reports that provide further evidence of climate change and its effects on the natural world. Assuming that a changing climate leads to changes in extreme weather events, more investigations into the effects of extreme weather, on various biotic variables, may futher demonstrate an association between climate change and biota (Reyer et al., 2013).

2.1.3 Phenology and climate change

Many species are unable to keep pace with climate change, particularly temperature and precipitation, where they are slow or fail to adapt to climate change. Phenological mismatching, where species phenology in relation to ecological associations becomes less synchronized, presents a particular set of problems resulting from climate change. There are some documented investigations in the literature, for example, Both et al. (2006) and McKinnon et al. (2012) report on mismatches between birds and plants.

Both et al. (2006) report that the new leaves of the oak tree (*Quercus robur*) are a main food source of the winter moth caterpillar (*Operophtera brumata*). Resulting from climate change, this species has adapted to the earlier onset of the oak tree budburst event over a 20-year period (Visser et al., 2006). The pied flycatcher bird (*Ficedula hypoleuca*), which preys on the caterpillar, has declined by approximately 90% in oak tree habitats in association with earlier food peaks, resulting from a phenological mismatch due to climate change. Conversely, the species declined by only 10% where food peaks are at their latest in the year (Both et al., 2006). A later study confirms this situation (Burger et al., 2012).

In a study, by McKinnon et al. (2012), evidence was found that shorebird phenology may be sensitive to the effects of climate-change. This investigation found that Baird's Sandpiper's (*Calidris bairdii*) egg hatching and chick growth rates were, in some cases, mismatched with food resource peaks between 1954 and 2000 (McKinnon et al., 2012); this could be problematic in evolutionary terms and species' extinctions. McKinnon et al (2012) suggest that climate change was the driving factor behind this observation.

Notwithstanding the studies by Both et al. (2006) and McKinnon et al. (2012), many other studies examine the relationship between plant phenology and climate change. For example, it is found that first flowering dates can act as a proxy that the GMST is rising due to global warming (Amano et al., 2014; Molau et al., 2005). Thus, changes in temperature will affect the timing of biological events such that, for example, the onset of the FFD of plants could be advanced (Mazer et al., 2013). FFD data may feed into climate change models e.g. earth system and terrestrial ecosystem models that incorporate basic phenological factors (Kostadinov et al., 2017; Ise et al., 2018), such that the way plants have reacted to climate change in the past could be extrapolated in future climate change projections.

For the reasons stated above *inter alia*, not only is it important to assess the impact of climate change on phenological events, it is also important to assess how plants react to associated extreme weather events. This could be particularly useful to the agricultural industry and may have wider implications for food security. Extreme weather events may have a similar impact on phenological events as the gradual changes in climate over a 10 or 20 year period, thus providing information on how plants can react to sudden changes in variables such as temperature and precipitation (Kreyling et al., 2009; Ingram et al., 2013).

Having identified a problem with phenological mismatching, it would be useful to track plant phenology in order to inform ecologists (and policy decision-makers), along with raising more awareness of the consequences of human-induced climate change.

Variations in climate could create problems like imbalances in ecosystems. Ecosystem imbalances could affect populations and communities of organisms, which could have devastating consequences such as species extinction and loss of biodiversity. These imbalances could reduce the effectiveness of ecosystem services provided by various species and create problems to humanity in relation to food security. Thus, phenological changes may also have adverse socio-economic and health consequences (Aoyama et al., 2012; Traidl-Hoffmann et al., 2003).

2.1.4 Phenology and invasive weeds

Additional to climate change studies, there is much phenological work in relation to the control of invasive weeds (Smith et al., 2013; Wu and Micheal, 2014; Chapman et al., 2014). It is widely reported that garlic mustard, for example, is an invasive species in many parts of the world, which negatively impacts many native species (Mullarkey et al., 2013; Herold et al., 2011; Barto et al., 2010; Rodgers et al., 2008). These studies have looked at methods to control the invasive effects of garlic mustard. An investigation into the way wild plant species react to environmental variables (particularly climate change variables) will be useful, to provide a greater knowledge on their ability at adapting to environmental changes, particularly for weed control purposes. This will also assist governments and researchers, since invasive weeds, particularly those able quickly to adapt to climate change, may impact on food security in the world (O'Mara, 2012).

3. Materials and methods

3.1 Study area and species under investigation

3.1.1 Study area

The study area for this project is the UK. This includes Northern Ireland, Scotland, Wales and England, but excludes Southern Ireland. In 2016, the population of the UK was 65.6 million. It has an area of 248.5 thousand km^2. The physical geography shows variation within the UK. England consists mostly of low-lying terrain with some mountainous areas to the Northwest of the country. Scotland is mix of highland and lowland; the area is distinctly split between a geological fault line separating the 2 regions. Wales is predominantly mountainous with lower lying terrain in the south. Northern Ireland has a similar topography to Wales with some mountainous and hilly terrain and lowland flat areas. The UK coastline is about 12400 km. The climate of the UK is considered temperate (mesic), where generally the north of the country is cooler than the south. The Gulf Stream allows the UK to be relatively warm compared to other locations of similar latitude. UK agriculture is mainly a mix of livestock and arable farming that produces, for example, meat, milk, wheat, barley, fruit and wool.

3.1.2 Species

For this study, the species investigated were: *Hyacinthoides non-scripta* (bluebell); *Anemone nemorosa* (wood anemone); *Tussilago farfara* (coltsfoot); *Alliaria petiolate* (garlic mustard); and *Cardamine pratensis* (cuckooflower). An example of FFD variation can be seen from the bluebell dataset, which shows that FFD can vary across the UK on both a spatial and temporal basis (Fig 3.1).

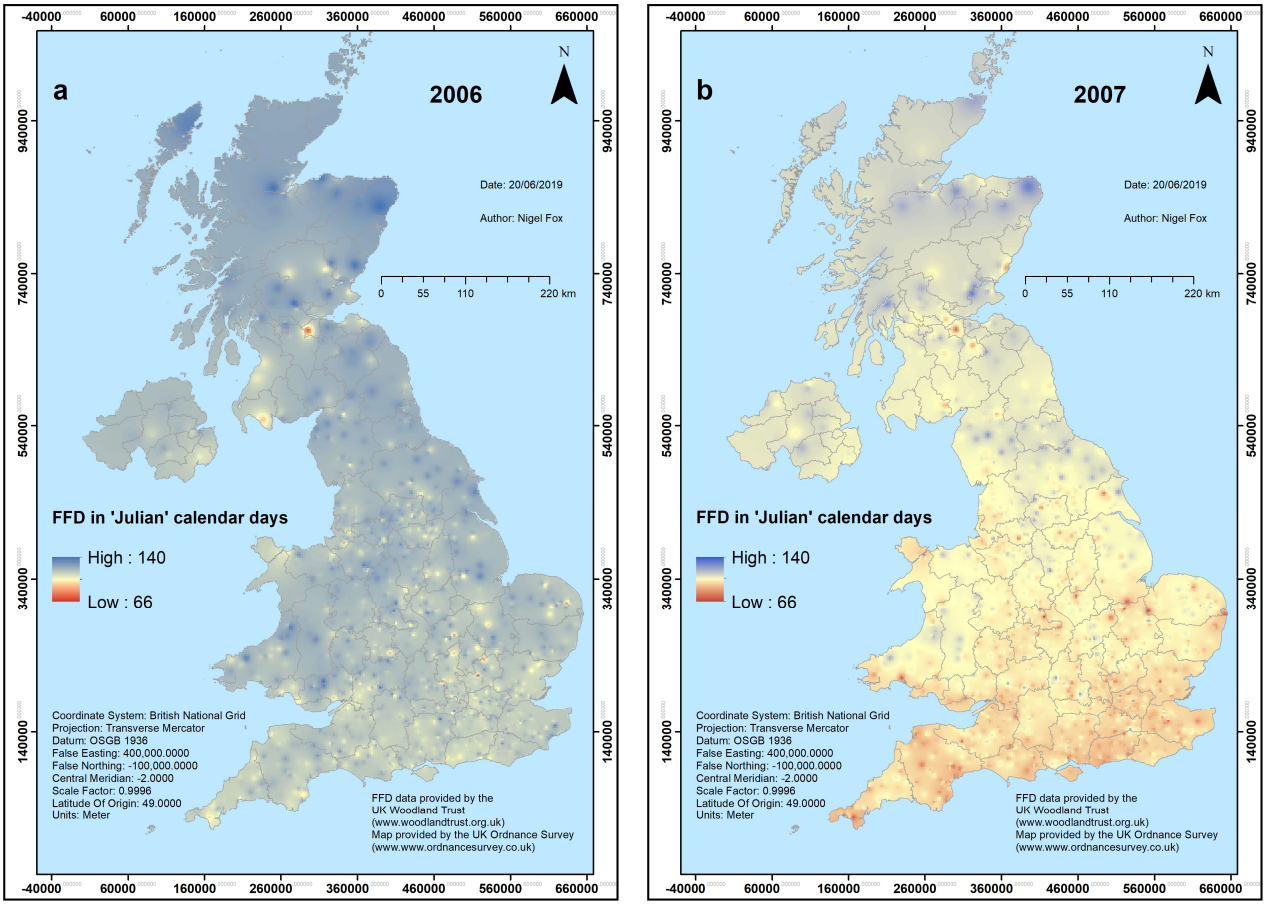

Fig 3.1 – **a** The FFD distribution of bluebell during 2006 (left map) compared with **b** in 2007 (right map). The maps were derived from FFD point location data and interpolated through inverse distance weighting. Note that these maps highlight the spatial distribution of the FFD and are not statistically compared, but show differences that warrant further investigation.

3.2 Materials

3.2.1 Maps

Geographical outline maps were provided by the UK Ordnance Survey (https://www.ordnancesurvey.co.uk/business-and-government/products/opendata.html).

GIS map products throughout this thesis were created using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved. For more information about Esri® software, please visit www.esri.com.

The extraction of the European Climate and Dataset (ECA&D) datasets (NetCDF files) throughout this thesis was conducted using MATLAB® (copyright © MATLAB 1994 – 2019 The Mathworks, Inc)

3.2.2 Temperature and elevation data

Elevation and temperature data were extracted using gridded ENSEMBLES datasets E-OBS from the European Climate and Dataset (ECA&D) (version v17, https://www.ecad.eu//download/ensembles/download.php) of daily mean surface 2-m temperatures covering the period: 1 Jan 1950 – 31 Dec 2017, this period was chosen because this was most recent range of data published by the ECA&D (ECA & D, 2018). The datasets covered an area: 25N-75N x 40W-75E. The files were in compressed NetCDF format on a spatial resolution of 0.25° regular lat-lon grid. Two files were downloaded that contained mean temperature (tg_ens_mean_0.25deg_reg_v18.0e.nc) and mean elevation values (elev_ens_0.25deg_reg_v18.0e.nc) gleaned from interpolated data, recorded at observation stations throughout Europe. Details about the dataset interpolation, including errors and uncertainties can be found in the literature associated with the gridded ENSEMBLES datasets E-OBS (Haylock et al., 2008; Klein Tank et al., 2002).

3.2.3 Phenological data

Phenological records were provided by the UK Woodland Trust (https://www.woodlandtrust.org.uk/). These data were collected in the UK, as part of a citizen science programme involving the general public to amass datasets over a large spatial and temporal range. Specifically, FFD records were extracted that provided UK point data for annual FFD observations dating back to the 1800s. For this study, FFD data were extracted covering the time period: 1950 – 2017 commensurate with the above ECA&D temperature and elevation datasets. The total number of FFD observations (all species) from the original FFD record (1950 – 2017) were 93219 from 13857 locations throughout the UK. Deletions were made for erroneous FFD data, such as location points that did not fit within the grid cells of the ECA&D temperature and elevation ENSEMBLES datasets E-OBS (e.g. data points that were in the Irish Sea, North Sea or the English Channel). Further removals were made to eliminate outliers; FFD observations that exceeded 3 standard deviations from the mean FFD for each species were deleted (Jochner et al., 2016). This left a dataset of 82158 FFD observations from 11865 locations (Fig 3.2).

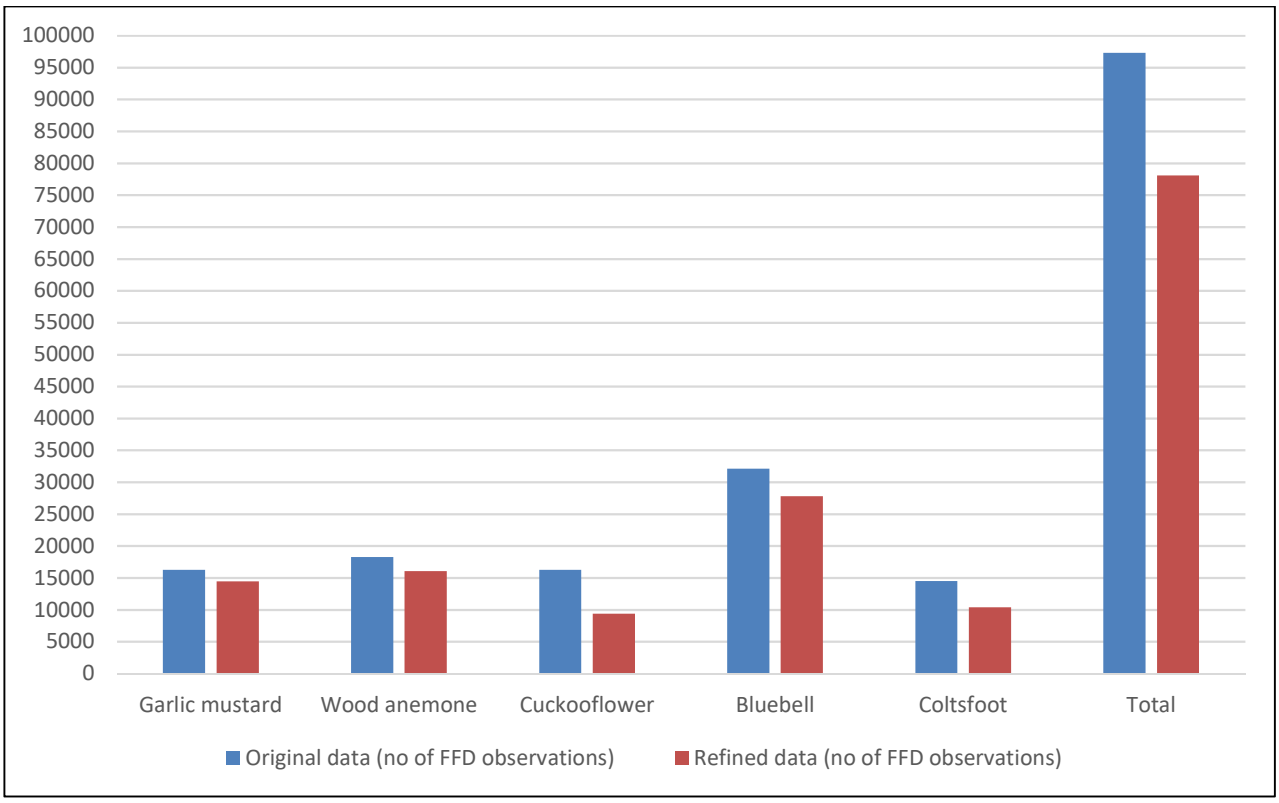

Fig 3.2 – Woodland Trust FFD dataset before and after FFD erroneous data and FFD data outside 3 standard deviations were removed.

3.3 Analysing the trends and variations in temperature from 1950 to 2017.

To confirm that the climate of the study region is warming, commensurate with reports that the global climate is warming (IPCC, 2014), ambient temperature data for the UK were converted from ECA&D NetCDF files. These data were then spilt between 2 time series: 1950 – 1983 and 1984 – 2017. The annual mean temperatures for each grid square were calculated for each 33-year time period. These datasets were then converted to GIS tables. Thereafter, maps were generated to show the spatial temperature differences. The time series were also statistically tested using a t-test to ascertain any significant temperature difference between the two time series.

3.4 Identifying the association between temperature and FFD variation.

The gradual changes in climate over a 10 or 20 year period could be replicated in one extreme weather event (e.g. a warm winter). Thus, the immediate observable effects of extreme weather events on phenology may provide an insight into the effects of subtler longer-term climate variations on phenology. An assessment into the relationship between an extremely warm winter

and plant phenology could provide information on how plants adapt to changes in variables, such as temperature (Kreyling et al., 2009; Ingram et al., 2013).

For this investigation, the European temperature data for the months of Jan – Mar and Feb – Apr, during the winter periods of 2006 and 2007 were used. The winter period of 2007 was considered a mild winter, where there was a sufficient deviation in the mean of daily mean temperatures from the baseline 1961 – 1990 mean average temperature to name it a *warm* winter (ECA & D, 2018). Indeed, it was shown that this winter was the warmest in over 500 years in Europe, with temperatures of 1.7°C and 2.4°C for autumn 2006 and winter 2007 (respectively) above the 1961 – 1990 baseline average (Delpierre et al., 2009; Luterbacher et al., 2007). The Jan – Mar and Feb – Apr of 2007 will be compared to the same periods a year earlier in 2006. It is assumed that 2006 was not a remarkably different year, in terms of mean daily temperatures, for Jan – Mar and Feb – Apr, compared to the 1961 – 1990 baseline average.

The ECA&D mean daily temperatures for the Jan – Mar and Feb – Apr periods of 2006 and 2007 were calculated, along with the same periods for 1961 – 1990 (baseline). Maps were produced, visualizing the differences in mean temperature between 2006 and 2007 and the baseline means for the same periods, respectively.

For the flowering data, the 2006 and 2007 data were selected where pairs existed according to their longitudinal and latitudinal coordinates between the 2 years. This removed a large amount of data and restricted much of the FFD data to the southern part of the UK, but the trade-off allowed a stronger paired statistical analysis. Data were analyzed using a paired t-test to see if there was a significant difference between the 2 years in the onset of the FFD. The mean of these FFD data for each county was calculated. Maps were produced to show the spatial distribution of the pairs of FFD data for each species studied. Having used only paired data, this necessarily reduced the spatial distribution of the FFD data in the maps, thus only showing data for counties where FFD pairs existed from the main FFD dataset. The number of pairs of FFD data for each species were: bluebell 876; coltsfoot 274; cuckooflower 451; garlic mustard 479; and wood anemone 503.

3.5 Identifying the spatial temperature characteristics that can explain the observational variations in time and space in FFD.

It is expected that there is a negative linear relationship between temperature and FFD. As temperature increases it is hypothesized that there is a corresponding advancement in FFD, i.e. plants will respond to increased early springtime temperatures, measured in days $°C^{-1}$. Once the mean FFD temperature response rate, at each location for each species, was calculated, then further analysis was conducted that showed whether or not the FFD temperature response rate was affected by: latitude; longitude; and altitude. It is documented that temperature is affected by these variables, where increasingly UK lower latitudes, lower altitudes and westerly longitudes are relatively warmer than higher latitudes, higher altitudes and easterly longitudes, inducing stronger FFD temperature response rates (Colling, 2001; Jochner et al., 2016; Menzel et al., 2006). Longitude was chosen as a variable because, particularly in the UK, the western coastal winters are generally warmer compared to the the eastern side. This results from the North Atlantic Current feeding off the Gulf Stream subtropical gyre that in turn affects atmospheric temperatures, bringing relatively warmer winters to western side of the British Iles and northwest Europe (e.g. Norway) (Colling, 2001).

The FFD data analyzed were for time series with at least 15 observation years between 1950 – 2017. Where more than one FFD record existed, at the same point location in the same year, for each species, the first recoded observation was retained in the dataset, the later records were deleted (Kolárová et al., 2017). After removing duplicate FFD records along with time series data (with less than 15 observation years between 1950 – 2017), a total of 5718 FFD observations within 163 FFD locations were available for statistical analysis (Fig 3.3 and Tab 3.1).

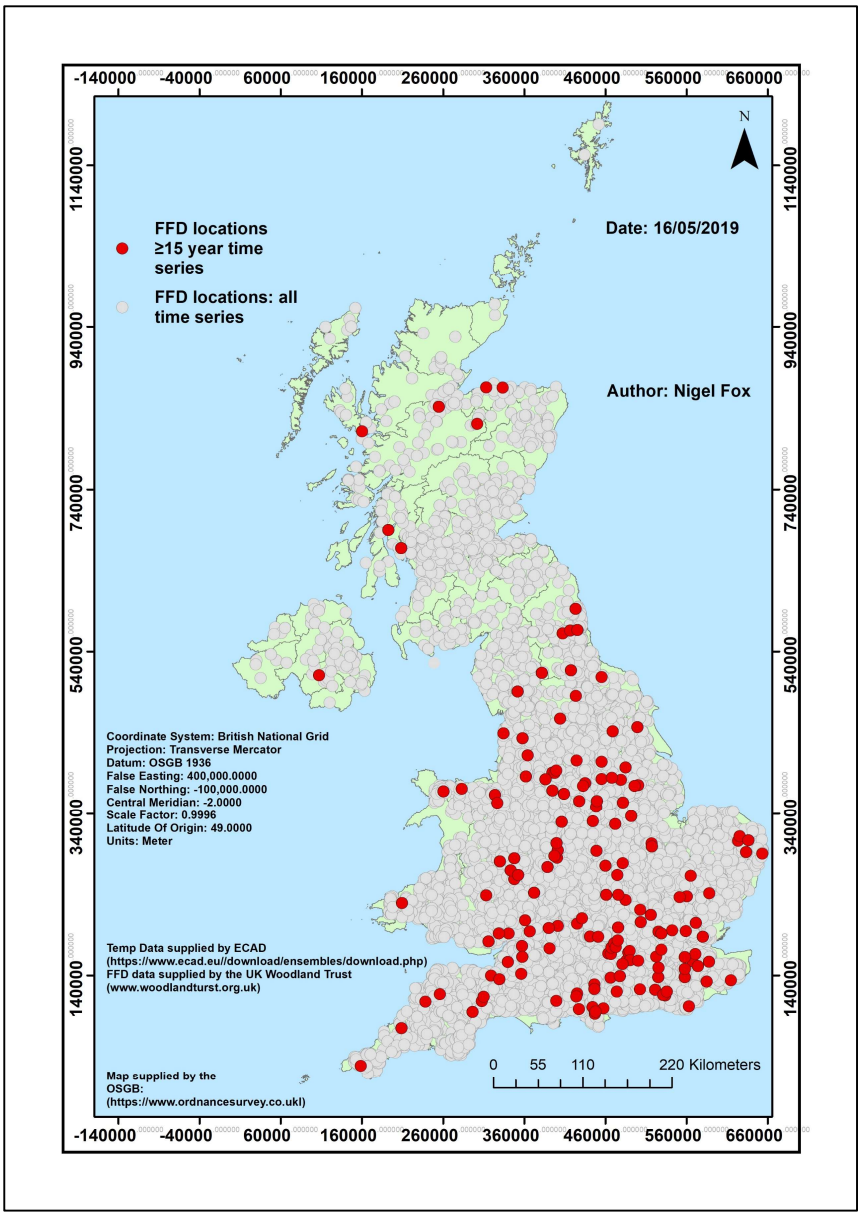

Fig 3.3 – Location of FFD sites in the UK ≥ 15-year time series. Each dot represents a FFD location. The grey dots are the FFD locations for all species after the anomalies and outliers were removed from the Woodland Trust data (11865 FFD sites containing 82158 FFD observations between 1950 - 2017). The red dots are the FFD locations for all species after the removal of time series with less than 15 years of FFD data collections (163 sites containing 5718 FFD observations between 1950 - 2017).

Tab 3.1 – Number of FFD observations for each species with time series ≥ 15 years, along with the months in which the species starts flowering.

Species	Mean flowering month	FFD Observations at sites with time series ≥ 15 years (all FFD observations for all time series)	number of sites with time series ≥ 15 years
Bluebell	Apr	2117 (27787)	132
Coltsfoot	Mar	534 (9390)	30
Garlic Mustard	Apr	1057 (14453)	65
Cuckooflower	Apr	994 (14475)	60
Wood anemone	Mar	1016 (16053)	64

Since neither temperature nor elevation data were recorded at each FFD location and, in order to determine how temperature affects FFD, it was necessary to add these data from other data sources (e.g. mean temperatures from the ECA&D ENSEMBLES). Specific elevation data were added to each FFD coordinate point using an online tool that adds elevation data to coordinate data (http://www.gpsvisualizer.com/elevation). This was required for refining the coarse mean temperature data (extracted from the above ECA&D ENSEMBLES) to provide a better/finer representation of temperature at each FFD location for later statistical analysis.

3.5.1 Data merge

The FFD point data were combined with the gridded temperature and elevation datasets. Elevation data, annual and monthly mean daily temperature data stored in the ECA&D NetCDF files were extracted.

3.5.2 Elevation

The mean elevation data were defined in 0.25° gridded squares, it was necessary to create a polygon shapefile so that this could later be joined with the FFD point location data. This was achieved over a number of steps through the creation of a 0.25 gridded polygon 'fishnet' (Appendix 1) (Larsson, 2018). The fishnet was spatially joined with the elevation point shapefile, created from the ECA&D NetCDF files, to create a gridded polygon shapefile that contained the elevation data. This polygon elevation file was then joined with the FFD data file through a GIS table join. This provided a table with each FFD data point (FFD, FFD elevation (masl) and lat/lon data) associated with a mean masl in each grid square, this would then later assist with refining the temperature data at each FFD location.

3.5.3 Temperature

The ECA&D NetCDF temperature files for each 0.25° grid, in each year, were converted to GIS tables. Each year of temperature data (e.g. 1950) was joined with the same year for FFD data record (along with the gridded elevation data, see above section on elevation extraction and Appendix 1). Each joined table was exported as an excel file. Each of these excel files were added together to produce one 'master' table with all temperature and elevation data associated with each FFD location in each year between 1950 - 2017. Thus, the final table contained, for each species, specific annual records for each FFD location (along with its specific elevation (masl)), joined with an associated 0.25° grid square mean temperature and mean elevation, in which that FFD location resided.

3.5.4 FFD temperature (lapse rate conversion)

The mean grid cell temperature for the preceding 2 months and the month in which the mean FFD occurs, for each species was used in determining the FFD location temperature. The 2 preceding months and the month of flowering are regarded as the most appropriate for phenological studies (Dose and Menzel, 2006). For coltsfoot and wood anemone the 3-month mean daily temperatures

were January, February and March and for bluebell, garlic mustard and cuckooflower it was February, March and April.

In order to provide a FFD temperature response rate (section 3.5.5) a better/finer representation of temperature at each FFD location was required. This was achieved through a temperature lapse rate calculation using FFD elevation, mean grid cell elevation and mean grid cell temperature data (Olsson and Jönsson, 2015), of which all 3 variables were now linked to each FFD record in one spreadsheet. The FFD temperatures were derived from these 3 variables through applying the environmental lapse rate (ELR), which is a rate of decrease in temperature with altitude due to adiabatic effects and air becoming less dense with increasing altitude. The equation for the environmental lapse rate is:

$\Gamma = -\frac{dT_0}{dz}$ where Γ is the lapse rate (°C km^{-1}), dT_0 is the change in environmental temperature (°C) and dz is the change in altitude (masl) (Thornton et al., 1997; Houston and Niyogi, 2007).

The ELR is found to be -6.5°C km^{-1} increase in elevation (Barry and Chorley, 1987) applied in various associated studies (Delpierre et al., 2009; Delpierre et al., 2008; Olsson and Jönsson, 2015).

The FFD temperature was found from the following equation:

FFD temperature = dz * Γ + MGCT

Where:

Γ (Lapse Rate (°C km^{-1})) = 6.5°C km^{-1}

dz (Altitude difference (masl)) = Mean Grid Cell Altitude – FFD Altitude

MGCT (°C) = Mean Grid Cell Temperature.

3.5.5 FFD response to temperature

Once the FFD temperature for each location was defined, it was possible to calculate the species FFD temperature response rate, generally following the methods employed by Jochner et al (2016). For each species studied, the temperature response rate was calculated through simple linear regression, where there were at least 15 years of FFD data collected at each location for each species (Fig 3.4). For example, bluebell had 132 time series of 15 years or more. Thus, 132 linear regressions were applied to the bluebell time series, where FFD was the dependent variable and FFD temperature was the independent variable. The mean temperature response rate (days °C^{-1}), for the whole 132 time series, was taken from the *x variable coefficient* and the error (± days °C^{-1}) was extracted from the *x variable standard error* from the linear regression outputs. A negative *x variable coefficient* represented an earlier FFD onset in days per °C increase, the opposite for a positive. This methodology was applied to the other species in this study.

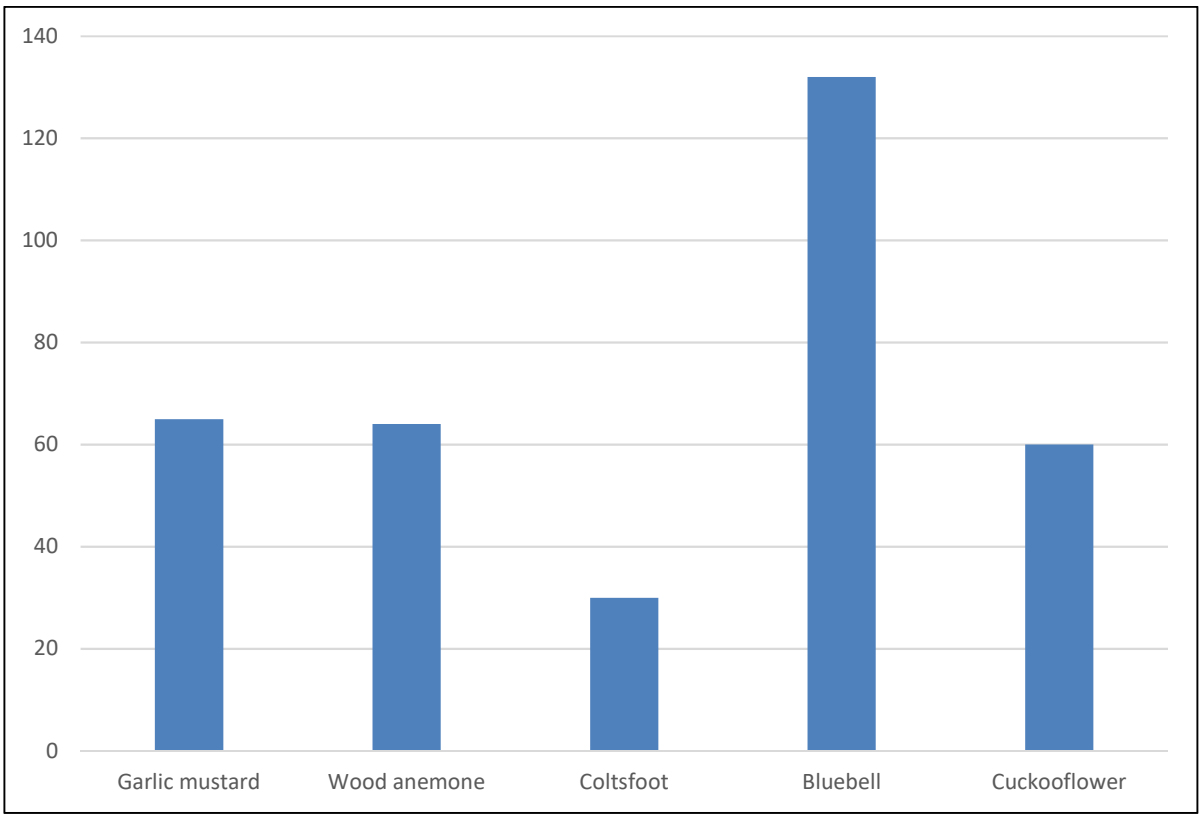

Fig 3.4 – The number of locations that possessed at least 15 years worth of FFD observations.

The FFD temperature response rates were ranked in 5 equal ranks according to percentiles, with the highest (negative) value scoring the highest rank value of 5. Other variables were ranked similarly: FFD latitude; FFD longitude; and FFD altitude. The ranking of the variables negated problems associated with negative and positive values. For example, moving east to west, longitude values transform from positive values to negative values as they cross the Prime Meridian line. Using raw

positive and negative values confound statistical comparison results. Thus, longitudinal values were ranked 1 – 5 moving east to west; latitudinal values were ranked 1 – 5 moving north to south and so on for the other variables. The lowest rank was based on the assumption that the FFD temperature was lower. For example, the 20% group of highest latitudes received a ranked value of 1 and also, for example, the 20% group of smallest FFD response rates were assigned a ranked value of 1 (Tab 3.2).

Tab 3.2 – Rank definitions for each variable, to be used in Spearman rank correlation analysis.

	Rank	Rank definitions
FFD temperature response rate (days $°C^{-1}$)	1 - 5	1 = smallest, 5 = largest
FFD altitude (masl)	1 - 5	1 = highest, 5 = lowest
FFD longitude (degrees east to west)	1 - 5	1 = most easterly, 5 = most westerly
FFD latitude (degrees south to north)	1 – 5	1 = most northerly, 5 = most southerly

The FFD temperature response rates were statistically analyzed against FFD latitude, FFD longitude and FFD altitude. Spearman rank correlation was used to evaluate if these variables had any effect on the FFD temperature response rate. It was hypothesized that the response rate in the north, east and higher altitudes associate with reduced FFD temperature response rates compared to the south, west and lower altitudes respectively. It was also hypothesized that as FFD advanced and as the FFD springtime temperature increased, the FFD response rate correspondingly increased.

4. Results

4.1 The trends and variations in ambient temperature from 1950 to 2017.

The mean daily temperatures for 3 monthly periods of Jan – Mar, Feb – Apr and the annual mean of the mean daily temperatures have changed between each 33-year period (1950 – 1983 and 1984 – 2017) and the mean differences were significant ($p<0.05$) (Fig 4.1 and Tab 4.1). The observed changes in the UK mean daily temperature for the 3 months of Jan – Mar reflect a mean daily value of 3.7°C between 1950 - 1983 and 4.3°C between 1984 – 2017. The observed changes in the UK mean daily temperature for the 3 months of Feb – Apr reflect a mean daily value of 4.9°C between 1950 - 1983 and 5.3°C between 1984 – 2017. The observed changes in the annual UK mean daily temperature reflect a mean daily value of 8.5°C between 1950 - 1983 and 9.1°C between 1984 – 2017.

Tab 4.1 – The observed differences in the UK mean daily temperature for the 3 months of Jan – Mar and Feb – Apr and the annual mean daily temperatures.

	n	Two-tail paired t – test. Mean temperature differences (°C ± 1 SD)
Between Jan - Mar 1950 - 1983 & Jan - Mar 1984 - 2017	601	0.62 ± 0.15 ($p<0.05$)
Between Feb - Apr 1950 - 1983 & Feb - Apr 1984 - 2017	601	0.34 ± 0.03 ($p<0.05$)
Annual mean daily temperature between 1950 - 1983 & 1984 - 2017	601	0.62 ± 0.07 ($p<0.05$)

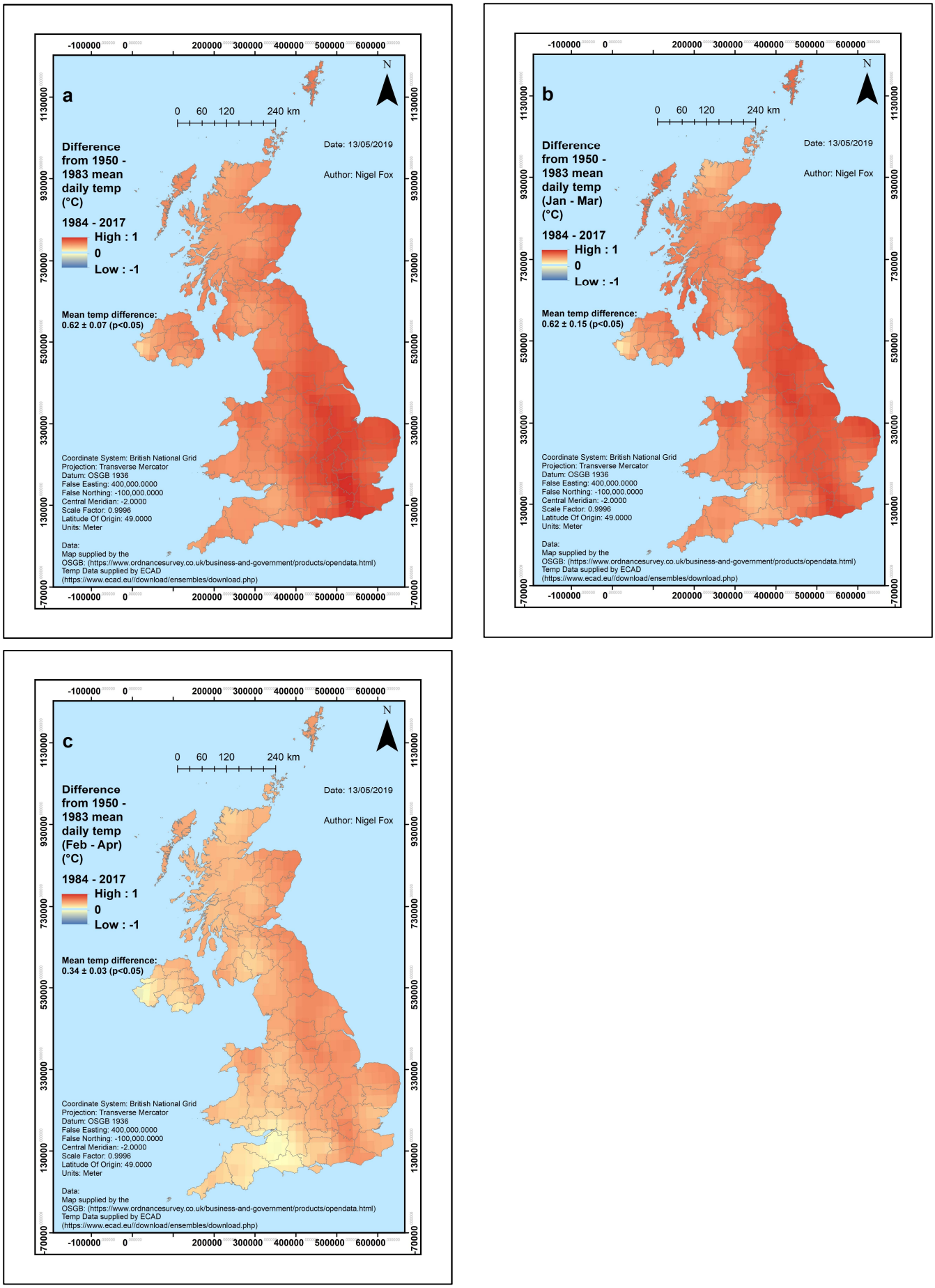

Fig 4.1 a – the observed changes in the UK annual mean daily temperature change **b** – the observed changes in the UK mean daily temperature for the 3 months of Jan – Mar. **c –** the observed changes in the UK mean daily temperature for the 3 months of Feb – Apr.

4.2 The association between temperature and FFD variation.

Temperature maps were generated to compare 2007 against the baseline 1961 – 1990 mean daily temperatures for the periods Jan – Mar and Feb – Apr and, also, between the two years of 2006 and 2007 for same three-monthly periods (Fig 4.2). The 2007 and 2006 mean daily temperatures have increased compared to the same periods between 1961 – 1990 (baseline average). A paired t-test showed that these increases were significantly different ($p<0.05$) (Tab 4.2). While the 2006 temperatures were significantly different to the baseline average, they were very similar and only just below this baseline (*cf* fig 4.2a & b and Tab 4.2). The 2007 mean daily temperature for both Jan – Mar and Feb – Apr have increased by 2.12 and 2.09 °C respectively, compared to the same periods of 2006; a paired t-test showed that these increases were significant ($p<0.05$) (Tab 4.3).

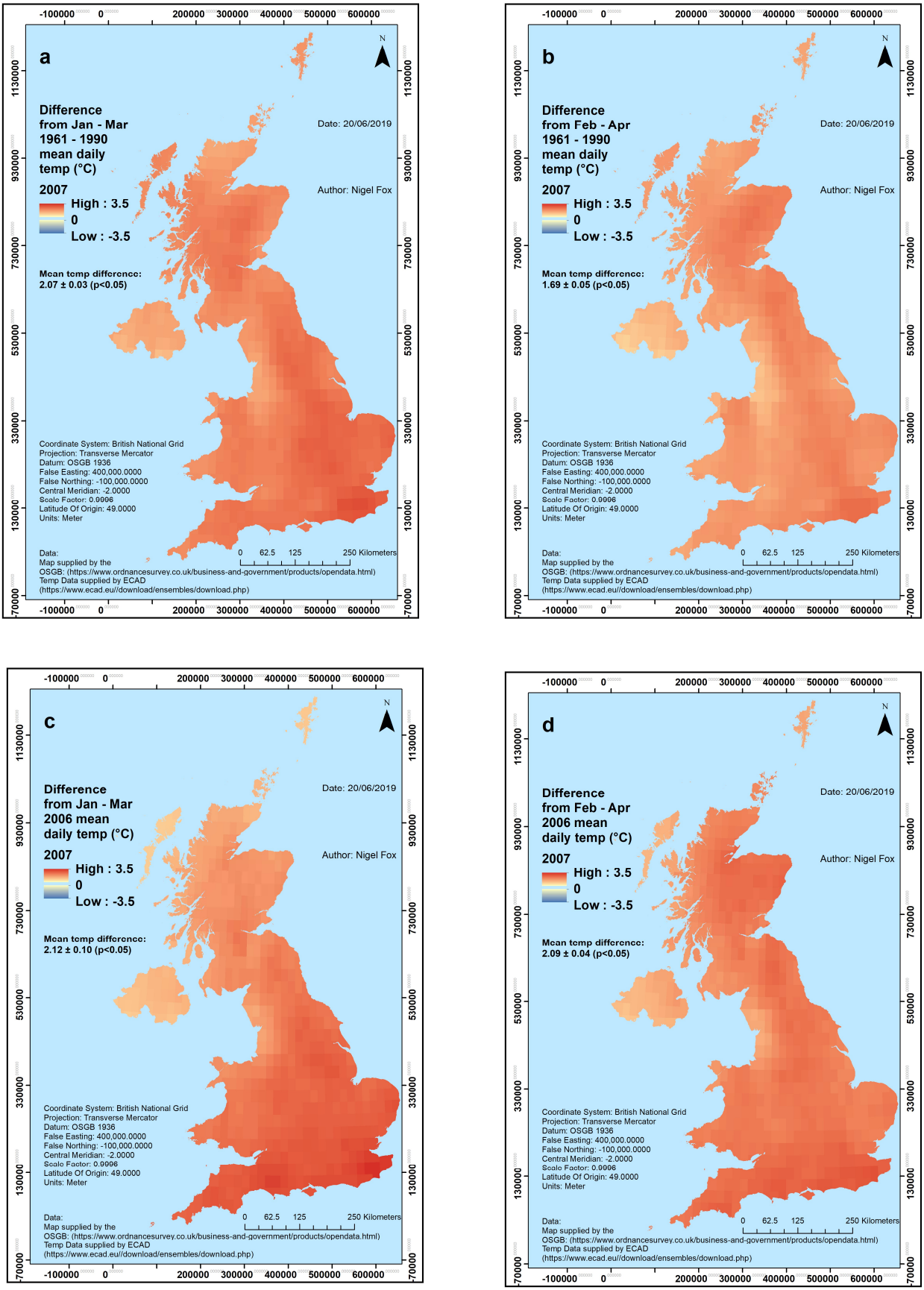

Fig 4.2 – Temperature anomalies. **a** – Jan – Mar 2007 and **b** – Feb – Apr 2007 mean daily temperature differences from the 1961 – 1990 baseline mean. **c –** Jan – Mar mean daily temperature between 2006 and 2007. **d –** Feb – Apr mean daily temperature between 2006 and 2007.

Tab 4.2 – The 2006 and 2007 mean temperature for the UK compared to the mean daily temperature for the periods of Jan – Mar and Feb - Apr for the 1961 – 1990 baseline period.

	1961 – 1990 Mean daily Temp Jan - Mar (°C) difference	1961 – 1990 Mean daily Temp Feb - Apr (°C) difference
2007	2.07 ± 0.03 (p<0.05)	1.69 ± 0.06 (p<0.05)
2006	-0.05 ± 0.06 (p<0.05)	-0.40 ± 0.02 (p<0.05)

Tab 4.3 – The 2006 and 2007 mean temperature difference for Jan - Mar and Feb - Apr.

	2006	2007	Mean difference (significance)
Mean daily Temp Jan - Mar (°C)	3.64 ± 0.98	5.75 ± 1.07	2.12 ± 0.10 (p<0.05)
Mean daily Temp Feb - Apr (°C)	4.36 ± 1.05	6.45 ± 1.01	2.09 ± 0.04 (p<0.05)

A summary for the differences observed in mean FFD for each data point pair, averaged for the whole UK, presents statistically significant results (Tab 4.4). By way of example, the temperature response for bluebell showed a mean FFD advancement in 2007 of 17.8 days. This is compared to 2006 where, for 2007 the average UK mean daily temperature for Feb – Apr was 2.09°C warmer than in 2006 (*cf* Tab 4.3). A paired t-test showed that these advances were significant (p<0.05) (Tab 4.4). A visual comparison for each species shows that, between 2006 and 2007, there was generally an advancement in FFD, although for some counties there were delays in FFD (Fig 4.3).
County FFD averages were not statistically analyzed but served visually to highlight the differences in FFD (*cf* Tab 4.4). Note that coltsfoot and wood anemone start their flowering period earlier in the calendar compared to garlic mustard, bluebell and cuckooflower.

Tab 4.4 – A comparison of the 2006 and 2007 mean FFD showed an advancement in FFD for all species.

	n (number of FFD data pairs)	Mean FFD 2006 ± 1SD	Mean FFD 2007 ± 1SD	Significance (p=0.05)	FFD Change ± 1SD (negative numbers indicate FFD advancement)
Bluebell	876	117.4 ± 8.0	99.6 ± 9.1	p<0.05	-17.8 ± 1.09
Coltsfoot	274	86.0 ± 17.0	71.0 ± 17.1	p<0.05	-15.0 ± 0.13
Cuckooflower	451	116.6 ± 11.3	102.0 ± 12.9	p<0.05	-14.7 ± 1.58
Garlic mustard	479	119.6 ± 8.5	106.9 ± 7.5	p<0.05	-12.6 ± 0.98
Wood anemone	503	98.3 ± 10.5	85.6 ± 11.4	p<0.05	-12.6 ± 0.92

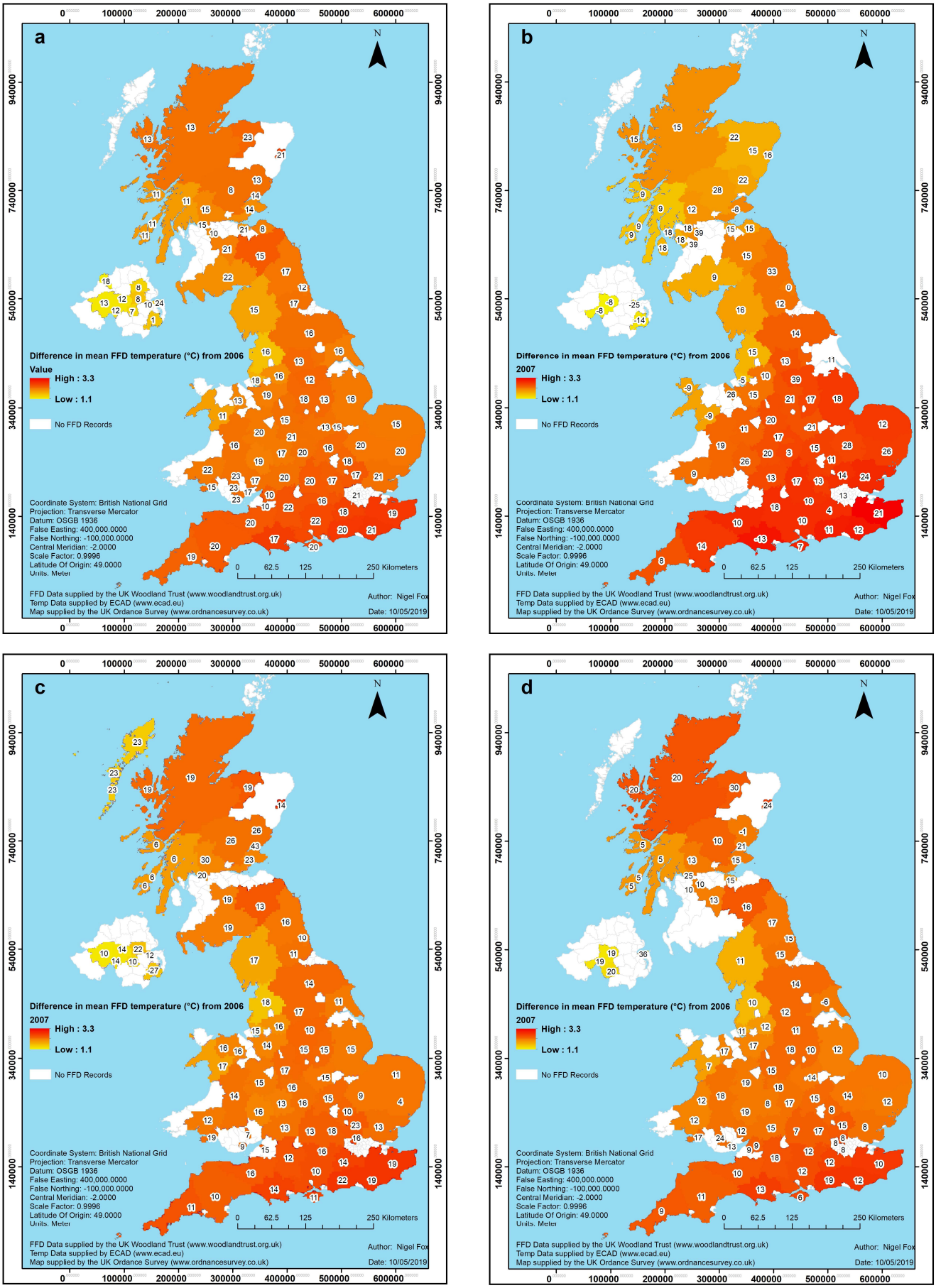

Fig 4.3 (a – d) – **a** bluebell: FFD change between Feb - Apr 2006 and the same period of 2007. **b** Coltsfoot: FFD between Jan - Mar 2006 and the same period of 2007. **c** Cuckooflower: FFD between Feb - Apr 2006 and the same period of 2007. **d** Garlic mustard: FFD between Feb - Apr 2006 and the same period of 2007. A positive value represents an advancement in the FFD calendar, the opposite (delay) for a negative value.

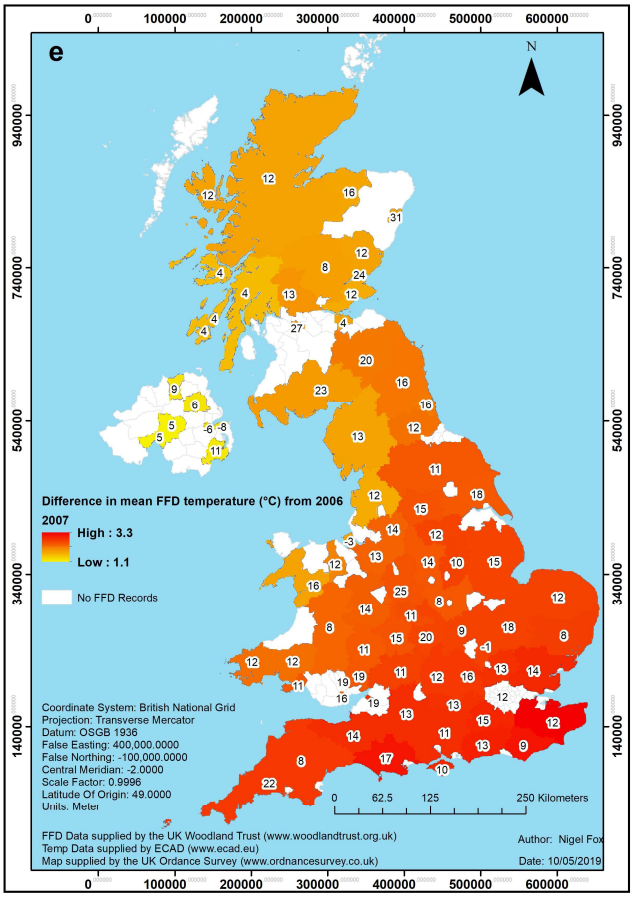

Fig 4.3 (e) – Wood anemone: FFD between Jan - Mar 2006 and the same period of 2007. Each number on the maps depicts the change in FFD from 2006 to 2007. A positive value represents an advancement in the FFD calendar, the opposite (delay) for a negative value.

4.3 The spatial temperature characteristics that explain the observational variations in time and space in FFD.

The results from the linear regression analysis of the 351 time series ≥ 15 years showed a total of 98.3% of the temperature response rates were negative, of which 74.6% were significant ($p<0.05$). Further, 1.7 % of the responses were positive, of which none were significant (Tab 4.5). Correlation coefficients for the FFD temperature response rates in relation to latitude, longitude and altitude were calculated based on the significant linear temperature response rates. Positive correlations (most of which were insignificant) showed that when latitude or altitude *decreased*, or with increased movement to the west, there was a corresponding increase in temperature response rate (e.g. for cuckooflower where the latitude decreases there is a significant corresponding increase in temperature response rate). Negative correlations (none of which were significant) showed that when latitude or altitude *increased*, or with increased movement to the east, there was a corresponding increase in temperature response rate (Tab 4.6).

Tab 4.5 – Results from the time series simple linear regression analysis. As an example, the mean UK temperature response rate for bluebell shows an advancement of 6.2 days for every 1°C rise in temperature.

Species	*n* (number of sites with time series ≥ 15 years)	*N* negative (significant)	*N* positive (significant)	Mean (sig) Linear Temperature Response Rate (days °C^{-1} ± SD)	Mean FFD Date (± SD)	Earliest FFD	Latest FFD	Mean 3 Month Temperature (± SD)
Bluebell	132	131 (117)	1 (0)	-6.2 ± 1.2	15 Apr ± 13 days	07-Mar	25-May	6.1 ± 1.2 °C (Feb – Apr)
Coltsfoot	30	30 (16)	0 (0)	-3.5 ± 2.7	7 Mar ± 17 days	18-Jan	1-May	4.6 ± 1.3 °C (Jan – Mar)
Garlic Mustard	65	65 (57)	0 (0)	-5.6 ± 1.2	19 Apr ± 10 days	13-Mar	25-May	6.0 ± 1.2 °C (Feb – Apr)
Cuckooflower	60	60 (46)	0 (0)	-6.7 ± 1.5	15 Apr ± 15 days	1-Mar	30-May	5.9 ± 1.2 °C (Feb – Apr)
Wood anemone	64	59 (26)	5 (0)	-5.6 ± 1.5	27 Mar ± 13 days	13-Feb	09-May	5.0 ± 1.3 °C (Jan – Mar)

Tab 4.6 – The correlation coefficients for the Spearman rank test using IBM SPSS.

	SPSS Spearman Rank Correlations (temp response rates against various variables)			
Species	Lat	Lon	Alt	n
Coltsfoot	-0.063	0.219	0.235	16
Bluebell	-0.034	0.096	-0.077	117
Cuckooflower	0.312*	-0.076	0.170	46
Garlic mustard	-0.194	0.141	-0.055	57
Wood anemone	0.305	-0.136	-0.186	26
*Correlation is significant at the 0.05 level (2-tailed).				

The results from the linear regressions that provided the temperature response rates (*cf* Tab 4.5) showed that there were varying levels in r^2 values, with the lowest average value of 0.32 for coltsfoot and the highest value of 0.51 for cuckooflower (Fig 4.4). Visual representations of the temperature response rates for each species depict their spatial distribution, mindful that none of the species were affected by longitude and only cuckooflower was significantly affected by latitude (Fig 4.5). There was a random and somewhat dispersed nature of the response rates commensurate with the mostly insignificant Spearman rank correlations; there are a number of significant and insignificant linear response rate values. (Figure 4.5 and Tab 4.6).

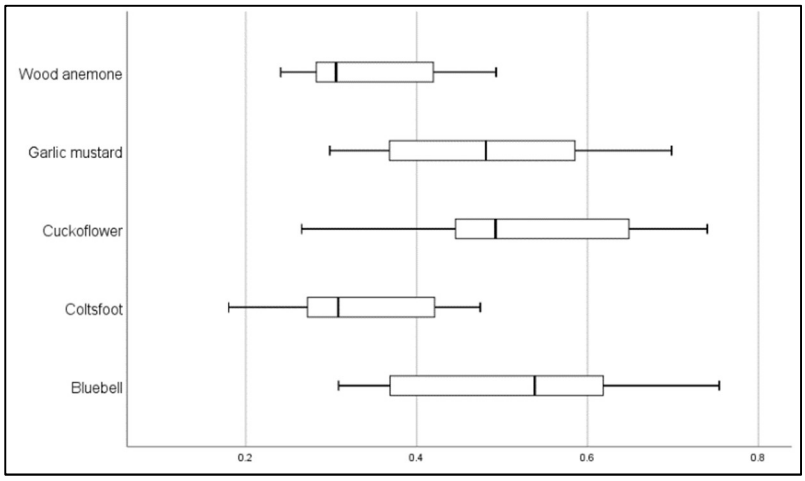

Fig 4.4 – r^2 values of the temperature response rate for each species.

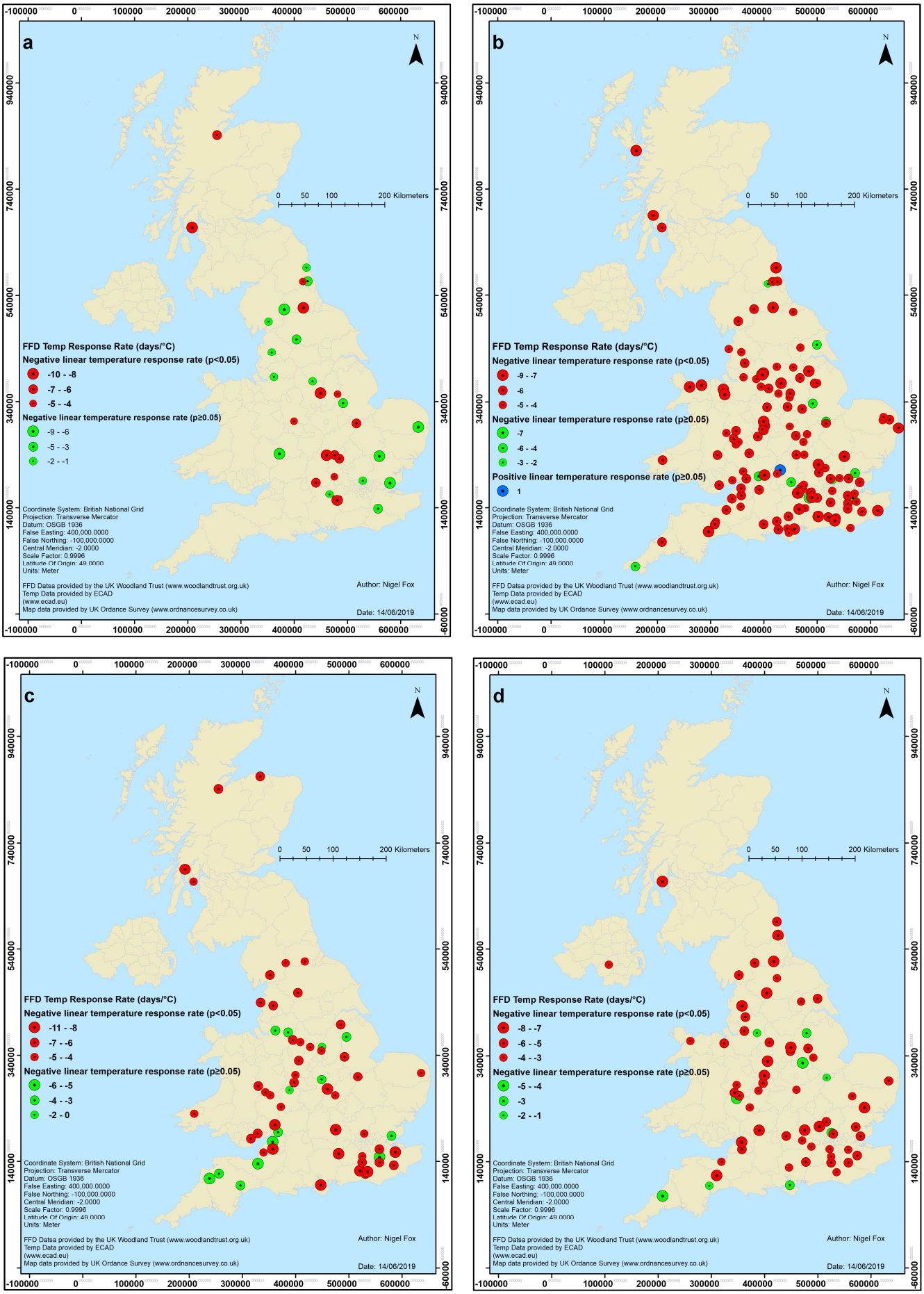

Fig 4.5 (a – d) – The spatial distribution for each species in the study in relation to temperature response rates. **a** – coltsfoot. **b** – bluebell. **c** – cuckooflower. **d** – garlic mustard.

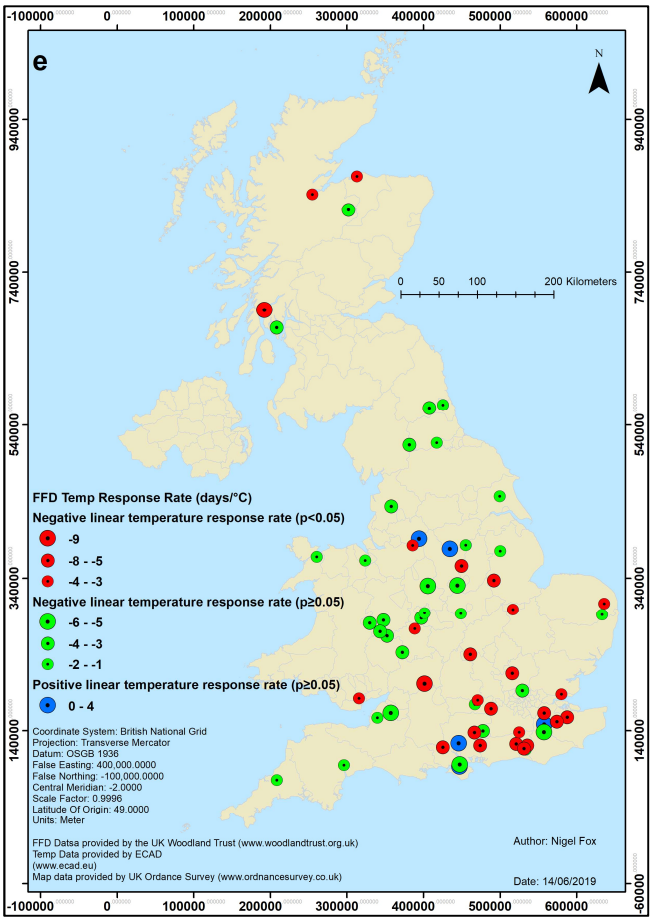

Fig 4.5 (e) – The spatial distribution for each species in the study in relation to temperature response rates for wood anemone.

5. Discussion

5.1 Temperature 1950 – 2017

The UK temperature has significantly increased between the two 33-year periods (1950 – 1983 and 1984 – 2017), in annual mean daily temperature and for the 3 monthly periods of Jan – Mar and Feb – Apr, explained in the next paragraph. These 2 time periods were chosen because they both had 33 years' worth of temperature data to make credible comparisons.

This study shows that the UK mean annual ambient daily temperature has increased by up to 1°C in places during the period 1984 – 2017 compared to 1950 – 1983 (Fig 4.1a), this corresponds with the conclusions of the IPCC that the *global* temperature is warming (IPCC, 2014; Edenhofer et al., 2014). A similar trend between the 2 time periods for Jan – Mar and Feb - Apr shows the UK mean daily temperature has increase by up to 0.9°C and 0.6°C, respectively (Fig 4.1b & 4.1c). These temperature differences will most likely have had an influence on plant phenology. Thus, it is concluded that ambient temperature may play an important causal part in relation to the observed variation in spring flowering phenology in this study. Although, as alluded to above, other factors may play a role in the observed changes in plant phenology such as pollinators and seed dispersal mechanisms, but these factors themselves may have been driven by the ambient temperature changes that have been reported in other studies (Fitter and Fitter, 2002; Menzel et al., 2006; Jochner et al., 2016).

5.2 The association between temperature and FFD variation

The results from this study show that there is a variation in FFD, which is most likely caused by changes in mean ambient temperature. The mean FFD of the plants were extracted between 2 years, 2006 and 2007. The year 2007 was reported as a significantly warm winter (extreme weather event), compared with the previous year of 2006, where, while significantly different, the winter period temperatures were not remarkably different to the 1961 – 1990 baseline averages (Tab 4.2) (Delpierre et al., 2009; Luterbacher et al., 2007). The results from this study seem to confirm reports that the winter period of 2007 differed significantly compared to the baseline average, with a mean of 2.07°C and 1.69°C for Jan – Mar and Feb – Apr, respectively, across the UK (Fig 4.2 & Tab 4.2), compared with the European winter mean temperatures of around 2.4°C (Delpierre et al., 2009; Luterbacher et al., 2007). Further, the UK temperature differences, resulting from this study,

between the winters of 2006 and 2007 for the Jan – Mar and Feb – Apr *mean* daily temperatures, differed significantly by 2.12°C and 2.09°C, respectively (Tab 4.3).

The wild plants investigated showed a significant mean advancement in FFD between the winters of 2006 and 2007, demonstrating an interannual variation due to a weather extreme and, thus, does not equate to a long-term trend. Of the species studied, the FFD advancements ranged from about 13 days for wood anemone to 18 days for bluebell, between 2006 and 2007 (Tab 4.4). Various studies have reported changes in FFD due to extreme weather events. In one of the first studies of this nature, the effects of severe drought and heavy rain events were investigated to see if these variables caused shifts in phenology (Kreyling et al., 2009). The researchers found for all species studied, across Central Europe, that the FFD (mid-flowering date) advanced by an average 4 days, under a regime of 32 days of drought, but heavy rainfall did not significantly affect the FFD (Kreyling et al., 2009).

In another study, researchers undertook a weather extreme investigation exploring the effects of winter warming on 22 species of flowering plants (Arfin Khan et al., 2018). They found that early springtime flowering plants significantly advanced their mid-flowering date, on average, by 4.9 days under a manipulated temperature increase of 1.2°C (Arfin Khan et al., 2018).

The results from the current study appear to confirm the results of the above studies (Kreyling et al., 2009; Arfin Khan et al., 2018) that extreme weather events, such as unusually warm winters, have an effect on flowering events. This may impact on ecosystems where earlier flowering onset may upset the community balance (Arfin Khan et al., 2018) and possibly cause phenological mismatching (Visser et al., 2006; McKinnon et al., 2012; Arfin Khan et al., 2018). This could lead to socio-economic problems for human society (Ingram et al., 2013) where extreme weather events occur.

The reason for the human impact is due to the changes in ecosystem dynamics, where ecosystem services may become less effective, for example insect pollinators maybe out-of-synch should the FFD of plants they pollinate shift significantly and rapidly causing a mismatch (e.g. McKinnon et al 2012). It is suggested that more studies are needed on the effects of extreme weather to provide further evidence of the impact of such extremes on flowering events (Kreyling et al., 2009). The results from the current study provide more indications of shifting phenology due to extreme weather, which warrants more work in the field in respect of related biotic associations.

5.3 The spatial temperature characteristics that explain the observational variations in time and space in FFD.

The results from this study show that there is a species-specific response to a warming climate, represented through a temperature response rate, ie the FFD of each species responds to a change in temperature in days (FFD) °C^{-1}. The temperature response rate (derived from simple linear regression) is different for individual species and the regression model r^2 values range from 0.32 to 0.51, meaning that between 32% and 51% of the observed variation in FFD can be explained by changes in temperature (Tab 4.6, Fig 4.4). The simple linear regressions were mostly negatively significant ($p<0.05$) with the x variable coefficient depicting the number of days per °C, with just 6 positive x variable coefficients resulting from insignificant simple linear regressions ($p\geq0.05$) for wood anemone (5) and bluebell (1). It is interesting that positive linear regressions emerged, which seem to counter the general trend of the significant negative linear regressions (Tab 4.5). This may be due to the small sample sizes where 15-year time series may not have been sufficient for climate change studies, or that there are extreme outliers that may influence results, even though outliers were removed outside 3 standard deviations following the methodology of one particular study (Jochner et al., 2016). However, it might be possible further to reduce the effects of outliers using data within 2 standard deviations, various studies have used this method (Jatczak and Walawender, 2009). Other methods could be applied such as analysing dotplots and boxplots to exclude outliers (Kolárová et al., 2017). There are various studies that look at the accuracy of data extracted from citizen science data recordings that may contribute to outliers, with some studies suggesting that the data recordings are not as accurate as professional scientists, but then some other studies imply that they are nearly as equal (Aceves-Bueno et al., 2017). It is feasible that there may be some inaccuracy in circumstances where insufficient training has been given to citizen scientists. For example, it is possible that citizen scientists may not work to a set standard when recording the emergence of a flower, with some recording the date when the flower is fully open, while others log the date just as the flower starts to open.

Various studies report that earlier springtime flowering events are more strongly associated with stronger temperature responses (Jochner et al., 2016; Menzel et al., 2006). Although, the results from the current study do show some relatively strong response rates, these results do not quite fit with Jochner et al (2016). For example, coltsfoot in Jochner et el's study shows a temperature response rate of -4.8 days °C^{-1} and this was for a priming temperature period of Jan – Mar, whereas in the current study it was -3.5 days °C. The temperature response rate for bluebell, garlic mustard and cuckooflower were -6.2, -5.6 and -6.7 days °C^{-1} respectively and, also, were all stronger than

coltsfoot, where the 3-monthly temperature priming period was Feb – Apr (Tab 4.5). Results from published studies (Jochner et al., 2016; Menzel et al., 2006) suggest that coltsfoot and wood anemone temperature response rates should have been stronger than bluebell, garlic mustard and cuckooflower, since coltsfoot and wood anemone flower earlier in the calendar. However, in Jochner et al (2016), comparisons were made with later flowering species that had an average FFD during late Apr up to mid-May (Sweet cherry, Rowan and Apple). Since the species in the current study all flower earlier than Sweet Cherry, Rowan and Apple and, also, flower within a month of each other (Tab 4.5), it is difficult to make to make meaningful comparisons. It simply may be that the UK is a lot smaller than the rest of Europe with a much smaller sample size over a much smaller land area to replicate the results of Jochner et al (2016).

Further, only time series of 15 years or more were used in the current study, the IPCC suggests using a 30-year period for time series data in relation to climate change (IPCC, 2013), however, the limitations of the species datasets in this study mostly preclude this time period. Jochner et al (2016) used 20-year time series for their phenological study, implying that is acceptable to use less than 30-year time series periods in phenological studies. It is recognized that using 15-year time series may not provide the degree of accuracy as 30 or 20-year time series, but will provide an indication of early spring flowering responses to changing temperatures, which may act as a prelude to future phenological/climate change studies.

It is also recognized that there may be error when obtaining FFD location temperatures, because the ECA&D gridded dataset provides mean elevation data over quite a large area (each grid is approximately 28 km^2). This area may span quite a range in topography that does not account for localised changes, for example, hill aspect, exposed areas and shady areas, leading to changes in microclimate, which all could impact on the timing of a FFD event. Finer resolution may come from, for example, using LiDAR images, such as those used in other phenology studies (Cope et al., 2017), where more information about localised topography, for example elevation and aspect, could reduce the error associated with using coarse mean elevation data such as those from the ECA&D dataset. The use of LiDAR images could be the subject of further investigations regarding plant phenology and climate change, which may yield FFD temperature results with a greater degree of accuracy, taking account of microclimates.

The results of the Spearman rank correlations that relate elevation, latitude and longitude to temperature response rates show that there was only one significant relationship, where the temperature response rate increased with decreasing latitude for cuckooflower. Thus, for the UK,

there appears to be no discernible trend apart from the fact that many of the response rates themselves are significant. However, there are some values that warrant a follow-up study, should more data become available over a greater number of years. For example, the wood anemone temperature response rate may become significantly dependent on latitude, given a greater dataset sample size with a time series of at least 20 years (Tab 4.6).

Some researchers suggest that plasticity within individuals of a plant species accounts for a plant's ability to track changes in the climate, as opposed to species evolutionary adaptation (Menzel et al., 2005). These researchers found that from a comparison between the first part of the last century and the latter, there was no significant difference in the temperature response rates of the species they studied (horse chestnut trees), thus suggesting that evolutionary adaptation had not been occurring, at least, for the species they studied (Menzel et al., 2005). Their study suggests that individuals within a species have the ability to track climate change without going through an evolutionary stage (Menzel et al., 2005). Another follow-up to the current study would be to determine if the species studied (e.g. bluebell) are going through an evolutionary process, which gives the species a competitive advantage, for example, an extended growing season associated with significantly greater temperature response rates.

It should be mentioned that many species require a chilling period prior to a phenology event occurring. For example, it is found that garlic mustard requires approximately 100 *chilling* days at temperatures between -1 and 6°C before it breaks dormancy and germination occurs at temperatures between 6 and 15°C (Raghu and Post, 2008). This genetic trait ensures that plants are not damaged by late frosts, where energy is not unnecessarily expended. Thus, it maybe that, with earlier springtime temperatures occurring due to climate change, many plant species may need to evolve measures that reduce the chilling periods to maintain a competitive edge, so that they can break dormancy and, also, survive the possibility of late spring frosts.

6. Conclusions

It was found that the temperature significantly increased over a protracted time period, with a significant difference noted between two consecutive 33-year periods (1950 – 1983 and 1984 – 2017). There was also a significant difference in temperature between 2 years (2006 and 2007), where there was an extreme weather event (unusually warm winter) in the latter year. These temperature differences seem to have had an impact on the all species in this study. There was an investigation into how extreme weather events affect the FFD of the species and it was found that all species were significantly affected by an extremely warm winter. Over the entire period 1950 – 2017, it was found that each species responded to increasing temperatures by advancing their FFD. Each of the results for the extreme weather event investigation and the response to changing temperatures (FFD $°C^{-1}$) tend to point towards the species of bluebell, cuckooflower, coltsfoot, garlic mustard and wood anemone are capable of tracking climate change and are significantly affected by changes to ambient temperature. Whether these species are going through an evolutionary change that provides them with evolutionary advantages requires further investigation. Given that these plants are able to track climate change, then it is reasonable to suggest that they can be identified as possible climate change indicators, and could be used in future climate change scenarios/predictions. Governments will need the best information to make effective decisions, particularly when it comes to climate change mitigation and adaptation strategies, especially when considering food security and endangered species that are unable to track climate change as successfully as other species.

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8. Appendix 1

Step-by-step process for extracting elevation data for the production of relative maps.
The elevation dataset was extracted using MATLAB and converted from a text file to an excel file, then uploaded to ArcGis 10.6 (Arc Toolbox > conversion tools > Excel > Excel to Table). The XY coordinates were displayed from this table and exported as a point shapefile. The resultant point shapefile was clipped to the UK shapefile and saved as a shapefile (UK_Ele_Pt_data) (WGS84 coordinate system).

Since the elevation data were defined in *mean* gridded squares, it was necessary to create a polygon shapefile so that this could later be joined with the FFD point location data. This was achieved over a number of steps through the creation of a 'fishnet' (Fig 3.1a).

In ArcGis 10.6, a fishnet file was created (Arc Toolbox > Data Management > Sampling > Create fishnet), using the UK shapefile as a template, with the cell size set at 0.25 (commensurate with the grid cell dimensions of the original elevation NetCDF file) (Figure 1). This file was spatially joined with the above newly created elevation point shape file (UK_Ele_Pt_data).

A raster was created from this joined file based on 0.25° grid squares, using the elevation grid codes (Arc Toolbox > conversion tools > to raster > point to raster) applying the WGS84 coordinate system. This file was then converted to 0.25° grid square polygons, (Arc Toolbox > conversion tools > from raster > raster to polygon), saved as a shapefile (UK_Fish_Ele) (Fig 3.1a). Each 0.25° polygon then represented a specific average elevation (masl) covering the whole of the UK (Fig 3.1b).

The elevation file was then joined with the FFD data file through a spatial join. This provided a table with each FFD data point (FFD, FFD elevation (masl) and lat/lon data) associated with a mean masl in each grid square, this would then assist with refining temperature data at each FFD location. This table was exported and saved as "FFD_sp_Ele".

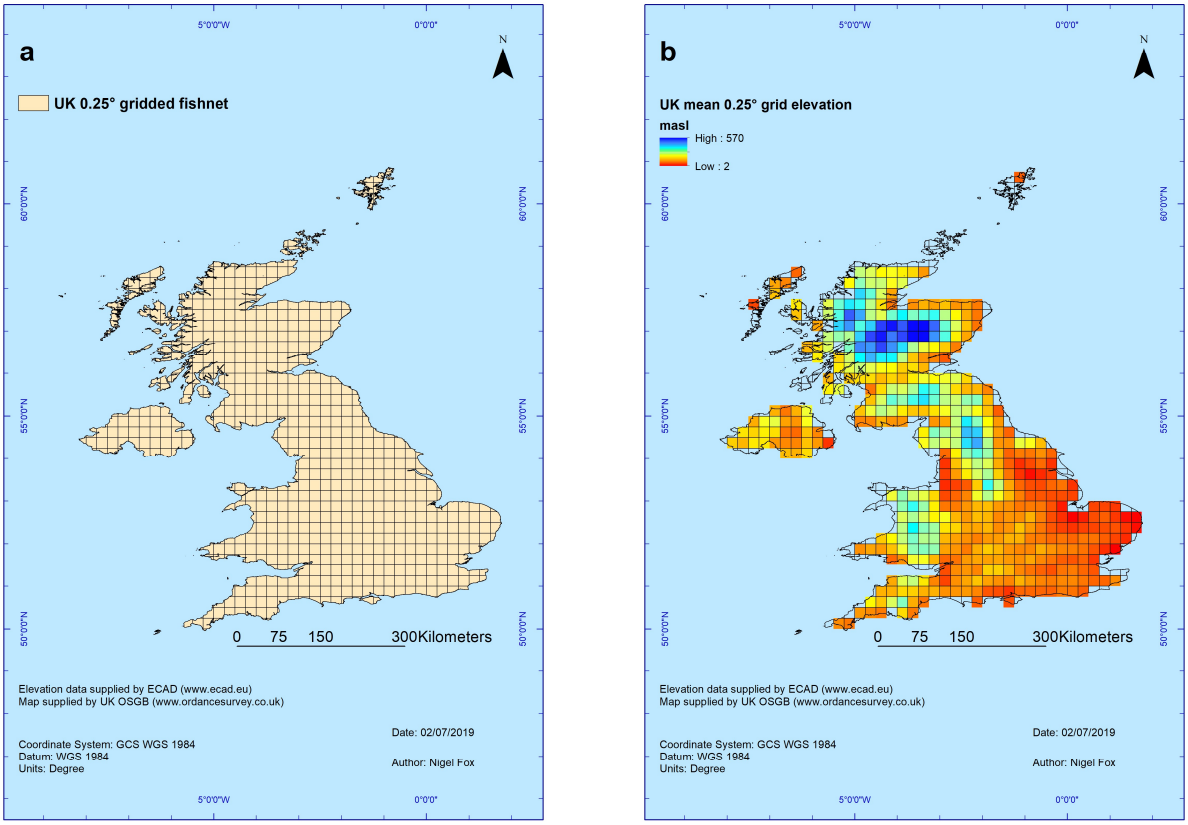

Fig 3.1 UK Fishnet. a the UK fishnet produced in ArcGis 10.6 (0.25° regular lat-lon grid). b the NetCDF elevation file (0.25° regular lat-lon grid) provided by ECA & D, overlaid on Fig 3.1a to show that each fishnet grid square is equal to that of the NetCDF file. Each grid square in Fig 3.1b represents the mean elevation value for the area covered by that grid square, thus the highest grid value (570 m) does not reflect the highest point in the UK (Ben Nevis mountain in Scotland (1334 m)).

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