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PhenoClimate: Impact of Climate Change on Phenology in Ireland

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Rialtas na hÉireann
Government of Ireland

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EPA RESEARCH PROGRAMME 2021–2030

PhenoClimate: Impact of Climate Change on Phenology in Ireland

(2018-CCRP-MS.54)

EPA Research Report

Prepared for the Environmental Protection Agency

by

University College Cork

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DISCLAIMER

This report is based on research carried out/data from March 2019 to June 2021. More recent data may have become available since the research was completed.

The EPA Research Programme addresses the need for research in Ireland to inform policymakers and other stakeholders on a range of questions in relation to environmental protection. These reports are intended as contributions to the necessary debate on the protection of the environment.

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Executive Summary

Phenology is the study of seasonal events in the life cycle of living organisms, such as leaf unfolding, flowering, bird migration and insect activity. Climate change affects the timing of these events. For example, the formation of leaves of deciduous trees in spring generally advances with warmer spring temperatures. However, this response to temperature differs geographically and is dependent on the species. Importantly, the advance may have slowed in recent years as factors other than spring temperatures, such as winter chilling or photoperiod (i.e. day length or the period of daily illumination), constrain the responses of trees. In addition, while spring phenology is well investigated, we know less about the climate response of autumn leaf senescence, which limits growing season length and thus limits the ability of trees to fix CO_2. Knowledge of how climate change affects not just spring but also autumn phenology is therefore vital to predict the future success of carbon sequestration in forestry.

In addition, climate change affects animal development, activity and migration. Observations of the timing of these phenological events suggest that asynchrony can arise from different responses to climate change, which results in phenological mismatch at different trophic levels, with potentially negative impacts on biodiversity.

Ireland is operating several phenological gardens where observations of tree phenology are recorded. However, this is labour intensive and consistency between observers is hard to maintain. The development of remote sensing and automated monitoring approaches can complement phenological gardens and citizen science projects to support recording of phenology at the national level in an objective manner.

Objectives

The PhenoClimate project investigated the impact of climate change on phenology in Ireland. The following three objectives were addressed:

1. to identify the start-of-season (SOS) and end-of-season (EOS) dates for different woodland types at locations across Ireland from Landsat satellite imagery;
2. to develop a suitable methodology for high-resolution monitoring of vegetation phenology in fragmented landscapes for future climate change research;
3. to identify the meteorological drivers of phenological events for a range of flora and fauna, and investigate interactions among phenological events across species.

Key Findings

- Over a period from 1990 to 2018, SOS advanced by an average of 0.09 days per year in deciduous woodlands across Ireland. SOS generally also showed an advance of 1.18 days per °C with a rising temperature, but temperature responses of EOS were more varied.
- Dates of the phenological events EOS, SOS and position of peak (POP; i.e. date of maximum greenness) derived from Sentinel-2 satellite imagery for individual trees in an urban setting can be matched to those derived from monitoring of canopy greenness using a phenological camera (phenocam).
- While first flight dates of moths and butterflies showed varying trends over the decade from 2008 to 2018, arrival of migratory birds generally advanced over time, alongside woodland spring phenology.
- The sliding time window analysis, which was undertaken to determine the time window that affects a phenological event, showed that climatic drivers of phenology are not always proximate to the event but can lie further back, with meteorological drivers for SOS in woodlands extending into the preceding year.
- Citizen science data can be successfully combined with vegetation phenology from satellite remote sensing to determine species interactions. Synchronous as well as asynchronous relationships were detected in the timing of phenological events across three trophic

levels: woodland vegetation, insects (moths and butterflies) and birds.

Recommendations

- Satellite remote sensing is the only feasible option for understanding national-scale variability. Continuous high-resolution imaging platforms, such as Landsat-9 and Sentinel-2C and 2D, are needed.
- Phenocams can be used at strategic sites in Ireland for the accurate monitoring of vegetation phenology at very high resolution. Such sites could include phenological gardens or sites with eddy covariance flux towers to determine the relationship between vegetation phenology and ecosystem CO_2 fluxes.
- Acoustic recorders are an inexpensive way to monitor migratory birds across the whole season and have the potential to complement citizen science projects, especially for the recording of last flight dates of birds in autumn.
- Coordination at the national level is required to secure the collection, analysis and availability of data required for phenological monitoring of climate change responses into the future.

1 Introduction

1.1 Background

Phenology is the science that studies seasonal events in the life cycle of living organisms. Such events include leafing, flowering and leaf senescence in plants, as well as animal migration, development and activity. Many studies have reported effects of climate on phenological events, and the timing of these events is therefore considered one of the key indicators of the impact of climate change on nature (Menzel, 2002; Peñuelas *et al.*, 2009). Phenology also influences ecosystem productivity, carbon cycling, succession and migration strategies, which makes the study of phenological patterns and drivers crucial to plan climate change adaptation and mitigation. This has fuelled curiosity in pioneering techniques such as remote sensing for the tracking of plant phenology at multiple temporal and spatial scales, with plant phenology also acting as a proxy for other organisms. Therefore, phenology, which started as a pastime whereby observers recorded periodic developments in plant development and animal activity, has become a well-established branch of ecological and climate science.

Observations of the timing of phenological events have provided invaluable information about the impact of climate change on the arrival of spring. They have demonstrated for example, that earlier leafing and flowering is occurring across Europe (Menzel *et al.*, 2006), and, similarly, that leafing has advanced in deciduous trees with increasing temperature in Ireland (Donnelly *et al.*, 2004, 2006; Gleeson *et al.*, 2013).

Events associated with the start of season (SOS), such as leaf unfolding in spring, and the end of season (EOS), such as leaf senescence in autumn, define the length of the growing season and thus the ability of vegetation to fix carbon in the form of CO_2. A climate-related lengthening of the growing season could therefore have a feedback effect on climate change by increasing photosynthetic CO_2 fixation (Peñuelas *et al.*, 2009). For example, Keenan *et al.* (2014) observed earlier spring and later autumn phenology in a temperate forest, which resulted in increased carbon uptake. Climate change mitigation projects (e.g. projects involving afforestation or reforestation) therefore need to take the impact of climate on growing season length into account.

Although the advance of leaf unfolding in spring has resulted in an extended growing season overall, this advance has more recently slowed down, possibly because warmer winters no longer fully meet the requirement for chilling to release bud dormancy (Fu *et al.*, 2015; Pletsers *et al.*, 2015). In addition, earlier leafing can result in damage caused by late spring freezes after bud burst ("false springs"; Chamberlain *et al.*, 2021). Moreover, altered spring phenology can have consequences for autumn phenology later in the year. For example, earlier leafing can result in earlier senescence (Fu *et al.*, 2014; Keenan and Richardson, 2015), with effects on growing season length.

Phenological events are also important drivers of plant invasions. Recent research based on data collected by a citizen science campaign coordinated by the USA Phenology Network revealed that invasive shrubs have an extended leaf phenology (indicating a longer growing season) compared with native shrubs, with both spring and autumn phenology contributing to this difference (Maynard-Bean *et al.*, 2020). Previously, it had been shown that deciduous forest understorey invaders have an extended autumn growing season compared with native species (Fridley, 2012).

The EOS can make a larger contribution to changes in the growing season length than the SOS (Yu *et al.*, 2017). However, compared with spring phenology, autumn phenological events have generally been neglected in climate change research (Gallinat *et al.*, 2015) and the autumn responses to climate change can vary widely depending on the species and local climatic conditions (Panchen *et al.*, 2015; Gamon *et al.*, 2016). In addition, photoperiod (i.e. the day length or the period of daily illumination), which is not affected by climate change, can constrain the autumn response of trees to climate change, especially at high latitudes (Gill *et al.*, 2015). Despite not influencing the actual photoperiod at any given time of the year, climate has an impact on the photoperiod that is experienced by an organism, with consequences for species distribution and fitness (Ettinger *et al*., 2021). In Ireland, autumn tree phenology occurred later at an urban site (National Botanic Gardens, Dublin) than at rural sites and was further delayed in response to rising temperatures (Donnelly *et al*., 2018). This can possibly be explained by a release of photoperiod constraints as a result of urban light pollution.

In the past, the recording of tree phenology was mainly based on ground observations, which can be time-consuming and unreliable, especially for the more gradual senescence-associated changes that occur in autumn. With the availability of high-resolution satellite remote-sensing imagery, there is now an increasing opportunity to determine the impact of climate change on tree and overall vegetation phenology using remote-sensing approaches (Misra *et al*., 2020; Caparros-Santiago *et al*., 2021). In addition, phenological cameras (phenocams) can provide high-resolution information on canopy greenness in vegetation phenology research (Hufkens *et al*., 2018; Richardson, 2019; see also section 2.1).

Phenological shifts in response to climate change also have consequences for biodiversity. As different plant and animal species react to changes in climate differently, shifts in the timing of phenological events can desynchronise species interactions (Thackeray *et al*., 2016; Simmonds *et al*., 2020). The complex and interlinked nature of ecosystems means that interactions among phenological events of different taxa have consequences for the entire food chain. This can result in phenological mismatches at different trophic levels (Visser and Gienapp, 2019), thus threatening biodiversity because of differences in phenological sensitivity to climate at different trophic levels (Thackeray *et al*., 2016; Kharouba *et al*., 2018). Observations for Ireland show that, while there was an overall advance in spring phenology, the responses of different groups of organisms to warmer springs varied; for example, a greater advance was recorded for moths (O’Neill *et al*., 2012) than for birds or trees, which could result in a mismatch between food supply and demand (Donnelly *et al*., 2015). Recent developments in the methods for automatic recording of animal and vegetation phenology, combined with spatially and temporally explicit models, provide new opportunities to analyse biotic interactions of phenological events across taxa (de la Torre Cerro and Holloway, 2021; see also section 2.2).

1.2 Project Overview

This PhenoClimate project built on previous EPA-funded research (2007–2013) on phenology and work conducted by Ireland’s National Phenology Network (IE-NPN) (Donnelly *et al*., 2013). As part of IE-NPN, collection of phenological data (including phenological gardens and citizen science projects) was coordinated at the national level; protocols were standardised and new phenological gardens were set up. Ireland has been recording tree phenological observations for the International Phenological Gardens of Europe (IPG) project since 1966, and IE-NPN coordinated the submission of these data to International Phenological Gardens of Europe (http://ipg.hu-berlin.de/) and the European COST Action Pan European Phenology Project PEP725 (http://www.pep725.eu/).

PhenoClimate focused on the use of current and historical datasets to develop methods of analysing past and future impacts of climate change on phenological events. Tree phenology was monitored through ground observations, phenocams and high-resolution (Sentinel-2) satellite remote sensing at local sites (Figure 1.1), and at the national level it was monitored using medium-resolution satellite remote sensing. Citizen science data and acoustic recorders were used to monitor the phenology of butterflies, moths and birds (Figure 1.2), and these data were combined with satellite remote sensing of forest phenology to investigate interactions in the timing of phenological events across fauna and flora. The phenological outputs from the long time series of satellite and insect data were evaluated in the context of MÉRA climate reanalysis (Whelan *et al*., 2018) data for the period 1990–2018 to establish any relationships between floral and faunal phenology and climate change.

1.3 Project Objectives

1.3.1 Objective 1

Objective 1 was to identify SOS and EOS dates for different woodland types at locations across Ireland from Landsat satellite imagery. Landsat was chosen on account of the platform’s long-standing and continuous archive of data acquisitions. This objective addresses the question of how climate change in Ireland has affected the length and timing of the growing season.

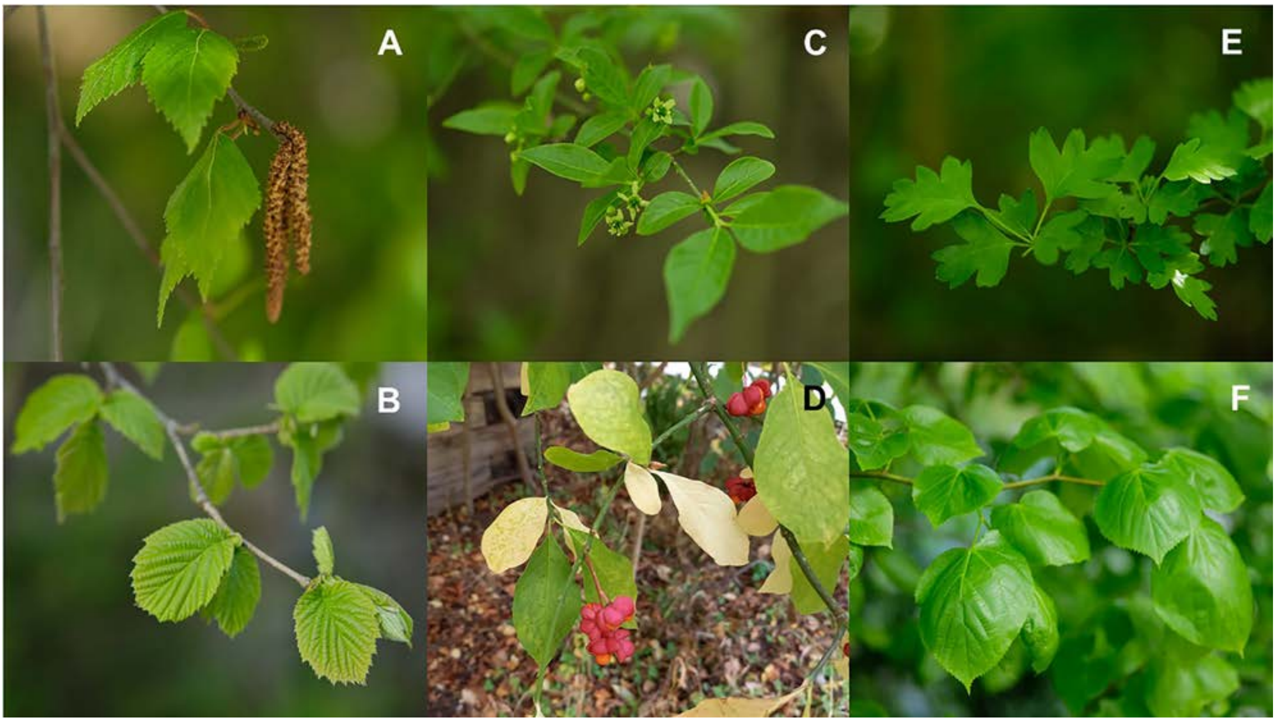


Figure 1.1. Examples of tree species included in the research project. (A) silver birch (*Betula pendula*); (B) common hazel (*Corylus avellana*); (C) spindle (*Euonymus europaeus*); (D) spindle with fruits in autumn; (E) common hawthorn (*Crataegus monogyna*); and (F) common lime (*Tilia* × *europaea*). Photos: Calum Sweeney and Astrid Wingler.

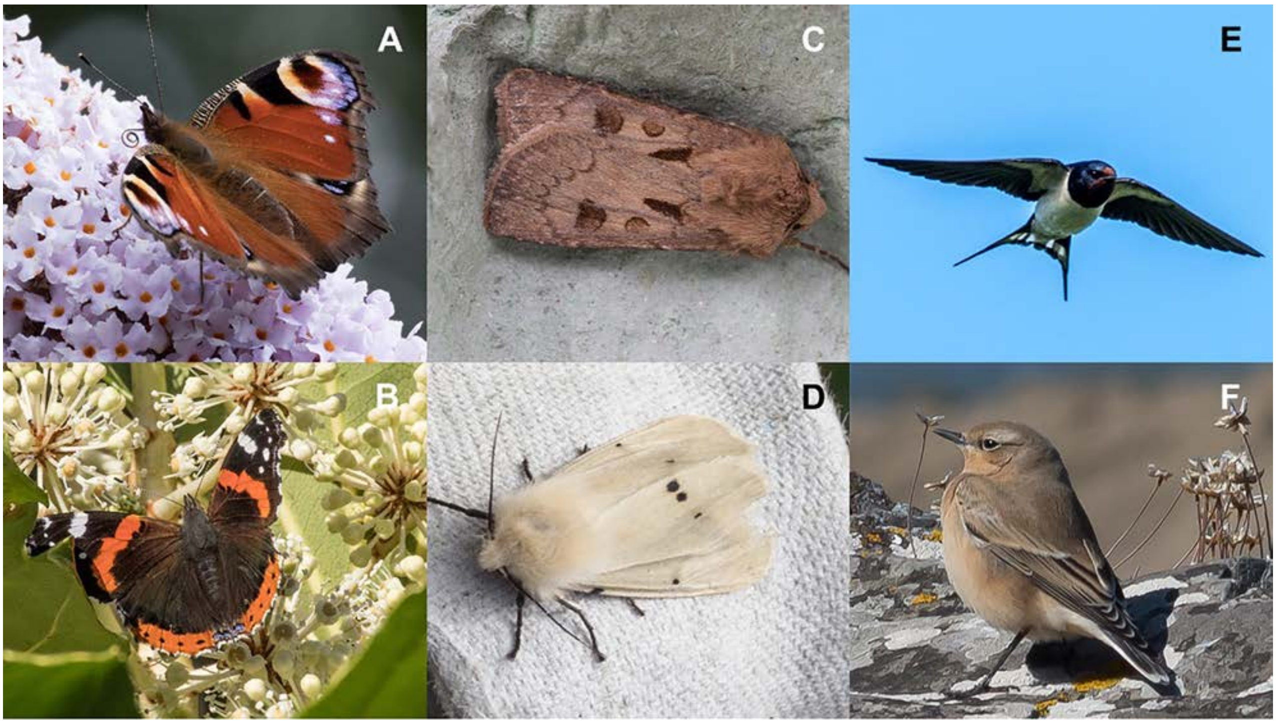


Figure 1.2. Examples of animal species included in the research project. (A) peacock (*Aglais io*); (B) red admiral (*Vanessa atalanta*); (C) heart and dart (*Agrotis exclamationis*); (D) white ermine (*Spilosoma lubricipeda*); (E) barn swallow (*Hirundo rustica*); and (F) northern wheatear (*Oenanthe oenanthe*). Photos: Thomas Wallenda.

Previous research had shown trends towards earlier leaf unfolding, but effects on autumn senescence were variable and no comprehensive monitoring of vegetation phenology in Ireland had been performed. Because satellite instruments used elsewhere, such as MODIS (Moderate Resolution Imaging Spectroradiometer) and MERIS (Medium Resolution Imaging Spectrometer), do not provide the high spatial resolution required for fragmented Irish landscapes, Landsat satellite imagery was used to analyse climate-related changes in unmanaged native woodland phenology across Ireland from 1990 to 2018.

1.3.2 Objective 2

Objective 2 was to develop a suitable methodology for high-resolution monitoring of vegetation phenology in fragmented landscapes for future climate change research. This objective addresses how phenological change can be monitored efficiently and at high spatial and temporal resolutions.

Satellite imagery from Sentinel-2 was used to achieve the spatial resolution required for analysing the effects of climate change on individual trees. Phenological change derived from Sentinel-2 vegetation indices was compared with ground-based measurements of chlorophyll content. However, taking these measurements is labour intensive and requires the continued presence of field scientists; phenocams were installed as an alternative method of ground-truthing satellite remote sensing data in a more efficient way. This will also allow data collection to continue into a future period extending beyond the duration of this project.

1.3.3 Objective 3

Objective 3 was to identify the meteorological drivers of phenological events for a range of flora and fauna, and investigate interactions among phenological events across species. This objective addresses the question of how climate change is likely to affect species interactions and biodiversity.

Animals and plants are connected through the trophic network. For example, pollinators are affected by flowering time, but there are also consequences at higher trophic levels. To date there has been a lack of a unified methodology to study phenology within biotic interaction or co-existence studies, which hinders efforts to establish comparisons on the effect of climate drivers on organisms and systems at spatial and temporal scales. While some research on the impact of climate change on the phenology of animals is available for Ireland, integrated studies on plant–animal interactions are required to identify the potential for phenological mismatches that could result in species extinction or migration. Phenological events were identified from national citizen science projects for migrant birds, butterflies, moths and vegetation over the period 2008–2018. The relative sliding time window analysis was applied to identify which meteorological drivers had greater influence on the phenological events of the study, and three novel interaction indices were created to quantify the degree of synchrony or asynchrony among species.

2 Current Methods in Phenological Research

2.1 Recent Developments in Remote Sensing Approaches for Monitoring Vegetation Phenology

Traditionally, phenological research is based on ground observations of the timing of phenological events. For plants, this includes the recording of developmental stages, such as bud burst, first leaf, flowering, fruiting, leaf colouring and leaf fall. While bud burst can be easily observed, leaf coloration in autumn is a gradual process and observations of, for example, 50% coloration are often subjective, resulting in inaccuracies. In addition, recording of ground observations is time-consuming and requires the availability of trained recorders over many years to investigate the impact of climate change.

Ground observations of phenology still serve as important indicators of vegetation response; however, with the advent of and subsequent progress in remote-sensing techniques, phenological studies can now benefit from a variety of platforms providing data from space and near-surface devices. Research has benefited immensely from free-to-use satellite data, primarily from the Advanced Very High Resolution Radiometer (AVHRR), Landsat and MODIS sensors that have been used in land surface phenology (LSP) research (e.g. Zhang *et al*., 2017; Cracknell, 2018; Wulder *et al*., 2019; Caparros-Santiago *et al*., 2021). These satellite sensors, with their large swathe, long record of data acquisition and repetitive coverage, provide vital clues to temporal changes occurring on the Earth’s surface. The Landsat mission and AVHRR and MODIS sensors continue to provide multispectral information, with datasets available from the 1970s, 1980s and 2000s (Wulder *et al*., 2019).

However, studies using satellite images are known to be affected by the pixel size when a coarse spatial resolution causes an averaged reflectance from multiple land surfaces in the pixel area to be returned, leading to difficulties in the unmixing of signals and in establishing the real cause of changes in the temporal behaviour of pixels (Helman, 2018; Misra *et al*., 2018). Apart from spatial resolution, the temporal resolution of satellites also determines the accuracy of the time series curve, as important phenophases of vegetation might be missed because of insufficient coverage due to the repeat cycle or to cloud cover, which obscures the ground surface.

Owing to the requirement of repeated observations to study landscape phenology, most satellite-based phenology studies have relied on medium- to coarse-resolution satellites, such as MODIS, Landsat and AVHRR, or have fused MODIS and Landsat imageries to improve the temporal and spatial resolution (Vrieling *et al*., 2018). To overcome the limitations of these medium-resolution sensors, newer satellite data from constellations of identical sensors with higher temporal and spatial resolution, such as Sentinel-2, have been explored in phenological research (Misra *et al*., 2020; Caparros-Santiago *et al*., 2021).

In addition, there is an urgent need to bridge the gap between satellite and ground observations of phenology that has been reported to cause mismatches in phenological estimates due to differences inherent in their definitions of phenology (Misra *et al*., 2016). Compared with ground observations, which are based on visual recording of key phenological stages, phenological estimates from satellites are based on pixel-averaged intensity of greenness of the plant canopy (including background) and have limited capabilities in detecting subtle changes in phenology, especially below the upper canopy. The latest developments in technology allow fixed digital cameras (phenocams) to capture several images of vegetation on a daily basis to monitor plant growth from a close range (Browning *et al*., 2017; Richardson, 2019). The spatial coverage of phenocams is limited; therefore, simultaneous monitoring of vegetation phenology across large landscapes can be achieved only through satellites (Vrieling *et al*., 2018). However, higher resolution satellite sensors and phenocams have become operational only in recent years, preventing their use in establishing relationships between phenology and longer-term climate change.

2.1.1 Sentinel-2

A comprehensive literature review on the status of phenological research using Sentinel-2 was undertaken as part of this project and published in 2020 (Misra *et al*., 2020). The Sentinel-2 (S2) satellite sensors were launched in June 2015 (Sentinel-2A) and March 2017 (Sentinel-2B), providing data at a much finer (10–20 m) spatial scale, though with a shorter time series, than Landsat and MODIS. With a 5-day repeat cycle for Sentinel-2A and Sentinel-2B combined, the higher temporal resolution compared with Landsat is one of the biggest advantages of Sentinel-2 data, allowing more frequent sampling of the ground, especially in areas where cloud cover may be prevalent. It has been observed that, for the same area, Sentinel-2 can sample a greater number of pixels (approximately 10 times more) than Landsat-8 owing to its higher data collection frequency from two sensors and a better spatial resolution. Sentinel-2 therefore provides improved capability of monitoring vegetation from space (Addabbo *et al*., 2016). Vrieling *et al*. (2018) studied the effect of cloud cover on the estimation of LSP metrics from Sentinel-2 NDVI data and concluded that both the frequency and location of data gaps (resulting from cloud cover) are important in ensuring correct estimation of LSP metrics. For example, the presence of above-normal cloud cover in the spring season in the slow-growing salt marshes of the Netherlands had fewer effects on the estimated LSP than it had in a fast-greening-up agricultural plot. Additionally, Sentinel-2 data are highly correlated with fresh biomass and green area index (GAI) and, with their ability to potentially capture short-lived phenological stages, enable more precise monitoring of crop development (Veloso *et al*., 2017).

With regard to the monitoring of phenological metrics, Sentinel-2 shows a better agreement with *in situ* measurements than MODIS, especially with respect to green-up (GU) dates, which were found to lag by 8 to 14 days compared with Sentinel-2 and *in situ* measurements (Lange *et al*., 2017). Senescence as calculated from MODIS data also occurred 4 to 11 days earlier than in Sentinel-2 and *in situ* data, which might be due to mixed pixel effects. Compared with Sentinel-1, Sentinel-2 is more accurate in predicting SOS (Stendardi *et al*., 2019); SOS based on Sentinel-1 and Sentinel-2 data had, on average, a 10- and 4-day difference, respectively, from the SOS calculated from phenocams.

The presence of red-edge bands on Sentinel-2 multispectral instruments also provides better opportunities for monitoring plant health and status, and research has already indicated an improved performance in monitoring leaf chlorophyll content (Zarco-Tejada *et al*., 2019). However, there has so far been very little research on the capacity of the additional red-edge bands to track vegetation phenology (Misra *et al*., 2020). A review of the literature also revealed very few instances where the all-weather capability of Sentinel-1 microwave data for phenology studies has been utilised. In contrast to optical data, the signals from microwave sensors are highly dependent on the land cover and hence need to be processed separately for each land cover class (Jones *et al*., 2011; Stendardi *et al*., 2019).

Overall, although the Sentinel-2 platforms have been operational for only a short period, their potential for phenological research has already been demonstrated for a range of vegetation types, including crops, forests and natural grasslands, in particular through fusion of the data with those from other sensors, such as Sentinel-1, Landsat and MODIS (Misra *et al*., 2020).

2.1.2 Phenocams

Phenological cameras are widely accepted as a cheap means by which to obtain near-surface repeat photography and aid in continuous monitoring of vegetation in all weather conditions (Sonnentag *et al*., 2012). Several camera devices have been adapted by researchers to capture images at regular intervals and daily scales, including simple point-and-shoot cameras, the more complex DSLR cameras and webcams with internet connectivity (Sonnentag *et al*., 2012). The PhenoCam Network in the USA (https://phenocam.sr.unh.edu/webcam/) recommends the 5-megapixel StarDot NetCam SC for its simplicity, additional infrared imaging capabilities and its reliability in a wide range of climatic conditions (Figure 2.1). Moreover, the researchers at the PhenoCam Network provide a detailed description of the set-up of the camera, in addition to information on software packages and statistical tools for processing of captured images (Hufkens *et al*., 2018). Similar camera networks are also active in Europe (EuroPhen), Australia (TERN Australian Phenocam Network) and Japan (Phenological Eyes Network – PEN) (Richardson, 2019).

Figure 2.1. Phenocam (StarDot NetCam SC) pointed at a tree canopy in Cork. For information on the use of phenocam images see Chapter 4. Photos: Calum Sweeney.

It has been reported that leaf greenness and redness measured using phenocams can efficiently track the concentration of both chlorophyll and leaf nitrogen (Yang *et al*., 2014). This is particularly useful when a lower leaf area index (LAI) at the SOS and EOS leads to mixing of reflectance from the leaves with reflectance from the stems and soil. A phenocam can, in this case, help with unmixing of reflectance from different sources and aid in concentrating on only the green leaves of the tree canopy. Moreover, phenocams have been reported to enable capture of species-specific responses to weather/climatic drivers. For example, in the autumn phenology of eight species, drought led to a delayed peak of redness (POR), a proxy for senescence, in two species and an earlier peak of redness in the remainder (Yingying *et al*., 2018). The colour indices from phenocams have also been found to be useful not only for capturing LSP, but also for improving eddy covariance-based estimates of gross productivity and canopy-scale modelling (Migliavacca *et al*., 2011).

Although phenocams can be the bridge between satellite and ground observations of phenology, a perfect match between phenological observations from any of the three sources cannot be expected (Hufkens *et al*., 2012). Mismatches in phenological estimates from satellites and phenocams can result from differences in their (1) spectral bands used for computation of vegetation indices; (2) fields of view, where satellite pixels are a mixture of reflectance from the upper canopy over larger areas; and (3) temporal resolution. Mismatches can lead to the capturing of subdaily patterns rather than characterising phenology over days, as dictated by the repetitive coverage of satellites (Hufkens *et al*., 2012). Additionally, the presence of non-photosynthetic organs and dead biomass from the previous season is also known to influence vegetation reflectance from phenocams (Vrieling *et al*., 2018). In such a situation, standardised protocols, such as those of the PhenoCam Network in the USA, can help to minimise errors resulting from the set-up of cameras and data processing, and to facilitate experiments or observations across multiple sites (Hufkens *et al*., 2018).

2.1.3 Vegetation indices for studying phenology

A few of the most commonly used vegetation indices for phenological studies are described below.

The normalised difference vegetation index (NDVI) has been the measure of choice for a variety of vegetation studies owing to its direct linkages to plant photosynthesis, transpiration and carbon assimilation (Glenn *et al*., 2008). Relying on just the red and near-infrared reflectance, it can be calculated from a multitude of different satellite platforms, including many of the early sensors, which had a more limited spectral range than the newer ones. NDVI has also been used to identify impacts of extreme events, record pest attacks and map species abundance and productivity (Spruce *et al*., 2011; Clerici *et al*., 2012; Matiu *et al*., 2017). It can, however, suffer from saturation and be unreliable for determining values of very high biomass. It has been reported to aid in accurate estimation of leaf expansion in cool temperate forests, but it is less able to detect defoliation (Nagai *et al*., 2010).

In contrast to NDVI, the enhanced vegetation index (EVI) was developed to improve sensitivity in regions with high biomass, minimise the contribution of the background in areas with low fractional cover and mitigate impacts of smoke and other atmospheric disturbances (Luo and Yu, 2017). A study by Testa *et al*. (2018) reports the superior performance of EVI (among EVI, NDVI and the wide dynamic range vegetation index) in predicting early EOS. Furthermore, EVI was reported to perform better in estimating the GU, or SOS, than NDVI for broadleaf forests in the USA (Peng *et al*., 2017). Lim *et al*. (2018) found a better agreement between both the SOS and EOS estimated from EVI with phenology from phenocams and *in situ* observations.

Chromatic coordinates (CCs) are the digital number values in the visible range of the spectrum in the phenocams and are used to measure vegetation activity (Richardson *et al*., 2018). RCC, GCC and BCC are the most commonly used indices that calculate the ratio of red (R), green (G) and blue (B) reflectances with respect to their sum ($R+G+B$) (Alberton *et al*., 2017). The excess green (ExG) is another frequently used index calculated from both phenocams and satellite data, and is valued for its ability to enhance signals from green leaves and minimise anomalies emanating from canopy background and illumination conditions (Sonnentag *et al*., 2012; Lim *et al*., 2018). In addition, it is reported to be highly correlated with canopy greenness (Hufkens *et al*., 2012).

The plant phenology index (PPI) is a newly developed index calculated from the red and near-infrared bands and is derived from a radiative transfer solution. It is known to be comparatively insensitive to snow and soil, and has a better linear relationship with the leaf area index than NDVI or EVI (Jin and Eklundh, 2014).

2.1.4 Methods for processing time series data

Several methods exist for the processing of satellite and phenocam data, and there is ample literature discussing their merits and limitations (White *et al*., 2009; Atkinson *et al*., 2012; Misra *et al*., 2016). The steps in processing any digital camera/phenocam image or satellite data are similar, and mainly consist of (1) stacking of images, (2) removal of anomalies or contaminated data, (3) filling of gaps, (4) smoothing or function fitting and (5) extraction of phenological parameters (Misra *et al*., 2016; Richardson, 2019). The main purpose of processing such time series data is to distinguish between clear and contaminated values (or detection of outliers), while being true to the available clean data, and to determine an optimal method for describing the seasonal shape of vegetation (Jönsson *et al*., 2018).

Some researchers have used pixel-quality data, such as those available with the pre-processed MODIS datasets, for detection of contaminated pixels or anomalies (Hamunyela *et al*., 2013; Misra *et al*., 2016), and the Sen2Cor tool for processing of Sentinel-2 data to identify clean data (Jönsson *et al*., 2018). Statistical measures, such as the standard deviations of the data points from the averaged seasonal curve (Hamunyela *et al*., 2013; Misra *et al*., 2016) and the best index slope extraction (BISE) (White *et al*., 1997), have been used for the detection of outliers in addition to information from good-quality layers. Subsequent to the removal of outliers, gap filling in time series data has been done in several ways, including by filling winter gaps with a fixed or minimum value (Beck *et al*., 2006; Forkel *et al*., 2015). Missing values in the non-winter period have been substituted using seasonal averages or linearly interpolated values, depending on the length of gaps in data (Misra *et al*., 2016). It is important to discriminate the data gaps into winter and non-winter periods and treat each separately, as the vegetation growth characteristic differs according to the weather or meteorological conditions (mostly the temperature and moisture controls on vegetation growth) (Tan *et al*., 2011; Forkel *et al*., 2015). The eventual aim of processing time series data is to remove sharp deviations (i.e. peaks and troughs) that are not representative of true conditions and extract phenological metrics with higher confidence (Misra *et al*., 2016, 2018).

Following gap filling, the time series data are subjected to smoothing or function-fitting operations. Atzberger and Eilers (2011) review various smoothing techniques (Savitzky–Golay filter, Whittaker smoother, running medians, mean compositing, etc.) and function-fitting techniques (double logistic, asymmetric Gaussian) and suggest the use of the Whittaker smoother to process coarse-resolution data because it has a faster processing time and enables semi-automatic determination of a smoothness parameter, which reduces bias that could result from the researcher's choice of techniques and parameters. Similarly, local smoothing functions such as the Savitzky–Golay filter (Hamunyela *et al*., 2013; Xu *et al*., 2017) and a weighted Gaussian filter (Misra *et al*., 2016, 2018) have been reported to perform satisfactorily in separate studies for the smoothing of time series vegetation index data for both broadleaf and conifer forests. Another extensive review of gap filling and smoothing approaches on global MODIS data by Liu *et al*. (2017) reports the superior performance of locally adjusted cubic splines (LACC) and the Savitzky–Golay filter in most cases.

2.1.5 Methods for calculating phenometrics

The methods that are suggested in the literature for extracting phenological metrics from gap-filled and smoothed time series data can primarily be grouped based on (1) thresholds of absolute values, (2) thresholds of amplitude, (3) delayed moving averages and (4) points of inflection or derivatives of seasonal curves. Misra *et al*. (2016) report a stronger linkage of the 20% amplitude with the early phases of understorey phenology, and 75% amplitude and first derivative having a higher correlation with leaf unfolding and greening of late understorey and broadleaf species. The first derivative or the inflection points on a fitted time series have been reported to accurately estimate the onset of greening and yellowing in the deciduous forests of northern France (Hmimina *et al*., 2013). Similarly, the 50% amplitude, or the "half-amplitude", method has been widely cited by studies for its ability to successfully extract phenological metrics, i.e. both SOS and EOS (White *et al*., 2009; Hamunyela *et al*., 2013; Matiu *et al*., 2017; Misra *et al*., 2018).

Techniques similar to those used for monitoring SOS have been employed in detecting the EOS metrics from the receding curve of the seasonal satellite data (Jin *et al*., 2017; Luo and Yu, 2017; Misra *et al*., 2018). Although the detection and modelling of SOS have been widely successful, the EOS lacks similar results and is in fact often miscalculated from satellite data (Stöckli *et al*., 2008; Matiu *et al*., 2017; Misra *et al*., 2018).

However, the selection of a single best technique or a general protocol of methods that is applicable in all situations is not straightforward. Research suggests the data properties (number of outliers and missing data or gaps), the land cover and the vegetation species under study must be meticulously considered before carefully selecting an appropriate protocol for processing the data (Eklundh and Jonsson, 2015; Misra *et al*., 2016; Liu *et al*., 2017). For example, in periods with persistent missing data (contaminated values), a function-fitting method might be better suited to getting an averaged global description of data rather than capturing interannual or seasonal variations (Jönsson *et al*., 2018). Another important consideration is to carefully select the most suitable method from the many ones available to calculate phenological metrics for LSP studies, as high correlation between any phenometric value and *in situ* observation does not guarantee superior performance of that method. Cong *et al*. (2013), for example, report that, although different methods of LSP-SOS estimation in the Tibetan Plateau led to similar signs of linear trends, they may differ in their magnitudes by a factor of five. It is therefore crucial to assign ecological meaning to phenological metrics before correlating to *in situ* observations and drawing conclusions from studies (Hufkens *et al*., 2012).

Many of the capabilities of processing time series data are available in the free-to-use TIMESAT software, which has been frequently used by researchers owing to its simple interface and ease of operation (Jönsson and Eklundh, 2004; Tan *et al*., 2011; O'Connor *et al*., 2012; Browning *et al*., 2017). Several other free-to-use tools are available in the form of Python (i.e. vegindex) and R packages (i.e. phenopix, phenor, phenocamr and greenbrown) for facilitating the process of extracting phenological information from time series data (Forkel *et al*., 2015; Filippa *et al*., 2016; Richardson *et al*., 2018). The presence of a large number of free-to-use tools, along with open-source codes, helps in making better-informed decisions about the selection of one or a combination of tools. Such open tools and standardised protocols for measurements support improvements to existing processing capabilities and make research more open and reproducible (Tang *et al*., 2016; Hufkens *et al*., 2018).

2.1.6 The issue of gaps in data and resolution

The adverse influence of cloud cover in areas with high rainfall on time series analysis of data is well known (Jain *et al.*, 2013). For Ireland, where data gaps arise from frequent and persistent clouds, O'Connor *et al.* (2013) showed that such gaps in data can be addressed by compositing clear images over a temporal period of 10 days (for MERIS data). The authors report, however, that longer compositing periods to maximise the cloud-free area might lead to a decrease in the sensitivity of the time series values in capturing changes in vegetation growth.

Different gap-filling techniques are also reported to introduce larger biases in data with long and continuous gaps mostly caused by cloud cover in the rainy season or snow in winter (Liu *et al.*, 2017). In such cases, the use of different satellite sensors together might be able to take advantage of different pass times and repetivity to provide a denser time series (Misra *et al.*, 2014). The Landsat-8 (30 m) in particular can provide a consistent time series with high spatial resolution and improved parameters, such as masking for clouds, atmospheric corrections and high geometric accuracies (Claverie *et al.*, 2018). Notably, use of Landsat-8 and Sentinel-2 together can provide, on average, a 33% higher data density (on account of a 25% decrease in revisit period) than the use of Sentinel-2 alone (Claverie *et al.*, 2018).

Errors associated with the estimated LSP can also be attributed to the mixing of land classes in a coarse-resolution satellite pixel (Misra *et al.*, 2018). LSP studies at the Irish scale have in the past mostly used coarse-resolution satellite data, i.e. from AVHRR (5 km), MERIS (1.2 km) or MODIS (250 m) (Donnelly *et al.*, 2013, 2018). These studies established the need to use higher spatial resolution satellite data to estimate phenological metrics. In a fragmented landscape, such as Ireland, the use of high spatial resolution data, such as Landsat-8 and Sentinel-2 data, is therefore of utmost importance.

2.1.7 Conclusions

LSP studies have benefited immensely from extensive phenological networks established over the years (both ground- and phenocam-based), access to data with improved spatial and temporal resolution, and low-cost or free satellite data and advanced computing facilities. However, it is necessary to establish standardised protocols for the processing of data. It is also critical to assign ecological meanings to LSP metrics (half amplitude, 10% of amplitude, point of inflection, etc.) obtained from satellite time series data and correctly associate them with corresponding observations of phenology on the ground. There are also opportunities to extend the findings from long-term satellite data archives (such as AVHRR, Landsat and MODIS) for aiding, and also improving, phenological estimates from newer satellites, such as Sentinel-2 (which has additional spectral bands and improved spatial and temporal resolution), and phenocams (for close-range remote sensing).

2.2 Methods for Studying Biotic Interactions in Phenological Analyses

The version of record of this research/manuscript was published in 2021 (de la Torre and Holloway, 2021). Some amendments to the version of record have been made.

Shifts in the timing of phenological events such as bird migration, leaf unfolding, flowering and insect emergence, across many taxa and ecosystems, are a result of climate change. Phenological shifts depend on different factors and species-specific sensitivity to changes in meteorological variables. Therefore, when phenological events shift within the trophic network, we might expect phenological mismatches between interlinked species to occur as a result of climate change, with potential negative effects for biodiversity and ecosystems. However, data that show how species interactions are affected by climate change are scarce, and there is still a lack of unified criteria on the methodologies for studying phenology and biotic interactions.

Most research to date has focused on evaluating the effect of mismatches in phenological events due to changes in abiotic environmental conditions, mostly on two-way interactions such as predator–prey (Visser *et al.*, 2006; Reed *et al.*, 2013; Mayor *et al.*, 2017) and herbivore–plant (McKinney *et al.*, 2012; Burkle *et al.*, 2013; de Souza Laurindo *et al.*, 2017). However, given the complexity of the food network and the implications of phenological mismatches for ecosystem functioning, research addressing how climate change influences a network of complex interactions among various species is needed (Visser, 2016). Given that environmental changes operate differently at species, organism and group scales, and that impacts may spread over the whole interaction network, there remains a need to investigate how climate change affects phenological interactions across species.

Moreover, biotic interactions have been relatively neglected in phenology research, despite the important role they play in life cycle events. There are a number of issues when studying biotic interactions in phenology. First, there is a lack of knowledge and information about the biology of countless species that is necessary when studying interactions. Furthermore, when there is information available, there is often a lack of replication, which makes it difficult to extrapolate the obtained results and methodologies used in other cases (Baselga and Araujo, 2009). The high complexity of biotic interactions makes it difficult to model them statistically, and they are typically parameterised in models as proxies of presence and absence of interactor partners (Palacio and Girini, 2018). In addition, many interactions are unknown, as associations between interactors are not always obvious, which hinders evaluation of biotic interactions for many species (Atauchi, 2018). Figure 2.2 provides a conceptual overview of some interactions among species and how these might change.

Studies addressing interactions among different trophic levels are very rare. Furthermore, interactions have typically been evaluated during only one part of the life cycle of organisms, with the assumption that interactions are static (Bateman *et al.*, 2012). There is a need to improve methodologies for the study of biotic interactions among different trophic levels, as well as to evaluate climate drivers responsible for changes

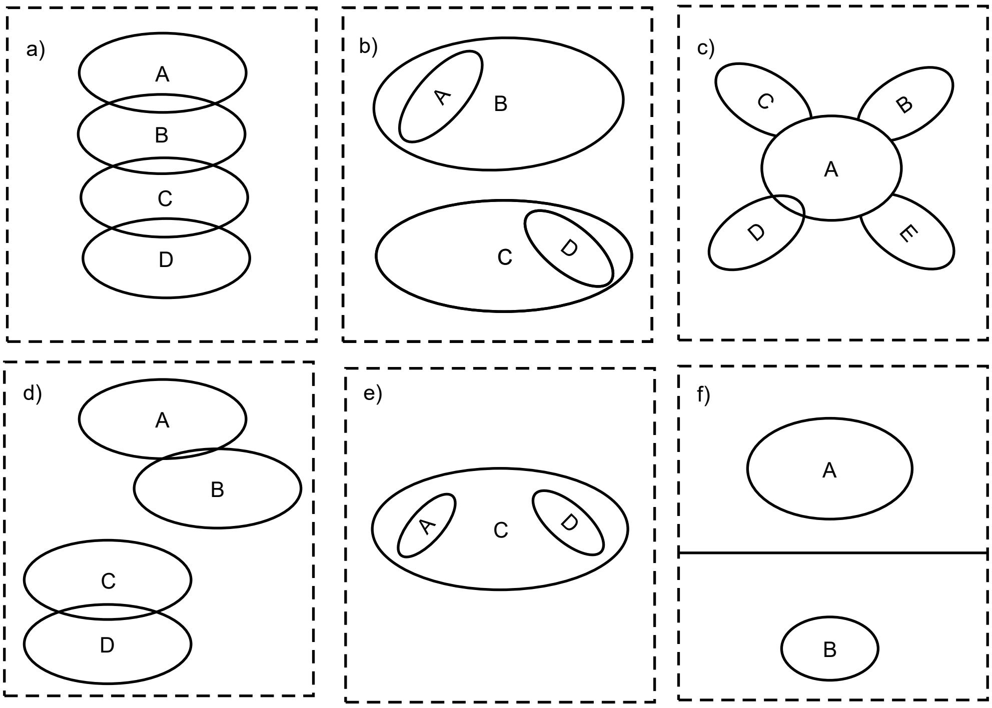


Figure 2.2. Conceptualisation of biotic interactions under normal conditions (i.e. matching phenologies) among different trophic levels (a–c) vs phenological mismatches (d–f) caused by an imbalance in the ecosystem, i.e. climate change or fragmentation. (a) Species (A, B, C, D) interaction through the trophic network, where A interacts with B, B interacts with C, and C, in turn, interacts with D. (b) Representation of obligated interactions (A+B) and (C+D), where species A depends on B, and species D depends on C. (c) Species A favouring the occurrence of species B, C, D and E through facilitation, under favourable conditions or a particular stage of its ontogeny, by providing nutrients, refugia or resources. (d) Interaction decoupling as C and D advanced their phenology while B delayed it and A remained constant as result of a perturbation (i.e. temperature rise). (e) A+B interaction lost after a perturbation (i.e. habitat modification or climate change); hence, A now depends on C, exerting pressure on both C and D. (f) Facilitation turned into competition, during which A excluded all species and reduced available space for B through competition. Reproduced from de la Torre Cerro and Holloway (2021).

in phenology that could modify, disrupt or decouple biotic interactions at different levels and scales. As part of this project, we undertook an extensive literature review (de la Torre Cerro and Holloway, 2021) on the topic, which allowed the identification of four broad categories of studies that have explored biotic interactions within phenology research, and revealed that phenological studies of seasons other than spring are very scarce.

2.2.1 Spatial and temporal asynchronies

Studies have used historical records of species' phenological events monitored over time together with spatially and temporally explicit records of abiotic parameters, such as temperature and precipitation. Most studies using historical datasets focus on monitoring changes in phenology of a single species or a group of species that are usually linked through the trophic network (Jones and Creswell, 2010; Dunn and Møller, 2014). O'Neill *et al*. (2012) used citizen science records of moths in Ireland to evaluate differences in flight periods from 1974 to 2000, concluding that most species' phenology had advanced over the study period and been positively related to the increase in temperatures in Ireland. Similarly, interannual fluctuations in bird migration have been documented in relation to decades of variation in temperatures in both wintering grounds and spring breeding areas (Gordo and Sanz, 2006). Furthermore, changes in migrant birds' arrival, laying dates and population dynamics have also been related to variation in temperature and precipitation by using datasets of arrival dates and abiotic parameters (Jones and Creswell, 2010; Dunn and Møller, 2014). However, most of these studies rely on the assumption that earlier arrival to breeding grounds will result in the mismatch of interactions, which are not evaluated or quantified in any way.

Studies using such datasets have generally focused only on spring phenology, such as leaf unfolding and flowering for plants and date of emergence for insects (Visser *et al*., 2006; Primack *et al*., 2009; O'Neill *et al*., 2012); studies addressing autumn phenology are scarce (Gordo and Sanz, 2005, 2006; Gallinat *et al*., 2015). Although evidence of advanced spring phenology is widespread (Hegland *et al*., 2009; O'Neill *et al*., 2012; Phillimore *et al*., 2016), this trend is unclear for autumn phenology, being mainly associated with interannual meteorological oscillations, although lack of comparative studies makes it difficult to discriminate patterns during this season (Gordo and Sanz, 2005). Neglecting the study of biotic interactions throughout the year can lead to unexpected loss of these interactions and failure to preserve them and their functions in the ecosystems in present and future climate change scenarios.

2.2.2 Biotic factors as covariates

Despite their relevance, biotic factors have been relatively neglected in phenological studies, particularly when compared with the historical use of abiotic drivers (Thackeray *et al*., 2016; Wolf *et al*., 2017); however, studies have begun to incorporate them as additional explanatory variables or covariates in statistical models. Research has tended to focus on interactions through the trophic network rather than evaluating competitive or facilitative interactions (Austin, 2007). In these studies, there is still a marked importance of abiotic factors, typically testing several climate change drivers (i.e. factors such as temperature increase and nutrient enrichment) on specialised trophic interactions (Lu *et al*., 2013). In a recent study, Terraube *et al*. (2017) showed the importance of climate factors and forest management on the foraging success of an owl species by using field data and generalised linear mixed models. The authors documented a trend of decreased prey biomass stored in nests related to increasing rainy days and days with frost, which, in turn, is expected to affect the biomass and fitness of the target owl species. Similarly, in a study by de Souza Laurindo *et al*. (2017), environmental conditions, such as rainfall and temperature, and biotic factors, such as fruit availability, were studied to determine abundance of bats in a plant–bat network. By using generalised linear models (GLMs), the authors showed that abiotic conditions influenced fruit availability, which, in turn, determined the number of interactions, whereas both abiotic and biotic factors explained bat abundance.

Despite these advancements, such studies lack any direct measurement of biotic interactions. For example, Merrill *et al*. (2008) documented contraction of the distributional range of a butterfly related to elevation in its lower distributional limit and to the lack of host plants in its upper limit. Because the target butterfly needed the presence of any of the host plants for completing different stages of its life cycle, the lack of host plants at higher elevations was presented as responsible for the butterfly's upper limit, despite there being no direct measurement of its biotic interaction. For example, Martin and Maron (2012) tested the effect of reduction in snow cover, given a 25-year period of snowfall decline, as a factor influencing bird and plant population declines through increased herbivory and nest predation. The authors studied changes in plant assemblages for herbivory-prohibited (i.e. simulated snow cover) and herbivory-exposed sites, finding that reduction in snow cover exposed plant assemblages to higher herbivory pressure, leading to declines in bird populations due to increased nest predation. However, an increase in plant and bird populations (including a reduced nest predation) was documented in herbivory-prohibited areas. Although this study tested for herbivory, plant host and predation interactions indirectly, none of these interactions was modelled or statistically tested. In addition, although most of these studies include environmental variables, given the scale and dimension of these open mesocosm experiments, there might be environmental variables that are not considered and could explain some of the statistical variation found in them (Wolf *et al*., 2017).

Conversely, there is usually a lack of spatial and temporal replication in most of the studies, meaning that, even when biotic interactions are statistically supported to be one of the main explanatory variables within a system, the lack of temporal replication of these studies and the scarcity of comparative ones might lead to misinterpretations. For example, Theobald *et al*. (2016) showed the importance of pollinator-mediated pollination of a montane plant and tried to investigate the role of pollinators in the range limit of the plant, demonstrating the importance of different pollinator groups for reproductive success. However, it was not possible to separate results on range limitation from plant interannual variations. Furthermore, some studies evaluate small populations, but small sample sizes might mask the effect of other possible factors and lead to erroneous interpretations (Post and Forchhammer, 2008). In addition, most of the studies address spring phenological events, monitoring weather conditions during the growing season and neglecting winter climate change conditions that are of great importance for the phenology of plant and pollinators (Makoto *et al*., 2014).

2.2.3 Simulation models

Studies use simulation models to project the effect of changes in abiotic or biotic parameters on phenological events or interactions. Simulation models employ a wide array of algorithms, so there are different types of models that can be used to evaluate changes in the response variable of interest, such as co-occurrence of interactor species to test for the importance of phenology on pollination interactions (CaraDonna *et al*., 2017), the role of plant–pollinator synchrony in community assemblages (Bartomeus *et al*., 2013) and the role of changing phenology in population trends (Dunn and Møller, 2014). Although modelling ecological responses under projected abiotic parameters is common, in very few published studies is the main topic the simulation of phenological events or biotic interactions (Cormont *et al*., 2013; Olito and Fox, 2015; Schleuning *et al*., 2016; Graham and Weinstein, 2018); in most cases, studies show high similarity to species distribution models. However, simulation models have been used as additional tools to support findings and make predictions in field studies or studies using historical datasets (Visser *et al*., 2006; Bartomeus *et al*., 2013; Dunn and Møller, 2014). Such studies have frequently used species extinction or survival models, fitness simulation models, generalised additive models, envelope models, ecological niche models or network models.

However useful this methodology is, these studies face similar challenges, such as the lack of robust data on interaction networks, which are undersampled, and sensitivity to the lack of knowledge about rare interactions (Olito and Fox, 2015). Recent approaches in this direction have shown that simulation models can be used to predict the probability of detecting pairwise biotic interactions. Using data of occurrence and detectability of species, the probability of interactions and connectivity of interaction networks can be estimated (Graham and Weinstein, 2018). Furthermore, variable selection for predictive models is a determinant factor that can lead to misinterpretation of ecological processes and to erroneous predictions. Most studies use mainly one or two variables for similar species, or variables from previous studies that may not be suitable for studies for different areas or for modelling different species (Van de Pol *et al*., 2016). Thus, Holloway *et al*. (2018) used a novel machine-learning approach with decision tree algorithms to show the importance of adequate meteorological parameter selection and the relevance of using appropriate temporal scales of abiotic parameters to predict phenological events. The use of machine learning can significantly increase the accuracy of predictions of phenological events and improve models by identifying meteorological variables that improve accuracy. However, availability of adequate datasets would be a limiting factor in this approach (Holloway *et al*., 2018).

2.2.4 Interaction indices

Interaction indices have been used to measure the degree of interaction among species, with research focusing on synchrony among interactor species (Donoso *et al*., 2016; Oleques *et al*., 2017), interactions within communities (Buxton *et al*., 2016; Molina-Venegas *et al*., 2016; Oliver *et al*., 2018) and interactions as a network (Junker *et al*., 2013; Robinson *et al*., 2018). For example, Buxton *et al*. (2016) developed a new index to monitor spring and winter phenology of songbirds. By placing acoustic recorders in the field and developing a novel acoustic index, they were able to identify changes in the acoustic landscape due to the arrival of migrant birds, showing that acoustic recorders are an important tool for the study of phenological events at large scales. Studies have begun to include Euclidean distance (Junker *et al*., 2013), beta diversity (Buxton *et al*., 2016) and species traits (Benadi *et al*., 2014) in such interaction indices, but there remains a lack of consideration of climate variables, despite the strong role that abiotic conditions play in phenology.

2.2.5 Conceptual and methodological framework

Phenology has developed within disparate fields, meaning there has been a wide variety of viewpoints on how to address this phenomenon (Visser *et al*., 2010; Pau *et al*., 2011). Moreover, biotic interactions are complex; they change over time, assemble and decouple by processes such as turnover, and depend on many factors such as modularity (strength of sets of interactions), climate change, local extinctions and the presence of invasive species (Schweiger *et al*., 2010; Schleuning *et al*., 2016; CaraDonna *et al*., 2017; Morente-López *et al*., 2018). In addition, interaction type, strength and effect (positive or negative) are expected to vary with species ontogeny (development of organisms within their lifespan); for example, herbivores can turn into pollinators or alternate between predation and competition. Thus, including the broad scope of interactions within the lifespan of species would be more accurate than focusing on seasonal interactions (Yang and Rudolf, 2010). Despite some efforts to provide frameworks for the study of phenology (Visser *et al*., 2010) and the shifts of phenology-ontogeny (Yang and Rudolf, 2010), there is a need to define a common framework for research addressing biotic interactions within phenology. Here, a framework is proposed for the inclusion of biotic interactions within phenology (Figure 2.3), apportioning this into two interconnected factions: (1) research aimed at conceptualising biotic interactions and (2) modelling biotic interactions.

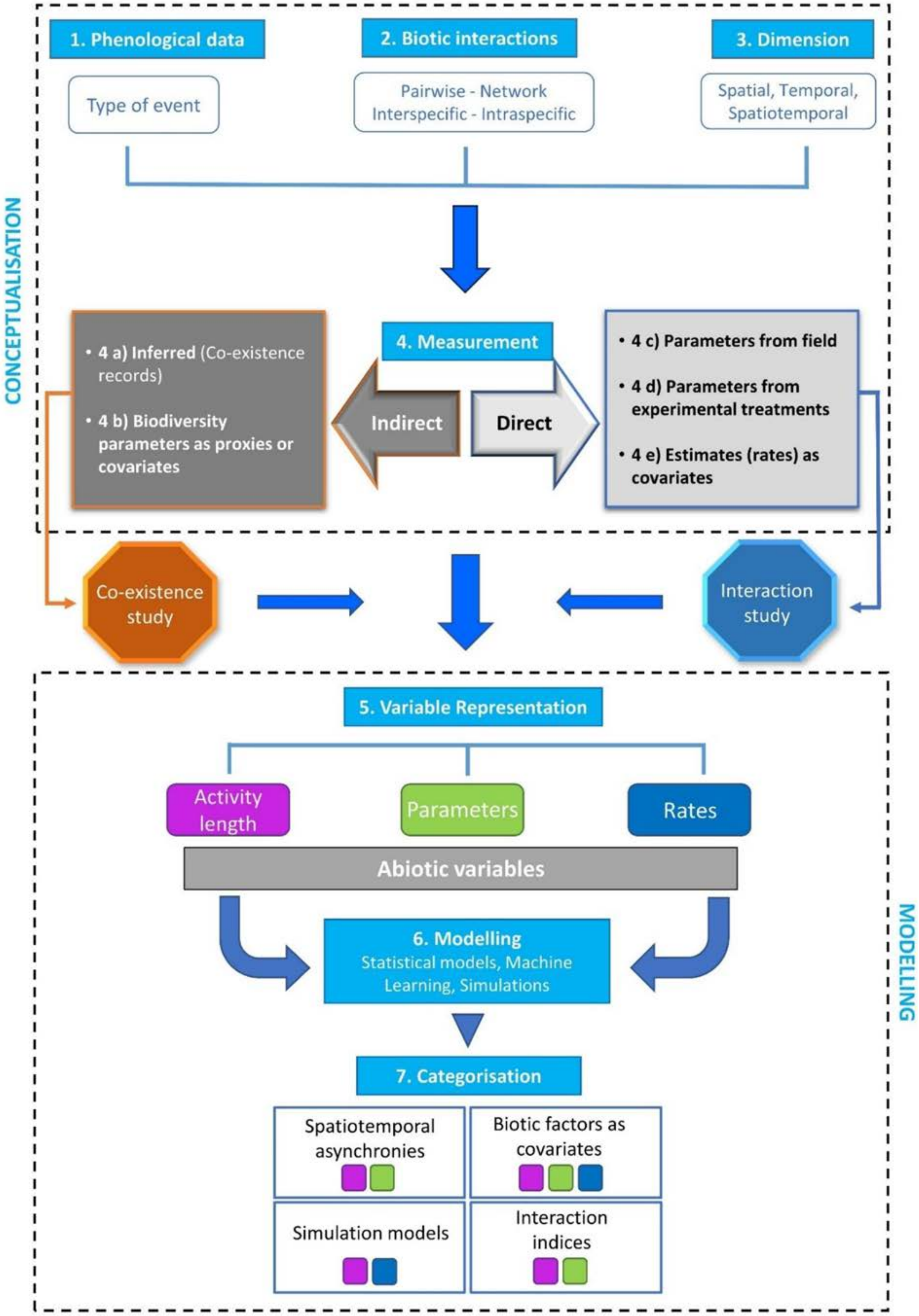


Figure 2.3. Framework illustrating the conceptualisation and modelling of biotic interactions in phenology research. Reproduced from de la Torre Cerro and Holloway (2021).

3 Impact of Climate Change on Phenology in Ireland

3.1 Changes in Irish Woodland Phenology over the Last 30 Years

3.1.1 Selection of woodland sites

To determine the impact of climate change on woodland phenology, woodlands were selected from the National Parks and Wildlife Service (NPWS) National Survey of Native Woodlands (https://data.gov.ie/dataset/national-survey-of-native-woodlands-2003-2008) and the Ancient and Long-established Woodland Inventory (https://data.gov.ie/dataset/ancient-and-long-established-woodland-inventory-2010), based on the assumption that these sites were not subjected to major changes in the type of vegetation or management approaches during the study period (1990–2018). The intersection of the surveyed polygons resulted in areas with known species cover and 100% tree cover. In total, 1365 polygons with predominantly deciduous woodland were retrieved by this process and used in further analyses (Figure 3.1).

3.1.2 Temperature and precipitation change across Ireland

Met Éireann Re-Analysis (MÉRA) climate data were analysed for trends in climate during the study period (1990–2018) across Ireland. Minimum temperature (T_{min}), maximum temperature (T_{max}) and precipitation data were transformed from the native .grd files to GeoTiffs. The climate variables were then aggregated based on a 3-month window preceding the median phenology dates calculated from Landsat: February, March and April (for pre SOS); April, May and June (for pre-POP); and July, August and September (for pre-EOS). While such pre-season time windows are frequently chosen in phenological research, the sliding

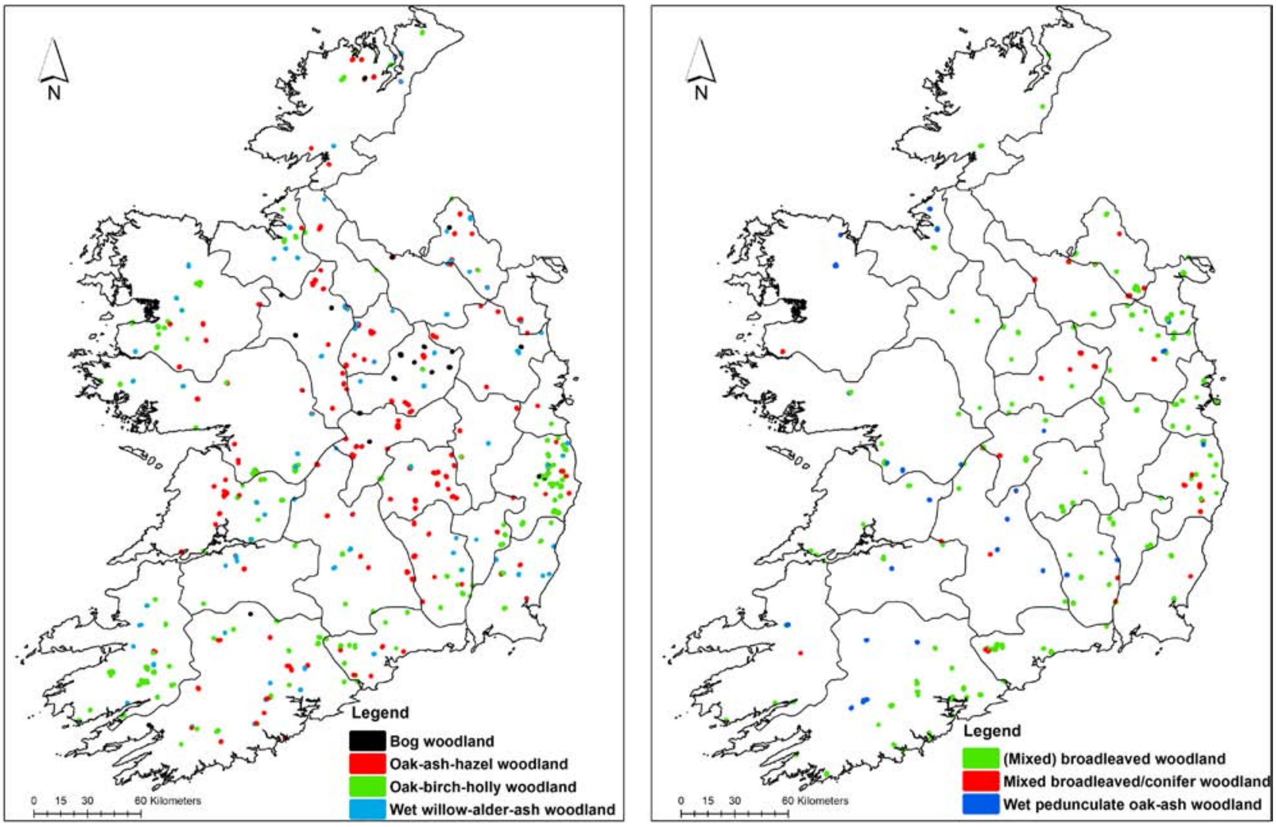


Figure 3.1. Intersecting sites selected from the NPWS National Survey of Native Woodlands and the Ancient and Long-established Woodland Inventory.

time window analysis in section 3.2 showed that sensitivity can be greater to climatic drivers that lie further back in time.

The trend maps of seasonal temperatures reveal a significant decrease in both the $T_{\min}$ (Figure 3.2) and precipitation (Figure 3.3) preceding the SOS for most of Ireland. Precipitation change was seasonally and regionally variable, but a recent EPA report (Cámaro García *et al*., 2021) reported an overall increase in precipitation in the 30-year period from 1989 to 2018 compared with the previous 30 years. However, a significant increase in $T_{\max}$ preceding the POP (Figure 3.4) was observed for the majority of Ireland, except the south-western part. In the months preceding EOS, $T_{\max}$ increased significantly along the eastern coast (Figure 3.4).

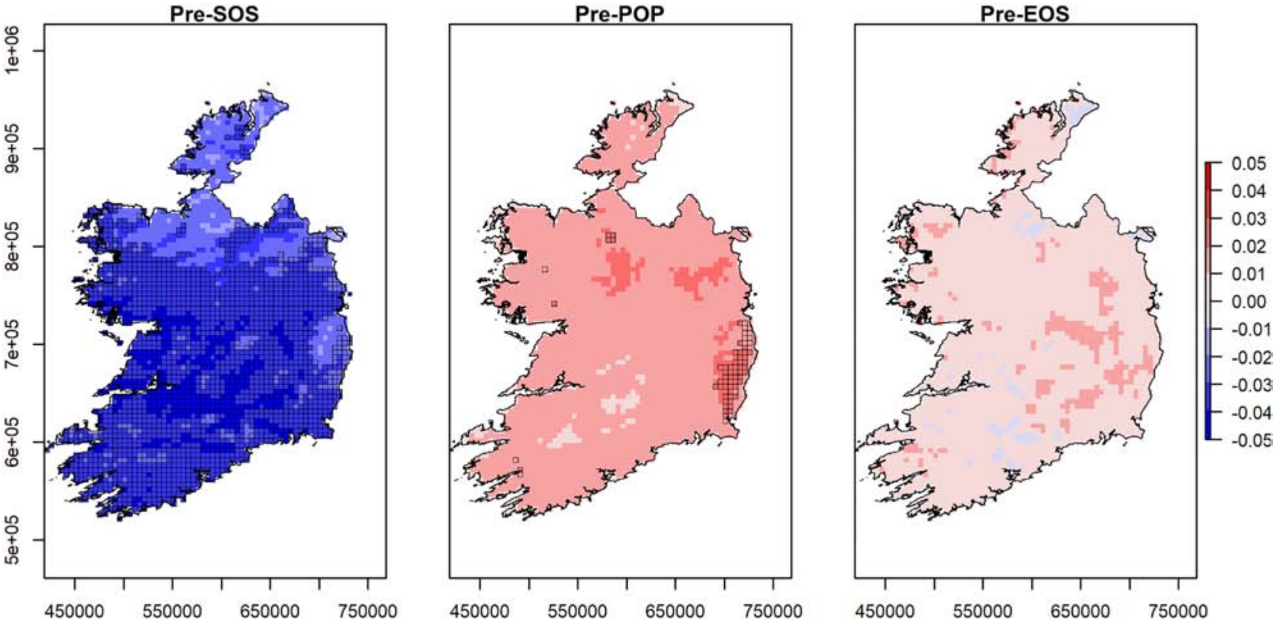


Figure 3.2. Trends (°C/year) in aggregated $T_{\min}$ values during the period 1990–2018. Black borders around pixels indicate pixels with significant trends at $p < 0.1$.

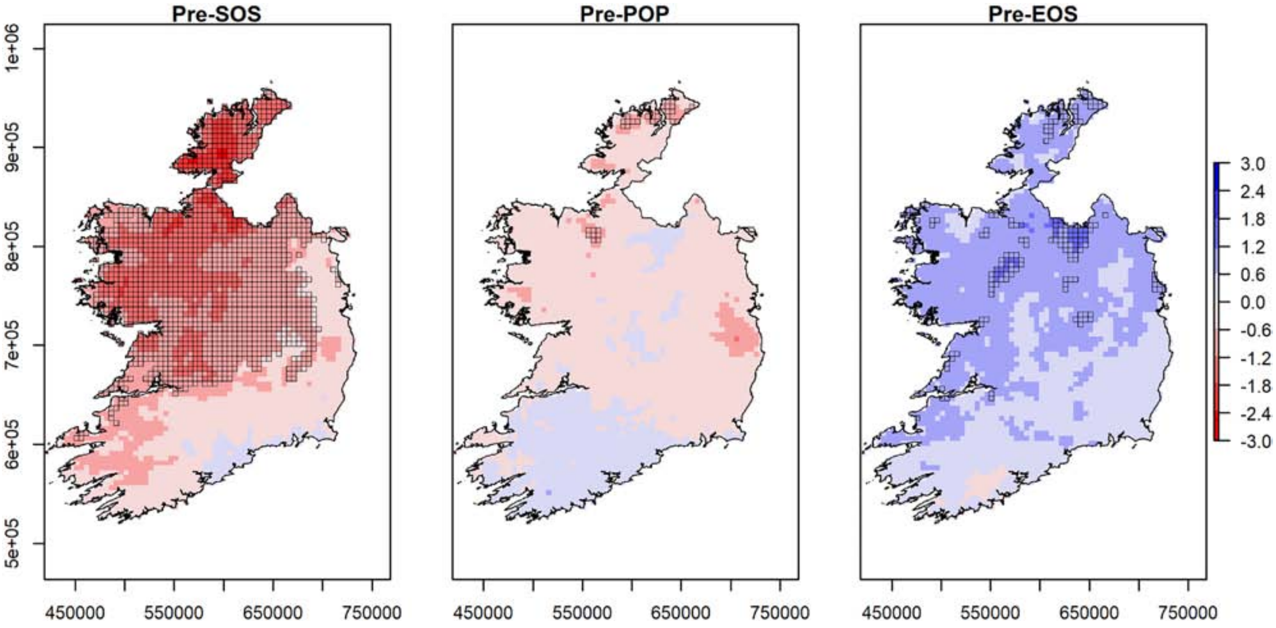


Figure 3.3. Trends (mm/year) in aggregated precipitation values during the period 1990–2018. Black borders around pixels indicate pixels with significant trends at $p < 0.1$.

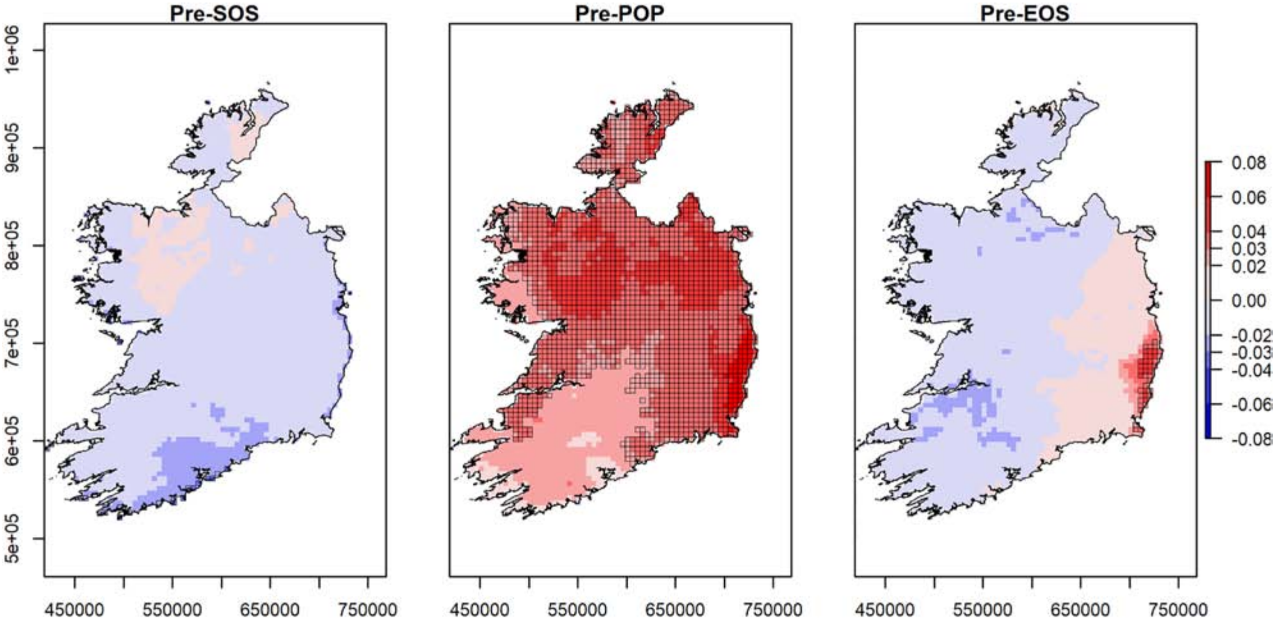


Figure 3.4. Trends (°C/year) in aggregated T_{max} values during the period 1990–2018. Black borders around pixels indicate pixels with significant trends at $p < 0.1$.

3.1.3 Use of Landsat imagery for remote sensing of woodland phenology

Changes in woodland phenology over time

Cloud and shadow-masked NDVI data from the Landsat suite of sensors were obtained from Teagasc. This NDVI dataset covered the Landsat-5 TM, Landsat-7 ETM+ and Landsat-8 OLI sensors, at 30 m resolution and every 16 days from 1990 to 2018. The mean values of NDVI were extracted for the selected woodland polygons and aggregated to monthly maximum values to reduce the impact of missing values due to cloud cover (Fensholt and Proud, 2012). Remaining missing values in the NDVI time series were subsequently filled using mean annual values (Kandasamy *et al*., 2013). Spikes in the time series data of NDVI were smoothed and interpolated to daily values using a local regression (locally estimated scatterplot smoothing – LOESS) function (Hufkens *et al*., 2019; Yuan *et al*., 2021). The SOS and EOS dates were extracted from those daily NDVI values using the half-amplitude method (Misra *et al*., 2018; White *et al*., 2009). POP was determined as the peak in the NDVI curve, and the length of season (LOS) was calculated as the difference between the estimated EOS and SOS dates.

Analysis of linear trends in woodland phenology revealed differences among the phenological metrics (SOS, POP, EOS and LOS; Figure 3.5). Of the woodland sites, 64% showed an advance in SOS, whereas a delayed POP was observed in 57% of the sites (predominantly in the eastern half of the country). The EOS advanced by 1–3 days over the study period in 55% of the woodland sites analysed, with south-western parts of the country showing a delay in EOS during the period 1990–2018. The LOS increased in over 53% of the woodlands during the same period and showed similar spatial patterns as the trends in EOS (Spearman's rank correlation coefficient of 0.77). The median trends in the estimated phenological metrics showed positive values for the POP (0.01 days per year) and negative values for the SOS and EOS dates (–0.09 and –0.07 days per year, respectively), indicating an advance in SOS and EOS, with an overall extended LOS by 0.04 days per year.

An analysis of linear trends grouped by woodland type is shown in Figure 3.6. Across all woodland types, more sites experienced an earlier SOS, in most cases of up to 1 day over the period 1990–2018, than a later SOS. Similar, negative trends (earlier start dates) are seen in the EOS dates for all woodland types except the mixed broadleaf class, which shows a delayed EOS in just over half of the sites. A clear delay in the POP dates is observed in the mixed broadleaf and oak–ash–hazel woodlands, whereas in other classes the negative and positive trends are almost equal.

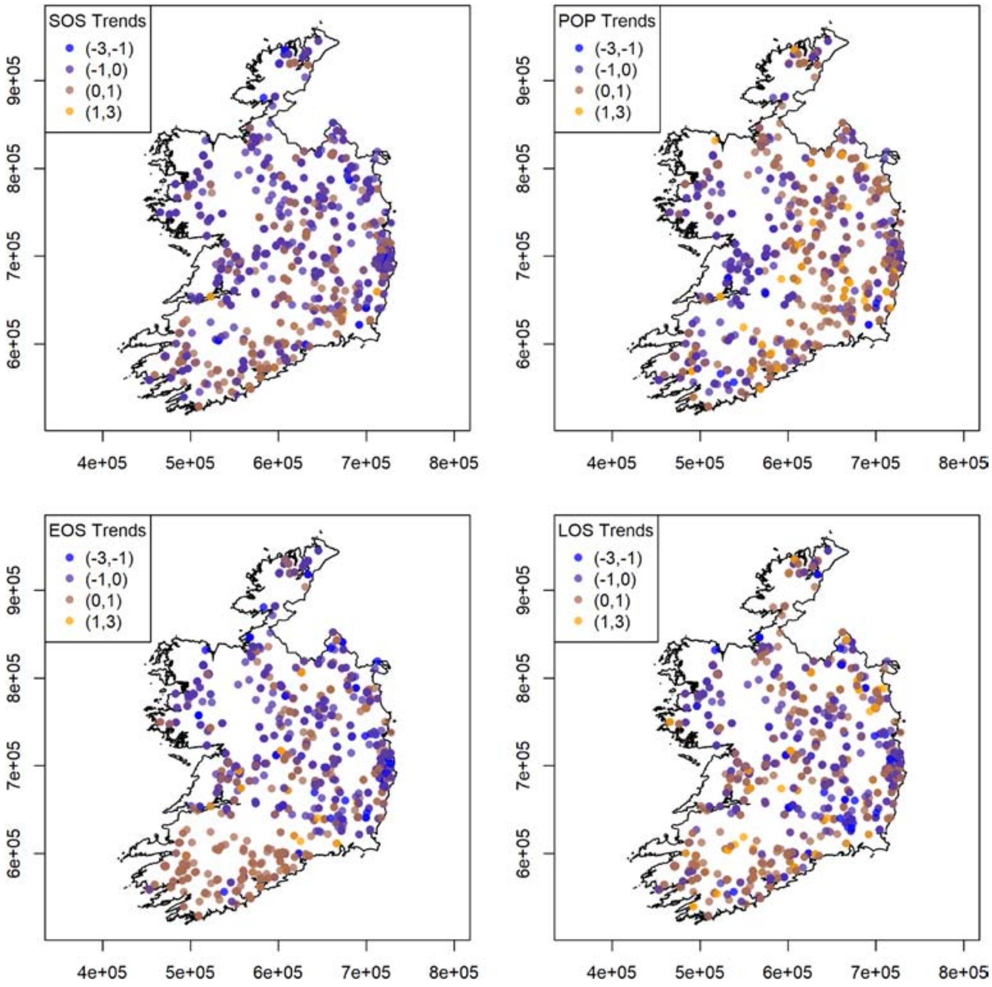


Figure 3.5. Linear trends (days/year) in woodland phenology for the period 1990–2018. (–3,–1) indicates an advance (SOS, POP, EOS) or shortening (LOS) of 1–3 days; (–1,0) an advance/shortening of 0–1 day; (0,1) a delay/lengthening of 0–1 day; and (1,3) a delay/lengthening of 1–3 days.

The calculated LOS has become longer across all woodland types with the exception of bogs.

Relationship between woodland phenology and climate change

Spearman's rank correlation analysis to determine the relationship between SOS, POP and EOS dates and climatic variables (Figure 3.7) revealed overall negative correlations of the timing of SOS and POP with temperature (T_{max} and T_{min}), indicating advances in GU during spring and in peak greenness in summer with rising temperatures. While the median correlation for EOS with the temperature parameters was also negative, autumn responses showed a larger range. Median correlations with precipitation were positive for SOS and POP (indicating later phenology with increasing precipitation), but negative for EOS (indicating earlier phenology with increasing precipitation). However, the responses varied widely among the woodland sites, and it is not clear if trends are caused by precipitation itself or a change in cloudiness.

The average SOS for all the woodland sites considered reveals a –1.18 days per °C sensitivity to mean temperature for the period 1990–2018. The number of polygons with significant correlations of phenology and climate variables is presented in Table 3.1 to illustrate the variation in the observed correlation strengths for different woodland types. The majority of phenological metrics were negatively correlated with temperature (both T_{min} and T_{max}) irrespective of the woodland type. Precipitation, on the other hand, was positively correlated with the SOS and POP, but negatively correlated with the EOS.

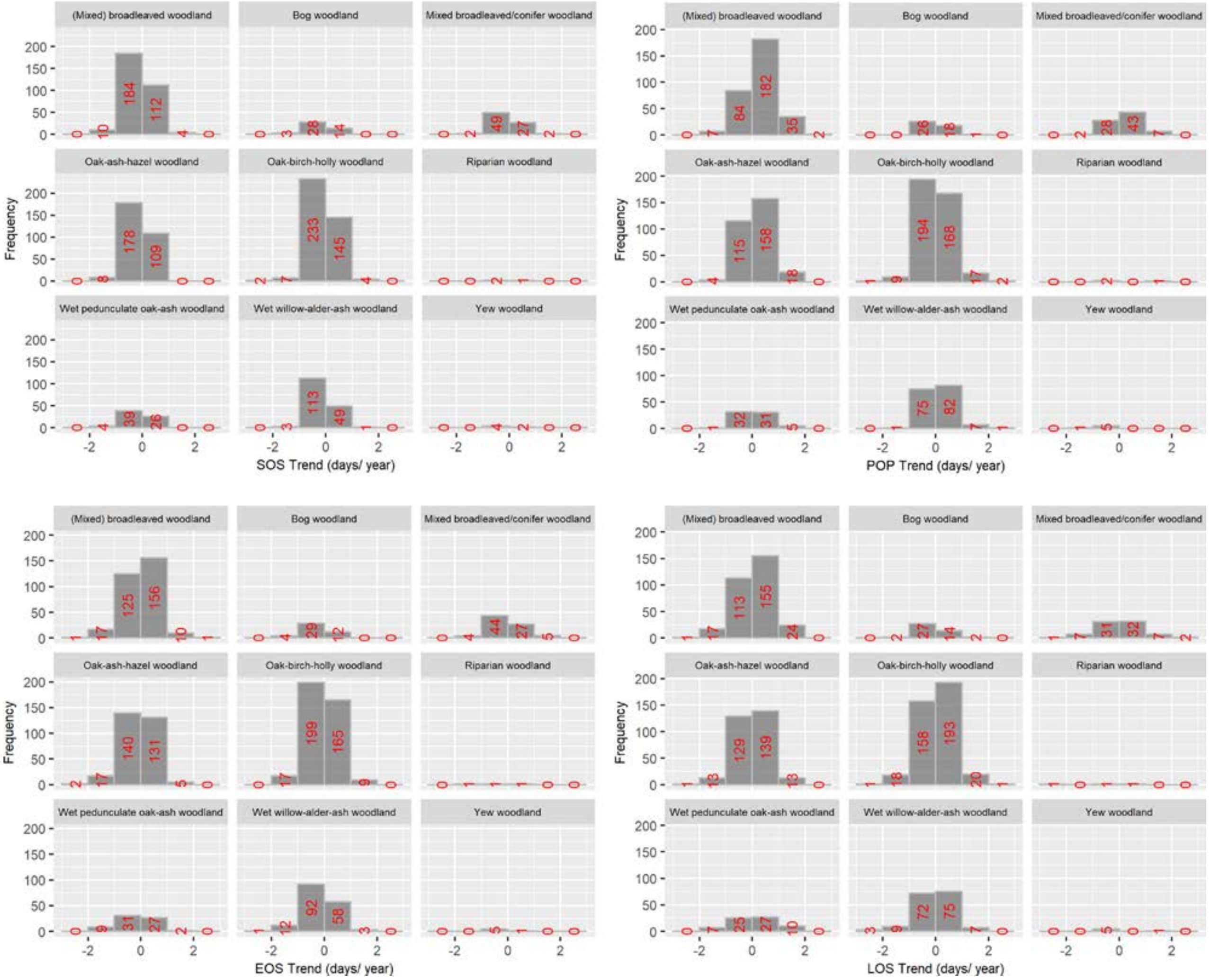


Figure 3.6. Phenological trends grouped by woodland type showing the number (frequency) of woodland polygons with negative (earlier dates, shorter LOS) or positive (later dates, extended LOS) trends.

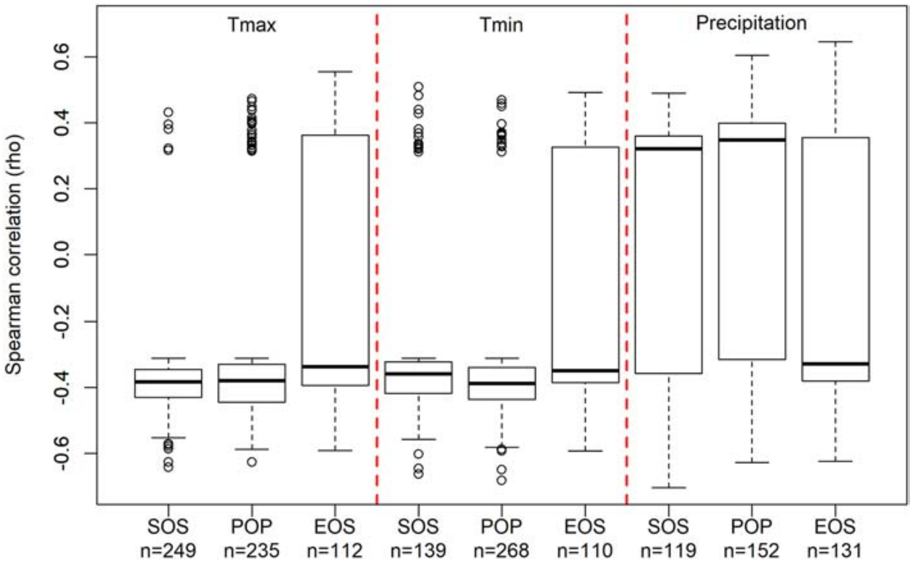


Figure 3.7. Spearman's rank correlation coefficients (rho) between phenological metrics (SOS, POP and EOS) from Landsat and climate variables (T_{max}, T_{min} and precipitation). The *n* variable in the *x*-axis shows the number of sites with significant correlations ($p < 0.1$) that were included.

Table 3.1. Number of woodland polygons with significant Spearman's rank correlation coefficients ($p < 0.1$) with climate variables during the period 1990–2018

	T_{min}						T_{max}					Precipitation						
	SOS		POP		EOS		SOS		POP		EOS	SOS		POP		EOS		
Woodland type	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
(Mixed) broadleaved ($n = 310$)	6	27	0	40	6	14	2	60	4	40	5	20	12	15	37	4	17	16
Bog ($n = 45$)	1	1	0	7	0	3	0	4	1	4	0	4	2	1	7	1	2	2
Mixed broadleaved/conifer ($n = 80$)	2	1	1	3	1	2	0	10	3	2	0	2	4	1	6	0	1	14
Oak–ash–hazel ($n = 295$)	1	20	4	58	6	27	0	49	3	51	9	25	22	5	22	8	8	7
Oak–birch–holly ($n = 391$)	4	45	6	88	10	24	2	70	9	65	15	8	11	26	18	15	7	23
Riparian ($n = 3$)	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2	0	0	0
Wet pedunculate oak–ash ($n = 69$)	1	7	2	17	1	3	0	18	2	16	3	2	4	1	6	2	5	5
Wet willow–alder–ash ($n = 166$)	2	21	3	37	10	3	1	32	2	32	14	3	10	4	13	10	9	14
Yew ($n = 6$)	0	0	0	2	0	0	0	1	0	1	1	0	0	0	0	1	0	1
Total	17	122	16	252	34	76	5	244	24	211	47	65	65	54	111	41	49	82

3.2 Using Citizen Science for Monitoring Phenology across Species

In a review of interactions in phenology, de la Torre Cerro and Holloway (2021) outlined a conceptual and methodological framework for incorporating interaction and/or co-existence into phenology. To date, there has been a lack of a unified methodology to study phenology within biotic interaction or co-existence studies, which hinders efforts to compare the effect of climate drivers among organisms and systems at spatial and temporal scales. Here, this framework is applied to use time series of co-existence records, as a proxy for possible species interactions, to model the synchrony of phenological events of species that are linked through the trophic network, while also including a high-resolution meteorological dimension. In this sense, the term climate is used here as a broad term and includes all the meteorological variables; when referring to climate change, the term meteorological driver (or variable) is used in this study, as there is a general consensus among researchers that at least 30 years of data are needed to analyse climate change. Four main questions are addressed:

1. How has phenology varied over the period of study across four groups of species and three trophic levels in Ireland?
2. What are the important meteorological drivers for phenological events for these species and groups of species within the study area?
3. Do these meteorological drivers and their critical time windows differ over a 10-year period?
4. Are windows of co-existence altering/changing across the trophic levels?

In answering the last question, a novel interaction index was developed that accounts for phenological events across multiple species and includes the impact of climate.

3.2.1 Phenological variation among species and groups of species between 2008 and 2018

Citizen science data were obtained from MothsIreland (http://www.mothsireland.com; moths), the National Biodiversity Data Centre (https://biodiversityireland.ie; butterflies), and eBird (https://ebird.org/; birds) and BirdTrack (https://www.bto.org/our-science/projects/birdtrack), while woodland vegetation GU was determined from Landsat imagery (in the same way as SOS in section 3.1.3).

Phenological trends were evaluated in 30 species interlinked through the trophic network; species names and codes are shown in Table 3.2. There was high variability in the timing of first flight (FF), date

Table 3.2. List of species studied shown by group; the common name of each species and the code each species or vegetation group is given

Species/group name	Code
Vegetation	
Bog woodland	BW
Mixed broadleaved/conifer woodland	MBC
(Mixed) broadleaved woodland	MBW
Oak–ash–hazel woodland	OAH
Oak–birch–holly woodland	OBH
Wet pedunculate oak–ash woodland	WOA
Wet willow–alder–ash woodland	WAA
Migrant birds	
Barn swallow	BS
Greater whitethroat	GW
Northern wheatear	NW
Sedge warbler	SW
Willow warbler	WW
Butterfly	
Green veined white	GVW
Large white	LW
Meadow brown	MB
Peacock	PC
Red admiral	RA
Ringlet	RI
Small tortoiseshell	ST
Small white	SMW
Speckled wood	SPW
Moth	
Brimstone moth	BM
Common marbled carpet	CMC
Dark arches	DA
Early thorn	ET
Flame shoulder	FS
Heart and dart	HD
Large yellow	LY
Small square	SS
White ermine	WE

of arrival (DA) and GU between 2008 and 2018 for all groups of species. Nonetheless, some trends can be distinguished within groups. For example, in the case of moths, for five out of nine species, FF took place between days 120 and 140 (Figure 3.8a). FF among butterfly species was more variable; five out of nine species showed median FF before day 100, and six species showed similar median FF values over the 11 years of study, but their interannual FF values varied considerably (Figure 3.8b). In the case of birds, barn swallow and northern wheatear showed an early spring arrival, while greater whitethroat and sedge warbler showed arrivals later in the spring (Figure 3.8c). Three species – willow warbler, sedge warbler and greater whitethroat – presented a low median DA value. In the case of vegetation, GU dates showed the greatest variation over the study period, while mean dates were close for four out of seven groups of vegetation (Figure 3.8d). The vegetation groups that showed lower variation in their GU dates over the study period were oak–ash–hazel woodland and oak–birch–holly woodland, while mixed broadleaved/conifer woodland and wet willow–alder–ash woodland GU days varied the most.

3.2.2 *Meteorological drivers of importance for phenological events*

We performed a sliding time window analysis using the climwin package in R (Van de Pol *et al*., 2016) to analyse the importance of the meteorological drivers. This is a regression-based method that identifies the critical time window in which a particular driver explains a higher variation in the phenological

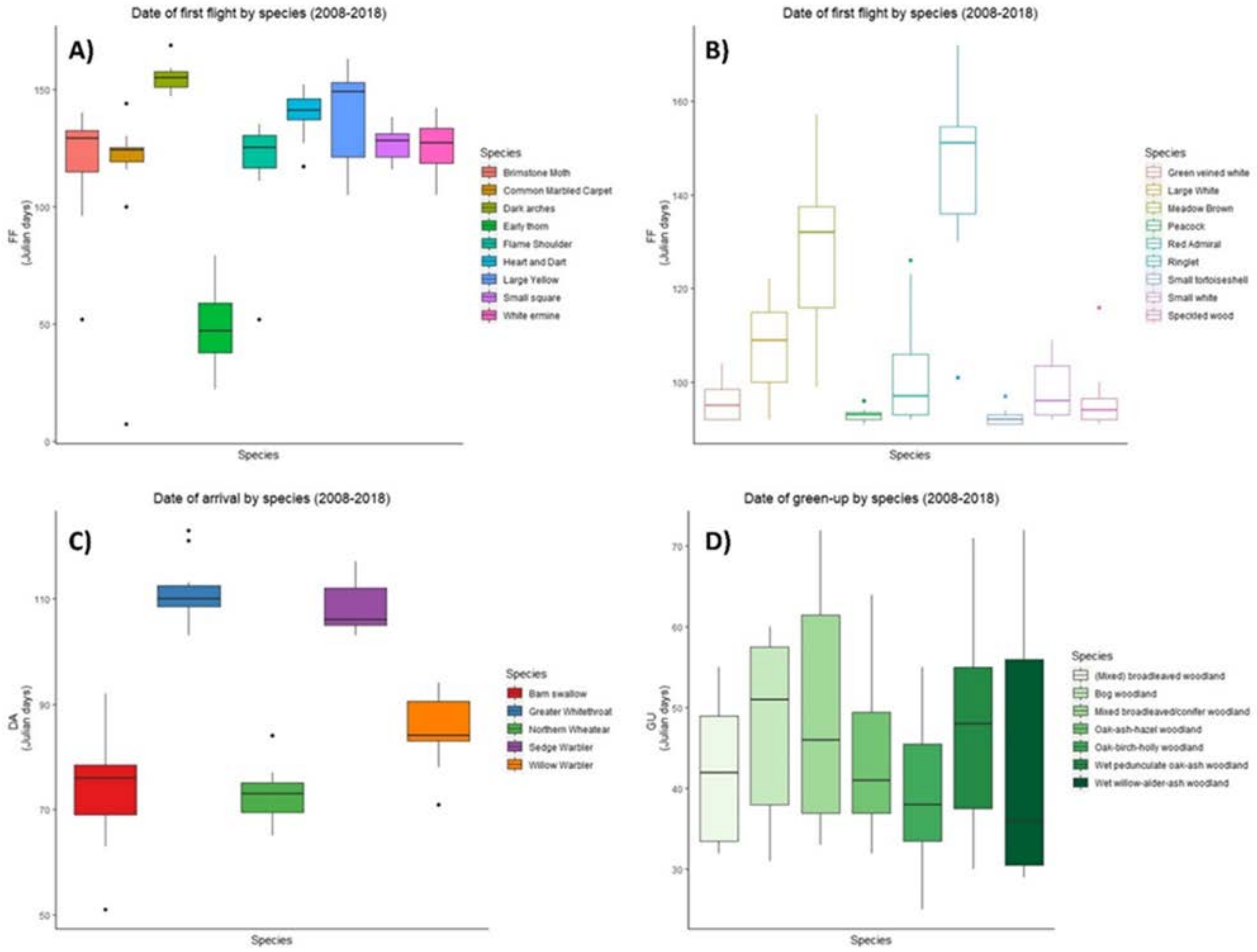


Figure 3.8. FF date for moths (A) and butterflies (B), date of arrival of migrant birds (C) and GU dates (D) for the period 2008–2018 at the national level in Ireland. The *x*-axis represents each species within groups; the *y*-axis represents the day of the year, in ordinal number, on which the events took place. Boxes represent the range of values, with a horizontal line showing the median value for each range. Species within each group are represented by different colours, as shown in the keys.

event. Our models showed that the timing in which species and groups were most influenced by the meteorological drivers (T_{min}, T_{max}, total precipitation – TPPT) varied over the study. In the case of vegetation, all three meteorological variables showed relevant climate signal on the time windows across all seven types of vegetation, and the corrected *p*-value (p_c) showed a significant effect across drivers and windows ($p_c < 0.05$), as illustrated by the case of oak–ash–hazel woodland in Table 3.3. Model coefficients showed, in general terms, a negative relationship between increased T_{max}, T_{min} and TPPT and GU dates. We found that model coefficients showed a general negative relationship between all three drivers and GU, being particularly negative for T_{max} and T_{min}, while the coefficients were lower for TPPT. These negative coefficients were often related to time windows happening further in the past, while in rare cases we found low positive relationships between TPPT and GU, and this generally occurred when time windows were closer to GU.

3.2.3 Variation in the time windows of species and groups over 10 years

When plotting earliest FF, DA and GU of each species against their yearly time windows (in Julian days), the interannual variability within species in their sensitivity to each meteorological driver is visible. We parameterised models exploring meteorological variable sensitivity up to 180 days preceding the phenological event. Through this method, climwin can establish the time window that explains a higher variation in the phenological event or, in other words, which weather conditions over a specific time period (e.g. 1, 2 or 3 weeks prior) can be suggested as driving the phenological event in question. At the group level, for migrant birds both temperature windows were frequently located within the same year, while precipitation time windows were more frequently distributed within the year preceding DA. For example, in the case of the barn swallow, while T_{min} time windows mainly fell within the same year as DA (9 out of 11 years), precipitation time windows showed marked interannual variability, with precipitation of the preceding year relevant to DA in six years (Figure 3.9). In the case of butterflies and moths, some common trends can be established: best time windows for T_{min} were usually closer to the FF date, while this trend blurred for T_{max} windows, as at the species scale some presented longer T_{max} time windows in which window open spanned to the preceding year. This pattern is also shown in a few other species (e.g. red admiral, small tortoiseshell, white ermine). By contrast, in the

Table 3.3. Climwin results for oak–ash–hazel woodland showing yearly time windows in which GU was most influenced by the meteorological variables

			T_{min}		T_{max}		TPPT	
Year	***N*[a]**	**GU[b]**	**W Open[c]**	**W Close[d]**	**W Open[c]**	**W Close[d]**	**W Open[c]**	**W Close[d]**
2008	129	64	168	147[e]	179	108[e]	89	56[e]
2009	129	38	165	118[e]	179	121[e]	82	42[e]
2010	129	57	175	141[e]	142	89[e]	147	96[e]
2011	129	42	175	140[e]	151	78[e]	60	1[e]
2012	129	41	179	144[e]	72	19[e]	90	57[e]
2013	129	54	15	0[e]	169	152[e]	89	49[e]
2014	129	37	177	148[e]	175	97[e]	56	6[e]
2015	129	37	46	5[e]	77	9[e]	61	33[e]
2016	129	35	178	144[e]	179	118[e]	76	12[e]
2017	129	32	180	159[e]	60.5	27[e]	29	1[e]
2018	129	45	37	7[e]	143	123[e]	92	14[e]

[a] *N* is the sample size or number of grids in which GU was measured.

[b] GU represents the day of the year in which GU took place at the national level (in ordinal date).

[c] Window (W) open reflects the day of the year (ordinal value) in which a driver started to influence the phenological event and takes place further back in time.

[d] Window (W) close (also shown in ordinal value) always takes place after window open, closer to the phenological event.

[e] Significance shown by climwin p_c-values: $p < 0.001$.

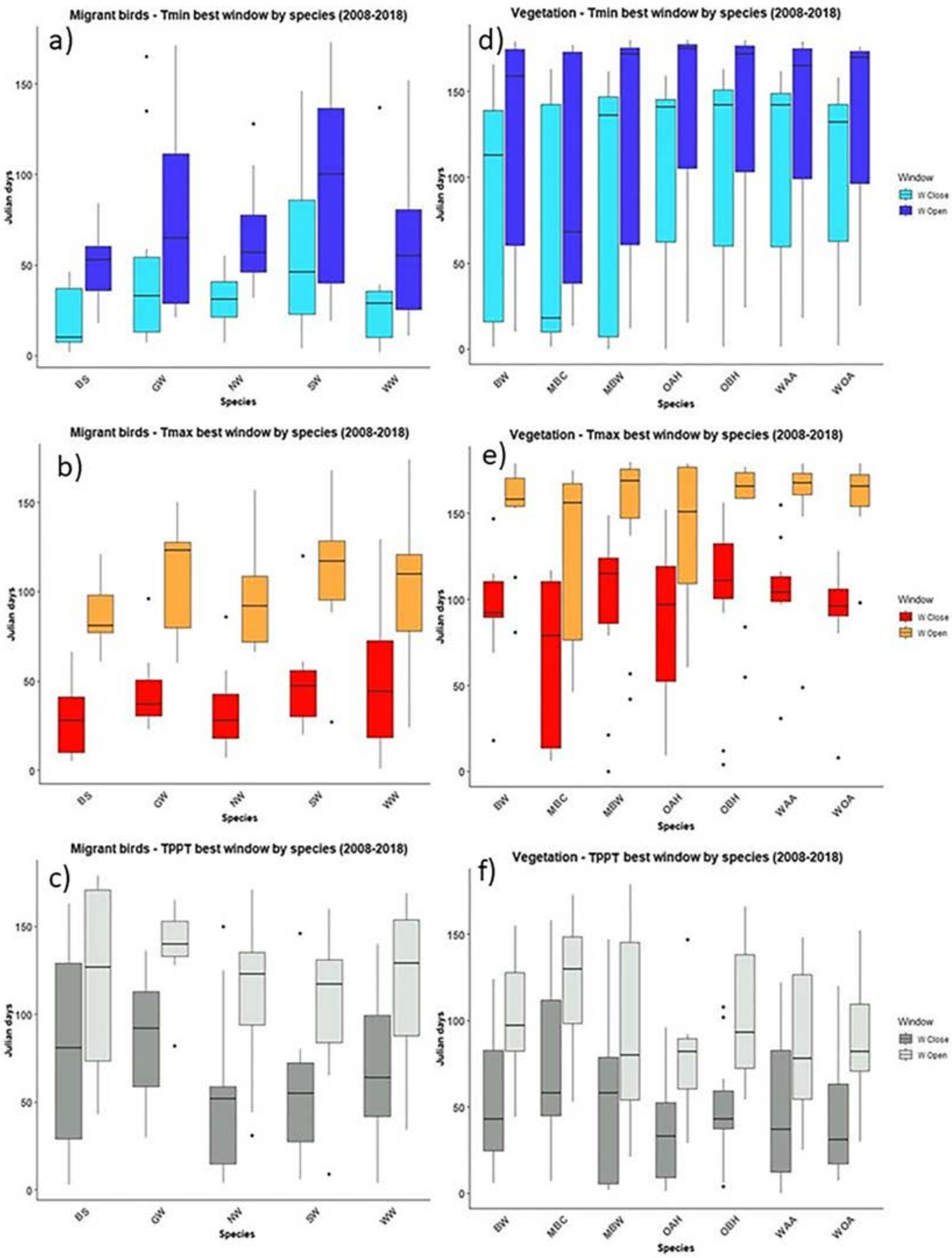


Figure 3.9. Best time windows from sliding window regression models performed with climwin for migrant birds (a–c) and vegetation groups (d–f) over the period 2008–2018. Time windows are shown by meteorological driver: T_{min} (a,d), T_{max} (b,e), and TPPT (c,f); window open and close are shown in different colours, as indicated in the keys. The *x*-axis shows species code; the *y*-axis shows the number of days prior to DA and GU that window open or close took place. Median values for all species, window open and close, are represented by horizontal black lines inside each box. The names of the species relating to the codes are listed in Table 3.2.

case of vegetation, in general terms all vegetation groups showed greater sensitivity to the evaluated meteorological drivers further back in time, meaning that most time windows for meteorological drivers took place in the preceding year GU. For vegetation, precipitation time windows were frequently closer to

GU (Figure 3.9), followed by T_{max} and T_{min} windows, respectively, although there was variation within each woodland type.

3.2.4 *Asynchrony among trophic levels*

We developed new asynchrony indices to evaluate the possible phenological asynchronies among different trophic levels. Asynchrony indices (asynchrony between trophic levels; AL) between birds and insects [$AL_{(3,2)}$], insects and vegetation [$AL_{(2,1)}$], and birds and vegetation [$AL_{(3,1)}$] were generated for 251 species combinations, with subscript numbers referring to the trophic level (i.e. vegetation 1, insects 2, birds 3). These indices normalised the difference in Julian days among the phenological events in question (e.g. DA, FF, GU). A value of 0.5 represents perfect synchrony, with values below this representing asynchronous interactions between the upper trophic level and the lower one (i.e. FF of insects before GU of vegetation) and values above 0.5 representing synchrony (i.e. FF of insects after GU of vegetation). It should be noted that values above 0.5 are synchronous, but the higher the value, the longer the gap between the two phenological events, which could also be indicative of trophic cascades.

Median values for all years of study showed that 77 species combinations could be classed as asynchronous ($AL < 0.5$), while values of the remaining 174 were synchronous ($AL > 0.5$). The most asynchronous species were barn swallow (BS), northern wheatear (NW), sedge warbler (SW), greater whitethroat (GW), willow warbler (WW), common marbled carpet (CMC) and early thorn (ET). BS showed generalised asynchrony ($AL_{(3,2)}$ values ranging between 0.41 and 0.12) with all but two insect species: CMC (0.7) and ET (0.63). In the case of insects, CMC showed asynchrony with all vegetation groups, with $AL_{(2,1)}$ values ranging from 0.47 to 0.43, while ET was asynchronous with three vegetation groups, BW, mixed broadleaved/conifer woodland and WOA, with values ranging between 0.489 and 0.49. Median AL index values were visually represented in a network of potential species interactions at the national level for all 30 species (Figure 3.10). This showed species that are potentially likely to interact more, as they were classed as synchronous according to their AL values, and those that showed asynchrony according to their AL indices (Figure 3.11). Asynchronies seemed to occur more often in upper levels of the trophic network, which could be indicative of possible trophic collapse and cascades.

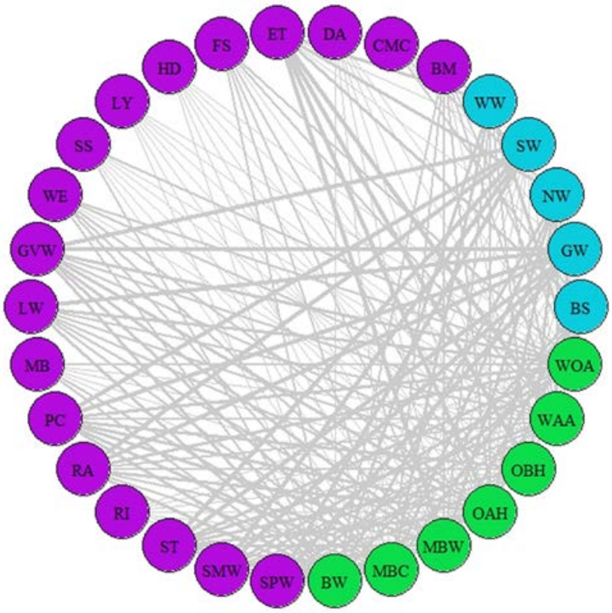


Figure 3.10. Possible interaction network developed from the AL indices. Species represented are those that were considered as synchronous by the different AL indices (AL ranged between 0.5 and 1). Different colours represent different trophic levels: blue represents migrant birds; purple represents butterflies and moths; green represents vegetation. Lines represent synchrony between pairs of species; line thickness represents synchrony degree: the thicker the line, the more synchronous the relationship (value closer to 0.5; considered as total synchrony by our indices). The names of the species and woodland types are listed in Table 3.2.

We also developed a novel asynchrony index that incorporated a climatic dimension. The index of climate window movement (ICWM) was computed for 90 species combinations. This index combined the existing AL indices with the variation in time windows for the three meteorological variables (T_{min}, T_{max}, TPPT) for each trophic-level interaction. We identified three possible categorisations (+, –, *) and two scenarios; ICWM was classified as positive (+) when a bird–insect combination was synchronous and, in general terms, when bird time windows took place further in the past and/or insect windows took place closer to FF (scenario a), while asterisks (*) represented

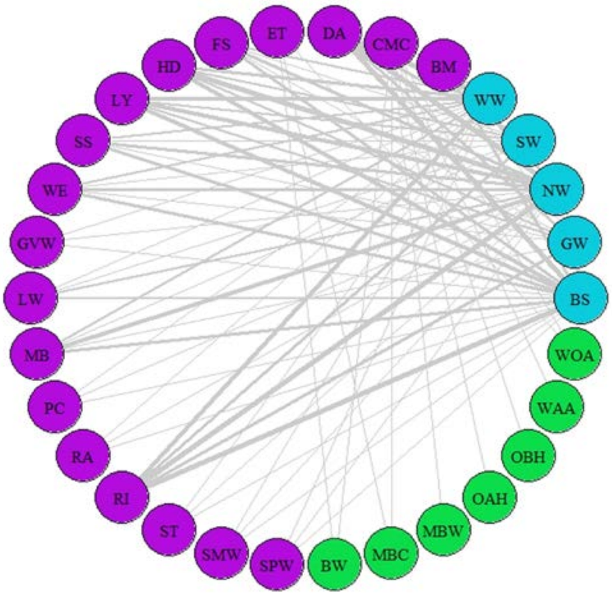


Figure 3.11. Network illustrating asynchrony degree among the study species according to the AL indices. Different colours represent different trophic levels: blue represents migrant birds; purple represents butterflies and moths; green represents vegetation. Lines represent asynchrony between pairs of species; line thickness represents asynchrony degree: the thicker the line the more asynchronous the relationship (value closer to 0; considered as total asynchrony by our indices), while narrower lines represent lower degree of asynchrony. The names of the species and woodland types are listed in Table 3.2.

a bird–insect asynchronous combination, together with bird time windows taking place closer to DA or insect time windows taking place further back before FF (scenario b). ICWM was classified as negative (–) in two cases: (1) when a particular bird–insect combination was asynchronous in combination with scenario a or (2) when a synchronous combination occurred together with scenario b.

We found that only 17 of the modelled interactions presented synchronies through three trophic levels over the study period (Table 3.4). Among these, sedge warbler and greater whitethroat were the only bird species that showed synchrony with their two immediate lower trophic levels on more than one occasion. Willow warbler showed synchrony with two species from its immediate lower trophic level and barn swallow with just one species from its immediate lower trophic level, which, in turn, for both cases, showed partial synchrony (four vegetation groups out of seven) with their lower level (producers). When comparing the ICWM to the AL index, we describe a positive (+) scenario 23 times; all of them matched with synchronous combinations described by AL indices, between birds, insects and vegetation, while six of these combinations showed total or partial asynchrony between insects and vegetation groups. The majority of the cases (67 out of 90), however, showed a negative scenario IWM/AL and all coincided with asynchrony between bird and insect, and synchrony between insect and vegetation.

Table 3.4. Qualitative AL values and ICWM index for 90 species combinations, showing species combinations from a tropic-level perspective, bird–insect–vegetation

Species	AL’ 3,2[a]	AL’2,1[b]	ICWM[c]	Species	AL’ 3,2[a]	AL’2,1[b]	ICWM[c]	Species	AL’ 3,2[a]	AL’2,1[b]	ICWM[c]	Species	AL’ 3,2[a]	AL’2,1[b]	ICWM[c]	Species	AL’ 3,2[a]	AL’2,1[b]	ICWM[c]
BS-BM	A	S7	*	GW-BM	A	S7	–	NW-BM	A	S7	*	SW-BM	A	S7	*	WW-BM	A	S7	–
BS-CMC	S	A7	–	GW-CMC	S	A7	–	NW-CMC	S	A7	+	SW-CMC	S	A7	–	WW-CMC	S	A7	–
BS-DA	A	S7	*	GW-DA	A	S7	–	NW-DA	A	S7	–	SW-DA	A	S7	–	WW-DA	A	S7	*
BS-ET	S	S4 A3	+	GW-ET	S	A7	+	NW-ET	S	S4 A3	–	SW-ET	S	S4 A3	–	WW-ET	S	S4 A3	+
BS-FS	A	S7	*	GW-FS	A	S7	*	NW-FS	A	S7	–	SW-FS	A	S7	*	WW-FS	A	S7	–
BS-HD	A	S7	*	GW-HD	A	S7	–	NW-HD	A	S7	–	SW-HD	A	S7	*	WW-HD	A	S7	*
BS-LY	A	S7	*	GW-LY	A	S7	*	NW-LY	A	S7	*	SW-LY	A	S7	*	WW-LY	A	S7	–
BS-SS	A	S7	–	GW-SS	A	S7	*	NW-SS	A	S7	*	SW-SS	A	S7	–	WW-SS	A	S7	*
BS-WE	A	S7	*	GW-WE	A	S7	*	NW-WE	A	S7	*	SW-WE	A	S7	–	WW-WE	A	S7	*
BS-GVW	A	S7	–	GW-GVW	S	S7	+	NW-GVW	A	S7	–	SW-GVW	S	S7	–	WW-GVW	A	S7	–
BS-LW	A	S7	–	GW-LW	S	S7	–	NW-LW	A	S7	*	SW-LW	A	S7	+	WW-LW	A	S7	*
BS-MB	A	S7	–	GW-MB	A	S7	–	NW-MB	A	S7	*	SW-MB	A	S7	–	WW-MB	A	S7	–
BS-PC	A	S7	*	GW-PC	S	S7	+	NW-PC	A	S7	–	SW-PC	S	S7	+	WW-PC	A	S7	*
BS-RA	A	S7	*	GW-RA	S	S7	+	NW-RA	A	S7	*	SW-RA	S	S7	–	WW-RA	A	S7	*
BS-RI	A	S7	*	GW-RI	A	S7	–	NW-RI	A	S7	*	SW-RI	A	S7	–	WW-RI	A	S7	–
BS-ST	A	S7	–	GW-ST	S	S7	–	NW-ST	A	S7	*	SW-ST	S	S7	+	WW-ST	A	S7	–
BS-SMW	A	S7	–	GW-SMW	S	S7	+	NW-SMW	A	S7	*	SW-SMW	S	S7	–	WW-SMW	A	S7	–
BS-SPW	A	S7	*	GW-SPW	S	S7	–	NW-SPW	A	S7	*	SW-SPW	S	S7	+	WW-SPW	A	S7	–

[a] AL’3,2 shows the qualitative value of synchrony (S) or asynchrony (A) of the AL’3,2 index for the given combination of species.

[b] AL’2,1 shows the qualitative value of synchrony or asynchrony between the given insect species and all vegetation groups. Numbers indicate the total number of times that insect species i was synchronous or asynchronous with all vegetation groups (i.e. AL’2,1 BS- ET = S4 A3, meaning ET was synchronous with four vegetation groups and asynchronous with three vegetation groups).

[c] ICWM indicates the positive (+), asterisk (*) and negative (–) cases. The names of the species relating to the codes are listed in Table 3.2.

4 Development of Methods for Future Phenological Research in Ireland

4.1 Monitoring Tree Phenology in Urban Settings

Nine common lime (*Tilia × europaea*) trees were selected on the University College Cork (UCC) campus for the monitoring of phenology by remote sensing, as well as by ground-based measurements of chlorophyll content and chlorophyll fluorescence in individual leaves. Three of these trees were also monitored using a phenocam.

In addition, a site that was planted with native tree species of Irish provenance in 2013 was chosen on the UCC campus. Within this site, five trees each of four species – silver birch (*Betula pendula*), common hazel (*Corylus avellana*), common hawthorn (*Crataegus monogyna*) and spindle (*Euonymus europaeus*) – were selected for the analysis of native tree responses (see Figure 1.1 for photos of the tree species).

4.1.1 High-resolution satellite remote sensing using Sentinel-2

Pixels 10 m × 10 m from Sentinel-2 imagery were matched to the individual trees as shown in Figure 4.1. NDVI, EVI, normalised difference red edge (NDRE) and green normalised difference vegetation index (GNDVI) were extracted to determine SOS, POP and EOS (Figure 4.2). The processing of the vegetation index time series and the extraction of the phenological metrics were done using the same approach as discussed in section 3.1.3. Specifically, the clouds were masked in the raw indices time series data, and gaps were filled with mean values and subsequently smoothed and interpolated to daily values using the LOESS regression. For all four vegetation indices, there was more variation among the trees for EOS than for SOS. Phenological dates determined using EVI were generally earlier than those determined using the other three indices, while median SOS dates were later when determined from NDRE and GNDVI than from NDVI.

An attempt was made to match NDVI from PlanetScope (https://www.planet.com/products/planet-imagery/) to the Sentinel-2 curves for gap filling, but Sentinel-2 NDVI values were found to be generally higher and could therefore not easily be matched without removal of intersensor differences in spectral and spatial resolutions. Evergreen groundcover

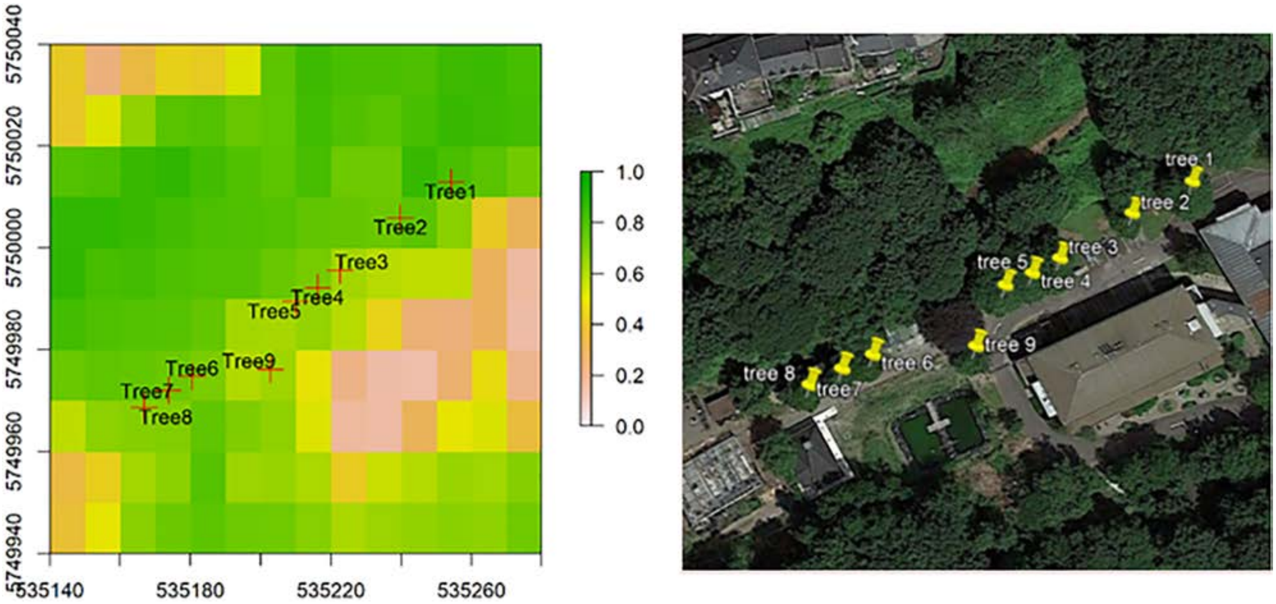


Figure 4.1. Matching Sentinel-2 NDVI pixels to individual common lime (*Tilia × europaea*) trees.

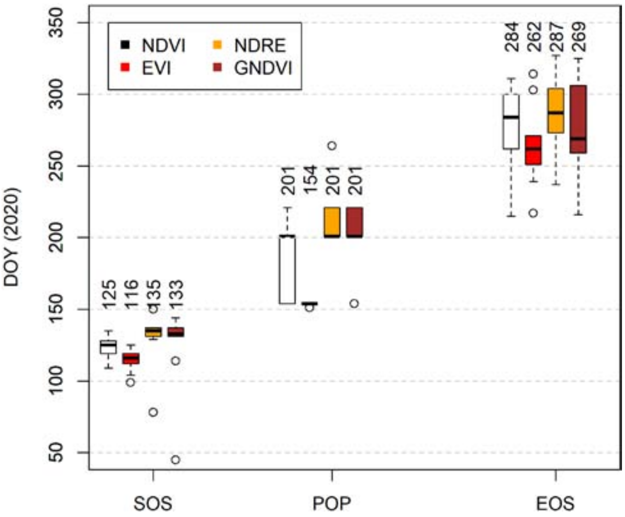


Figure 4.2. SOS, POP and EOS determined using different Sentinel-2 vegetation indices for nine common lime (*Tilia* × *europaea*) trees.

may also have contributed to this higher NDVI in the Sentinel-2 pixels.

4.1.2 Validation using phenocam imagery

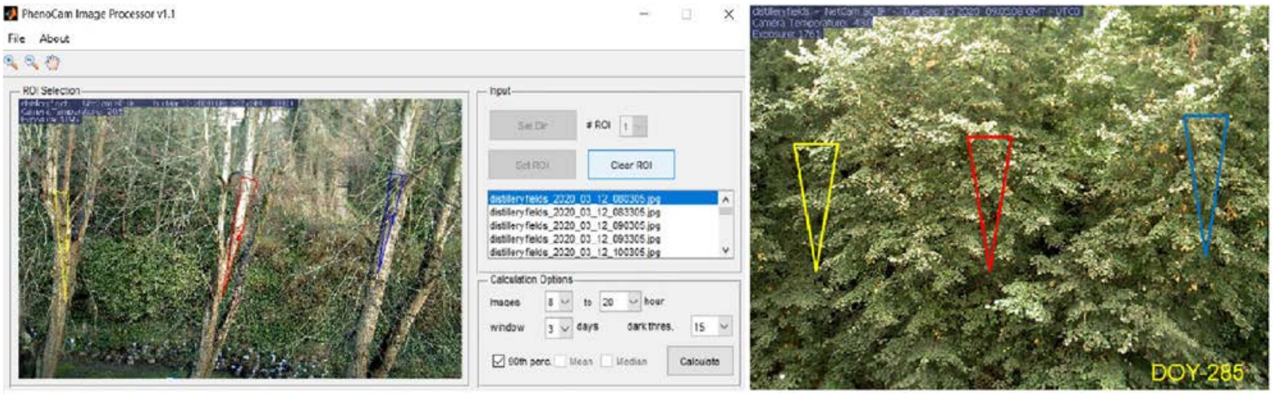
A phenocam (StarDot NetCam SC) was installed to monitor the canopy greenness of the common lime trees and was registered with the PhenoCam Network (https://phenocam.sr.unh.edu) (Figure 4.3). The green chromatic coordinate (GCC) time series (Figure 4.4) was used to determine SOS, POP and EOS during 2020. Spring GU was rapid, and SOS for the three trees matched closely. POP dates also differed little between the trees. However, the decline in GCC later in the year was less consistent and varied among the trees. Visual inspection (Figure 4.3) revealed differences in coloration not just among the trees but also within each canopy in autumn.

For all four Sentinel-2 vegetation indices, day of year (DOY) values from phenocam GCC and Sentinel-2 were significantly correlated, with R^2-values ≥ 0.89 (Figure 4.5). No clear difference in the performance of the vegetation indices was found. Monitoring over several years would enable a more detailed analysis of the suitability of the indices.

The phenocam, which was installed before bud break in 2020, reliably sent data to the PhenoCam Network without any need for maintenance during the closure of university buildings in the spring/summer of 2020 on account of the Covid-19 pandemic. Overall, the reliability, high spatial resolution and high frequency of available pictures without interference from cloud cover make phenocams ideal for monitoring phenology at selected locations, provided that a suitable attachment site (e.g. on a building) can be identified and a power supply provided. A connection to the university internet was installed for sending images to the PhenoCam Network. At another site, where no such connection was available (Figure 2.1), a phenocam was set up to send data via the mobile phone network.

4.1.3 Leaf chlorophyll content and photosystem II efficiency

To obtain information on phenological change at the individual leaf and tree levels, dates of leaf unfolding were recorded and handheld devices were used to measure chlorophyll content and chlorophyll fluorescence in individual leaves. Chlorophyll



\# ROI 1

distilleryfields_2020_03_12_080305.jpg
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images 8 to 20 hour
window 3 days
dark thres. 15
☑ 90th perc. ☐ Mean ☐ Median

Figure 4.3. Phenocam images showing the areas selected (coloured triangles) for the three common lime trees (*Tilia* × *europaea*) to avoid monitoring of evergreen ground vegetation.

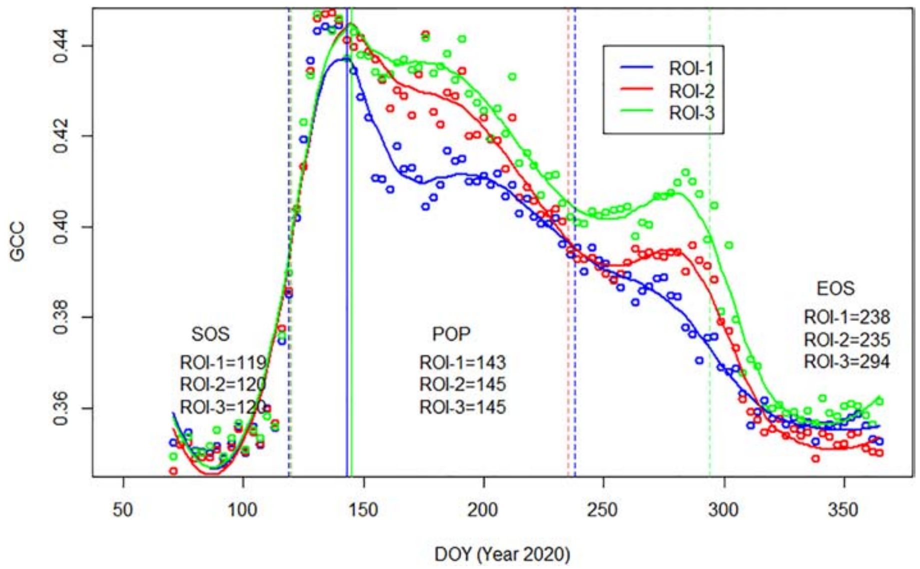

Figure 4.4. Green chromatic coordinate index determined from phenocam imagery for three common lime (*Tilia × europaea*) trees (ROI-1, ROI-2 and ROI-3). Vertical lines indicate SOS, POP and EOS.

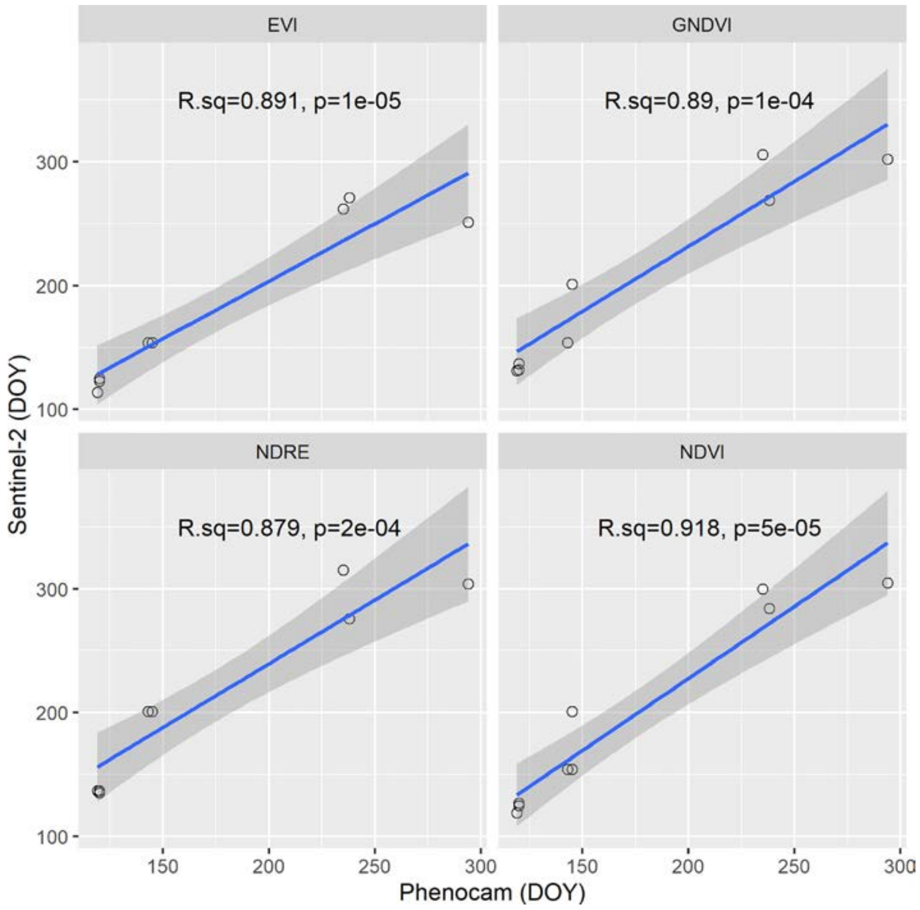

Figure 4.5. Correlation of the DOY of SOS, POP and EOS for three common lime (*Tilia × europaea*) trees determined using PhenoCam and Sentinel-2 imagery.

measurements (Figure 4.6) were performed with a CCM-200 Chlorophyll Content Meter (Opti-Sciences), which derives the chlorophyll content index (CCI) by measuring the transmittance of far-red relative to red light. Spring phenology measurements could not be performed in 2020 because of the Covid-19 pandemic; 2021 measurements are ongoing.

A gradual decline in CCI during autumn was observed for all species, including four native species – silver birch, common hazel, common hawthorn and spindle. CCI values in autumn 2019 were higher than in autumn 2020, and continued measurements in future years will be required to investigate if this variation is related to climatic events.

For common lime trees, the peak in CCI (DOY = 196) matched the median POP estimated from Sentinel-2 NDVI (DOY = 201) quite closely. Measurement of CCI over complete years will be required to match phenological dates to those from Sentinel-2 and phenocams.

Maximum photosystem II efficiency (Fv/Fm) was determined using a FluorPen (Photon Systems Instruments) to monitor photosynthetic function (Figure 4.7). In contrast to chlorophyll content, the decline in Fv/Fm in autumn was more abrupt. Overall, this parameter appears more suitable for addressing plant health and more difficult to match to vegetation indices from remote sensing than chlorophyll content.

Ground-based measurements of chlorophyll content and fluorescence are time-consuming and were therefore not conducted for all species over the summer. In contrast to satellite remote sensing and phenocams, these measurements capture mainly the lower canopy. Together with visual observations of leaf unfolding, autumn coloration and leaf fall, they complement remotely sensed phenological variables and provide information on within-tree variation. It is therefore recommended that these measurements and observations be continued as ground-truthing activities.

4.2 Use of Novel Technologies to Monitor Phenology

The use of new technology (e.g. acoustic recorders and telemetry) has also been shown to provide novel insights for quantifying intra-species and

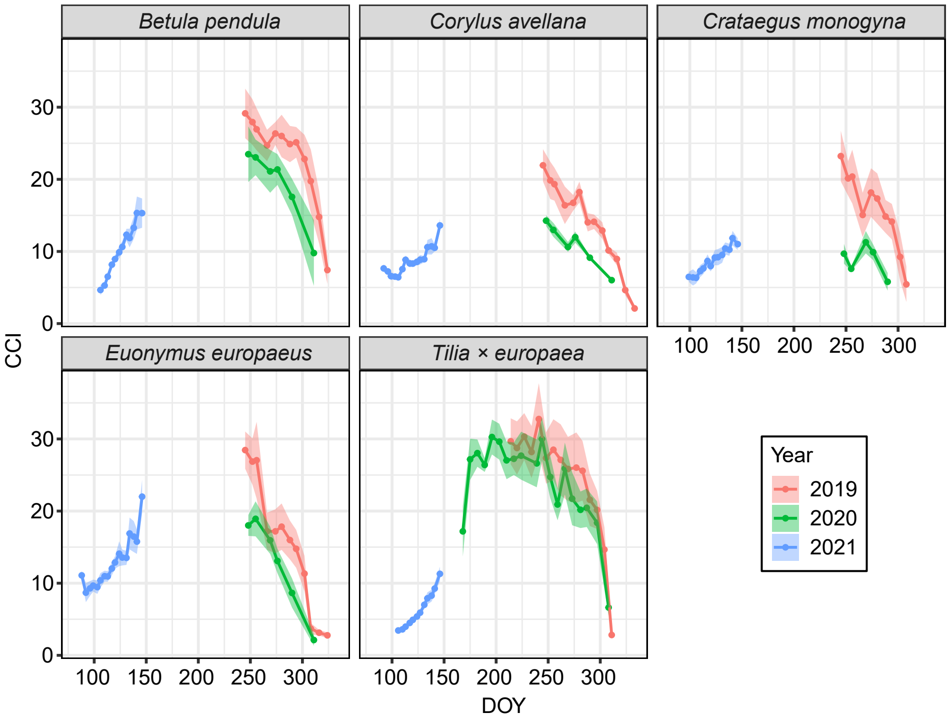

Figure 4.6. Ground-based measurements of chlorophyll content index (CCI) in individual leaves of five tree species. Data are means of leaves from five trees per species – *B. pendula* (silver birch), *C. avellana* (common hazel), *C. monogyna* (common hawthorn), *E. europaeus* (spindle) – or nine trees per species (*Tilia × europaea*) ± standard error.

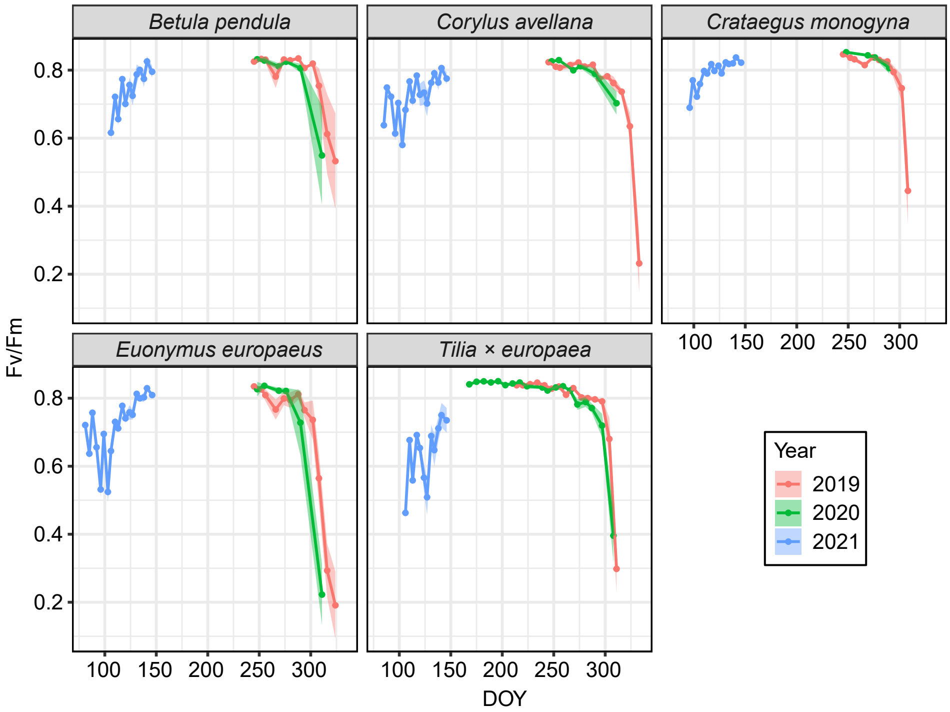

Figure 4.7. Ground-based measurements of maximum photosystem II efficiency (Fv/Fm) in individual leaves of five tree species. Data are means of leaves from five trees per species – *B. pendula* (silver birch), *C. avellana* (common hazel), *C. monogyna* (common hawthorn), *E. europaeus* (spindle) – or nine trees per species (*Tilia* × *europaea*) ± standard error.

inter-species interactions (Isbell and Binder, 2016). Telemetry acquires precise spatial and temporal animal position and movement data (Hebblewhite and Haydon, 2010), and has been used to capture information on phenological interactions, such as mating, boundary patrolling and hunting (Long and Nelson, 2013; Benhamou *et al*., 2014; Long *et al*., 2014). Similarly, camera traps have also been used to capture information on phenology (e.g. Graham *et al*., 2010; Tape and Gustine, 2014; Alberton *et al*., 2017), allowing the examination of community structures and interspecific interactions (Steinmetz *et al*., 2013; Jachowski *et al*., 2015; Buxton *et al*., 2016; Camargo-Sanabria and Mendoza, 2016). Figure 4.8 illustrates examples where camera traps, acoustic recorders and telemetry data capture co-existence in space and time, as well as direct interactions. New methods of quantifying these interactions, such as image analysis or through acoustic signals and movement parameters, will subsequently be needed to ascertain in what instances interactions can be recorded.

Figure 4.9. demonstrates the ability of acoustic recorders to capture the presence of barn swallows in Cork for the entire season compared with that of citizen science projects. FF dates were successfully captured across both methods, but acoustic recorders captured observations throughout the season, presumably when citizens are no longer reporting these migrants, allowing us to capture the last flight (LF) dates. These relatively inexpensive pieces of equipment could enable continuous monitoring at various locations, allowing full seasons to be explored. They are cheap to set up (approximately €60), but battery duration (about 60 days) may be problematic for continued operation of acoustic recorders in remote locations.

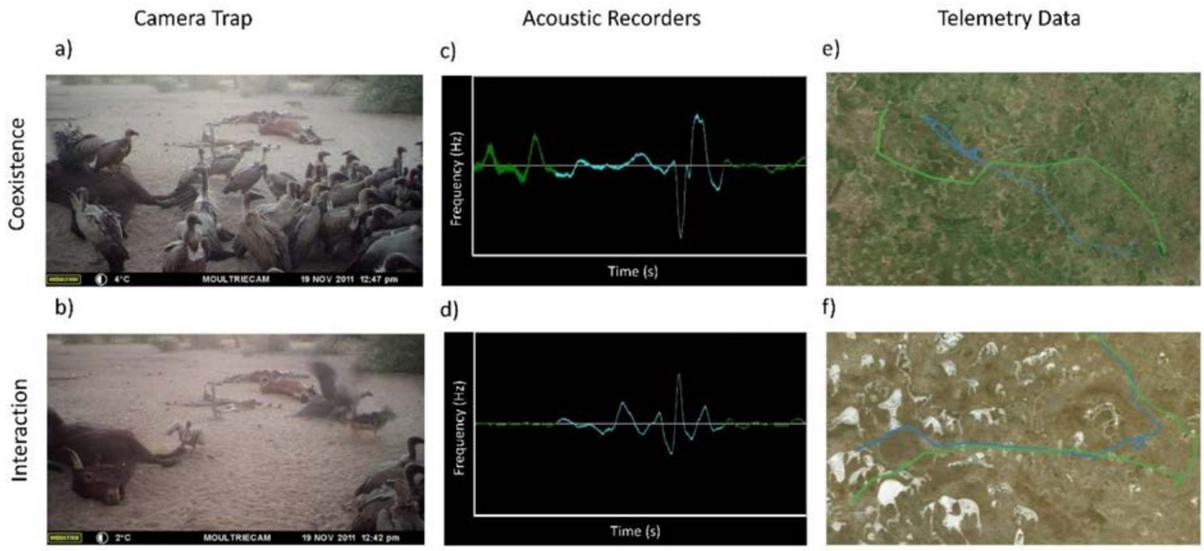

Figure 4.8. Illustration of co-existence between species vs biotic interactions using technology including camera traps, acoustic recorders and telemetry. (a,b) Image captured from a camera trap in the Ghanzi region of Botswana, showing (a) the presence of the black-backed jackal and hooded vultures in the same location at same time, not interacting, and (b) an interaction (competition) between two individuals. Photos: Thoralf Meyer. (c,d) Audiograms from acoustic recorders (AudioMoth) (Hill *et al.*, 2018) in Cork, Ireland, showing waveforms of recorded calls (green lines) and the fragment of the calls analysed with SoundID (Boucher, 2014) identifying vocalisation (blue lines). (c) Illustrates co-existence through vocalisations of various individuals of two Corvidae species, jackdaw and rook, where no apparent interaction was taking place, and (d) illustrates interaction (competition) between jackdaws and rooks, with the audiogram reporting corresponding patterns for alarm and territorial calls. (e,f) Global positioning system (GPS) of Burchell's zebra in Botswana, showing (e) co-existence and (f) interaction (herding) between individuals over a 24-hour period. Zebra data from Bartlam-Brooks and Harris (2013a) and Bartlam-Brooks *et al.* (2013) via Movebank (2013), visualised in DYNAMOVis (Dodge *et al.*, 2018). Reproduced from de la Torre Cerro and Holloway (2021).

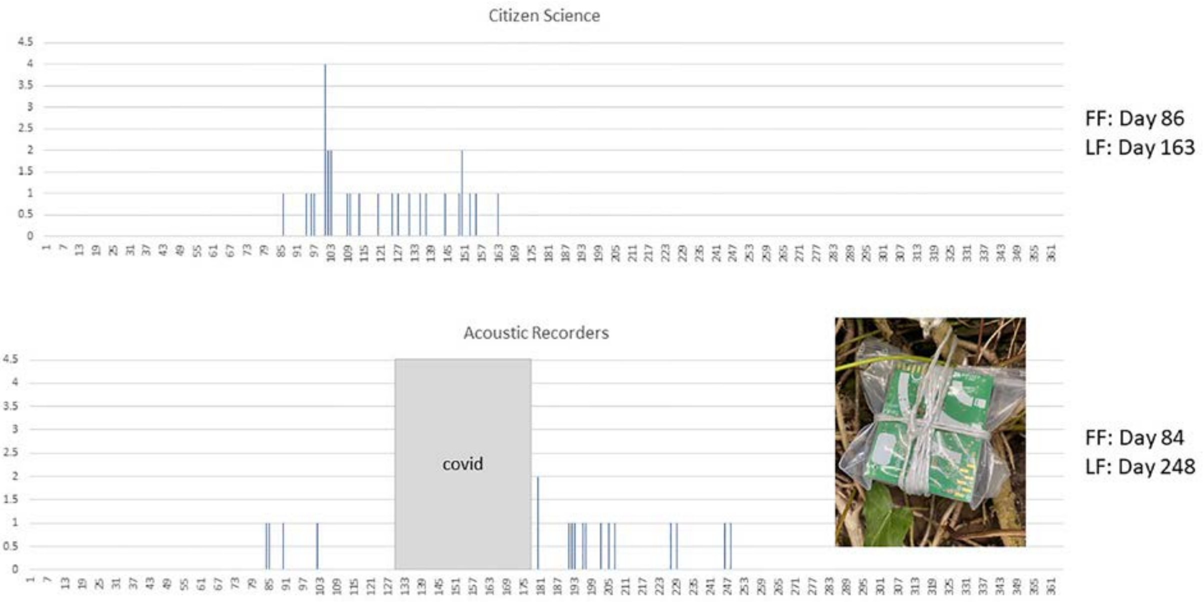

Figure 4.9. Dates of observations of barn swallow in Cork as recorded by citizen science projects (including BirdTrack, ebird and the National Biodiversity Data Centre; top) and two acoustic recorders on the UCC main campus and at the Environmental Research Institute (bottom).

5 Summary and Recommendations for Future Phenological Monitoring in Ireland

5.1 Phenological Responses to Climate Change

Trends in woodland phenology across Ireland over the last 30 years, analysed using Landsat imagery, showed an overall advance in SOS, but regional differences in the change in POP and EOS over time. Earlier SOS and POP in response to warmer temperatures were detected, but EOS responses to temperature varied more widely. More detailed analyses differentiating between different woodland types are required to separate effects of geographical location from differences in the response of different tree species, in particular in relation to the more diverse responses observed in autumn.

Overall, the advance in spring phenology of woodlands described in this project is in agreement with previous findings based on tree clones planted in phenological gardens in Ireland (Donnelly *et al*., 2004, 2006; Gleeson *et al*., 2013).

While FF dates of moths and butterflies showed varying trends over two decades from 2008 to 2018, the arrival of migratory birds generally advanced over time, alongside woodland spring phenology. Sliding time window analysis shows that climatic factors influencing phenology are not always proximate to the event but can lie further back, sometimes in the previous year. It is therefore recommended that sliding time window analysis be considered in future phenological research projects, including research to support biodiversity conservation, but also for management of invasive species and pest spread.

This report also demonstrates that citizen science data can be successfully combined with vegetation phenology from satellite remote sensing (Landsat) to determine synchrony and asynchrony among species at different trophic levels. The possible interactions among trophic levels are asymmetrical; while birds and insects seemed to follow (be synchronous with) vegetation GU, there were many instances in which migrant birds showed asynchrony with butterflies and moths. Therefore, climate change might prolong the period of asynchrony for asynchronous interactions, with the risk of interaction uncoupling, which could have great impacts on biodiversity (Visser *et al*., 2006; Both *et al*., 2010; Morente-López *et al*., 2018). Furthermore, even though most birds and insects followed GU dates, there were noticeable gaps between the DA of birds and vegetation GU, and between FF of insects and vegetation GU. These were considered as “delayed synchrony” and might indicate that these organisms are not keeping the same pace tracking climate change (Mayor *et al*., 2017).

Acoustic recorders were explored as an inexpensive way to monitor migratory birds across the whole season. While LF dates may be missed by citizen science projects, which often focus on bird arrival in spring, acoustic recorders, if widely deployed, have the potential to determine autumn bird phenology more accurately.

5.2 Combining Phenocams and Satellite Remote Sensing for Monitoring Vegetation Phenology

This project demonstrates that satellite imagery from Landsat can be used to determine past climate impacts on woodland phenology in Ireland. However, in fragmented (e.g. urban) settings, a higher-resolution platform, such as Sentinel-2, is required. No clear advantages of the selection of particular Sentinel-2 vegetation indices were found; use of EVI generally resulted in earlier estimates of the phenophases, but less variation among trees.

Time gaps, mixed pixels and ground vegetation, especially if evergreen, can complicate the analysis of phenological parameters for individual trees using Sentinel-2 imagery. Gap filling with very high-resolution imagery (PlanetScope) was problematic, with Sentinel-2 consistently providing higher NDVI values. Instead, validating Sentinel-2 data with phenocams is proposed for future research. Overall, dates of phenological events in individual trees determined using Sentinel-2 matched those determined using GCC values from phenocams well. Although complex procedures are required for determining phenological events from satellite imagery, analysis of phenocam pictures is facilitated by the PhenoCam Network (https://phenocam.sr.unh.edu/). Masks can be applied to select specific parts of the field of vision, which provides more flexibility in the selection of trees than the fixed pixels from the satellite remote sensing. Once installed, phenocams require little maintenance; however, the power source and internet requirements can make setting up phenocams difficult in remote locations. If no internet is available, the mobile phone network can be used, but connection may not be as reliable.

Overall, we recommend the increased deployment of phenocams in Ireland for accurate monitoring of vegetation phenology at very high resolution. After registration with the PhenoCam Network, the data become easily and openly accessible, which is beneficial for the wider dissemination at the international level.

Moreover, acoustic recorders could be deployed at existing phenological monitoring locations (phenological gardens, phenocams, pollen traps) to record fine-scale daily data across multiple trophic levels, supporting cutting-edge research that is looking to combine multisensor recording of species (Buxton *et al.*, 2016; Isbell and Bidner, 2016).

5.3 Coordination of Future Phenological Monitoring in Ireland

Owing to its small size, distinct climate, past and current record of phenological research and well-connected research community, Ireland is an ideal place for coordinating phenological research at the national level. Ireland also benefits from existing citizen science projects, in particular the coordination of data collection, analysis and publication by the National Biodiversity Data Centre. In addition, Ireland has a long record of phenological research (Stelfox, 1927). For example, recording phenology in phenological gardens (going back to the 1960s) is supported by Met Éireann and the National Botanic Gardens (Office of Public Works), alongside private organisations and individuals. Furthermore, herbarium collections in the National Botanic Gardens can be used in phenological research, especially once digitised. In the future, phenocams could be deployed for the analysis of vegetation phenology at suitable sites across Ireland, alongside acoustic recorders to monitor bird migration.

Future research should make use of phenological data to develop recommendations for the selection of tree species to prevent maladaptation in a future climate and support mitigation through an extended growing season, resulting in higher carbon sequestration. In agroforestry, an extended growing season can also result in the uptake of excess soil water, which supports longer livestock grazing. This has associated benefits, such as reduced greenhouse gas and ammonia emissions.

Monitoring of the phenology of insects and birds and their interactions, as reported here, is also required to determine the impact of climate change on pests. As stressed in the Agriculture, Forest and Seafood Climate Change Sectoral Adaptation Plan (Government of Ireland, 2019), climate change influences the spread of pests and disease. Phenological mismatch and its consequences for biodiversity could have negative consequences for the control of pests in agriculture and forestry.

While this PhenoClimate project has shown that different sources and types of data can be combined for analysing the impact of climate change across different taxa, not all phenological observations for Ireland are currently easily accessible. Furthermore, the future maintenance and coordination of citizen science projects, data collections and phenological equipment, in addition to liaison with recorders at the phenological gardens, require continued support. Quality control of phenological observations, especially of those submitted by citizen scientists, is another key aspect that needs to be secured into the future. Overall, it would be beneficial to coordinate phenological activities at the national level and publish phenological observations in an open and easily accessible format at a central site.

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Abbreviations

AL	Asynchrony between trophic levels
AVHRR	Advanced Very High Resolution Radiometer
CC	Chromatic coordinate
CCI	Chlorophyll content index
DA	Date of arrival
DOY	Day of year
EOS	End of season
EVI	Enhanced vegetation index
FF	First flight
Fv/Fm	Maximum photosystem II efficiency
GCC	Green chromatic coordinate
GNDVI	Green normalised difference vegetation index
GU	Green up
ICWM	Index of climate window movement
LOESS	Locally estimated scatterplot smoothing
LOS	Length of season
LSP	Land surface phenology
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
NDRE	Normalised difference red edge
NDVI	Normalised difference vegetation index
Phenocam	Phenological camera
POP	Position of peak
SOS	Start of season
T_{max}	Maximum temperature
T_{min}	Minimum temperature
TPPT	Total precipitation
UCC	University College Cork

AN GHNÍOMHAIREACHT UM CHAOMHNÚ COMHSHAOIL
Tá an Ghníomhaireacht um Chaomhnú Comhshaoil (GCC) freagrach as an gcomhshaol a chaomhnú agus a fheabhsú mar shócmhainn luachmhar do mhuintir na hÉireann. Táimid tiomanta do dhaoine agus don chomhshaol a chosaint ó éifeachtaí díobhálacha na radaíochta agus an truaillithe.

Is féidir obair na Gníomhaireachta a roinnt ina trí phríomhréimse:

Rialú: *Déanaimid córais éifeachtacha rialaithe agus comhlíonta comhshaoil a chur i bhfeidhm chun torthaí maithe comhshaoil a sholáthar agus chun díriú orthu siúd nach gcloíonn leis na córais sin.*

Eolas: *Soláthraímid sonraí, faisnéis agus measúnú comhshaoil atá ar ardchaighdeán, spriocdhírithe agus tráthúil chun bonn eolais a chur faoin gcinnteoireacht ar gach leibhéal.*

Tacaíocht: *Bímid ag saothrú i gcomhar le grúpaí eile chun tacú le comhshaol atá glan, táirgiúil agus cosanta go maith, agus le hiompar a chuirfidh le comhshaol inbhuanaithe.*

Ár bhFreagrachtaí

Ceadúnú

Déanaimid na gníomhaíochtaí seo a leanas a rialú ionas nach ndéanann siad dochar do shláinte an phobail ná don chomhshaol:
- saoráidí dramhaíola *(m.sh. láithreáin líonta talún, loisceoirí, stáisiúin aistrithe dramhaíola)*;
- gníomhaíochtaí tionsclaíocha ar scála mór *(m.sh. déantúsaíocht cógaisíochta, déantúsaíocht stroighne, stáisiúin chumhachta)*;
- an diantalmhaíocht *(m.sh. muca, éanlaith)*;
- úsáid shrianta agus scaoileadh rialaithe Orgánach Géinmhodhnaithe *(OGM)*;
- foinsí radaíochta ianúcháin *(m.sh. trealamh x-gha agus radaiteiripe, foinsí tionsclaíocha)*;
- áiseanna móra stórála peitril;
- scardadh dramhuisce;
- gníomhaíochtaí dumpála ar farraige.

Forfheidhmiú Náisiúnta i leith Cúrsaí Comhshaoil

- Clár náisiúnta iniúchtaí agus cigireachtaí a dhéanamh gach bliain ar shaoráidí a bhfuil ceadúnas ón nGníomhaireacht acu.
- Maoirseacht a dhéanamh ar fhreagrachtaí cosanta comhshaoil na n-údarás áitiúil.
- Caighdeán an uisce óil, arna sholáthar ag soláthraithe uisce phoiblí, a mhaoirsiú.
- Obair le húdaráis áitiúla agus le gníomhaireachtaí eile chun dul i ngleic le coireanna comhshaoil trí chomhordú a dhéanamh ar líonra forfheidhmiúcháin náisiúnta, trí dhíriú ar chiontóirí, agus trí mhaoirsiú a dhéanamh ar leasúchán.
- Cur i bhfeidhm rialachán ar nós na Rialachán um Dhramhthrealamh Leictreach agus Leictreonach (DTLL), um Shrian ar Shubstaintí Guaiseacha agus na Rialachán um rialú ar shubstaintí a ídíonn an ciseal ózóin.
- An dlí a chur orthu siúd a bhriseann dlí an chomhshaoil agus a dhéanann dochar don chomhshaol.

Bainistíocht Uisce

- Monatóireacht agus tuairisciú a dhéanamh ar cháilíocht aibhneacha, lochanna, uiscí idirchriosacha agus cósta na hÉireann, agus screamhuiscí; leibhéil uisce agus sruthanna aibhneacha a thomhas.
- Comhordú náisiúnta agus maoirsiú a dhéanamh ar an gCreat-Treoir Uisce.
- Monatóireacht agus tuairisciú a dhéanamh ar Cháilíocht an Uisce Snámha.

Monatóireacht, Anailís agus Tuairisciú ar an gComhshaol

- Monatóireacht a dhéanamh ar cháilíocht an aeir agus Treoir an AE maidir le hAer Glan don Eoraip (CAFÉ) a chur chun feidhme.
- Tuairisciú neamhspleách le cabhrú le cinnteoireacht an rialtais náisiúnta agus na n-údarás áitiúil *(m.sh. tuairisciú tréimhsiúil ar staid Chomhshaol na hÉireann agus Tuarascálacha ar Tháscairí)*.

Rialú Astaíochtaí na nGás Ceaptha Teasa in Éirinn

- Fardail agus réamh-mheastacháin na hÉireann maidir le gáis cheaptha teasa a ullmhú.
- An Treoir maidir le Trádáil Astaíochtaí a chur chun feidhme i gcomhair breis agus 100 de na táirgeoirí dé-ocsaíde carbóin is mó in Éirinn.

Taighde agus Forbairt Comhshaoil

- Taighde comhshaoil a chistiú chun brúnna a shainaithint, bonn eolais a chur faoi bheartais, agus réitigh a sholáthar i réimsí na haeráide, an uisce agus na hinbhuanaitheachta.

Measúnacht Straitéiseach Timpeallachta

- Measúnacht a dhéanamh ar thionchar pleananna agus clár beartaithe ar an gcomhshaol in Éirinn *(m.sh. mórphleananna forbartha)*.

Cosaint Raideolaíoch

- Monatóireacht a dhéanamh ar leibhéil radaíochta, measúnacht a dhéanamh ar nochtadh mhuintir na hÉireann don radaíocht ianúcháin.
- Cabhrú le pleananna náisiúnta a fhorbairt le haghaidh éigeandálaí ag eascairt as taismí núicléacha.
- Monatóireacht a dhéanamh ar fhorbairtí thar lear a bhaineann le saoráidí núicléacha agus leis an tsábháilteacht raideolaíochta.
- Sainseirbhísí cosanta ar an radaíocht a sholáthar, nó maoirsiú a dhéanamh ar sholáthar na seirbhísí sin.

Treoir, Faisnéis Inrochtana agus Oideachas

- Comhairle agus treoir a chur ar fáil d'earnáil na tionsclaíochta agus don phobal maidir le hábhair a bhaineann le caomhnú an chomhshaoil agus leis an gcosaint raideolaíoch.
- Faisnéis thráthúil ar an gcomhshaol ar a bhfuil fáil éasca a chur ar fáil chun rannpháirtíocht an phobail a spreagadh sa chinnteoireacht i ndáil leis an gcomhshaol *(m.sh. Timpeall an Tí, léarscáileanna radóin)*.
- Comhairle a chur ar fáil don Rialtas maidir le hábhair a bhaineann leis an tsábháilteacht raideolaíoch agus le cúrsaí práinnfhreagartha.
- Plean Náisiúnta Bainistíochta Dramhaíola Guaisí a fhorbairt chun dramhaíl ghuaiseach a chosc agus a bhainistiú.

Múscailt Feasachta agus Athrú Iompraíochta

- Feasacht chomhshaoil níos fearr a ghiniúint agus dul i bhfeidhm ar athrú iompraíochta dearfach trí thacú le gnóthais, le pobail agus le teaghlaigh a bheith níos éifeachtúla ar acmhainní.
- Tástáil le haghaidh radóin a chur chun cinn i dtithe agus in ionaid oibre, agus gníomhartha leasúcháin a spreagadh nuair is gá.

Bainistíocht agus struchtúr na Gníomhaireachta um Chaomhnú Comhshaoil

Tá an ghníomhaíocht á bainistiú ag Bord lánaimseartha, ar a bhfuil Ard-Stiúrthóir agus cúigear Stiúrthóirí. Déantar an obair ar fud cúig cinn d'Oifigí:
- An Oifig um Inmharthanacht Comhshaoil
- An Oifig Forfheidhmithe i leith cúrsaí Comhshaoil
- An Oifig um Fianaise is Measúnú
- Oifig um Chosaint Radaíochta agus Monatóireachta Comhshaoil
- An Oifig Cumarsáide agus Seirbhísí Corparáideacha

Tá Coiste Comhairleach ag an nGníomhaireacht le cabhrú léi. Tá dáréag comhaltaí air agus tagann siad le chéile go rialta le plé a dhéanamh ar ábhair imní agus le comhairle a chur ar an mBord.

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PhenoClimate: Impact of Climate Change on Phenology in Ireland

Authors: Astrid Wingler, Fiona Cawkwell, Paul Holloway, Gourav Misra, Rubén de la Torre Cerro and Calum Sweeney

Identifying Pressures

Changes in the timing of phenological (i.e. seasonal biological) events, as identified in the PhenoClimate project, are key indicators of the impact of climate change on organisms in nature, forestry and agriculture. Phenology also directly affects the productivity of natural and managed ecosystems, the capacity of vegetation to capture carbon and the intricate biological interactions underlying biodiversity.

This project has shown that the ability of trees to respond to climate change varies across Ireland, with consequences for future growing season length, carbon sequestration and survival of extreme weather events. A better understanding of tree phenology is therefore urgently required for the success of tree planting in forestry, agroforestry and urban environments.

The PhenoClimate project developed methods for monitoring climate change impacts on biodiversity. The findings of this project revealed examples of synchrony and asynchrony in the phenology of organisms at different trophic levels (vegetation, insects, birds) in response to climate. These can threaten Irish biodiversity through a lack of available food sources for some species, while other species may become dominant and disrupt the balance of ecosystems.

Informing Policy

In 2019, Ireland declared a climate and biodiversity emergency. A review of the National Biodiversity Action Plan (2017–2020) by the National Biodiversity Forum in 2021 made vital recommendations to halt Ireland's biodiversity loss and improve accountability of the next National Biodiversity Action Plan. Prediction of future impacts of climate change on biodiversity requires phenological research. Findings from phenological research are also key for climate mitigation and adaptation, for example by selecting the most suitable trees for a future climate. This is recognised in the Agriculture, Forest and Seafood Climate Change Sectoral Adaptation Plan (2019), which stresses the threat of maladaptation to a future climate, resulting in not just biodiversity losses and reduced capacity to sequester carbon, but also lower productivity of forests. As outlined in the Ag Climatise roadmap, forestry and agroforestry play a key role in the carbon dioxide abatement potential of land management; this is also highlighted in the draft Agri-Food Strategy 2030. To deliver on the potential to increase future carbon sequestration, impacts of climate change on phenological events that determine growing season length, as investigated by the PhenoClimate project, need to be taken into account.

Developing Solutions

The PhenoClimate project draws conclusions on the past impact of climate change on phenological indicators such as the start and end of the growing season of trees, the emergence of butterflies and moths, and bird migration. The project also makes recommendations for future phenological monitoring in Ireland. In conjunction with high-resolution satellite remote sensing (e.g. Sentinel-2), phenological cameras (phenocams) are an effective means of accurately monitoring seasonal changes in canopies and individual trees. A wider deployment of phenocams is therefore recommended for forest and urban settings to monitor climate responses. This project also applied new methods using citizen science and remote sensing data for the analysis of climate change impacts on phenology. These methods enable the investigation of species interactions across trophic levels and the prediction of threats to these interactions. To ensure that the management of existing data (from phenological gardens and citizen science) is coordinated at the national level, and future monitoring schemes (e.g. using phenocams) are integrated in phenology monitoring projects, this report recommends the re-establishment of a national Irish phenology network.

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