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Characterising UK Vegetation Phenology: An examination of *in situ*, near-surface and remote sensing techniques

by

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ABSTRACT

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CHARACTERISING UK VEGETATION PHENOLOGY: AN EXAMINATION OF *IN SITU*, NEAR SURFACE AND REMOTE SENSING TECHNIQUES

Gillian Louise Mountford

The aim of this research was to comprehensively characterise UK vegetation phenology, investigate the controlling factors for vegetation development, and to evaluate current vegetation phenology monitoring techniques at a national and site-specific level from 2005 to 2012. This research combined several observational datasets to detect phenophase events, including the Nature's Calendar citizen science *in situ* dataset, canopy and understory digital camera photography, and MODIS and MERIS remote sensing imagery utilising the MTCI, NDVI and EVI vegetation indices. Supporting data used were; the LCM 2007 land classification dataset to define the six main broad habitats of the UK, STRM digital elevation data, and Met Office climate data.

Several techniques were utilised including; geostatistical analysis, geographically weighted regression, spatial interpolation, Fourier smoothing and delayed moving average. The scope of this research included; an assessment of citizen science phenophase data, a comparison of the relationship between citizen science *in situ* phenophase observations and satellite-derived vegetation phenological parameters, an in-depth assessment of the controlling factors at two sites, Alice Holt and Wytham Wood, and a sensitivity analysis of satellite-derived estimates of start and end of season to composite period and spatial resolution.

The citizen science *in situ* data were effective in assessing vegetation phenology at a national scale at a fine spatial resolution, showing the spatial variation and relationship with latitude and elevation. In addition, digital camera photography proved to be a useful resource for comparing *in situ* and satellite-derived parameters, helping to define the phenophase stages detected. This assessment indicated that the senescence of temperate vegetation is more sensitive to declining temperatures, than the decrease in sunlight hours. In addition, remotely sensed vegetation phenological parameters were found to be more sensitive to variation in composite period.

Finally, an important conclusion from this research is that it provides a baseline from which the national trend of vegetation phenology for the UK can be assessed further. The characterisation of phenology is a crucial step in understanding the potential impacts of climate change and anthropogenic stresses on vegetation.

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Academic Thesis: Declaration Of Authorship

I, Gillian Louise Mountford declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Characterising UK Vegetation phenology: An examination of *in situ*, near surface and remote sensing techniques

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Definitions and Abbreviations

AICc	Akaike Information Criterion
APAR	Absorbed photosynthetically-active radiation
ASI	Italian Space Agency
AVHRR	Advanced Very High Resolution Radiometer
BB	Budburst
BBCH	Biologische Bundesanstalt, Bundessortenam und Chemische Industrie
BISE	Best Index Slope Extraction
BVOCs	Biogenic Volatile Organic Compounds
CEH	Centre for Ecology and Hydrology
CET	Central England Temperature
ChEAS	Chequamegon Ecosystem Atmosphere Study
CN	Composite Number
CPON	Chinese Vegetation Phenological Observation Network
CUP	Carbon-uptake Period
DEM	Digital Elevation Model
DFT	Discrete Fourier Transform
DMA	Delayed Moving Average
DOY	Day of Year
EC	Eddy Covariance
ECN	Environmental Change Network
EGI	Excess Green Index
ENSO	El Nino Southern Oscillation
Envisat	Environmental Satellite

Definitions and Abbreviations

EOS	End of Season
EPN	European Vegetation Phenology Network
ESA	European Space Agency
ETM	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
FF	First Flower
FL	First Leaf
FLF	First Leaf Fall
FT	First Tint
FUT	Full Autumn Tint
FOV	Field of View
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GCC	Green Chromatic Coordinate
GCM	Global Climate Model
GDD	Growing Degree Days
GEM	Global Ecosystem Monitoring
GPP	Gross Primary Productivity
GRVI	Green-Red Vegetation Index
GS	Growing Season
GWR	Geographically Weighted Regression
IE-NPN	Ireland’s National Vegetation Phenology Network
IPG	International Vegetation Phenological Gardens
JaLTER	Japan Long Term Ecological Research Network
LAI	Leaf Area Index
LCM	Land Cover Map

LGS	Length of Growing Season
LiDAR	Light Detection and Ranging
LOS	Length of Season
LSP	Land Surface Vegetation Phenology
LTER	Long-Term Ecosystem Research
MERIS	Medium Resolution Imaging Spectroradiometer
MGVI	MERIS Global Vegetation Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner System
MSAVI	Modified Soil Adjusted Vegetation Index
MSS	Multispectral Scanner
MTCI	MERIS Terrestrial Chlorophyll Index
MVC	Maximum Value Compositing
NAO	North Atlantic Oscillation
NASA	National Aeronautics and Space Agency
NEON	National Ecological Observatory Network
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NIMA	National Imagery and Mapping Agency
NIR	Near-infrared
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
OGS	Onset Date of Growing Season
OK	Ordinary Kriging
OSAVI	Optimised Soil Adjusted Vegetation Index

Definitions and Abbreviations

P	Annual Total Precipitation (mm)
PAR	Photosynthetically-active Radiation
PAT	Pixels-above-threshold
PEN	Vegetation Phenological Eyes Network
PEP725	Pan European Vegetation phenology Project
RGB	Red, Green, Blue
RMSE	Root Mean Square Error
ROI	Region of Interest
RS	Remote Sensing
SAVI	Soil Adjusted Vegetation Index
SeaWiFs	Sea-viewing Wide Field-of-View Sensor
SNR	Signal-to-Noise Ratio
SOS	Start of Season
SPOT	Système Probatoire pour l’Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SWC	Soil Volumetric Water Content
SWE-NPN	Swedish National Vegetation Phenology Network
SWIR	Shortwave Infrared
T	Air Temperature Above Forest Canopy (℃)
TM	Thematic Mapper
UK	United Kingdom
UKPN	UK Phenology Network
VI	Vegetation Index/Indices
VNIR	Visible Near Infrared

Chapter 1 Introduction

1.1 Introduction

Vegetation phenology, the study of the timing of recurrent biological events, is one of the most responsive and easily observable phenomena to assess the impact of climate change (Sparks *et al.,* 2000; White *et al.,* 2003). Monitoring and characterising vegetation phenology is a significant component of identifying and modelling global changes in terrestrial ecosystems, and provides an insight into the temporal organisation, evolution and functioning of ecosystems (Menzel *et al.,* 2001; Badeck *et al.,* 2004; Delbart *et al.,* 2005; Zhang, *et al.,* 2006; Cleland *et al.,* 2007). Plants are adapted to the seasonality of their environment; however, a change in their seasonal vegetation phenology indicates that ecosystems are being influenced by variations in environmental factors, such as climate change (Cleland *et al.,* 2007). Understanding the controlling factors of vegetation phenological events is highly important for the estimation of biological productivity, understanding land-atmosphere interactions and biome dynamics of vegetation resources.

Global climate affects the timing of vegetation phenological events, and changes in the timing of spring onset affect carbon sequestration, plant-animal interactions and other essential ecosystem processes (Richardson *et al.,* 2013). In recent years there has been an increase in the number of vegetation phenological studies to assess the effects of climate change on plant mediated land atmospheric interaction, such as carbon cycles (Menzel *et al.,* 2001; Cleland *et al.,* 2007). Several studies have documented the impact of climate on vegetation phenological changes, and have shown that spring events are occurring earlier (Menzel and Fabian, 1999; Menzel *et al.,* 2001; Peñuelas *et al.,* 2002; Menzel *et al.,* 2006; Doi and Katano, 2008; Nordli *et al.,* 2008; Thompson and Clark, 2008; Chen and Xu, 2012).

Vegetation phenology markers focus on the beginning and end of photosynthesis or flowering and are characteristic of deciduous plant species (Hmimina *et al.,* 2013). The beginning of the photosynthetically active period relates to the emergence of buds and leaves, whilst the end of season is characterised by the depigmentation of leaves and leaf fall. The photosynthetically active canopy affects regional and global ecosystem models, global climate models (GCMs) and land surface parameterisation schemes (White *et al.,* 1997). There is a range of terminology used to describe vegetation phenological events, such as green-up, first leaf, green wave and start of season (SOS) which could appear to be identical between studies. However, they may represent different processes or events depending on the monitoring technique and study (White *et al.,* 2009). Changes in the timing of onset of 'greenness', 'end of 'greenness', duration of the growing season, rate of 'green up' and rate of senescence provide important information regarding the effects of environmental change on vegetation.

Recent warming trends have been linked with an earlier onset of vegetation in spring, a delayed senescence and a prolonged growing season. Across Europe there has been an advancing trend of spring phenophase events (Menzel and Fabian, 1999; Menzel *et al.,* 2006). However, the rate of advance is spatially heterogeneous (Ahas *et al.,* 2002; Kozlov and Berlina, 2002; Schaber and Badeck, 2005). Chmielewski and Rötzer (2011) found that warming of 1°C during early spring (February to April) advances the growing season by 7 days. In central England, increasing temperatures advanced first flowering by 4 days per degree (Fitter *et al.,* 1995). However, high autumn temperatures the previous year delayed first flowering events of some early flowering species, whilst some late flowering species advanced. Sparks *et al.* (2000) also assessed the flowering time of species in Great Britain, and attributed a 2 to 10 day advance of flowering times per degree increase in temperature for several spring and midseason species.

The timing of vegetation phenological events are assessed using five main methods; utilising networks to observe specific species of plants and plant communities with concurrent climate observations, vegetation phenology modelling, eddy covariance flux towers, global change experiments and remote sensing techniques (White *et al.,* 2009). The advance of spring in the Northern Hemisphere has been observed by both remote sensing techniques (Myneni *et al.,* 1997; Zhou *et al.,* 2001; Zeng *et al.,* 2011) and *in situ* monitoring (Menzel and Fabian, 1999; Sparks *et al.,* 2000; Beaubien and Freeland, 2000; Chmielewski and Rötzer, 2001). Generally, i*n situ* monitoring techniques capture specific phenophases of species within a specific study area, and are widely used to study climate influences on vegetation phenological events (Kramer *et al.,* 2000*;* Beaubien and Freeland*,* 2000*;* Primack *et al.,* 2004). However, this method is time consuming, leading to sparse temporal and spatial sampling and, therefore, is an unfeasible method over large areas and across harsh biomes. In addition, alternative observation protocols for specific phenophases across different study areas are difficult to compare and use in a global context.

In situ observations are seen as being the most accurate monitoring technique for vegetation phenological monitoring. However, one of the main limitations of this technique is the spatial coverage of observations as stations are primarily located in the Northern Hemisphere. Voluntary citizen science initiatives offer the opportunity to extend the global coverage of environmental observations (Cohn, 2008; Conrad and Hilchey, 2011). Citizen science refers to members of the public that participate in scientific initiatives and in collaboration with organisations in research and environmental monitoring (Kruger and Shannon, 2000). Citizen science has also influenced the scale of research being carried out and the relationship between members of the public and professionals (Dickinson, *et al.,* 2010). Within the scientific community, there has been a realisation regarding the effectiveness, and usually minimal cost, of utilising the public to assist with large scale research projects (Cohn, 2008). In addition, advancements in technology, the internet and smart phones have made it easier and less time consuming for volunteers to record (Silvertown, 2009; Burke *et al.,* 2006).

Satellite-derived observations have been used to assess vegetation phenology for over 30 years (Justice, 1985; Reed *et al*., 1994a; Moulin *et al.,* 1997; White *et al.,* 1997; Duchemin *et al.,* 1999; Asner *et al.,* 2000). Remote sensing is the science of collecting information from an object or an area without physical contact. The use of remote sensing in vegetation phenology studies allows seasonal changes in vegetation at regional, continental and global scales to be assessed at regular, even daily, intervals (Justice *et al.,* 1985; Xiao and Moody, 2005; Schott, 2007). Vegetation indices (VI) are commonly used as they indicate the level of canopy greenness (Myneni *et al.,* 1997). The Normalised Difference Vegetation Index (NDVI), derived from the Advanced Very High Resolution Radiometer (AVHRR), is one of the most commonly used indices for the assessment of vegetation phenological parameters (White *et al.,* 1997; Duchemin *et al.,* 1999). Specific phenophases, such as flowering or fruiting, cannot be traced in satellite sensor imagery, due to limited spatial and spectral resolution, impact of understory vegetation, and the characteristics of the background soil (Reed *et al*., 1994a).

Near surface techniques can assist to ‘bridge the gap’ between the two extreme spatial and temporal scales of satellite and *in situ* observations. Digital cameras can be utilised as inexpensive multi-channel imaging sensors (Richardson *et al.,* 2007; Ahrends *et al.,* 2009). Analysis of digital camera photography has been shown to be effective for monitoring vegetation phenology (Richardson *et al.,* 2007; Richardson *et al.,* 2009; Ahrends *et al.,* 2009; Ide and Oguma, 2010). This method predominately utilises the extracted red, green and blue (RGB) channels extracted from photographs to be applied to a vegetation index in order to assess changes in the spectrum within the region of interest (ROI) (Richardson *et al.,* 2009; Sonnentag *et al.,* 2012; Alberton *et al.,* 2014). Digital repeat photography and eddy covariance CO^2 flux data have been successfully combined in several studies to assess vegetation phenology and ecosystem processes (Cleland *et al.,* 2007; Migliavacca *et al.,* 2011; Mizunuma *et al.,* 2013; Knox *et al.,* 2017).

In temperate climates, such as the UK, temperature is known to be one of the dominant factors controlling spring phenophase events (Rutishauser *et al.,* 2009). For autumn phenophase events, the controlling factors are less understood. However, photoperiod is understood to be a limiting factor in the extension of the growing season (Richardson *et al.,* 2013). At higher latitudes vegetation phenology may be more sensitive to climate change due to increased warming occurring compared to lower latitudes (Parmesan, 2007; Oberbauer *et al.,* 2013; Prevéy *et al.,* 2017). In addition, winter chilling, or lack thereof, could impact tree vegetation phenology (Cumming and Burton, 1996; Saxe *et al.,* 2001). Certain species of vegetation require winter chilling and, without this period, some species may become vulnerable to frost damage or unviable within temperate habitats (Cannell and Smith, 1984; Cumming and Burton, 1996).

The characteristics and controlling factors of vegetation phenology, and the vegetation phenological parameters observed by each technique, has to date not been fully assessed across the UK for both spring and autumn. Regional and larger scale variation in community composition, micro and regional climate regimes, soils, and land management equate to complex spatiotemporal vegetation phenology variation (Zhang *et al.,* 2003). Complex feedbacks and responses to change make it difficult to project future effects of climate change from past or present vegetation phenology patterns (Price and Waser, 1998). A complete grasp of the mechanisms that control spring onset and how the timing will be affected by climate change, would be beneficial in the management and conservation of natural areas, and to forecast the future changes of ecosystem carbon budgets (Polgar and Primack, 2011).

Changes to the vegetation phenology of UK species and the diversity of species has been reported (Collinson and Sparks 2003; Sparks and Collinson 2006; Parry *et al.;* 2007; Sparks *et al.,* 2000). Areas of semi-natural grassland once covered a large proportion of the UK (Critchley *et al.,* 2003). However, with an increase in intensive farming this has led to a 90% decrease in semi-natural grassland across

UK lowlands over the last 60 years (Watson *et al.,* 2011). This has also equated to a substantial decrease in the biodiversity of these areas with high-diversity grasslands now accounting for only 2% of grassland areas (Watson *et al.,* 2011). The cause of this degradation is due to urbanisation, intensive agricultural practices, pollution and climate change (Sier *et al.,* 2016). Vegetation is an important factor within land surface processes and land-climate feedbacks, as exchanges of water, soil nutrients and CO_2 are driven by solar radiation, temperature, soil moisture and air humidity (Lorenz *et al.,* 2013). Shifting ranges of species, changes to vegetation phenology, extinction and a reduction in biodiversity are all related to the effects of climate change and land cover change across the UK. The future of UK vegetation phenological cycles is dependent on the sprawl of residential areas of major towns and cities and the impact of the loss of natural land, increase in managed land areas, and changes to upland species.

Within the UK, several studies have researched changes in the timing of vegetation phenological events (Smith and Jones, 1991; Collinson and Sparks, 2004; Collinson and Sparks, 2008; Boyd *et al.,* 2011; Comber and Brunsdon, 2014, Amano *et al.,* 2014; Roberts *et al.,* 2015). The majority of studies of vegetation phenology studies within the UK have been focused on single locations, covered specific local areas, or have measured single phenophase events (Sparks *et al.,* 2000). Changes in the timing of vegetation phenological events are associated with changes in mean temperature, water availability, precipitation, photoperiod length, nitrogen deposition and CO_2 concentration (White *et al.,* 1997; Menzel, 2003; Zhang el al., 2007; Morisette *et al.,* 2009; Lorenz *et al.,* 2013). In temperate environments, such as the UK, there is a large correlation between the growth and dormancy of vegetation, and temperature (Lang, 1987; Kramer *et al.,* 2000; Heide and Prestrud, 2005; Rohde and Bhalerao, 2007; Tooke and Battey, 2010; Atkinson *et al.,* 2013; Yu *et al.,* 2016).

The UK is projected to have wetter, milder winters and hotter, drier summers, with a greater number of precipitation extreme events (Osborn and Hulme, 2002). Since 2000, 15 of the 16 warmest years on record have occurred, with 2016 being recorded as the warmest year on record globally (European Environment Agency, 2016; NASA, 2017). Average UK temperatures on land were 0.9°C warmer from 2005 to 2014 compared with the long-term average of 1961 to 1990 (CCC, 2016). Changes have increased further in upland regions, with rapid warming and changes in precipitation (Holden and Adamson, 2002; Kendon *et al.,* 2015). It is estimated that a 1°C increase in temperature will significantly affect Scottish Flora, by extending the growing season and accelerating growth via the temperature response curve (Cannell *et al.,* 1997; Orr *et al.,* 2008; Gottfried *et al.,* 2012; Pauli *et al.,* 2012).

1.2 Research Aim and Objectives

The aim of this research is to comprehensively characterise UK vegetation phenology and to evaluate and compare current vegetation phenological monitoring techniques. This research combines several observation techniques, including citizen science data, near-surface photography, and remote sensing imagery to detect phenophase events at a national and site-specific level in the UK.

The specific objectives of the study are:

- To evaluate the utilisation of several vegetation phenological monitoring techniques to characterise the start of season (SOS) and end of season (EOS).
- To investigate the presumed controlling factors for phenophase events of temperate vegetation species in the UK utilising temperature, precipitation, photoperiod, elevation and latitude metrics.
- To analyse the variants of SOS and EOS events due to the utilisation of multiple monitoring techniques and processing steps, with a focus on satellite-derived estimates.

Chapter 2 Literature Review

2.1 Background of Vegetation Phenological Research

2.1.1 History of Monitoring Vegetation Phenology

The origin of the word ‘phenology’ for research purposes has been traced to Charles Morren, a botanist at the University of Liege in Belgium (Demarée, 2011). The term was used as an answer to an invitation from Adolphe Quetelet to carry out observations of periodical phenomena at the Belgian Royal Academy of Sciences in Brussels in 1849. Adolphe Quetelet coordinated an observational network, “Observations of periodical Phenomena of the Animal and Vegetable Kingdom”, with climate oriented instructions for the observations alongside the term “periodical phenomena” (Demarée, 2011).

Historically, vegetation phenological records focused on the passing of the seasons, with China and Japan having two of the oldest records of vegetation phenology dating back to the 8th century (Hameed and Gong, 1994; Menzel, 2003). In Europe, there are two notable historical records of vegetation phenology, Carolus Linnaeus’s records in Sweden, and Robert Marsham’s in England. Carolus Linnaeus systematically recorded the flowering times and climate conditions at 18 locations across Sweden. Robert Marsham is considered to be the founding father of vegetation phenological recording in the UK. Marsham began recorded spring species and events in 1736, with his family continuing this until 1958. The Marsham family record of vegetation phenology has been utilised in several studies to assess UK vegetation phenology and the relationship with climate (Kington, 1974; Sparks and Carey, 1995; Thompson and Clark, 2008). During the 19th century the Royal Meteorological Society formed a phenological committee to collate phenological and climate data (Sparks and Carey, 1995). The annual reports from the committee began in 1875 until 1948.

Previously, vegetation phenology was dismissed as having little scientific merit and was an overlooked feature of plant ecology (Cleland *et al.,* 2007). However, vegetation phenology is now recognised as being a vital component for environmental monitoring (Sparks *et al.,* 2000). This has lead to a notable increase in the number of observation initiatives, particularly in the Northern Hemisphere. Today, there are monitoring initiatives across the world at local, regional and national levels (Table 2-2).

2.1.2 Relationship to Global Systems

Climate change has been related to changes in migration, reproduction, occurrence and senescence of plants, animals and insects (Parmesan and Yohe, 2003; Brown *et al.,* 2016; Harsch *et al.,* 2017). There are several implications of changes to the annual cycle of vegetation phenology, due to the relationship with ecological processes, agriculture, human health and the economy (Peñuelas and Filella, 2009). In the context of agriculture, vegetation phenology has been used for assisting the planning of agricultural practices, including the choice of optimum species for given bioclimatic conditions, the selection of optimum seeding dates and the prediction of harvest dates (Justice *et al.,* 1985; Schwartz *et al.,* 1997). In recent years, the importance of vegetation phenology to global studies has increased, especially in regards to plant vegetation phenology serving as an indicator of the impacts of global climate and anthropogenic change (Cleland *et al.,* 2007; Richardson *et al.,* 2013; Park *et al.,* 2016). However, the inter-annual variation of global circulation patterns, such as the El Nino Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), complicate the detection of a trend in vegetation phenology and the attribution to global warming (Badeck *et al.,* 2004).

The importance of accurately characterising seasonal vegetation phenology has been recognised the need of realistic representations of vegetation cycles in GCMs (Xue *et al.,* 1996). Vegetation phenology has the potential to influence both regional weather patterns and the global climate by influencing the seasonal patterns of surface-atmosphere energy exchanges, trace gases, biogenic volatile organic compounds (BVOCs), albedo, surface roughness length, canopy conductance, water and energy fluxes, photosynthesis and CO_2 fluxes (Hayden, 1998; Peñuelas and Filella, 2009; Richardson *et al.,* 2013; Wang *et al.,* 2017). The onset of spring leafing has shown to affect meteorological conditions, including, wind, temperature and humidity (Schwartz, 1996). However, there is uncertainty related to the scale of the influence of these feedbacks to local and global systems (Peñuelas and Filella, 2009).

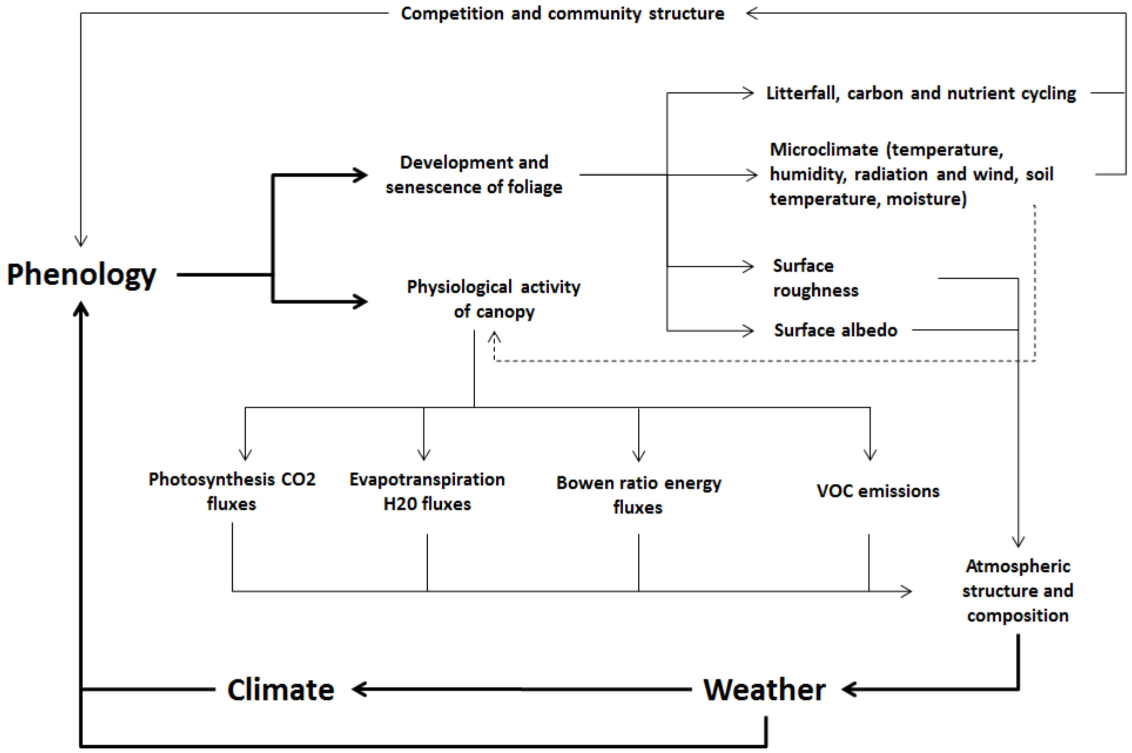


Figure 2-1 Conceptual model showing the primary feedbacks between vegetation and the climate system that are influenced by vegetation phenology (Richardson *et al.*, 2013).

Figure 2-1 highlights the link between vegetation phenology and climate and atmospheric systems, and the connections and interactions between each process. Therefore, changes in one process will have a progressive effect on the various interacting processes. For example, albedo is fundamental in the surface energy budget and is a direct feedback of vegetation to the climate system (Richardson *et al.*, 2013). Albedo varies with vegetation type, vegetation development and senescence of the canopy. Climate change feedbacks through vegetation phenology on albedo will alter depending on the ecosystem, particularly during winter as a reduced amount of snow cover would decrease albedo (Loranty *et al.*, 2014).

Gross primary productivity (GPP) and net primary productivity (NPP) are affected by changes to the growing season (Piao *et al.*, 2007). The net flux of carbon between the atmosphere and terrestrial vegetation can be shown as an annual net biomass accumulation or NPP (Goetz and Prince, 1996; Saxe *et al.*, 2001). Temperature affects NPP by changing the rates of photosynthesis, autotrophic respiration, nutrient mineralisation, and the period of foliation and frost hardiness (Saxe *et al.*, 2001). GPP and NPP are the main aspects for modelling terrestrial carbon uptake and therefore heavily influence atmospheric carbon content (Piao *et al.,* 2007; Jeong *et al.,* 2011). Jackson *et al.,* (2001) proposed that an increased growing season of 5-10 days could increase the annual NPP of forest ecosystems by up to 30%.

Spring is noted to have the strongest control over the annual carbon budget of ecosystems (Goulden *et al.,* 1996; Richardson *et al.,* 2009; Ahrens *et al.,* 2009; Ganguly *et al.,* 2010), due to leaf development indicating a distinct carbon gain in spring. The length of the growing season has a lesser impact on annual carbon budgets, due to an increase in ecosystem respiration (White and Nemani, 2003). Annual CO_2 exchange is sensitive to four aspects of climate; the length of the growing season, cloud cover in summer, snow depth and soil temperature, and summer drought (Goulden *et al.,* 1996). The advance of spring alters surface energy balance and can accelerate transpiration (White *et al.,* 2009). However, earlier growth in spring advances soil water depletion may enhance mid-summer drought and spring carbon assimilation (White and Nemani, 2003).

2.2 Vegetation Phenology Monitoring Techniques

The observation of vegetation phenological events has changed from a traditional data collection method undertaken by public enthusiasts, to an integral parameter of GCMs. Therefore, characterising vegetation phenology utilising multiple methods is necessary to record various responses from individual species to global vegetation phenological change. There are advantages and limitations of utilising each of the main techniques, including spatial and temporal sampling (Table 2-1).

Satellite observations data can be compiled at a global scale with regular observation intervals (Moulin *et al.,* 1997; MacBean *et al.,* 2015; Verger *et al.,* 2016). However, satellite data integrate across heterogeneous species and land cover types, which may hinder the interpretation of seasonal trends (Richardson *et al.,* 2013). *In situ* observations capture vegetation phenophases specific to individual species that cannot be detected with the use of sensors. However, data collected by individuals using *in situ* techniques can be subjective and difficult to scale up to a satellite pixel.

Table 2-1 Synopsis of the advantages and limitations of vegetation phenology monitoring techniques.

Technique	Method	Advantages	Limitations
In situ	*In situ* observations, Citizen Science	Capture phenophases: flowering, fruit, etc. Observe individual plants and species	Labour intensive, Sparse temporal and spatial sampling, Time consuming, Observer bias, Subjective based on observer accuracy.
Near-Surface	Flux Tower observations, Aerial imagery, Digital Photography, Eddy Covariance	Spatial integration, Continuous in time, Not as labour intensive as *in situ*	Infrastructure required, Instruments may fail, Uncertain interpretation.
Satellite	MODIS, AVHRR, MERIS, Landsat etc.	Regional, Continental and Global scales, Regular intervals of coverage	Coarse spatial and temporal resolution, Data drop outs, Atmospheric corrections, Uncertainty, Aggregation of observations.

2.2.1 *In Situ* Monitoring

Historical and contemporary *in situ* vegetation phenology datasets are generally sparse, and long-term repeated measurements of different species are uncommon (Reed *et al.*, 1994a; Schwartz *et al.,* 2013). In addition, international datasets are usually not coordinated and can be incomparable, due to the differences in monitoring methodology and reporting on vegetation phenology (Schwartz *et al.,* 2013). However, ground-based observations are believed to be the most reliable basis for characterising vegetation phenology. The majority of *in situ* studies concentrate on individual organisms or species (Reed et al., 1994a). On both sides of the North Atlantic, vegetation phenological networks were extremely active during the first half of the 20th century, however, this interest slowly declined (Sparks *et al.,* 2000). In recent years, the scientific recognition of vegetation phenology being an effective indicator of climate change has been the main factor leading to the creation of, or the reestablishment of, vegetation phenology networks (Sparks *et al.,* 2000). The majority of vegetation phenology networks are located in temperate ecosystems, with very few long-term observations located in the tropics (Cleland *et al.,* 2007). Therefore, currently a complete *in situ* record covering global biomes is non-existent.

There are several vegetation phenology networks that aim to understand the relationship between vegetation phenology and environmental change, for example the USA National Vegetation phenology Network and the Woodland Trust's Nature's Calendar, UK (Table 2-2). One of the largest joined networks is the International Vegetation phenological Gardens (IPG). The IPG is a network of botanical gardens across 89 sites in 19 countries, with the aim of undertaking large scale and standardised vegetation phenological observations across Europe, monitor environmental changes, climate impacts, develop vegetation phenological models, calibrate remotely sensed data, and calculate vegetation phenological maps (Schnelle and Volkert, 1974).

Full global coverage of *in situ* phenophase observations would prove highly difficult to collate (Atkinson *et al.,* 2012). In several studies, the observed areas are centred near to a field station, or observe only a select number of species. Typically the outcome of vegetation phenology studies is to analyse site specific responses, and the temporal and spatial patterns of vegetation phenology (Post and Stenseth, 1999; Estrella *et al.*, 2006). The main limitations of utilising ground observations are low spatial density and the limited frequency of data collected, due to the sampling strategy of *in situ* observation methods. This makes is difficult to calculate trends at a national or global level solely through *in situ* observations.

Classifying vegetation phenological stages are not straight forward and the definition for each stage varies depending on the study. For example, a United States vegetation phenology network, Project BudBurst, acknowledges first leaf to be the date in which there are completely opened leaves on at least three parts of a tree or shrub (Polgar and Primack, 2011). Whereas, the IPG in Europe define first leaf as when the surface of the leaf is visible in three to four places on the plant (Polgar and Primack, 2011). In Germany, the Biologische Bundesanstalt, Bundessortenam und Chemische Industrie (BBCH) scale, has been developed through several government agencies, as a vegetation phenological scale for species of agricultural crops and defines each phenophase by a number. For example, phase 1 is defined as principle plant growth (Polgar and Primack, 2011).

Table 2-2 A selection of some of the vegetation phenology networks/sites across the world.

Site/Network name	Location	EST.
Arctic LTER	USA	1996
BioWatch	Australia	2003
Chequamegon Ecosystem Atmosphere Study (ChEAS)	USA	1994
Chinese Vegetation phenological Observation Network (CPON)	China	1963
ClimateWatch	Australia	2009
De Natuurkalender	Netherlands	2001
Global Observations to Benefit the Environment	Global	1998
Harvard Forest LTER	USA	1907
Howland Research Forest	USA	1989
Hubbard Brook Experimental Forest	USA	1955
INPA Vegetation phenology Project	South America	1965
International Vegetation phenology Gardens (IPG)	Europe	1957
Ireland’s National Vegetation phenology Network (IE-NPN)	Ireland	2008
Konza Praire LTER	USA	1980
Long Lake Conservation Center	USA	1998
Nature’s Calendar	UK	1998
Niwot Ridge LTER	USA	1980
North American Lilac Network	USA	1956
Northeast Regional Vegetation phenology Network	USA/Canada	2007
Oak Ridge National Laboratory DAAC	USA	1943
Pan European Vegetation phenology Project (PEP725)	Europe	2010
Plantwatch	USA	1987
Project BudBurst	USA	2007
RENECOFOR	France	1992
Rocky Mountain Biological Laboratory	USA	1928
Savilleta LTER Site	USA	1989
SCANNET	Scandinavia	2001
Shortgrass Steppe LTER	USA	1982
Swedish National Vegetation phenology Network (SWE-NPN)	Sweden	2008
USA National Vegetation phenology Network	USA	2007

Vegetation phenology networks typically rely on volunteers to collect observations of various phenophases of wild plants, trees and agricultural crops at numerous stations. The term “citizen science”, composed by Irwin (1995), is now used commonly to describe data collected by amateurs and volunteers. The relatively low cost and ease of recording *in situ* data has led to an increasing number of volunteer-based networks of observations (Bonney *et al.,* 2014; Schwartz *et al.,* 2013; Dunkley, 2016). In addition, citizen science initiatives provide a means to demonstrate climate change and ecology to the general public (Sparks and Smithers, 2002; Brossard *et al.,* 2005; Schwartz *et al.,* 2013; MacKenzie *et al.,* 2017). There is a continuing debate on the scientific value of citizen science projects and the consistency of the data gathered (Mayer, 2010; Polgar and Primack, 2011). For example, it is difficult to ensure standardisation of the tasks performed by volunteers and there is great potential for errors in reporting (MacKenzie *et al.,* 2017). There is an additional fear that with increasing popularity, vegetation phenological studies may reach a saturation point, be duplicated, or compete with one another (Whitfield, 2001). However, due to traditional field based vegetation phenology observation methods being time consuming and requiring regular visits in order to gain extensive records over a given area, participation of volunteers is a necessity for vegetation phenological studies (Mayer, 2010).

The collection of ground data is imperative for a greater understanding of vegetation phenological events and emerging trends in relation to environmental factors. The *in situ* record of vegetation development throughout annual and inter-annual cycles is required to validate and compare to other monitoring techniques, and assess the accuracy of results. In order to gain a greater comprehension of individual species development and the effects of climate change on individual species, greater coverage and compatibility of vegetation phenology network results is required.

2.2.2 Near-Surface Monitoring

Near surface monitoring techniques predominately use radiometric instruments, imaging sensors or digital cameras. By combining different types of near-surface data, such as photography and eddy covariance data, it is possible to separate changes in vegetation structure to vegetation function, such as photosynthetic capacity or efficiency (Migliavacca *et al.,* 2011; Richardson *et al.,* 2013; Knox *et al.,* 2017). Near-surface monitoring techniques are not as labour intensive as *in situ* monitoring. In addition, vegetation phenological changes can be monitored at a high temporal frequency over a broad area with both the understory and canopy able to be monitored, and are rarely obscured by cloud cover (Ide and Oguma, 2010). However, they do require infrastructure, such as towers, to be placed above the canopy, are limited to the durability of the equipment (e.g. web cameras), as the instruments may fail.

Table 2-3 A selection of some of the near-surface monitoring networks available across the world.

Network	Monitoring	Location	Link
Phenocam	Digital Camera	USA	https://phenocam.sr.unh.edu/webcam/
European Vegetation phenology Network (EPN)	Digital Camera	Europe	
Australian Phenocam Network	Digital Camera	Australia	https://phenocam.org.au/
Vegetation phenological Eyes Network (PEN)	Spectral Radiometer and Digital Camera	Global	http://www.pheno-eye.org/
AmeriFlux	Flux Tower Eddy Covariance	North and South America	http://ameriflux.lbl.gov/
FLUXNET	Flux Tower Eddy Covariance	Global	https://fluxnet.ornl.gov/
International Long Term Ecological Research network ILTER	Flux Tower Eddy Covariance	Global	http://www.ilternet.edu
National Ecological Observatory Network (NEON)	Digital Camera	USA	http://www.neonscience.org/
AsiaFlux	Flux Tower Eddy Covariance	Asia	http://asiaflux.net/
Japan Long Term Ecological Research network (JaLTER)	Flux Tower Eddy Covariance	Japan	http://www.jalter.org/
Global Ecosystem Monitoring (GEM)	Flux Tower Eddy Covariance and Digital Camera	Global	http://gem.tropicalforests.ox.ac.uk/

Near surface monitoring techniques have been utilised for agricultural (Hague *et al.,* 2006, Slaughter *et al.,* 2008), ecological monitoring (Luscier *et al.,* 2006; Booth and Cox, 2008), vegetation growth and biomass (Boyd and Svejcar, 2005; Crimmins and Crimmins, 2008; Graham *et al.,* 2009), and for vegetation phenological analysis (Richardson *et al.,* 2009). Several networks of digital cameras and flux tower measurements have been established across the globe (Table 2-3). With the advances in technology and ease of telecommunications over the last few decades, several of these databases are available freely over the internet and are becoming increasingly popular.

Digital cameras and web cameras have been effectively utilised as multi-channel imaging sensors (Richardson *et al.,* 2007; Ahrends *et al.,* 2008; Richardson *et al.,* 2009; Ahrends *et al.,* 2009; Kurc and Benton, 2010). The use of digital cameras to assess vegetation phenology has increased in recent years due to the reduction in cost of equipment and the increased need for real-time imaging at a high spatial resolution (Ide and Oguma, 2010; Graham *et al.,* 2010).

The RGB channels from digital photographs provide spectral information. Indices can be constructed using the RBG channels to assess seasonal vegetation changes (Richardson *et al.,* 2007; Richardson *et al.,* 2009; Ide and Oguma 2010; Nagai *et al.,* 2011). The relative brightness of the RGB channels can detect the canopy green up. Similarly to remote sensing methods, the start of season (SOS) and end of season (EOS) are characterised by an abrupt increase or decrease in the index value. There are several RGB derived vegetation indices that have been utilised in previous research, such as the Green Chromatic Coordinate (GCC), Excess Green Index (EGI) and Green-Red Vegetation Index (GRVI) (Sakamoto *et al.,* 2011; Richardson *et al.,* 2012; Anderson *et al.,* 2016).

The photographic images taken during any vegetation phenology study will have variations over the study period due to tree movement and tree and understory growth. Abiotic factors, such as varying ambient illumination conditions and wind, affect the noise ratio within the time-series of digital camera photographs. Imagery used from RGB cameras are best taken during high illumination, clear sky conditions (Sonnentag *et al.,* 2012). The brightness levels are controlled by the illumination and viewing geometries, due to the digital camera orientation, viewing angle, shadowing effects, time and the day of year, and lastly, weather conditions (Sonnentag *et al.,* 2012). One way to increase the accuracy of results from digital camera photography is to increase the sampling frequency, as there will be a greater spectrum of results with varying illumination across the time-series. In several studies a ROI within a photograph is selected to assess the brightness of the RGB channels. The ROI can exclude areas of different light conditions, skyline, including cloud and fog, and varying land cover types (Migliavacca *et al.,* 2011). The main disadvantage of near-surface monitoring is to what degree the field of view/interest is representative of the landscape which is dependent on the species present within the ROI (Hufkens *et al.,* 2012).

One aspect that needs to be considered is the choice of camera used to detect vegetation phenological changes. There is a wide range of cameras utilised for vegetation phenological research, including web cameras, game and plant cameras, and low and high end digital cameras, such as digital single-lens reflex cameras (DSLRs). The utilisation of cameras varies due to the imaging sensor, resolution, light sensitivity, maintenance and cost of the equipment. In addition, the file format of the image should be assessed, for example RAW and TIFF files, and the most commonly used format, JPEG. The choice of camera and image file format may affect the results, and the interpretation of the images, depending on the initial formats (Sonnentag *et al.,* 2012).

Terrestrial ecosystems are important to land surface and trace gas exchanged in the atmosphere. Flux measurements of carbon dioxide using eddy covariance (EC) techniques have enabled the dynamics of plant community photosynthesis to be studied. Canopy flux data has also been successfully linked with remotely sensed data (Hufkens *et al.,* 2012). However, accurately estimating carbon fluxes is complex due to vegetation phenological variations and biotic and abiotic influences (Mizunuma, *et al.,* 2013).

There has been an increase in the number of FLUXNET sites that combine the use of EC and digital camera monitoring techniques. There are global and regional networks of eddy covariance towers established to study the variations in plant vegetation phenology, such as the global flux network (FLUXNET) of eddy covariance towers which provides continuous half-hourly estimates of CO_2 and H_2O exchange over 500 sites (Baldocchi, 2008). EC towers measure the difference between gross photosynthesis and ecosystem respiration. Recent progress of CO_2 EC techniques and accumulation of measurements offer a new way of extracting land surface phenology (LSP) through GPP. Variations in CO_2, water and energy fluxes between vegetation and atmosphere are measured via EC techniques.

Radiometric sensor methods include calculating the fraction of absorbed photosynthetically active radiation (fAPAR) absorbed by the canopy. fAPAR can be calculated from above or below the canopy and is also linked to leaf area index

(LAI). Another method is to calculate broadband NDVI; this differs from NDVI as it is calculated from albedos of photosynthetically-active radiation (PAR) and global radiation.

The use of near-surface techniques assists in the comparison of the diverse spatial extremes of *in situ* and remotely sensed data. The main limitation of comparing the two extreme methods is the scale of pixel to point, particularly when using low-resolution data (8 km), therefore, by using an intermediate data source this will assist in the accurate assessment of vegetation phenology and trends.

2.2.3 Satellite Monitoring

Satellite-sensor derived analysis of vegetation phenology varies significantly from ground-based studies. Remote sensing has expanded the scope of vegetation phenology monitoring from an individual plant or forest to full global coverage of ecosystems. Variations in the measurements of reflected electromagnetic radiation of the land surface reflectance show the recurring variations that are determined by vegetation phenology (Hanes *et al.,* 2014). The timing of remotely sensed seasonal patterns in vegetated land surfaces are described by the term land surface phenology (LSP) (White and Nemani, 2006, Reed *et al.,* 2009, Dunn and de Beurs, 2011, Jones *et al.,* 2011). LSP differs from traditional definitions of vegetation phenology, which usually refer to a specific event such as first leaf and leaf fall. Metrics of LSP represent the timing of reflectance changes that are driven by the activity of vegetation within the area measured (Hanes *et al.,* 2014). Estimation of LSP may be affected by atmospheric contamination, snow and cloud cover, and bidirectional viewing effects. Therefore, LSP is not identical to vegetation phenology. Time-series of remotely sensed data are an important source for understanding vegetation dynamics over time. This includes the seasonal development of vegetation for start, peak, duration and end of growing season (Pouliot *et al.,* 2011).

Since the 1970s researchers have accepted the potential of multi-temporal satellite sensor observations to provide information about vegetation phenological development across ecosystems (Reed *et al.*, 1994a; Rees and Rees, 2013). The main advantage of using remote sensing in vegetation phenology studies is the spatial extent of coverage, in particular in regions with no ground observations (Justice *et al.,* 1985; Xiao and Moody, 2005). Remote sensing methods are repeatable and cost effective over large areas (Song and Woodcock, 2003; Cleland *et al.,* 2007). In addition to capturing the trend of vegetation phenology over an extended period of time, the inter-annual anomalies of vegetation dynamics can also be assessed using remote sensing imagery which an important factor in relating the response of vegetation to meteorological forcing (Maignan *et al.,* 2008). However, remote sensing has limitations; for example, the limited ability to monitor individual plants or species, as well as generally only capturing images from the canopy and overlooking the understory vegetation (Reed *et al.*, 1994a).

Spectral transformations are used to prepare satellite data for vegetation phenological studies, known as VI. VI provide an indication of canopy ‘greenness’ and enhance spectral reflectance and emissive characterisations of vegetation and environmental conditions, including leaf area, soil moisture, and vegetation water content (Curran and Steven, 1983). Remote sensing utilises the electromagnetic spectrum to categorise electromagnetic waves, specifically the visible and near-infrared wavelengths (Schowengerdt, 2006; Schott, 2007) (Figure 2-2).

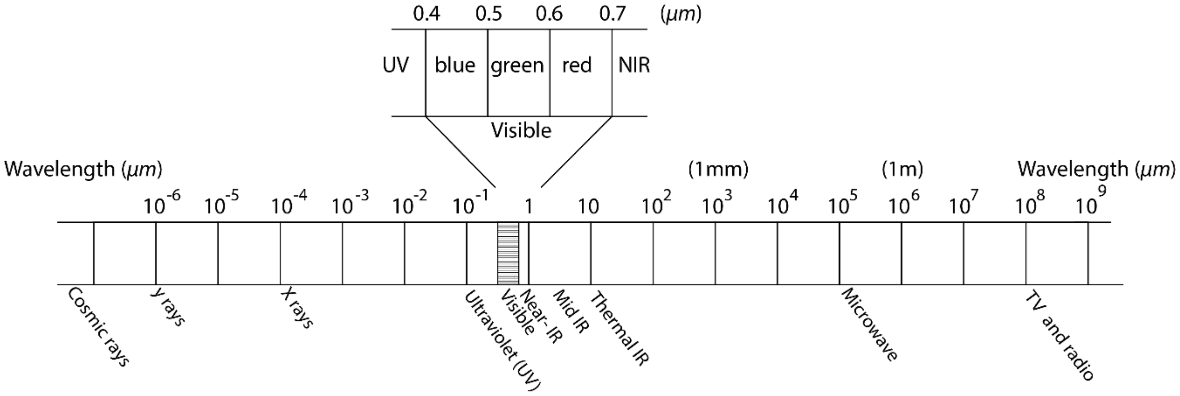


Figure 2-2 Electromagnetic spectrum assessed by satellite sensors micrometre (μm).

Satellite-derived vegetation phenological estimates are interpreted through vegetation VI time-series (Figure 2-3). The most commonly used vegetation phenology metric within remote sensing studies is the Julian day of year (DOY) for (1) the onset of greenness increase (greenup), (2) maturity onset (onset of greenness maximum), (3) senescence onset (onset of greenness decrease, and (4) end of senescence (the onset of greenness minimum or dormancy) (Zhang *et al.,* 2009).

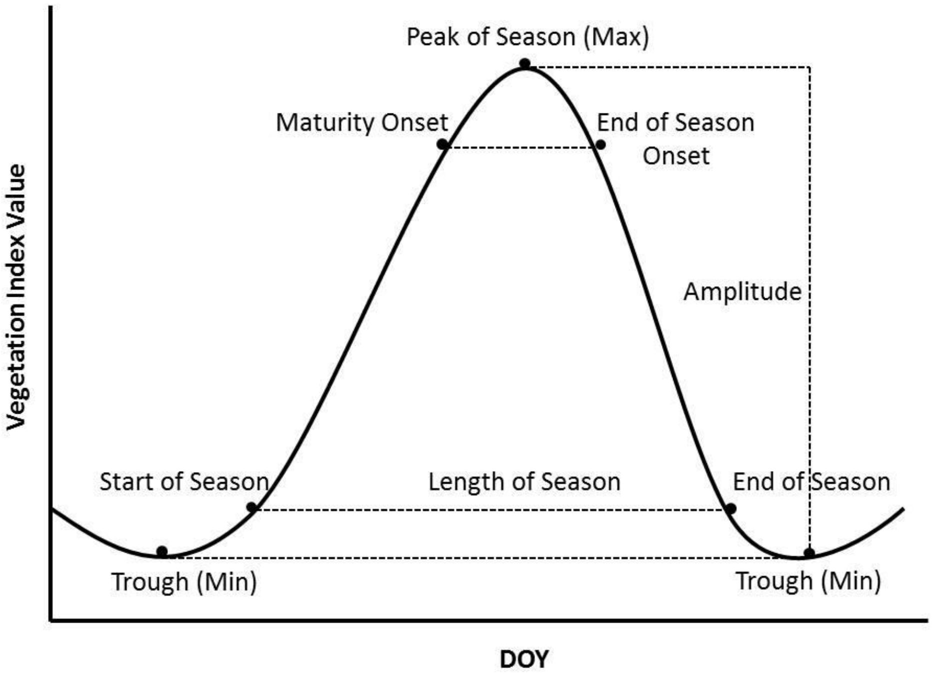


Figure 2-3 Basic diagram of a time-series of vegetation phenology data and estimated transition date. Adapted from Zhang *et al.,* (2003).

There are several instruments, passive and active, which are used to detect energy and radiation (Table 2-4) including, radiometer, imaging radiometer, spectrometer, spectroradiometer, scatterometer, LiDAR (Light detection and ranging) and laser altimeter. The longest record of satellite observation of the Earth is the Landsat series. The use of Landsat imagery was previously effected by the high cost of the data, but are now freely available from the USGS, which has allowed researchers to freely utilise the data available (Song and Woodcock, 2003). However, the temporal frequency of 16 days is far greater than other satellite sensors, and may not collect the precise day for key vegetation phenological observations (Reed *et al*., 1994a). In addition, collecting cloud free multiple images from different years for the same date is frequently not possible, which affects the ability of monitoring the change or trends of vegetation phenology over a given area (Song and Woodcock, 2003). With the launch of new sensors with a finer spatial and spectral resolution, such as the ESA Sentinel missions and the NOAA WorldView-3 satellite sensor, research has focused on achieving greater accuracy from satellite sensor imagery (Kross *et al.,* 2011; Lange *et al.,* 2017).

Table 2-4 A selection of the satellite sensors used for vegetation phenology studies taken from Reed *et al.,* (2009).

Satellite	Sensor	Operation	Resolution	Frequency
Landsat	MSS	1973-1985	79 m	18 days
Landsat	TM	1984-present	30 m	16 days
Landsat	ETM+	1999-present	30 m	16 days
NOAA	AVHRR	1982-present	8 km	Bimonthly
NOAA	AVHRR	1989-present	1 km	Biweekly
OrbView	SeaWiFs	1997-present	1.1 km, 4.5 km	1 day
SPOT	Vegetation	1999-present	1km	1-2 days
Terra	MODIS	2000-present	250 m, 500 m, 1 km	1-2 days
Aqua	MODIS	2002-present	250 m, 500 m, 1 km	1-2 days
Envisat	MERIS	2002-2013	300 m	1-3 days

The Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectrometer (MODIS) are the two main data sources for regional-to-global vegetation monitoring (Hmimina *et al.,* 2013). MODIS has an improved spatial resolution, spectral resolution, geolocation accuracy, atmospheric correction scheme and cloud screening, and sensor calibration (Hmimina *et al.,* 2013).

2.2.3.1 Vegetation Indices and Methods Utilised to Identify Vegetation Phenology Parameters

VI were developed primarily for vegetation study and are calculated by varying combinations of visible and near-infrared spectral measurements (Reed *et al.*, 1994a). They indicate the abundance and the level of activity of green vegetation, and have been used to assess leaf area index (LAI), percentage green cover, green biomass and fPAR (Running *et al.,* 1994; Barati *et al.,* 2011). VIs are not intrinsic physical quantities and are used as proxies for biophysical and biochemical variables (Jiang *et al.,* 2008). The most commonly used VI, NDVI, is related to the absorption of photosynthetically active radiation by plant canopies, and is often used as a proxy indicator of vegetation canopy function. NDVI is calculated from a normalised transform of the near-infrared (NIR) and red reflectance ratio and is a measure of greenness or density of chlorophyll and leaf tissue (Tucker, 1979; Chen *et al.,* 2004). The normalisation within the formula compensates for changing illumination and surface terrain (Reed *et al.*, 1994a).

There are several other indices, including Enhanced Vegetation Index (EVI), which improves the detection of bare soil from vegetation (Cleland *et al.,* 2007; Jiang *et al.,* 2008). The Soil Adjusted Vegetation Index (SAVI), a more stable VI, with a higher dynamic range at high end but less dynamic range and low end (Huete, 1988). Several other indices include, MERIS Terrestrial Chlorophyll Index (MTCI) (Dash and Curran, 2004), Normalised Difference Water Index (NDWI) (Gao,1996), Optimised Soil Adjusted Vegetation Index (OSAVI) and the Modified Soil Adjusted Vegetation Index (MSAVI) (Barati *et al.,* 2011). Each VI has its own advantages and limitations. For instance, NDVI is affected by the variation of soil optical properties, which is particularly important in areas with low vegetation cover (Baret and Guyot, 1991).

The full potential of long-term time-series is affected by data drop outs, data gaps, bidirectional reflectance distribution function (BRDF), atmospheric and sensor noise, that create difficulties in assessing vegetation phenology parameters (Bradley *et al.,* 2007; Song and Woodcock, 2003; Atkinson *et al.,* 2012). Several methods have been developed to derive metrics of LSP from time-series of satellite sensor observations (Hanes *et al.,* 2014; White *et al.,* 2009). The first step is to convert noisy temporal vegetation index data into a smooth time-series in order to assess vegetation phenology events (Atkinson *et al.,* 2012). There are multiple methods in which vegetation phenology parameters are identified from multi-temporal satellite sensor data, ranging from simple smoothing to non-linear inverse modelling approaches (Fisher *et al.,* 2006). The methods include threshold techniques (Table 2-5), derivative techniques (Table 2-6), smoothing algorithms (Table 2-7) and model fitting (Table 2-8) (de Beurs and Henebry, 2010). Each method has advantages and limitations depending on the purpose of the study and will need to be adjusted (Beck *et al.,* 2007; Fisher *et al.,* 2006; Atkinson *et al.,* 2009).

Commonly used methods include, best index slope extraction (BISE) (Vivoy *et al.,* 1992), Fourier-adjusted, logistic function (Bendix, 2006; Zhang *et al.,* 2003), median smoothing (Reed *et al.*, 1994a), moving average (White *et al.,* 2009), interpolated, reconstructed (FASIR), and Savitzky- Golay filter (Chen *et al.,* 2004).

Table 2-5 Threshold techniques used within vegetation phenology studies.

Method	Full Name	Algorithm	Citation
0.099 NDVI Threshold	0.099 NDVI Threshold	Point at which the data value exceeds the pre-defined threshold of 0.099	(Lloyd, 1990)
0.17 NDVI Threshold	0.17 NDVI Threshold	Point at which the data value exceeds the pre-defined threshold of 0.17	(Fischer, 1994)
NDVI 0.2	NDVI 0.2	NDVI exceeds 0.2	(Suzuki *et al.,* 2003)
NDVI 0.3	NDVI 0.3	NDVI exceeds 0.3	(Zhou *et al.,* 2003)
Half Maximum	Half Maximum	Point at which the data sigmoid reaches its half maximum value (midpoint between minimum and maximum)	(White *et al.,* 1997)
10% Amplitude	10% Amplitude	Point at which the value exceeds 10% of the distance between the minimum and maximum	(Jonsson and Eklundh, 2002)
PAT	Pixel Above Threshold	NDVI exceeds locally tuned threshold, run for the group behaviour of all pixels within an ecoregion	(White and Nemani, 2006)
$\text{Midpoint}_{\text{cluster}}$	$\text{Midpoint}_{\text{cluster}}$	NDVI exceeds locally tuned threshold, run for the time-series aggregated to a cluster level	(White *et al.,* 2005)
$\text{Midpoint}_{\text{pixel}}$	$\text{Midpoint}_{\text{pixel}}$	NDVI exceeds locally tuned threshold, run for every pixel	(White *et al.,* 2005)
SMN	Pixel-Specific Seasonal Midpoint	The midpoint between annual minimum and maximum values for each pixel	(White *et al.,* 2003)

Global threshold technique (Lloyd, 1990; Fischer, 1994), is simplified as the DOY where the NDVI value exceeds a threshold. In order to determine on which DOY the NDVI exceeds a given threshold for a vegetation phenology parameter, the time-series is interpolated to a daily dataset. This threshold varies with vegetation type, soil background, and illumination conditions, which makes it difficult to establish a single meaningful threshold that indicates the start or end of season for a wide variety of vegetation types (Reed *et al.*, 1994a). Therefore, this method creates inconsistencies when applied over a large area using a single threshold to assess the onset or offset of vegetation (Reed *et al.*, 1994a). Researchers use threshold values set at a certain level or amplitude, for example 0.099, 0.17 and 0.3 (Lloyd, 1990; Fischer, 1994; White *et al.,* 1997; Zhou *et al.,* 2003). Table 2-5 highlights the range of threshold values used within remotely sensed vegetation phenological studies. Jenkins *et al.,* (2002) elaborate on the implications of using a threshold to determine the DOY when a vegetation phenology parameter has been reached. For example, areas with a high VI value, such as forested areas with a high population of conifers, will pass over the threshold quickly, whereas sparse canopy forests may pass the threshold later in the year or not at all.

Table 2-6 Desription of dervivative techniques used within vegetation phenology studies.

Method	Algorithm	Citation
Time Derivative	Derivative calculated on 3 composites	(Moulin *et al.,* 1997)
Camelback Vegetation phenology Algorithm	Based on Moulin *et al.,* (1997). 5 composites passed over the time-series for every pixel then a second order derivative is calculated	(Balzter *et al.,* 2007)

Derivative techniques (Table 2-6) are defined as the maximal increase in VI showing the SOS, and the maximal decrease showing the EOS (Balzter *et al.,* 2007; Tateishi and Ebata, 2004). Derivative methods do not have an analytic error structure, therefore it is difficult to conclude if observed changes relate to the natural variability of data or from significant change (Hudson and Keatley, 2009). These methods are restricted in determining SOS and EOS when the vegetation index value does not have a sudden increase or decrease.

Table 2-7 Description of smoothing algorithms used in vegetation phenology studies.

Method	Full Name	Algorithm	Citation
Inflection Point	Inflection Point	Inflection points meet on a bell shaped curve	(Badhwar, 1984)
Maximum Curvature	Maximum Curvature	Truncation based on detecting the maximum curvature of curve segments at each scale	(Zhang and Lu, 2003)
DMA	Delayed Moving Average	Smoothed NDVI exceeds expected value of near-term historical NDVI	(Reed *et al.*, 1994a)
Time of largest increase	Time of largest increase	Date of largest increase in NDVI for each pixel after monthly mean temperature reached 5°C	(Kaduk and Helmann, 1996)
Fourier Analysis	Fourier Analysis	Approximates complicated curves with a sum of sinusoidal waves at multiple frequencies	(Moody and Johnson, 2001)
HANTS-FFT	Harmonic Analyses of NDVI Time-Series Fast Fourier Transform Timesat	Maximum increase on Fourier approximation of NDVI	(Roerink *et al.,* 2000)
Timesat	Timesat	High amplitude divergence from a multiple-model NDVI fit	(Jonsson and Eklundh, 2002)
PCA	Principal Component Analysis	Orthogonal linear transformation that transforms data to a new coordinate system	(Hall-Beyer, 2003)
Savitzky-Golay	Savitzky-Golay filter	Simplified least squares-fit method using a weighted moving average filter	(Savitzky and Golay, 1964)

There are several smoothing algorithms that are used within vegetation phenology studies (Table 2-7), used to smooth the satellite-derived data and to increase the signal to noise ratio without disturbing the signal. Signal to noise ratio (SNR) compares the level of signal to the level of background noise. Fourier analysis, approximates complicated curves with a sum of sinusoidal waves at multiple frequencies (Bradley *et al.,* 2007; Moody and Johnson, 2001). The increased number of sinusoidal waves is able to approximate vegetation phenology signals more closely. There are limitations within Fourier analysis, as it requires a long time-series or equally spaced observations. Therefore, an increased length of time-series data available equates to a finer resolution of the frequency decomposition.

Table 2-8 highlights the most commonly used model fitting methods for assessing variations of vegetation parameters. There are several methods available, for example, Jonsson and Eklundh (2002) model the shape of the vegetation phenological profile with fused half-Gaussian functions. Zhang *et al.,* (2003) pursue a similar method, using non-linear least-squares methods to fit composite MODIS EVI data with two sigmoid functions (one increasing with greenup, the other falling with senescence). A sigmoid fit method both utilises all possible information and is robust to the addition of random noise. Fisher *et al.,* (2006) and Beck *et al.,* (2006) model the entire growing season as two sigmoid logistic growth curves controlling greenup and senescence in a six parameter technique, which is similar to the technique utilised by Badhwar (1984). There are limitations with using model fitting techniques such as, the ratio of the number of parameters that must be estimated from a limited number of satellite-sensor observations per year (de Beurs and Henebry, 2010). It is also unclear how the temporal resolution of the sensor data influences parameter estimation within these techniques (Ahl *et al.,* 2006).

Table 2-8 Description of model fitting techniques used within vegetation phenology studies.

Method	Full Name	Algorithm	Citation
Gaussian	Gaussian	Average date when Gaussian fit of NDVI exceeds three global thresholds	(Jonsson and Eklundh, 2002)
Logistic Model	Logistic Model	Estimation of a number of parameters which relate to SOS, difference between the min and max of VI, shape of the curve, and EOS	(Badhwar, 1984)
Quadratic	Quadratic	First composite period of growing degree accumulation best fitting the observed NDVI time-series	(de Beurs and Henebry, 2008)

Hird and McDermid (2009) compared a number of NDVI time-series noise reduction techniques. This included; asymmetrical Gaussian function-fitting (Jonsson and Eklundh, 2002), double logistic function fitting (Beck *et al.,* 2006), Savitzky- Golay filter (Chen *et al.,* 2004), 4253H twice filter (Velleman, 1980), mean value iteration filter (Ma and Veroustraete, 2006) and the ARMD3-ARMA5 filter (Filipova-Racheva and Hall-Beyer, 2000). Hird and McDermid (2009) assessed that the asymmetric Gaussian and double logistic function-fitting techniques performed best.

From all the above techniques used, no ideal technique has been identified. Each has its own advantages and limitations, depending on the satellite sensor and area being studied and these can equate to greater sources of uncertainty within the results. However, the uncertainty in each technique available needs to be fully evaluated and discussed. These include the uncertainties from the initial data, pre-processing techniques used, the smoothing algorithms, as these will all affect the results collated for vegetation phenology SOS, EOS and length of season (LOS).

2.2.4 Comparison of Techniques

'Validation' is a commonly used term for the comparison of satellite-derived estimations of vegetation phenological parameters to *in situ* or near surface observations. Validation and comparisons are required in order to assess the accuracy of the estimated parameters. Accurate measurements of vegetation phenology are required to understand inter-annual variability of ecosystem processes. Ground based observations are perceived to be the most accurate, however, this method is time labour intensive and time-consuming (Zhang *et al.,* 2009). The comparison of *in situ* observations, canopy greenness from digital canopy imagery, and VI from satellite imagery is complex (Migliavacca *et al.,* 2011).

Linking ground-based observations with remotely sensed observations has the potential to enhance the ability to track biotic responses to climate change (Studer *et al.,* 2007). The spatial extent of near surface data is limited in comparison to satellite imagery, however, it does bridge the spatial gap between *in situ* to satellite, as single trees can be observed in addition to the surrounding species. In addition, canopy development, GPP, and CO_2 fluxes can be monitored and linked to phenophase events.

Comparing remote sensing data to ground observations is the subject of continuing research and has the potential to enhance the understanding of climate change and the effects on vegetation phenological parameters (Justice *et al.,* 1985; Delbart *et al.,* 2005; Studer *et al.,* 2007; Fisher and Mustard, 2007). Near-surface techniques are showing promise to assist the comparison of *in situ* and satellite derived vegetation phenology. As near-surface monitoring networks increase, the relationship of surface vegetation phenology and satellite-derived vegetation phenology is being understood to greater level. This includes the impact of vegetation phenology on carbon sequestration, carbon fluxes and photosynthetic efficiency (Piao *et al.,* 2008; Richardson *et al.,* 2010). The comparison of understory and canopy vegetation development is another area of research to be also considered. *In situ* observations are taken from the ground, and may not fully represent the upper canopy changes, whereas near-surface techniques observe changes from below and above canopy depending on the strategy used by researchers.

Several challenges may be encountered when comparing *in situ* and satellite sensor data, including field-to-satellite scaling and the comparability of vegetation phenological parameters (Fisher and Mustard, 2007; Hufkens *et al.,* 2012). Several recent papers have shown that regional satellite leaf out data can be accurately matched with *in situ* ground data observations (Delbart *et al.,* 2005; Fisher and Mustard, 2007). Satellite-derived vegetation phenology has a full spatial coverage of the radiative characteristics of vegetation (Studer *et al.,* 2007). However, satellite-derived pixel-based estimates are necessarily aggregates of the reflectance of several species, and the influence on reflectance that these multiple species have compared to a single species or a species type is unknown (Maignan *et al.,* 2008). The species present in the study area can affect the estimation of vegetation phenology parameters; e.g., SOS and EOS (Beck *et al.,* 2007).

The SOS is the date on which pixels start to green-up, or reach a defined percentage of the season maximum. The increase in greenness is quantified by an increase in a vegetation index as the photosynthetic tissue increases within a pixel (Delbart *et al.,* 2015). Estimating EOS using satellite-derived data has been less successful, as there are known limitations, particularly due to EOS being controlled by different environmental conditions than SOS (Pouliot *et al.,* 2011).

Scaling *in situ* point observations to a pixel level is difficult and highly dependent on the strategy used in recording each phenophase on the ground. Constant and consistent observations within the given study areas are needed in order to be able to understand the variation of individual species, which then can be up scaled to a community level vegetation phenology. The majority of ground data observations collected are of single isolated points which lack the spatial coverage needed to match satellite pixels (Liang *et al.,* 2011). In addition, the majority of ground vegetation phenology data available are for discrete events, which lack temporal continuity (Liang *et al.,* 2011).

Ground-based vegetation phenology methods collate detailed information about individual species, but have a low spatial coverage (White *et al.,* 2005; Studer *et al.,* 2007). In areas with only single tree species present, phenotypic variability and local adaptations create a wide window of vegetation phenological response (Badeck *et al.,* 2004). *In situ* to satellite scaling is difficult due to the large spatial step required to associate point studies to coarse resolution satellite data, especially due to compositional errors and loss of high frequency data (Fisher *et al.,* 2006). Few vegetation phenology studies have metrics with validated physical meaning and the *in situ* data collected may not represent information that can be interpreted using satellite sensor data.

The spatial resolution of satellite imagery can vary from AVHRR, SPOT and MODIS with spatial resolutions from 250 m to 8 km. Therefore, the coarse spatial resolution means that small localised changes within a pixel may go unnoticed and not be fully represented in the data available (Fisher and Mustard, 2007). Badeck *et al.* (2004) found that even with a single tree species in one area the physical or biochemical characteristics and local adaptations create a wide window of vegetation phenological response. Unless the study area is large and perfectly homogeneous or a sufficient number of ground point measurements can be made as the satellite records the area, ground measurements may not be sufficient to validate sensor observations (Liang *et al.,* 2002). Infrequent satellite observations and cloud cover reduce the number of satellite pixels for comparison (Jonsson and Eklundh, 2002; Liang *et al.,* 2011).

There are several techniques utilised to correlate remote sensing data with *in situ* observations (Polgar and Primack, 2011). Fisher and Mustard (2007) utilised a validation technique for ground based time-series to be utilised as vegetation phenological metric or vegetation phenology index, to then be compared with MODIS. The data observed differs to the traditional day of flowering or budburst records, as the canopy development is recorded throughout the season. Fisher and Mustard (2007) also propose a criterion to understand the accuracy of satellite datasets, while expanding the reach of field studies through validation across instruments and scales, and between satellite and field data. The criteria are based upon three factors. Firstly, the vegetation phenological metric should be observable from both ground and satellite perspectives, the vegetation phenological metric should also have a similar meaning from both the ground and satellite perspectives, and lastly, spatial vegetation phenological heterogeneity may create discrepancies between satellite and ground observations.

Liang *et al.* (2002) up-scale the ground ‘point’ measurements to MODIS resolutions using high resolution remotely sensed imagery. The ground measurements are used to calibrate the products from high-resolution imagery, which are then aggregated to MODIS resolutions. The Committee on Earth Observation Satellites (CEOS) adopted a hierarchical approach to classify land product validation stages. This was agreed through a consensus of the Land Product Validation (LPV) community in 2003 and revised in 2009. This validation approach has four stages. Stage one encompasses assessing product accuracy with a small set of locations and time periods with *in situ* or suitable data. Stage two is where the accuracy of the product is conducted over a significant area and over a long period of time. The spatial and temporal consistency of the product is then evaluated over global locations and over a time period, the results can then be published within a peer-reviewed paper. Stage three is where the uncertainties within the product are well quantified and are assessed over multiple locations and time periods. Validation results from stage three are then updated when a new product version is released and the time-series expands which equates to stage four.

2.3 Observed Vegetation Phenological Trends and Controlling Factors

2.3.1 Vegetation Phenological Trends

During the second half of the 20th century a trend of temperature driven lengthening of the growing season by up to 2 weeks can be seen in mid-to-high northern latitudes (Parry *et al.,* 2007). Across Europe the growing season in certain species increased by 10.8 days between the years 1959 and 1993 (Menzel and Fabian, 1999, McCarthy, 2001). The Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report states that spring has been progressing at a rate of 2.3 and 5.2 days per decade since 1970 (Parry *et al.,* 2007). This has been reflected in both *in situ* (Table 2-9) and satellite based (Table 2-10) observations that have shown a change in leaf vegetation phenology across the globe (Gitay *et al.,* 2002). On the other hand, there is less agreement on the effects of climate change in autumn due to the signal being less pronounced and more heterogeneous (Parry *et al.,* 2007), although effects such as frost have been observed to be occurring later (Richardson *et al.,* 2013).

Table 2-9 Station-observed long-term changes in vegetation phenology trends.

			Change (days)		
Reference	Period	Region	Start	End	Length
(Menzel and Fabian, 1999)	1951-1996	Europe	-6.3	4.5	10.8
(Beaubien and Freeland, 2000)	1987-1996	Canada	-8		
(Menzel *et al.*, 2001)	1951-1996	Germany	-0.2/ year	6.6	5
(Ahas *et al.*, 2002)	1951-1998	C and W Germany	-28		
(Ahas *et al.*, 2002)	1951-1999	E Europe	10		
(Chmielewski and Rotzer, 2002)	1969-1998	Europe	-8		
(Peñuelas *et al.*, 2002)	1952-2000	Spain	-16	13	29
(Wolfe *et al.*, 2005)	1965-2001	NE USA	-6		
(Sparks *et al.*, 2000)	1891-1948	UK	-5.5		
(Ho *et al.*, 2006)	1922-2004	Korea	-13		
(Schwartz *et al.*, 2006)	1955-2002	NH	-4.8		

In recent decades, many studies have shown the observed vegetation phenological changes across the northern hemisphere. These include earlier spring onset, and longer growing season across boreal and temperate zones (Guyon *et al.,* 2011). Longer vegetation growing seasons are recognised to be attributed to temperature, water availability and humidity (Jeong *et al.,* 2011), particularly in the Northern Hemisphere. Therefore, changes in the growing season of vegetation could be mainly explained by changes to temperature and precipitation (Jeong *et al.,* 2011). In the Northern Hemisphere over the past 20 years temperatures have risen by 1.1°C in spring and 0.8°C in autumn (Zeng *et* *al.,* 2011). Along with increasing temperatures, there has been a change in precipitation levels, with some areas increasing whereas other areas have become drier (de Beurs and Henebry, 2008).

There are several studies that show evidence of an earlier onset of spring in Europe and America (Studer *et al.,* 2007). The earlier spring onset for several species ranges from 1.4 to 3.8 days per decade over the last 50 years (Studer *et al.,* 2007). The timing of leaf development correlates with cumulative springtime temperatures. Warmer temperatures have increased growing degree days in Alaska by 20% and boreal forests are expanding North by 100 to 150 km per ^{0}C (Gitay *et al.,* 2002). Across Europe there is a vast difference in results ranging from a 5 day extension of the growing season, to a 28 day extension, indicating variances in the results produced (Table 2-9).

The IPG network has summarised vegetation phenological observations across Western and Central Europe (Ahas *et al.,* 2002). Menzel and Fabian (1999) analysed observations from the IPG of leaf unfolding, May shoot, flowering, leaf colouring and leaf fall from 1959 to 1993. Using a unified vegetation phenology model they found that spring events will advance by six days per 1°C in winter temperatures. Spring showed an overall negative trend, indicating that spring is starting earlier in later years and the overall positive trend in autumn indicating that autumn is occurring later.

In satellite-derived studies, vegetation phenology in water controlled areas is difficult to model and has a greater degree of error in results. Botta *et al.,* (2000) states that the causes for this may be due to instrumental limitations of satellites, due to cloudiness near the inter-tropical convergence zone and the pre-processing techniques that are used to filter out noise in satellite sensor imagery. In areas such as Brazil, this was due to low frequency of satellite sensor observations, due to intense cloud cover, which prevents the detection of a change in NDVI (Botta *et al.,* 2000).

Vegetation phenology studies differ across the globe in regard to species, events observed, and methodology. White *et al.* (2009) highlight the conflicting results obtained from satellite-based vegetation phenology methods for North America. Reed (2006) found a scattering trend between an earlier and later SOS. However, Zhang *et al.,* (2007) found an earlier SOS everywhere apart from the South East. In contrast, Menzel *et al.* (2008) found that spring greening only in the South East. The inconsistent results of changes in vegetation phenological parameters could be due to several factors; study area chosen, VI, smoothing algorithm, and data drop outs. Satellite observations revealed an 3 to 8 day advance in spring vegetation phenology in northern latitudes from 1982 to 1991 (Myneni *et al.*, 1997), and a 6.4 day advance between 1982 and 1999 in Eurasian forests (Zhou *et al.*, 2001).

Table 2-10 Observed long-term (> 10 years) changes in vegetation phenology from satellite-sensor studies. Start (S), End (E) and Length (L) in days.

Reference	Period	Type	Region	S	E	L
(Myneni *et al.*, 1997)	1981-1991	PAL	Global	-8	4	12
(Tucker *et al.*, 2001)	1982-1991	AVHRR	45-75°C	-6		4
(Tucker *et al.*, 2001)	1992-1999	AVHRR	45-75°C	-2		0.4
(Zhou *et al.*, 2001)	1981-1999	GIMMS	Eurasia	-7		18
(Zhou *et al.*, 2001)	1981-1999	GIMMS	N America	-8		12
(Stöckli and Vidale, 2004)	1982-2000	PAL	Europe	-10.8		19.2
(Chen *et al.*, 2005)	1982-1993	PAL	China			17
(De Beurs and Henebry, 2005)	1985-1999	PAL	N America	-9.3		
(De Beurs and Henebry, 2005)	1985-2000	PAL	Eurasia	-6.7		
(Piao *et al.*, 2006)	1982-1999	GIMMS	China	-14	6.65	19
(Julien and Sobrino, 2009)	1982-2003	GIMMS	Global	-6.3	1.1	12.1
(Jeong *et al.*, 2009)	1982-1999	PAL	East Asia	-7		
(Jeong *et al.*, 2011)	1982-1999	AVHRR	Northern Hemisphere	-3.1	2.5	5.6
(Jeong *et al.*, 2011)	2000-2008	AVHRR	Northern Hemisphere	-0.2	2.6	2.8
(Zhang *et al.*, 2007)	1982-2005	AVHRR	North America	-0.7/ year		

Several authors have utilised NDVI, such as, Hogda *et al.,* (2001) that found a delay of spring in the alpine belts during 1981-1996 using time-series of NOAA AVHRR NDVI data. The LOS increased by 0.6-14 days due to the advancement of the SOS by 0.2-8 days per decade and a delayed EOS by 0.5-6.1 days per decade (Zeng *et al.,* 2011). Advances in satellite remote sensing and accumulation of multi-sensor time-series of vegetation phenology, has improved the prediction of recent trends (Zeng *et al.,* 2011).

2.3.2 Controlling Factors

Within vegetation phenology studies there are several gaps in phenological research that need to be further researched, including the controls that initiate first leaf in certain ecosystems, vegetation development, senescence, and the effects of climate change. In addition, the possible effect of snow melting at the time of vegetation growth, leaf dynamics and senescence in autumn (Guyon *et al.,* 2011). The inter-annual variation of global circulation patterns, such as the El Nino Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO), complicate the detection of a trend in vegetation phenology and the attribution to global warming (Badeck *et al.,* 2004). The significance of individual climate drivers of both SOS and EOS trends is still debated, due to the variability of dominant factors (de Jong *et al.,* 2013).

Vegetation phenological divergence allows species to be exposed to different environment characteristics, and therefore could lead to new adaptations (Muller, 1978). Understory species that emerge early have exposure to increased sunlight than those than emerge later in the season and, therefore, have more time to grow and accumulate more resources. However, early emerging species have a lower chance of survival due to their susceptibility to frost and freezing conditions, which may damage the plants development. Richardson and O'Keefe (2009) state that the budburst of most understory species is earlier than dominant canopy species, suggesting the understory vegetation uses the strategy of vegetation phenological escape. However, the period of escape was only for a few days for the majority of the understory species. The divergence in autumn were less visible, due to varying controlling factors.

Several herbaceous species emerge earlier in the spring than the canopy species above in order to maximise the potential photosynthesis for growth (Muller, 1978). This is particularly apparent within deciduous environments where temporal variations in the canopy cover create variations in the understory environment. Due to this variation in environmental conditions there can be two peaks of the flowering of species, one prior to leaf expansion within the canopy, and one after (Muller, 1978). Evergreen vegetation species show little seasonal change in foliage biomass and, as satellite noise may mask seasonal variations, this has led to few studies being focused on remote sensing monitoring of evergreen vegetation (Moulin *et al.,* 1997; Hmimina *et al.,* 2013).

Individual species have different dominant controlling factors, and specific responses to climatic and environmental change. Coexisting tree species are known to leaf out at different times. Species that emerge earlier, such as *Betula* and *Populus*, budburst more than 3 weeks earlier in the season than later emerging species, such as *Quercus* and *Fraxinus* (Lechowicz, 1984). There is also variability between young and adult plant species in autumn. The dynamics of photosynthesis within plant communities comprises of diurnal and seasonal cycles (Gu *et al.,* 2009). The diurnal photosynthetic cycle is driven by variations in light due to the rotation of the Earth, in addition the seasonal cycle is driven by environmental factors such as radiation, temperature, photoperiod, moisture, and nutrient availability.

The exact physiological mechanisms and interactions that control first leaf and leaf fall are still unknown for some plant species. However, for most plant species in temperate regions it is understood that leaf development is sensitive to temperature (Perry, 1971). The advancement of vegetation onset in the Northern Hemisphere is a response to rising temperatures in both remote sensing studies (Myneni *et al.,* 1997; Zhou *et al.,* 2001) and *in situ* studies (Sparks *et al.,* 2000; Maignan *et al.,* 2008). The rates of chemical reactions within vegetation increase with increasing temperatures, which is especially true for enzyme-catalysed reactions (Badeck *et al.,* 2004). Temperature affects the photosynthetic process associated with light by altering the pigment content, which is typically increased by warmer temperatures (Saxe *et al.,* 2001). It is expected that higher temperatures will have a beneficial effect on the yield of trees. In temperate and boreal woody plants air temperature is the most important factor in bud and leaf development and in mid-latitudes rainfall is the controlling factor (Polgar and Primack, 2011). Daily temperature patterns equate to 70% of interannual variations of budburst in a group of European species (Menzel and Fabian, 1999). Reported changes in summer and autumn phenophases are less consistent than spring changes (Walther *et al.,* 2002). However, most studies report delays of 3-5 days per degree Celsius (°C) in autumn events in relation to temperature increases (Kai *et al.,* 1996; Matsumoto *et al.,* 2003). Winter chilling impacts tree vegetation phenology (Cumming and Burton, 1996; Saxe *et al.,* 2001), as species use winter chilling as a dormancy indicator, and thus, protects vegetation from being vulnerable to frost damage or unviable within temperate habitats (Cannell and Smith, 1984; Cumming and Burton, 1996).

In arid and semi-arid regions, vegetation is primarily controlled by precipitation, and the rainy season is critical to agriculture (Zhang *et al.,* 2005). Annual and perennial species of desert species react to rainfall (Zhang *et al.,* 2006; Kimball *et al.,* 2010). For tropical forests, precipitation and drought can prompt flowering (Brearley *et al.,* 2007). However, for the relationship between precipitation and flushing date in temperate regions most studies show no relationship (Thompson and Clark, 2008).

Photoperiod is also a controlling factor for spring and autumn phenophase events. Photoperiod is the length of time that an organism is exposed to sunlight each day, which is generally equivalent to day length, and the effect of the photoperiod length trigger is species-specific (Badeck *et al.,* 2004; Cleland *et al.,* 2007). Photoperiod controls the formation of winter buds and the resistance to winter chilling (Korner and Basler, 2010). In spring, photoperiod also controlls end of dormancy, budburst and flowering events. In temperate areas, photoperiod is assumed to be the main controlling factor for autumn (Basler and Korner, 2012). Shorter photoperiod and declining temperatures occur parallel to changes to leaf biochemistry and physiology before the seasonal period of winter dormancy (Hänninen and Tanino, 2011). Precipitation and temperature may change due to changes in climatic conditions. This may lead to asynchrony between historically paired environmental cues to changes in the season (Visser and Both 2005; Hänninen and Tanino, 2011), which may affect vegetation located in northern regions, such as the UK, causing a constrained response to the warming climate (Saikkonen *et al.,* 2012).

There are regional and elevational variations in the effects of climate change on vegetation phenophases for both spring and autumn. At higher latitudes vegetation phenology may be more sensitive to climate change due to increased warming compared to that at lower latitudes (Parmesan, 2007; Oberbauer *et al.,* 2013; Prevéy *et al.,* 2017). A widespread increase in the SOS has been particularly noticeable in high latitude regions due to increased spring temperatures (Forkel *et al.,* 2014). Elevation effects have also been noted in relation to spring and autumn phenophase events. The delay in budburst, first leaf, flowering and leaf fall in relation to elevation is dependent on the species. Earlier studies state leaf unfolding of beech is 1 to 4 days later per 100 m increase (Menzel, 1997). A delay of 1.1 to 3.4 days for leaf vegetation phenology for every 100 m increase in elevation is noted in Vitasse *et al.,* (2009). In comparison, for leaf unfolding other studies note a delay of 3.5 days of *Ribes alpinum* (Rotzer and Chmielewski, 2001), 2 to 3 days for beech (Dittmar and Elling, 2006), 2.8 days for downy birch (Rotzer and Chmielewski, 2001). For flowering a 1.34 day delay per 100 m increase for *Fagus sylvatica*, 4.27 days for *Corylus avellana*, 1.9 days for *Syringa vulgaris* (Jochner *et al.,* 2012) and for leaf fall of *Ribes alpinum* occurs 1.6 days earlier per 100 m increase (Rotzer and Chmielewski, 2001).

Other environment impacts that affect the timing of phenophases are snowmelt and the urban heat island effect. Snowmelt is particularly important for spring phenophase events in Northern and alpine areas and is controlled by temperature and precipitation, which affects species that flower earlier (Inouye and McGuire, 1991). The timing of snowmelt has advanced in many Northern Hemisphere regions due to climate change (Ahas, 1999). The urban heat island affect has shown an advancement of flowering of 4 days over a 30 year period in central Europe (Rötzer *et al.,* 2000). Changes in temperature in urban sites in Massachusetts, USA, suggested that urban effects accounted for half of the total change in vegetation phenology in greater Boston (Primack *et al.,* 2004). With urban expansion across the world, this may also play a role in the advanced SOS for many species. However, the effects on EOS have not been fully evaluated.

2.4 UK Vegetation Phenology

Shifting ranges of species, changes to vegetation phenology, extinction and a reduction in biodiversity are due to various factors including, climate change and land cover change across the UK. The annual vegetation phenology cycle of the UK is typical of the Northern Hemisphere with the seasons divided into three month periods. The meteorological seasonal calendar defines spring as March to May, summer, June to August, autumn, September to November, and winter as December to February. Within the UK, spring is defined by various parameters, such as the first flowering of the year of *Galanthus nivalis* (snowdrops) and *Primula vulgaris* (primroses), or when woodland begins to green with budburst (Sparks and Smithers, 2002).

The Climate Change Act 2008 has established legally binding targets for the UK and commits the UK to reduce emissions by a minimum of 80% by 2050, in relation to 1990 levels (CCC, 2016). In addition to the Climate Change Act, the UK is also included in the United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement. The Paris Agreement includes 195 nations that collectively endeavour to prevent more than a 2°C increase in global temperatures (UNFCCC, 2016). However, the commitment to this goal may be unreachable, as even if the agreement is fully implemented across the 195 nations, global temperatures are estimated to increase by 2.7°C by 2100 (CCC, 2016).

The UK government have agreed to several legal binding targets in order to tackle climate change and greenhouse gas emissions. Climate policies are agreed and set by two key government agencies, the Department for Energy and Climate Change (DECC) and the Department for Environment and Rural Affairs (Defra). Change in vegetation phenology are one of the easiest ways to assess the changes in climate, and it is vital that the current characteristics of UK vegetation phenology are assessed. Across Europe, leaf unfolding and flowering of species occurred 1 to 3 days earlier per decade over the last 30 to 50 years due to climate change. Changes in temperature are affecting species in upland areas at an increased rate (Gottfried *et al.,* 2012; Pauli *et al.,* 2012; Chapman, 2013), in addition to agricultural and perennial species (Atkinson *et al.,* 2013).

Pressures including afforestation, the development of intensive agricultural practices, increasing grazing pressures, airborne pollution, a growing population and climatic change are affecting and changing the vegetation of the UK. There are several concerns regarding shifts in vegetation phenology including; changes to pollution dynamics, interaction and competition between species, increases in the ranges of species and initial changes in community composition (Thuiller *et al.,* 2005; Morin *et al.,* 2009; Morin *et al.,* 2010; Miller-Rushing *et al.,* 2010). Areas of heathland and moorland that are located in upland regions have become fragmented and have decreased diversity of species (Watson *et al.,* 2011). These areas are important for the population of the UK for drinking water supplies and carbon storage (Orr *et al.,* 2008). Over 50% of the UK is now managed agricultural land or developed land. This has resulted in a loss in biodiversity and degradation, for instance across semi-natural grasslands (Watson *et al.,* 2011). However, in the UK the total agricultural land has decreased to 17 million ha in 2005 from 19.8 million ha in 1961 (Graves *et al.,* 2016).

In 2011, over 10% of the land in the UK is classed as urban, with only 2% in Scotland, 3% in Northern Ireland and 4% in Wales (Watson *et al.,* 2011). The future of UK vegetation phenological cycles is dependent on UK sprawl of residential areas of major towns and cities. With a growing population and a need for further housing, in addition to the impacts of a changing climate, the UK will face further challenges. The population of the UK is expected to grow to 72 million by 2033, in addition to the increase of single person household from 12% to 30% over the last few decades, which is also expected to continue to increase (Watson *et al.,* 2011).

There are several long-term environmental monitoring and research programmes across the UK including the Tree Health Survey, Treezilla, Track-a-Tree and Nature's Calendar (Lawrence, 2009; Moss, 2013; Sier *et al.,* 2016) (Table 2-11). The most notable record of UK vegetation phenology is the two centuries of Marsham family records (Sparks and Menzel, 2002). The data from these long-term observation networks have been utilised for research purposes (Last, 2001; Fitter and Fitter, 2002; Harper *et al.,* 2004; Sparks and Lines, 2008; Roberts *et al.,* 2015). Datasets such as these are important for historical modelling of vegetation phenological events, and an increasing number of historical observations by the public are being given to Nature's Calendar to assist in research (Whitfield, 2001).

The UK Phenology Network (UKPN) was launched in 1998 by the Centre for Ecology and Hydrology and the Woodland Trust (Collinson and Sparks, 2008). The UKPN was launched as an online project in autumn 2000 and involves over 11,000 active volunteers across the UK (Collinson and Sparks, 2008). The UKPN expanded and observations of both spring and autumn events are recorded through Nature's Calendar (www.naturescalendar.org.uk). Nature's Calendar has the longest biological record within the UK (Woodland Trust, 2016). However, there has been a decline in the number of 'expert' recorders that submit more than 50 observations per year. Nature's Calendar and the UKPN enables volunteers to monitor vegetation phenological events, raises awareness of climate change, and connects with the natural world (Sparks and Smithers, 2002).

The results from Nature's Calendar highlight that many vegetation species are responding to climate change. The average first flowering date of 385 British plant species has advanced by 4.5 days over the past decade compared with the previous four decades (Fitter and Fitter, 2002). However, some species within the UK appear to be showing no response to climate change, suggesting an inability to adapt, and others have demonstrated delayed seasonal vegetation phenological events (Parmesan and Yohe, 2003; Gordo and Sanz, 2005; Both *et al.,* 2009; Yang and Rudolf, 2010). Thompson and Clark (2008) utilised the long-term Marsham family records of tree first leaf from England and found that all 13 species have an association to temperature. In addition, when modelling future responses, leaf out of species that are sensitive to chilling could be delayed by up to 30 days in comparison to species primarily controlled by warming spring temperatures.

Table 2-11 A selection of UK Environmental monitoring programmes, year established and spatial coverage.

Research Programme	Est.	Coverage	
GB Countryside Survey (CS)	1978	UK	countrysidesurvey.org.uk
UK Environmental Change Network (ECN)	1992	UK	ecn.ac.uk
Open Air Laboratories (OPAL) (Tree Health Survey)	2013	UK	opalexplorenature.org
Treezilla	2013	UK	treezilla.org
Track-a-Tree	2013	UK	trackatree.bio.ed.ac.uk
Woodland Trust's Nature's Calendar	1998	UK	naturescalendar.org.uk
Moors for the Future	2003	Peak District/ South Pennines	moorsforthefuture.org.uk

Several studies have focused on the vegetation phenology of individual areas and species across the UK, with a focus on Southern England (Gyan and Woodell, 1987; Mitchley, 1988; Tryjanowski *et al.,* 2006; Boyd *et al.,* 2011; Mizunuma *et al.,* 2013). There are fewer vegetation phenology focused studies located in northern regions (Murray *et al.,* 1994; Deans and Harvey, 1996; Salmela *et al.,* 2011). To date there has been no complete assessment of UK vegetation phenology utilising national spatial datasets, such as remotely sensed imagery and *in situ* observations. In addition, the majority of research into the controlling factors have focused on a single factor, phenophase event, species and/or study site (Margary, 1926; Murray *et al.*, 1989; Sparks and Carey, 1995; Fitter and Fitter, 1995; Somers-Yeates *et al.,* 2016).

To thoroughly characterise UK vegetation phenology the full range of monitoring techniques available need to be assessed, as well as investigating the controlling factors for both SOS and EOS. In addition, the accuracy of the each observation technique used to estimate SOS and EOS and species-specific phenophase events need to be evaluated. The aim of this research is to comprehensively characterise UK vegetation phenology, including the controlling factors for vegetation development, and to evaluate and compare current vegetation phenological monitoring techniques.

Chapter 3 Study Area

3.1 Overview

The UK is the collective of England, Scotland, Wales, Northern Ireland and the associated islands (49°N to 61°N, and 8°W to 2°E) (Figure 3-1). Great Britain (GB) excludes Northern Ireland, and has an area of 209,331 km^2, and due to a variety of plate tectonic processes and glaciation of the north during the last glacial period, has a complex geology and geomorphology. There is a varied landscape with the Tees-Exe line dividing GB into a lowland region to the south-east and upland region in the north-west. The variation in elevation influences the vegetation and vegetation phenology, with a high proportion of arable land located in the south-east and heathland, rough grazing, woodland and moorland in the north, predominantly in the Scottish Highlands, and across the Pennines.

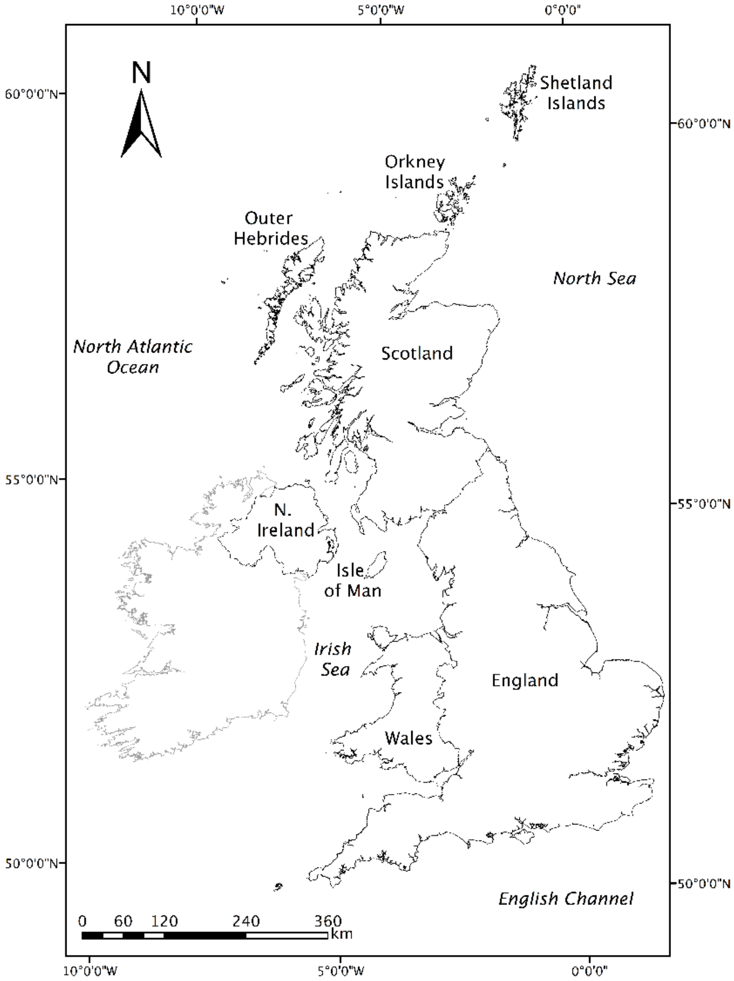


Figure 3-1 Map of the UK.

3.2 Climate

The climate of GB is classed as temperate maritime with an average annual rainfall of 926.91 mm and average temperature of 9.74°C (1971 to 2000 average HadCet and HadUKP data). Figure 3-2 shows the mean monthly temperature (°C) and precipitation (mm) for the study period (2005-2012). The temperate climate results in mild wet winters and relatively warm wet summers, and a defined start of season and end of season for vegetation (Met Office, 2011). Typically, July and August are the warmest months, and February the coldest. Precipitation is lowest during February to April and the highest levels occur during October to January. Temperatures in the UK have increased by 0.85°C since 1880, in line with the global average (CCC, 2016). Between 2005 and 2014 UK land temperatures were 0.9° C higher than the 1961 to 2000 long-term average. In addition, there has been a notable 10% increase above average in rainfall in western Scotland, with a smaller increase in England, Wales and Northern Ireland (CCC, 2016).

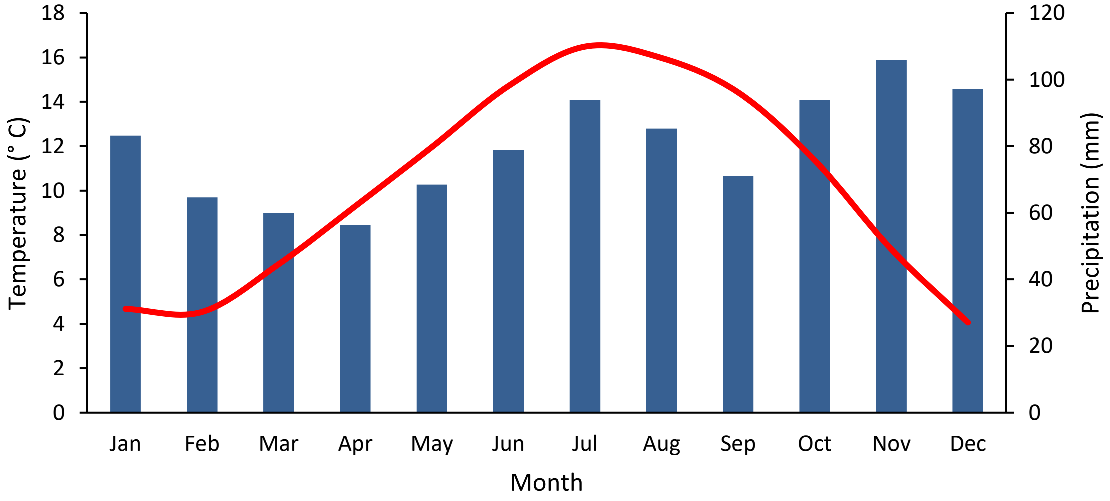


Figure 3-2 Monthly mean temperature (° C) (red line) and precipitation (mm) (blue bars) 2005 to 2012 HadCet and HadUKP data.

Across the study period (2005 to 2012) there were fluctuations from national climate averages, including several extreme weather events, such as the 2006 European heatwave with the maximum July temperature reaching 28.24°C (Met Office, 2011). Figure 3-3 highlights the yearly variation from the 1971 to 2000 long-term central England Temperature (CET) average across the study period. December 2008 to February 2009 was the most prolonged spell of freezing temperatures and snowfall across the UK since 1981, and the worst snow storm since February 1991 (Met Office, 2011). The temperatures in January and December 2010 were exceptionally cold in comparison to the long-term CET.

December 2010 was the coldest for over 100 years with daytime temperatures in areas of the UK falling to below -10°C and -20°C at night (Met Office, 2011). Temperatures during spring were elevated relative to the CET monthly mean, in particular in 2007 and 2011.

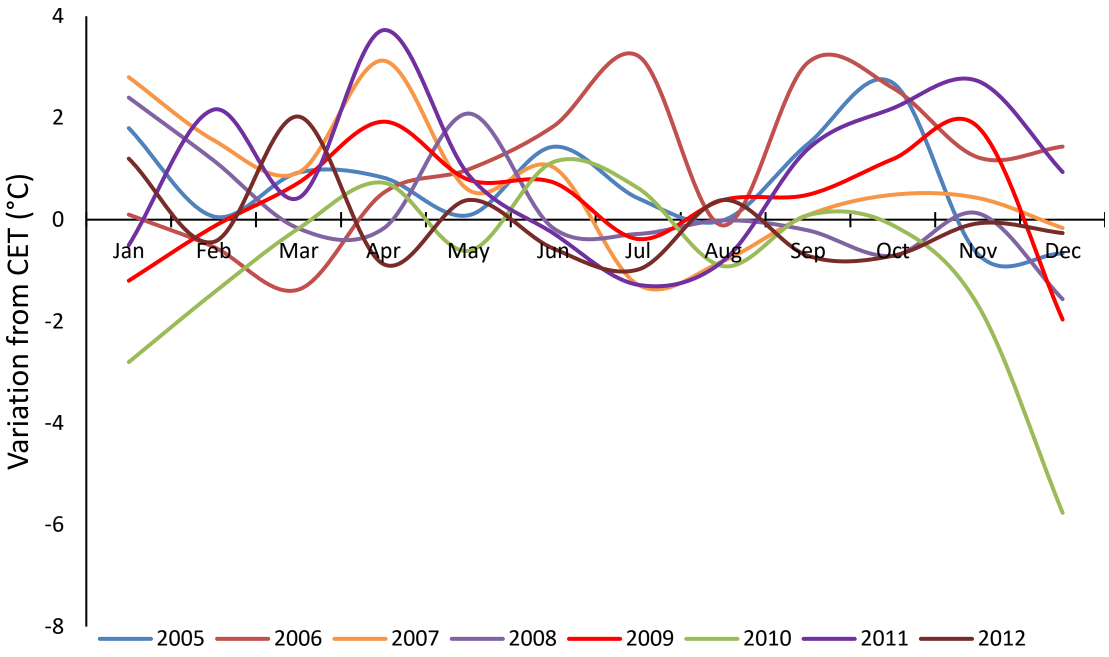


Figure 3-3 Variation of mean monthly temperatures from CET long-term average 1971- 2000.

Annual precipitation across the UK is highly variable between years (Figure 3-4). From October 2004 to June 2005 drought conditions affected much of Western Europe and rainfall was below average. From June to July 2007 the UK experienced the worst flooding in 60 years following the wettest May to July since records began in 1766 (Met Office, 2011). June to August in 2008 was one wettest summers since records began in 1914 for the UK. November 2009 had the highest amount of rainfall since records began, causing severe flooding in Northern areas of the UK.

The variants in weather across the UK, including the increasing trend in temperature has impacted UK vegetation phenology. The Met Office has reported that the average growing season (measured in growing degree days (GDD) between 2006 and 2015 was 29 days longer compared with between 1961 and 1990. In addition, a 17% decrease in the number of frost days was observed.

The study period of 2005 to 2012 was chosen to include the several extreme weather events that occurred during this time and due to the availability of the observation data across this period, including MERIS imagery, *in situ* observations and near surface photography.

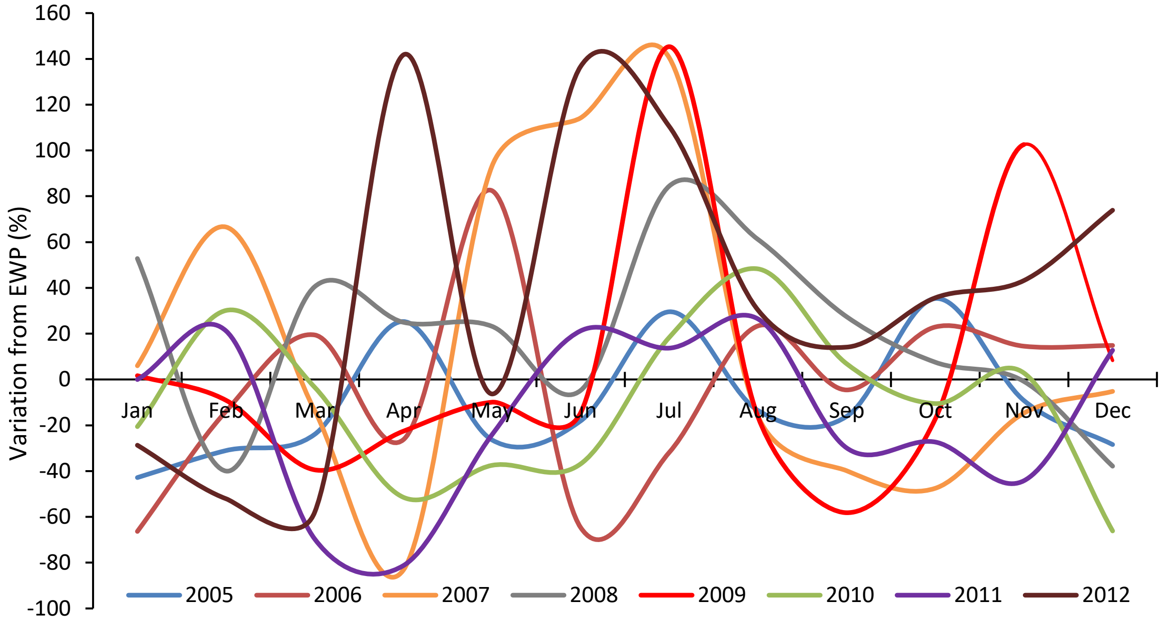


Figure 3-4 Variation of mean monthly precipitation from EWP long-term average 1971- 2000.

3.3 Vegetation and Land Cover

Historically, GB had large areas of natural woodland which covered 75% of the land up to 6,000 years ago (Watts, 2006). Today, woodland areas are located sporadically across the UK and account for approximately 12% of the total land cover (Morton *et al.,* 2011). Areas of woodland, particularly semi-natural and ancient woodland, are small, isolated and typically surrounded by agricultural land (Watts, 2006). The largest area of natural woodland remaining in England is the New Forest (270 km^2), located in the south of England, and Galloway Forest Park (770 km^2) located in Scotland. Common species of trees include, *Quercus robur* (Pendunculate oak)*, Quercus petraea* (Sessile oak), *Fagus sylvatica* (beech), *Pinus sylvestris* (pine), *Betula pendula* (birch), *Ulmaceae* (elm) and *Fraxinus excelsior* (ash). The dominant land cover of the UK is arable and natural grassland, due to the increase in farming, recreation and amenity land required.

There are thousands of species of wild flowers found in the UK, including, G*alanthus nivalis* (snowdrop), *Narcissus* (daffodil), *Anemone nemorosa* (wood anemone), *Bellis perennis* (daisy), *Tussilago farfara* (colt's-foot), *Primula vulgaris* (primrose) and *Hyacinthoides non-scripta* (bluebell). Around 75% of the flora in GB come into flower between March and June (Fitter and Peat, 1994). Each species has a characteristic flowering period; however, annual variation of first flowering occurs for most species due to the variance in annual season temperatures (Fitter *et al.,* 1995).

The range of habitats in Scotland is due to varying altitude, distance from sea and coastal weather systems, and geology (Cannell *et al.,* 1997). Across the highlands of Scotland there are remnants of ancient Scots Pine forests, also referred to as Caledonian pine forests. Natural upland areas in Scotland typically have low productivity in relation to lowland areas (Powell and Malcolm, 1974). However, in recent years the migration of low elevation species and an increase in species richness has occurred in highland areas due to warming (Gottfried *et al.,* 2012; Pauli *et al.,* 2012; Chapman, 2013). Upland areas (200 to 300 m above sea level) have a low population density and are predominately areas of agricultural land and forestry (Orr *et al.,* 2008). Moorlands and heathland cover around 18% of the UK (Watson *et al.,* 2011). These areas are vital as they are the source of 70% of the UK's drinking water and 40% of the UK soil carbon (Watson *et al.,* 2011). Heather moorland, typically found in upland regions has decreased by 23% since the 1940's and replaced by conifer plantations or converted to grazing land (Orr *et al.,* 2008).

The Land Cover Map 2007 is a parcel-based classification of UK land cover, based on the UK Biodiversity Action Plan (BAP) Broad Habitats (Figure 3-5). The dominant land cover classes are broadleaf woodland, coniferous woodland, arable, improved grassland, semi-natural grassland, mountain heath and bog, saltwater, freshwater, coastal and built-up areas and gardens. The definition of certain land cover types varies from the broad habitat definitions, due to the inclusion or exclusion of certain species (Morton *et al.,* 2011). Arable and horticultural land and improved grassland are the largest land cover classes across the UK (Table 3-1). Arable land is predominately located in south and east England, with improved grassland covering much of the north and west of England and Northern Ireland. Across highland regions of Scotland and Northern England, the predominant land cover is semi-natural grassland and mountain, heath and bog.

Within each broad habitat there are predominant species present. Broadleaf woodland typically contain two native oak species, sessile oak (*Quercus petraea)* and penduncùlate oak (*Quercus robur*) as well as beech (*Fagus*), ash (*Fraxinus*), and two species of birch, silver birch (*Beula pendula*) and downy birch (*Betula* *pubescens*). Coniferous woodland is dominated by non-native species, such as Douglas fir (*Pseudotsuga menziesi)*, and Sitka Spruce (*Picea sitchensis)*. The native species of conifer species are Scots Pine (*Pinus sylvestris)*, Juniper (*Juniperus)* and Yew (*Taxus baccata)*. Larch (*Larix)*, a deciduous conifer is also included within the coniferous woodland land class. The dominant crop species grown in the UK is wheat. Other crops include oats and barley, potatoes, sugar beet, beans, peas, cabbages, apples and hay. Semi-natural grassland include areas of vegetation dominated by grasses and herbs including dry hay meadows and pastures. A range of species are present due to the combination of precise habitiats within the broad habitat description. Species include, bracken (*Pteridium aquilinum*), species from the heath family (ericoids) or dwarf gorse *Ulex minor*, and tall emergent vegetation such as reedbeds (*Phragmites australis*).

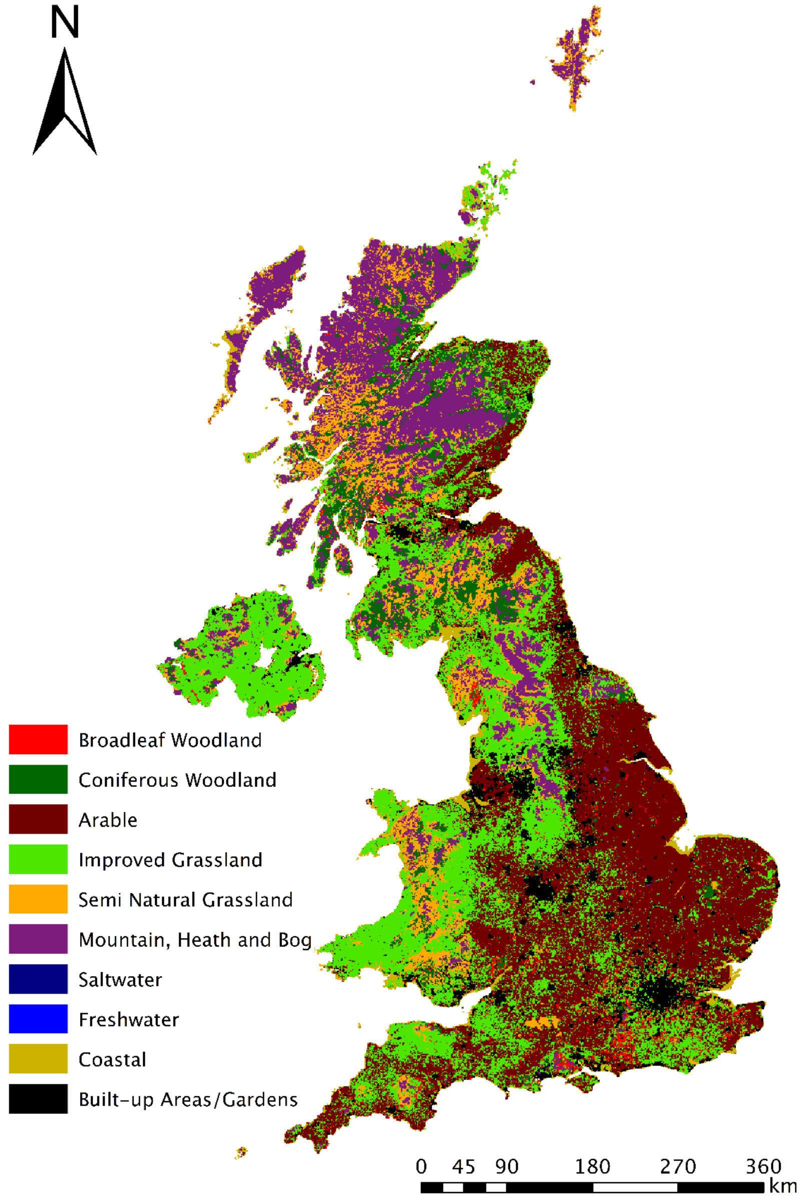


Figure 3-5 Dominant Aggregate Land Cover Classes 1 km (LCM 2007).

Table 3-1 Broad Habitat descriptions for vegetated land areas used for LCM2007 (Morton *et al.*, 2001). Excludes urban and marine land cover types.

Vegetation Types	Coverage	Vegetation Characteristic
Broadleaf Woodland	6%	Dominated by more than 20% coverage of mature trees over 5m in height. Includes scrub over 30% coverage. Includes native and non-native species.
Coniferous Woodland	6%	Dominated by more than 20% coverage of mature trees over 5m in height. Includes native and non-native species.
Arable	25%	Annual crops, perennial crops, woody crops, intensively managed commercial orchards, commercial horticultural land, ploughed land, annual leys, rotational set-aside and fallow.
Improved Grassland	25%	Dominated by a fast growing grasses such as *Lolium* spp., and white clover (*Trifolium repens),* on fertile, neutral soils. Typically managed as pasture, for silage production or for recreation and amenity.
Semi-natural Grassland	13%	Includes rough grassland, calcareous grassland, acid grassland, fen, marsh and swamp.
Mountain, Heath and Bog	16%	Includes heather, heather grassland, bog, montane habitats, and inland rock.

Chapter 4 Characterising Vegetation Phenology using Citizen Science Data

4.1 Introduction

Ground-based data are usually limited in both temporal and spatial extent (Zhang *et al.,* 2009). There is often a lack of spatial extent and number of repeated observations, (e.g. through scientific and government *in situ* initiatives), due to the time consuming nature of the recording technique (Conrad *et al.,* 2011). This has led to an increase in the number of citizen science initiatives for scientific research (Schwartz *et al.,* 2013; Dunkley, 2016). Citizen science datasets are important for historical modelling of vegetation phenological events, since widespread vegetation phenological observations assist in assessing large-scale patterns of species response to climate change, including advances and delays in the growing season (Spano *et al.,* 1999; Betancourt *et al.,* 2005; Dickinson *et al.,* 2010). Certain species of plant appear to show no response to climate change suggesting an inability to adapt, and yet others have demonstrated delayed seasonal vegetation phenological events (Parmesan and Yohe, 2003; Gordo and Sanz, 2005; Both *et al.,* 2009; Yang and Rudolf, 2010).

Typically participants of citizen science networks access guides, materials, gather data and relay the information to central national databases (Dickinson *et al.,* 2010). The volunteers are typically amateurs, members of the public, teachers and students, conservation group members, bird-watchers, hikers, or other outdoor enthusiasts (Cohn, 2008). Advancements in technology, including 4g internet and smart phones, have made it easier for recorders in the field to participate in citizen science (Burke *et al.,* 2006; Silvertown, 2009).

One main concern when utilising citizen science data is the skill and accuracy of the observer, in comparison to professionals (Dickinson *et al.,* 2010). This may lead to increased error or bias within the dataset, especially as few citizen science initiatives offer training to the participants. Very few citizen science initiatives implement quality assurance and quality control checks. Nevertheless, the large number of data from a dispersed acquisition model can reduce error in volunteer collated data through averaging (Dickinson *et al.,* 2012). In addition, observers may have a differing perceived idea of vegetation phenological events than the scientific community, and one concern with *ad hoc* observations is how carefully and systematically these are taken (Whitfield, 2001). Observer accuracy is known to improve over time, with ‘first year’ or ‘learner’ effects documented (Bas *et al.,* 2008; Schmeller *et al.,* 2009; Dickinson *et al.,* 2010). The age of observers can be an important factor of data quality with older, university-educated volunteers having a greater level of accuracy (Delaney *et al.,* 2008).

Several vegetation phenological networks produce more spring observations in comparison with autumn events (Schaber and Badeck, 2003). In addition, there may be an increase in observations of rare species as opposed to common species, and few repeated observations as interest declines (Dickinson *et al.,* 2010). Spatial heterogeneity of sampling is also a factor to consider when utilising data collected by citizen science networks, as typically there are ‘hot spots’ of observations where there is an increase in population density.

Characterising the vegetation phenology of the UK at the national scale offers the opportunity to characterise changes at a smaller scale than current European and Global models. It also assists in expanding smaller site-specific research. While some studies to date have used the Nature’s Calendar dataset to investigate temporal responses in phenophases, none has investigated these responses at a fine spatial resolution. Characterising the current UK vegetation phenology spatially is necessary to provide a baseline against which to understand future responses to environmental and climate changes (Thuiller *et al.,* 2008). The aim of this chapter was to characterise at a fine spatial resolution the current vegetation phenology across the UK utilising the Nature’s Calendar *in situ* dataset and investigate, in detail, the spatial variability related to latitude and elevation. Latitude and elevation were chosen as they can be used as a proxy for climate indicators.

4.2 Data and Methodology

4.2.1 Nature’s Calendar Data

Nature’s Calendar is a network of point-based phenophase observations from around the UK collated by the Woodland Trust. The data includes spring and autumn observations for trees, shrubs, grasses, flowers, fungi, birds, amphibians and insects. To increase the accuracy of observed phenophases, a guide is provided to all volunteers describing the techniques for observing events. When recording an event it asks that the event is recorded only when three plants of the same species in close proximity are showing the same event; therefore, recording the trend, instead of individual plant anomalies. Volunteers are also asked to record events on mature trees (over 30 years old). For each phenophase a description is given to assist with observing species phenophase events. For example, budburst is described as when the colour of the new green leaves is just visible between the scales of the swollen/elongated bud (Woodland Trust, 2016). There are also instructions for the effects of drought on tree species, for example for beech and birch the effects can be similar to the observed onset of autumn. For each description they are accompanied with images for all species to limit the misidentification of species.

Observations of budburst (BB), first leaf (FL), first flower (FF), first tint (FT), full tint (FuT) and first leaf fall (FLF) are produced for the species shown in Table 4-1. The data were collated from the Woodland Trust's Nature's Calendar dataset (www.naturescalendar.org.uk) from 1st January 2005 to 31st December 2010 across GB. The advantage of utilising the Nature's Calendar dataset is that vegetation phenological phases covering the full extent of the vegetation growing period from spring to autumn can be assessed.

The number of observations in the dataset varies significantly according to phenophase and species (Table 4-3, 4-5, and 4-6). Primarily, this is due to a bias in public observations during the spring months, which is noted in several other studies (Steege and Persaud, 1991). A geographic information system (GIS) enables spatially referenced data to be compiled and manipulated spatially, in particular, allowing mapping in areas where there are few or no samples (Liebhold *et al.,* 1993; Burrough, 2001). The Nature's Calendar dataset is limited spatially due to preferential sampling according to the population density of GB and the inaccessibility of highland areas. This is highlighted in the number of data points in Scotland v. the South East of England; for example, 4,474 and 11,523 data points for bud burst, respectively (Figure 4-1).

Spatial interpolation can be used to mitigate the effects of preferential sampling within citizen science datasets. In particular, the geostatistical technique known as Kriging enables the spatial prediction of unobserved locations (Rodrigues, 2016). Kriging has been used widely for spatial prediction as it provides the 'optimal linear unbiased predictor' in space from known observations (Cressie, 1990). Ordinary Kriging (OK) interpolation was chosen as it is a reliable, simple and flexible method that has been used widely and can be implemented using ArcMap (Yamamoto, 2000).

Table 4-1 Species and phenophase data utilised from Nature's Calendar. BB (Budburst), FL (First Leaf), FF (First Flower), FT (First Tint), FuT (Full Tint) and FLF (First Leaf Fall).

Latin Name	Common Name	Spring Phenophase	Autumn Phenophase
Alnus glutinosa	Alder	BB, FL	
Fraxinus excelsior	Ash	BB, FL	FT, FuT, FLF
Fagus sylvatica	Beech	BB, FL	FT, FuT, FLF
Prunus spinosa	Blackthorn	FF	
Hyacinthoides non-scripta	Bluebell	FF	
Dactylis glomerata	Cocksfoot	FF	
Tussilago farfara	Colt's-foot	FF	
Cardamine pratensis	Cuckooflower	FF	
Rosa canina	Dog Rose	FF	
Sambucus nigra	Elder	BB, FL, FF	FT, FuT, FLF
Larix decidua	European Larch	BB, FL	
Acer campestre	Field Maple	BB, FL	FT, FuT, FLF
Alliara petiolata	Garlic Mustard	FF	
Crataegus monogyna	Hawthorn	BB, FL, FF	FT, FuT, FLF
Corylus avellana	Hazel	FF	FT, FuT, FLF
Aesculus hippocastanum	Horse Chestnut	BB, FL, FF	FT, FuT, FLF
Ranunculus ficaria	Lesser Celandine	FF	
Syringa vulgaris	Lilac (purple)	FF	
Alopecurus pratensis	Meadow Foxtail	FF	
Quercus robur	Oak (*Pendunculate*)	BB, FL, FF	FT, FuT, FLF
Quercus petraea	Oak (*Sessile*)	BB, FL, FF	FT, FuT, FLF
Leucanthemum vulgare	Oxeye Daisy	FF	
Sorbus aucuparia	Rowan	BB, FL, FF	FT, FuT, FLF
Betula pendula	Silver Birch	BB, FL, FF	FT, FuT, FLF
Acer pseudoplatanus	Sycamore	BB, FL	FT, FuT, FLF
Phleum pratense	Timothy	FF	
Anemone nemorosa	Wood Anemone	FF	
Holcus lanatus	Yorkshire Fog	FF	

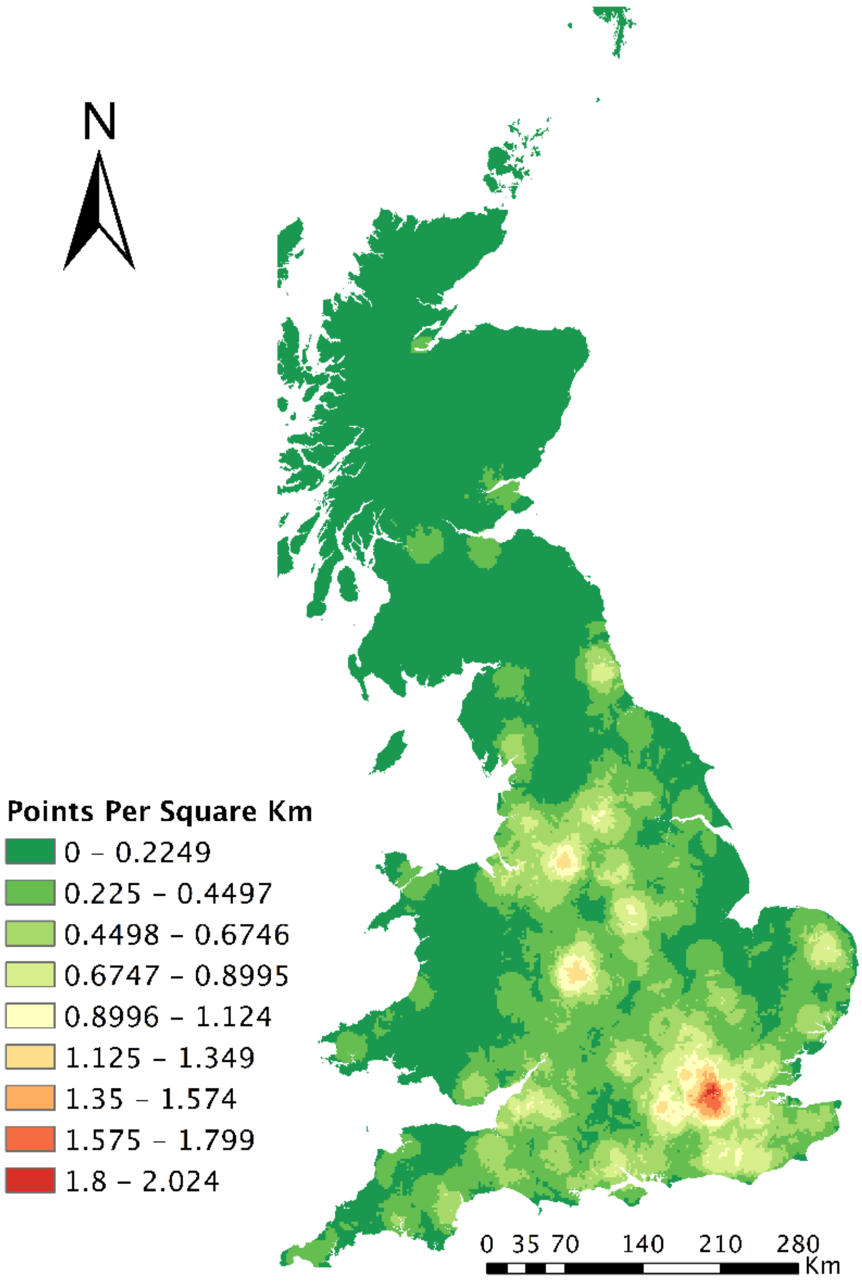


Figure 4-1 Point Density of observations of BB across the UK (2005 to 2010).

The analysis included descriptive statistics of each phenophase for all species, and per-species. The summary statistics included the mean, median, and standard deviation. The median has been shown to be superior to the mean in certain situations, particularly where the distribution is non-Gaussian (Schwartz and Reed, 1999). To assess the correlation of the vegetation phenological phases for each species with elevation and latitude a partial regression analysis was undertaken since both elevation and latitude are collinear. Specifically, the residuals from the regression of phenophase with latitude were regressed on elevation.

4.2.2 SRTM Digital Elevation Data

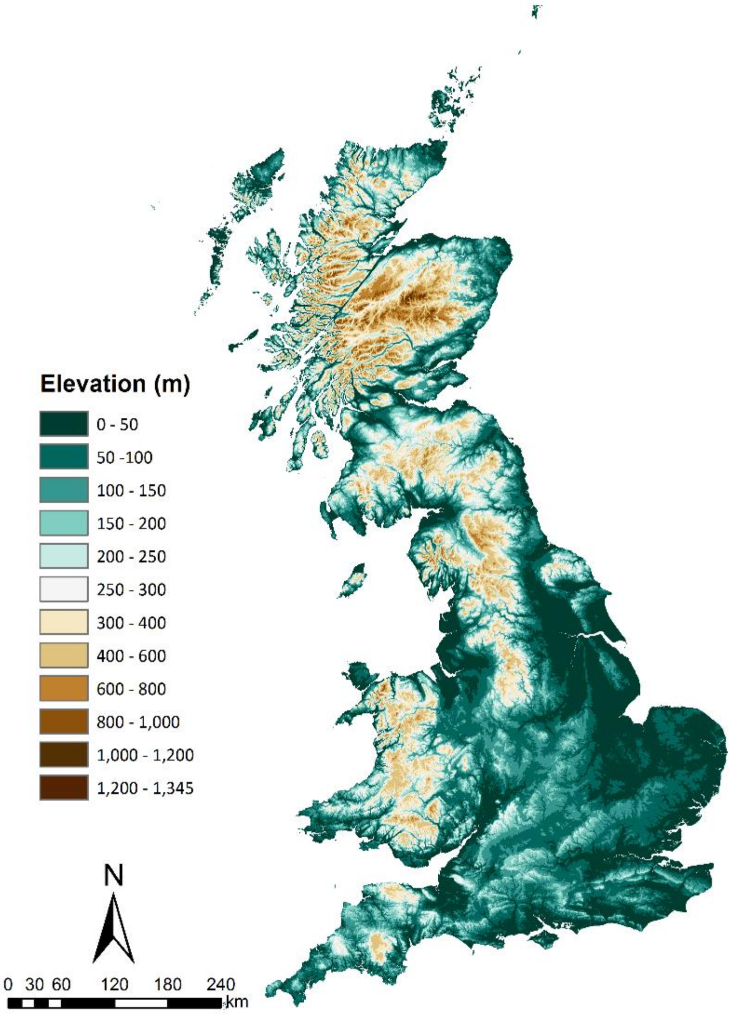


Figure 4-2 Map of UK elevation highlighting the areas of highest elevation using 3 arc second SRTM elevation data (NASA Jet Propulsion Laboratory JPL, 2015).

The Shuttle Radar Topography Mission (SRTM) dataset is a free, publicly accessible digital elevation model (DEM) (Wendi *et al.,* 2016, Yang *et al.,* 2011). The SRTM data are the result of collaboration between the National Aeronautics and Space Agency (NASA), the National Imagery and Mapping Agency (NIMA), the German Aerospace Centre (DLR) and the Italian Space Agency (ASI). The mission acquired data between 11 and 22 February 2000 on board the Space Shuttle Endeavour (Yang *et al.,* 2011). The DEM is available with a 3 arc-second (approximately 90 m) spatial resolution for approximately 80% of the world between the latitudes of 56^{0}S to 60^{0}N (Rabus *et al.,* 2003). The STRM uses interferometric radar data collected by dual radar antennae to produce topographic data of the globe. The dataset for the UK was downloaded via http://earthexplorer.usgs.gov/ and then clipped to the extent of GB (Figure 4-2)

(Farr and Kobrick, 2000; Rosen, 2000; Kobrick, 2006; Farr *et al.,* 2007). The dataset was converted to a shapefile, georeferenced with the *in situ* Nature's Calendar data, and intersected using ArcMap to obtain the elevation for each observation.

4.2.3 Data Quality Check

Since the *in situ* observations from Nature's Calendar are mostly provided by volunteers, a quality assessment of the data was completed using the methodology from Menzel *et al.,* (2001). The method is a general quality check and seeks to identify and remove values that may have significant errors due to recording date, phenophase observation and geographic coordinate issues. The data were screened for extreme values and inhomogeneous records. The data points with distinct gaps in observation date were also removed. In total 5676 data points were removed which equated to 1.35% of the full dataset. This process was completed using current estimates of the expected time of year for each species per phenophase utilising several horticultural agencies (Appendix A), and removing extreme anomalies.

Table 4-2 Sample of frequency distribution (%) of days of the week and the data collected for species and phenophase events.

	Alnus glutinosa BB	*Quercus petraea FL*	*Holcus lanatus FF*	*Tussilago farfara FF*	*Acer pseudo. FT*	*Acer campestre FuT*	*Fraxinus excelsior FLF*
Monday	13.5	13.7	15.5	12.5	13.9	14.8	14.5
Tuesday	13.5	14.2	13.3	13.1	13.8	12.3	12.6
Wednesday	11.6	14.2	13.3	13.4	14.0	14.2	13.7
Thursday	14.7	14.8	13.8	13.0	13.8	13.4	13.9
Friday	14.2	14.1	14.1	13.7	13.3	13.9	15.1
Saturday	16.2	13.9	13.3	15.8	15.2	14.9	14.6
Sunday	15.9	14.8	16.4	18.2	15.8	16.3	15.3

Due to the nature of volunteer records, the day of observation may have a temporal preferential bias due, for example, to recorders preferring weekends to record observations (Courter *et al.,* 2013). An equal distribution of observations across recording days would produce 14.29% observations per day. Table 4-2 highlights a sample of the data collected on each day of the week. For all species recorded no set of observations was distributed evenly throughout the week, revealing a weekend temporal bias within the dataset.

4.3 Results

Figure 4-3 shows the spatial variation in six different vegetation phenophase events in GB, as predicted using all species of the Nature's Calendar dataset. In the higher latitudinal region of Great Britain (Scotland, Northern England) the spring phenophase events (BB, FL, and FF) evidently occur later (Figure 4-3a, b and c). Areas of higher elevation (the Pennines and Highlands of Scotland) also reveal later spring phenophase events. In the lower latitudinal regions (South East England), earlier spring phenophase events are observed. The spatial variation in phenophases is, therefore, attributable to latitude and elevation (which correlate to temperature, photoperiod and precipitation) (Kramer *et al.,* 2000; Tooke and Battey, 2010).

For the autumn phenophase events (first tint, full tint and first leaf fall) (Figure 4-3d, e and f), the South and South East England show that autumn phenophase events occur later in the year in comparison to observations at higher latitudes. Note that Scotland is expected to have earlier autumn phenophase events, due to its higher latitude and higher elevation. Areas of higher latitude are expected to have a stronger vegetation phenological response to environmental changes (Parmesan, 2007).

Table 4-3 Descriptive statistics of the six phenophases for all species assessed in DOY units (N: Number of Observations).

Phenophase	*N*	Mean	Median	Standard Deviation
Budburst	62240	91.61	93	21.42
First Leaf	63943	102.33	105	20.06
First Flower	149241	109.58	116	31.53
First Autumn Tint	49474	267.62	269	20.19
Full Autumn Tint	32735	295.82	297	18.04
First Leaf Fall	35589	295.82	297	20.1

The number of observations per phenophase event highlights a public bias in recording spring events, in particular first flower, relative to autumn events (Table 4-3). This is likely due to two factors: autumn weather conditions being unfavourable to the public, and the influence of 'Springwatch', a BBC television series which, through collaboration with the Woodland Trust, has publicised Nature's Calendar to the general public on several occasions since 2005. The increase in the standard deviation for first flower is due to the greater variability in the number of observed species (22) in comparison to the number of observed species for other phenophase events (13). In addition, there is greater variability in observation dates due to the species observed, such as *Corylus avellana* (mean DOY 40) flowering much earlier than other species, such as *Phleum* pratense (mean DOY 145) and *Holcus lanatus* (mean DOY 148) (Table 4-5).

The spring phenophase observations have a mean DOY of 1st to 19th April, which is during the meteorological spring season. In addition, the mean DOY for the autumn phenophase events (24th September to 22nd October) also occurs within the meteorological calendar for autumn; September to November.

The accuracy of the Kriging predictions was assessed by estimating standard prediction errors using the ArcGIS Geostatistical Analyst tool within ArcGIS 10.4 (Table 4-4). The assessments of Root Mean Square Standardized Error (RMSSE) are close to 1, and both the mean error (ME) and the mean standardised prediction error (MSPE) are close to 0, highlighting that the interpolation of results are satisfactory and unbiased.

Table 4-4 Prediction errors of Kriging predictions for each phenophase. BB (Bud Burst), FL (First Leaf), FF (First Flower), FT (First Tint), FuT (Full Tint) and FLF (First Leaf Fall). ME (Mean error). MSPE (Mean standardised prediction error). RMSSE (Root mean square standardised mean error).

Prediction Error	BB	FL	FF	FT	FuT	FLF
ME	0.011	-0.0313	-0.070	0.029	-0.0003	0.049
MSPE	0.0007	-0.001	-0.003	0.001	-0.0002	0.002
RMSSE	1.012	1.002	1.004	0.987	1.054	0.938

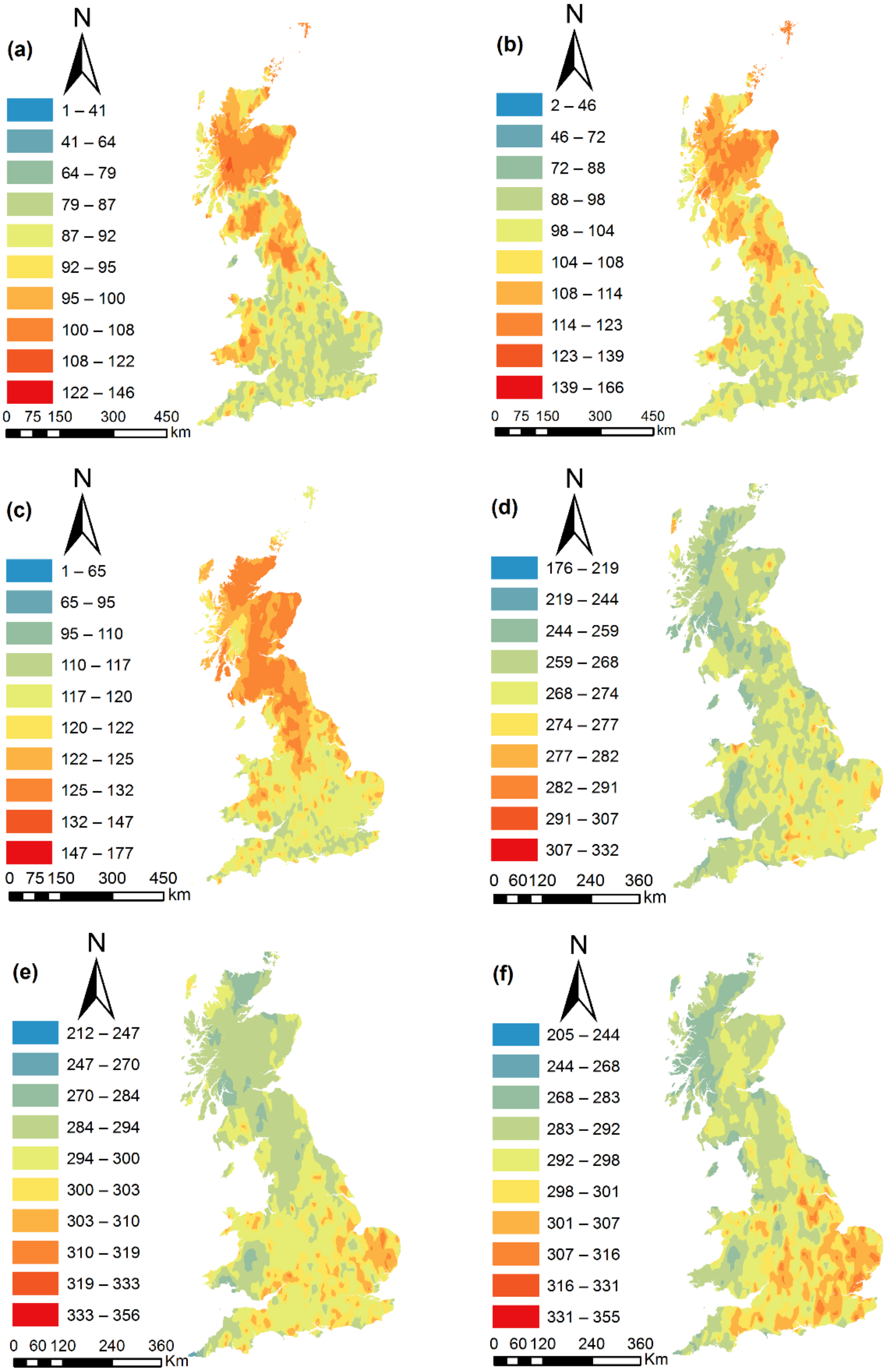


Figure 4-3 Spatial variation in the vegetation phenophase events (represented in mean DOY units) of (a) Bud burst, (b) First leaf, (c) First flower, (d) First Tint, (e) Full Autumn Tint and (f) First leaf fall for all species analysed from Nature's Calendar.

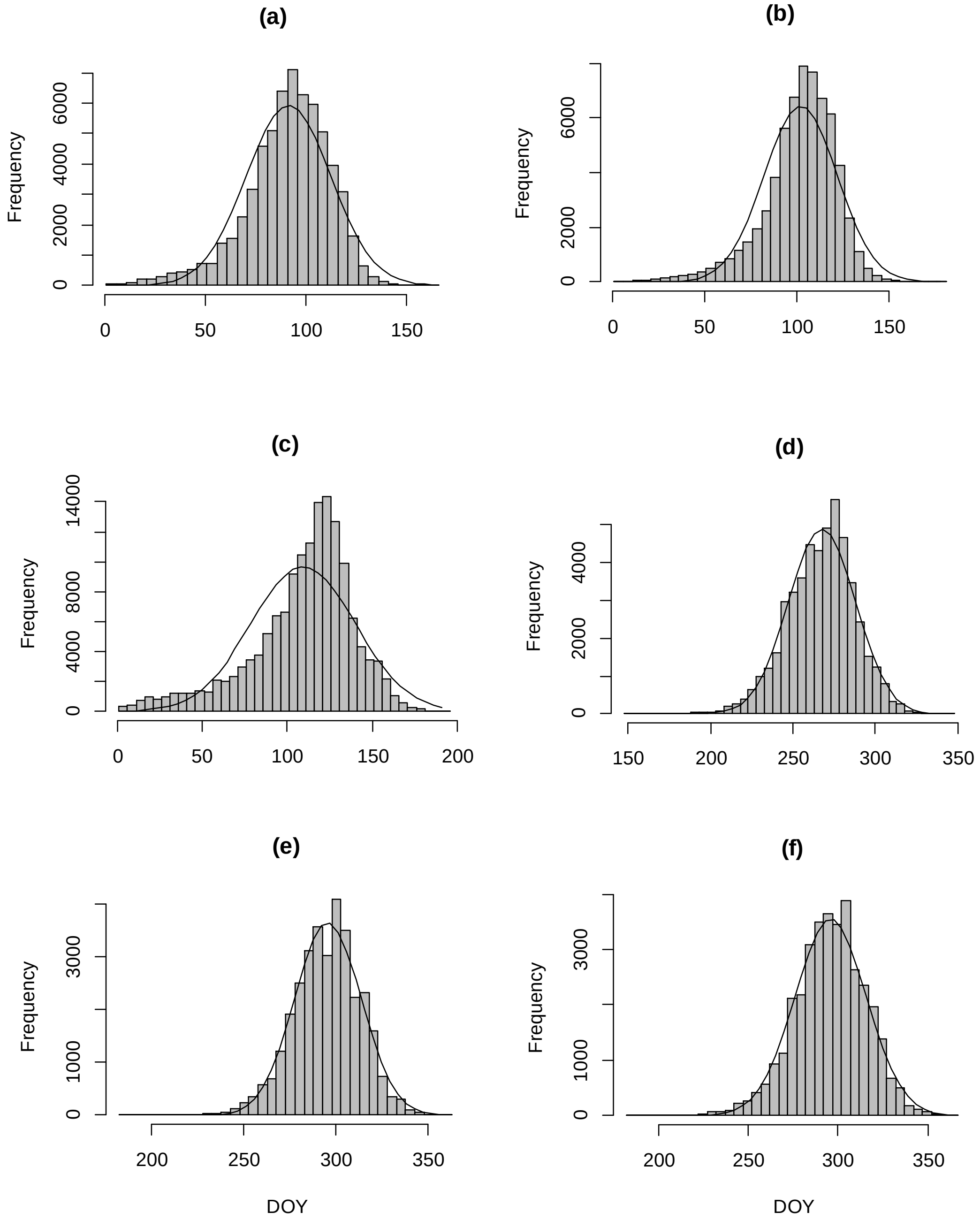


Figure 4-4 Variation in the observed phenophase (in DOY) for (a) Bud burst, (b) First leaf, (c) First flower, (d) First Tint, (e) Full Autumn Tint and (f) First leaf fall. All observation points included for 2005 – 2010.

Figure 4-4 presents the distribution of the observed phenophase events (2005-to-2010). A Gaussian model was fitted to each dataset to characterise the distribution in each phenophase. The distribution of budburst, first leaf and first flower are slightly negatively skewed (Figure 4-4a, b and c). First flower observations show a delayed cluster of values primarily due to variation between the species recorded. Autumn phenophase events (Figure 4-4d, e and f) show a more symmetrical distribution, highlighting that these observations were a homogeneous mix of deciduous woodland species in comparison to the species observations for spring events.

Tables 4-5 and 4-6 highlight the variability in the observed phenophase events (in DOY) between species across the UK. The most recorded species are *Crataegus monogyna* (Hawthorn), *Hyacinthoides non-scripta* (Bluebell) and *Ranunculus ficaria* (Lesser celandine). *Ranunculus ficaria* is one of the first flowering species within the UK (late February to May), which is highlighted in the mean and median (4 March and 7 March). First leaf observations are slightly greater in number than budburst observations. This may be due to the ease of observing first leaf in comparison to bud burst. For all of the spring phenophase observations, the mean and median highlight that the collective records are within or close to the expected annual time period for each species' phenophase events (Appendix A). However, flowering for several species occurs slightly earlier than the expected flowering period: for example, *Sambucus nigra,* mean DOY 20 May with an expected flowering period of June; and *Holcus lanatus,* mean DOY 28 May with an expected flowering period of June to September (Appendix A).

There is less variability in the DOY estimates per species for autumn phenophase events. Typically, this indicates that the controlling factors for autumn phenophase events for the species recorded are similar. The observations of FT, FuT and FLF were recorded for deciduous woodland species only. Therefore, the factors that control autumn senescence will be similar and occur simultaneously. For example, one of the known dominant controlling factors for autumn events in temperate regions is photoperiod (Richardson *et al.,* 2013). The dates of FuT and FLF are closely related as these events often coincide. FuT and FLF occur latest in *Quercus robur* (307 -309 DOY). Figure 4-5 shows the length of season (LOS) for all species with continuous observations from spring to autumn. The variability in mean DOY observations between deciduous woodland species (49.5 days) is larger than FLF mean DOY (16.5 days), thus highlighting the differing controlling factors for bud burst for temperate deciduous woodland species.

Table 4-5 Statistical summary per species for budburst (BB), first leaf (FL) and first flower (FF). (*N*: Number of Observations, SD: Standard deviation). Empty values are due to no recording of the phenophase event for that species.

Latin Name	BB				FL				FF			
	N	Mean	Med	SD	*N*	Mean	Med	SD	*N*	Mean	Med	SD
Alnus glutinosa	2694	96.82	98	15.71	2728	108.87	109	13.29	–	–	–	–
Fraxinus excelsior	5348	112.52	114	14.34	5198	123.55	123	11.28	–	–	–	–
Fagus sylvatica	4790	105.66	107	12.99	5298	114.54	115	10.16	–	–	–	–
Prunus spinosa	–	–	–	–	–	–	–	–	9432	81.87	84	10.35
Hyacinthoides non-scripta	–	–	–	–	–	–	–	–	11511	105.86	106	13.2
Dactylis glomerata	–	–	–	–	–	–	–	–	2151	140.86	143	19.28
Tussilago farfara	–	–	–	–	–	–	–	–	3715	78.22	78	19.1
Cardamine pratensis	–	–	–	–	–	–	–	–	5742	108.09	109	14.44
Rosa canina	–	–	–	–	–	–	–	–	5654	148.64	150	12.52
Sambucus nigra	5414	62.99	65	18.97	6425	75.95	78	15.82	5725	140.63	142	15.55
Larix decidua	1615	88.65	89	13.8	1718	99.71	100	12.73	–	–	–	–
Acer campestre	2728	97.17	98	13.8	2853	108.81	109	11.58	–	–	–	–
Alliara petiolata	–	–	–	–	–	–	–	–	5945	111.66	112	11.64
Crataegus monogyna	8579	74.55	77	18.8	8811	84.51	87	18.73	42820	121.76	123	13.66
Corylus avellana	–	–	–	–	–	–	–	–	5937	40.25	33	13.06
Aesculus hippocastanum	8463	86.31	86	12.32	7383	98.42	98	11.65	6720	119.61	120	10.2
Ranunculus ficaria	–	–	–	–	–	–	–	–	11869	63.58	66	17.15
Syringa vulgaris	–	–	–	–	–	–	–	–	7058	119.04	120	10.68
Alopecurus pratensis	–	–	–	–	–	–	–	–	2129	127.43	126	16.93
Quercus robur	4440	106.01	106	12.42	4936	114.58	115	11.13	1634	120.26	120	12.94
Quercus petraea	1677	107.32	108	13.44	1756	116.88	118	11.78	659	123.93	124	13.63
Leucanthemum vulgare	–	–	–	–	–	–	–	–	4876	136.33	138	17.73
Sorbus aucuparia	4888	94.68	95	13.79	4916	106.31	106	11.2	4296	127.7	128	11.31
Betula pendula	5848	95.71	96	12.57	6285	105.76	105	10.23	2043	110.88	111	15.79
Acer pseudoplatanus	5756	93.93	94	15.05	5636	106.2	106	11.64	–	–	–	–
Phleum pratense	–	–	–	–	–	–	–	–	1232	145.54	144	12.14
Anemone nemorosa	–	–	–	–	–	–	–	–	6615	90.51	91	14.93
Holcus lanatus	–	–	–	–	–	–	–	–	1478	148.62	150	15.76

Table 4-6 Statistical summary per species for first tint (FT), full tint (FuT) and first leaf fall (FLF). (*N*: Number of Observations, SD: Standard deviation).

Latin Name	FT				FuT				FLF			
	N	Mean	Med	SD	*N*	Mean	Med	SD	*N*	Mean	Med	SD
Fraxinus excelsior	3608	276.67	277	16.31	2166	293.54	293	13.73	3633	294.55	294	15.67
Fagus sylvatica	4547	265.33	267	19.64	3846	299.47	301	16.14	3444	298.17	299	18.44
Sambucus nigra	2860	263.89	263	10.91	1688	286.69	287	10.14	2427	290.63	292	10.71
Acer campestre	2728	269.58	270	18.83	2413	297.81	299	15.95	2100	299.97	301	17.91
Crataegus monogyna	3790	271.19	272	19.15	2455	296.41	297	16.37	3051	297.08	298	18.46
Corylus avellana	2887	271.94	273	10.09	2088	301.56	303	17.04	2218	303.14	305	19.18
Aesculus hippocastanum	5321	252.86	253	19.23	4110	283.57	284	17.02	3918	287.46	288	18.81
Quercus robur	9455	273.63	275	18.4	3443	309.16	310	15.48	3158	307.13	309	11.05
Quercus petraea	1503	274.52	276	10.48	1225	305.64	305	15.82	1177	305.97	308	10.19
Sorbus aucuparia	3399	264.39	266	19.64	2464	289.23	289	16.61	2778	290.73	291	18.58
Betula pendula	5219	263.73	264	19.14	3933	296.03	298	16.97	4055	293.6	295	11.87
Acer pseudoplatanus	4157	267.48	269	19.43	2904	294.47	295	16.62	3630	292.65	294	19.7

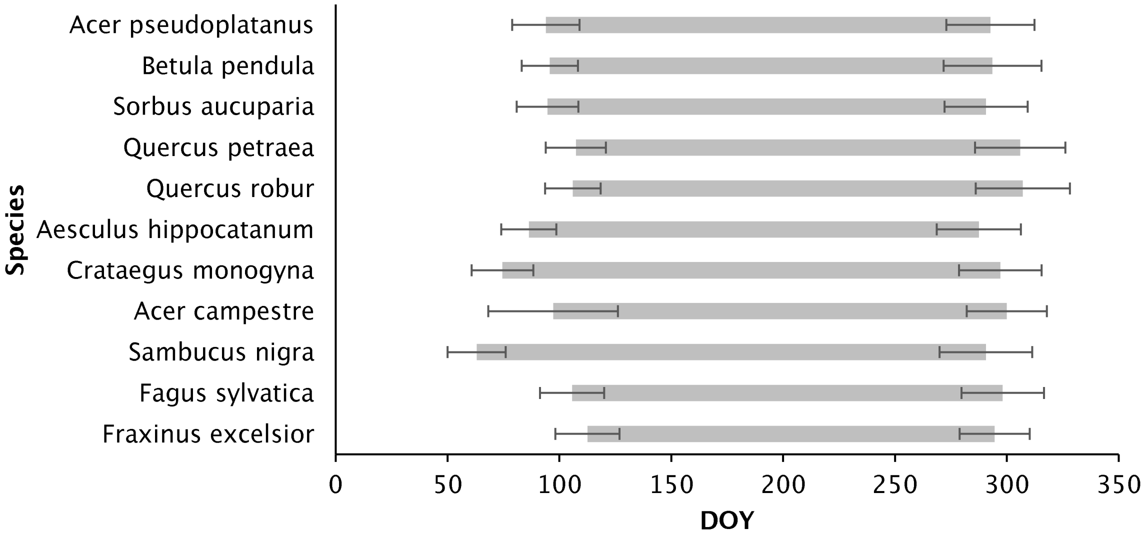


Figure 4-5 Length of the growing season for species with vegetation phenological observations covering the full extent of the growing period from spring to autumn. Budburst (BB) utilised for the start of season (SOS) and first leaf fall (FLF) for the end of season (EOS).

4.3.1 The Effect of Latitude

To analyse the effect of latitudinal variation on each phenophase, several latitudinal zones with an interval of 0.1° were created. The relationship between phenophase to geographical latitude was assessed by linear regression (Table 4-7). Figure 4-6 highlights the latitudinal relationship for a selection of species and phenophase events that showed the greatest correlation to latitude. The correlation coefficients for budburst and latitude for species are between 0.28 – 0.85. The species with the largest correlation coefficient (>0.7) are *Quercus robur*, *Fraxinus excelsior*, *Aesculus hippocastanum* and *Quercus petraea*, which are all deciduous tree species. There is generally a delay in budburst at higher latitudes. However, the magnitude of the delay is dependent on the species.

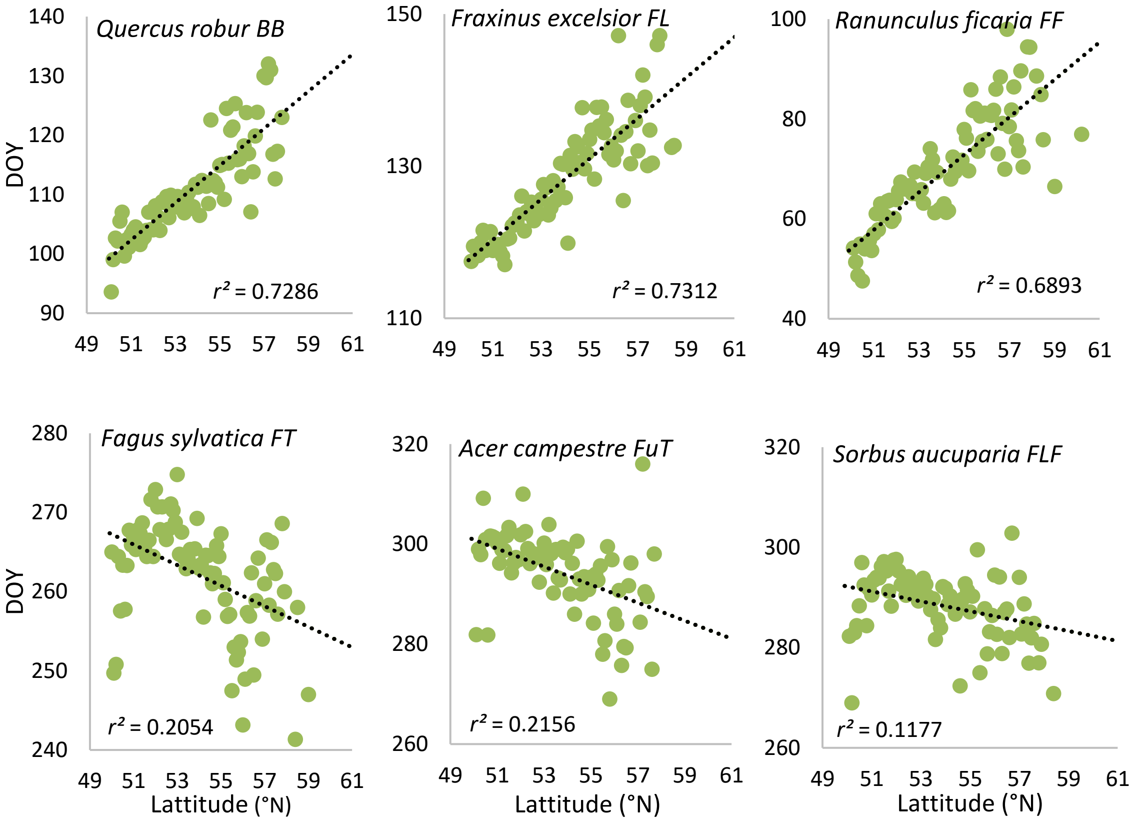


Figure 4-6 A sample of scatterplots between species DOY observations for phenophase and latitude, utilising the mean DOY per 0.1° latitude zone. Budburst (BB), first leaf (FL), first flower (FF), first tint (FT), full tint (FuT) and first leaf fall (FLF).

Table 4-7 Correlation coefficient *(r)* representing the relation between each phenophase event and latitude for each species; budburst (BB), first leaf (FL), first flower (FF), first tint (FT), full tint (FuT) and first leaf fall (FLF). Empty values are due to absence of recording of the phenophase event for that species.

Species	BB	FL	FF	FT	FuT	FLF
Alnus glutinosa	0.51**	0.65**	–	–	–	–
Fraxinus excelsior	0.75**	0.85**	–	–0.21	–0.34**	–0.09
Fagus sylvatica	0.61**	0.73**	–	–0.45**	–0.47**	–0.38**
Prunus spinosa	–	–	0.79**	–	–	–
Hyacinthoides non-scripta	–	–	0.83**	–	–	–
Dactylis glomerata	–	–	0.73**	–	–	–
Tussilago farfara	–	–	0.14	–	–	–
Cardamine pratensis	–	–	0.76**	–	–	–
Rosa canina	–	–	0.69**	–	–	–
Sambucus nigra	0.44**	0.42**	0.77**	0.22	0.14	0.15
Larix decidua	0.54**	0.57**	–	–	–	–
Acer campestre	0.28*	0.53**	–	–0.27*	–0.46**	–0.42**
Alliara petiolata	–	–	0.7**	–	–	–
Crataegus monogyna	0.44**	0.6**	0.86**	0.12	–0.09	0.05
Corylus avellana	–	–	0.39**	–0.23*	–0.12	–0.23*
Aesculus hippocastanum	0.73**	0.84**	0.82**	0.27*	–0.05	0.25*
Ranunculus ficaria	–	–	0.83**	–	–	–
Syringa vulgaris	–	–	0.76**	–	–	–
Alopecurus pratensis	–	–	0.75**	–	–	–
Quercus robur	0.85**	0.86**	0.74**	0.16	–0.19	–0.37**
Quercus petraea	0.72**	0.69**	0.45**	0.13	–0.25*	–0.32**
Leucanthemum vulgare	–	–	0.82**	–	–	–
Sorbus aucuparia	0.67**	0.8**	0.85**	–0.18	–0.36**	–0.34**
Betula pendula	0.67**	0.79**	0.45**	–0.29**	–0.53**	–0.28*
Acer pseudoplatanus	0.42**	0.74**	–	–0.4**	–0.36**	–0.29*
Phleum pratense	–	–	0.59**	–	–	–
Anemone nemorosa	–	–	0.67**	–	–	–
Holcus lanatus	–	–	0.53**	–	–	–

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

There is a larger positive correlation coefficient between first leaf and latitude than between budburst and latitude of between 0.42 – 0.86. For first flower, the majority of species showed a large or moderate positive correlation *(r* >0.45), excluding *Tussilago farfara* and *Corylus avellana*.

The correlation between the autumn phenophase events and latitude is much lower than for the spring events. The majority of species show a negative correlation with latitude as expected. However, *Sambucus nigra, Crataegus monogyna* and *Aesculus hippocastanum* show no significant correlation, which is also noted in previous studies (Menzel *et al.,* 2001). The majority of *r* values are small (<0.3) indicating that the effect of latitude on autumn phenophase events is limited.

4.3.2 The Effect of Elevation

The areas of highest elevation in GB are mostly located at higher latitudes (e.g., Scotland, Northern England), with lowland areas located in the South and South East of England (Figure 4-2). Partial regression was used to assess the correlation of the residuals (from the regression of phenophase on latitude) with elevation, that is, to investigate the effect of elevation while controlling for latitude. As expected, the influence of elevation on spring phenophase events was found to be smaller than that of latitude (Table 4-8).

The partial correlation coefficients *(r)* between the budburst residuals and elevation for each species are between 0.063 and 0.187. The results show that there is a small delay in BB, FL and FF at higher elevations. The correlation is moderate-to-small and the magnitude of the delay is dependent on the species. For FT, FuT and FLF, there is only a slight negative correlation with elevation (-0.041 to -0.146). In both cases the effect, while small, is clear and the direction of the effect is as expected.

Note that one of the main limitations within the Nature's Calendar dataset is the limited number of observations at higher elevations. More specifically, there is a very limited number of observations above 500 m. Therefore, the correlation between the phenophase events and elevation is limited to the vertical extent of the collection points.

Table 4-8 Correlation coefficient *(r)* representing the relation between each phenophase event and elevation for each species; budburst (BB), first leaf (FL), first flower (FF), first tint (FT), full tint (FuT) and first leaf fall (FLF).

Species	BB	FL	FF	FT	FuT	FLF
Alnus glutinosa	0.13**	0.15**	–	–	–	–
Fraxinus excelsior	0.164**	0.207**	–	-0.107**	-0.106**	-0.17**
Fagus sylvatica	0.133**	0.136**	–	-0.086**	-0.122**	-0.117**
Prunus spinosa	–	–	0.153**	–	–	–
Hyacinthoides non-scripta	–	–	0.112**	–	–	–
Dactylis glomerata	–	–	0.104**	–	–	–
Tussilago farfara	–	–	0.044**	–	–	–
Cardamine pratensis	–	–	0.133**	–	–	–
Rosa canina	–	–	0.191**	–	–	–
Sambucus nigra	0.063**	0.065**	0.163**	-0.082**	-0.095**	-0.1**
Larix decidua	0.102**	0.126**	–	–	–	–
Acer campestre	0.108**	0.111**	–	-0.041*	-0.043*	-0.76**
Alliara petiolata	–	–	0.067**	–	–	–
Crataegus monogyna	0.07**	0.084**	0.17**	-0.089**	-0.138**	-0.143**
Corylus avellana	–	–	0.004	-0.069**	-0.112**	-0.127**
Aesculus hippocastanum	0.106**	0.12**	0.155**	0.041**	0.028	0.005
Ranunculus ficaria	–	–	0.064**	–	–	–
Syringa vulgaris	–	–	0.198**	–	–	–
Alopecurus pratensis	–	–	0.056*	–	–	–
Quercus robur	0.169**	0.167**	0.108**	-0.049**	-0.099**	-0.106**
Quercus petraea	0.187**	0.175**	0.157**	-0.073**	-0.103**	-0.146*
Leucanthemum vulgare	–	–	0.097**	–	–	–
Sorbus aucuparia	0.124**	0.115**	0.188**	-0.084**	-0.137**	-0.142**
Betula pendula	0.144**	0.167**	0.138**	-0.098**	-0.124**	-0.126*
Acer pseudoplatanus	0.044**	0.067**	–	-0.071**	-0.126**	-0.12**
Phleum pratense	–	–	0.00	–	–	–
Anemone nemorosa	–	–	0.091**	–	–	–
Holcus lanatus	–	–	0.066*	–	–	–

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level

4.4 Discussion

Citizen science initiatives such as Nature’s Calendar play a vital role in measuring and assessing vegetation phenological trends. The results highlight that citizen science datasets can be utilised to assess and explain spatial variation in vegetation phenology at a national scale. There are several advantages in utilising citizen science datasets, including greater spatial coverage in comparison to traditional recording methods. As with many citizen science vegetation phenological networks, the Nature’s Calendar dataset for autumn events has fewer observations in comparison to spring events. Within this dataset there are over twice as many spring observations as for autumn (275,424 and 117, 789). An increase in the number of observations in citizen science initiatives can increase the accuracy of the results and decrease the influence of outliers within the data, due to the collective mean phenomenon (Delbart *et al.,* 2015). The spatial coverage of phenophase observations is concentrated in England, in particular, in urban areas (Figure 4-1). Areas of high population density, such as London, Birmingham and Manchester, are visible as observation ‘hot spots’ (Figure 4-1), which is apparent across all of the observed phenophases.

Kriging enabled spatial prediction of each phenophase in areas with few or no observations. There is a west-to-east variation in SOS and EOS across the UK which does coincide with areas with low spatial coverage of observations. A larger spatial coverage and higher density of observations within areas of higher latitude and elevation would increase the accuracy of spatial prediction. However, the west-to-east variance may be partially explained by the spatial variation of the British climate, and the influence of several air masses and prevailing winds. The coldest winter temperatures occur in eastern Scotland and England, whereas winter temperatures in the west are softened by the influence of the Gulf Stream. In addition, during spring and summer eastern parts of GB experience greater continentality and east-to-west temperature isotherms are evident.

There is a distinct latitudinal gradient up the UK, with the northern (and higher elevation) areas showing a later BB, FL, and FF, in addition to an earlier occurrence of FT, FuT and FLF (Figure 4-3). For the spring phenophase events, BB, FL and FF, latitude has a greater influence on the start of season for all species studied (Table 4-5). However, it is unknown whether this influence is due to latitudinal variation in climate, for example, in temperature and precipitation. In temperate regions such as the UK, the vegetation phenology of many species is assumed to be controlled by temperature. Phenophase events such as first flower are associated with spring. Latitude and elevation are only proxies for climate variation; however, the influence of these variables on phenophase events across the UK is visible (Figure 4-3). The majority of species show a small, negative correlation for the autumn phenophase events. The *r* values of < 0.15 across all species for FT, FuT and FLF highlights that autumn phenophase events are controlled partially by latitude and elevation. However, other environmental factors are most likely to dominate, for instance, photoperiod.

Here, latitude and elevation were used as proxies for climatic variation. A more direct means of capturing the effect of climate is the number of growing degree days (GDD). Due to the latitudinal variation in the UK, there exists spatial variation in the seasonal profiles of temperature. Northern Scotland has lower annual temperatures than Southern and South East England. Therefore, in spring the required number of GDD will occur earlier in the year in the south compared with northern latitudes. The GDD threshold varies depending on the study location, and is used to predict when crops will reach maturity (Thuiller *et al.,* 2005). The Met Office applies a threshold of 5.5°C to the calculation of growing degree days in the UK. Comparing the mean monthly temperatures (based on daily temperature) between Scotland and the South East, Scotland does not reach this threshold until March (Met Office, 2011). However, in the South East the mean monthly temperature in January is 5°C. Therefore, the number of cumulative days that would be required to reach this threshold is greater in Scotland (i.e., threshold reached later in the season), primarily due to its high latitude and colder temperatures.

When utilising any dataset collected by volunteers' central quality control is crucial (Menzel, *et al.,* 2001). Extreme anomalies and errors were present for species phenophase events within the Nature's Calendar database. These were mostly due to geolocation errors and extreme observations indicating phenophase events much earlier or later than the surrounding vegetation. The influence of temporal bias (Table 4-2) is one factor that cannot be changed when utilising a citizen science dataset, but does need to be highlighted. Temporal bias has the potential to effect and limit the accuracy of the assessment of temporal variations (Tessarolo *et al.,* 2017). These inaccuracies can lead to misleading interpretations about the extent and rate of changes to vegetation phenology. In addition, there is a need to define each phenophase event for each species in citizen science, primarily due to perceived event and recorder bias (Tooke and Battey, 2010). To increase the accuracy of the observed phenophases, a guide is provided to all volunteers describing the techniques for observing events. It asks that the event is recorded only when three plants of the same species in close proximity are showing the same event, thus, helping to record the general trend, rather than anomalies. Volunteers are also asked to record events on mature trees (over 30 years old). These measures should increase the accuracy of the individual observations by volunteers, but recorders accuracy in assessing the phenophase event not only one plant or tree but of the surrounding vegetation cannot be quantified.

A limitation in recording the location of Nature's Calendar observations is that volunteers can record within 6 miles (9.65 km) of a postcode and an elevation of 100 m. The spatial extent of a 6 mile radius of a single postcode equals an area of 113.09 miles^2 (292.92 km^2). To increase the locational accuracy of the observations it would be highly beneficial for volunteers to utilise a GPS device to record the location of each single observation. However, this may deter observers who are unable to use a 'smart' device such as a modern mobile phone. Another aspect of using postcodes as location points is that within the UK the area covered by a postcode varies depending on the number of households in any given area, the density of houses and the location (rural v. urban). A postcode can cover a street, close or cul-de-sac, or a larger rural area. However, in areas of high population density and high participation the accuracy of each phenophase estimate can be increased through aggregation of observations.

It is reported that there has been a decline in Nature's Calendar recorders. This decline is particularly apparent within volunteers who would be classed as 'expert recorders', who submit 100 or more observations per year. One of the reasons for this decline is the increasing age of the recorders. Citizen science initiatives are popular with retirees, and combined with an increasing aging population in the UK, many of the volunteers who were previously involved are now unable to record.

The number of citizen science networks is increasing globally. To increase the comparison of results across the globe, standards need to be agreed and 'best practice guidelines' given prior to the initialisation of networks. However, individual professionals would need to be consulted in order to gain the correct knowledge of species and phenophase events. An emphasis on data quality needs to be enforced within each observation network. A unified strategy to increase data quality could include; repeated sampling at agreed intervals, evaluation of observer accuracy and an improved technique to reduce spatial biases.

The integration of global networks, development of new monitoring strategies and utilisation of mobile applications, including the inclusion of GPS and digital photography, could assist with the expansion and data quality of citizen science. In addition, the automation of data collection and usage of near-surface techniques, for instance flux tower and digital camera photography, will make it easier to collect large volumes of vegetation phenological data with a finer spatial resolution than some satellite sensors. Mobile applications may also gain popularity with younger members of the public, as ecological monitoring is a hobby typically undertaken by mature adults and retirees.

For citizen science initiatives to be effective and worthwhile, historical datasets need to be combined with national data. Nature's Calendar has successfully implemented this by requesting assistance from the public, and have received several long-term vegetation phenological observation datasets given to them from members of public, such as the flowering times of a single garden plant.

The UK landscape has changed significantly over the last 60 to 70 years, with further change expected due to the expansion of urban and suburban areas. Areas of agricultural land, woodland and managed land have expanded, whereas areas of semi-natural grassland, moorlands and heaths, freshwater, wetlands and floodplains and coastal margin have decreased and become more fragmented (Watson *et al.,* 2011). Citizen science initiatives engage members of the public and communities to interact with their environment and learn about local ecology and ecosystems. They also help to educate members of the public to the impacts of climate change on their local and national environment.

4. Conclusion

This research analysed the main national vegetation phenological database currently available within the UK, Nature's Calendar, to characterise, at a fine spatial resolution, the spatial variation in the vegetation phenology of the whole UK. The observed spatial variation was found to be correlated with two controlling factors, latitude and elevation, which are effectively proxies for climatic variation.

The fine spatial resolution mapping of vegetation phenology produced here offers greater detail than provided by current European and global models. It can also assist with extrapolating current site-specific, ground-based research. This assessment was achieved without using any additional image-based datasets (e.g., from remote sensing), demonstrating the untapped potential of this very large crowd-sourced dataset.

Marked spatial variation was observed across the UK in the six phenophases studied, specifically a distinct latitudinal trend for spring phenophase events, with spring events at northern latitudes occurring later than at southern latitudes and autumn phenophases occurring earlier. The correlation between the phenophase events and elevation was as expected (smaller effect than latitude; later arrival of Spring at higher elevations) meaning that the Nature’s Calendar database is capable not only of capturing the major effect of latitude, but also the minor effect of elevation while controlling for latitude, even over the small elevation range measured (up to 500 m).

Chapter 5 Intercomparison of *In Situ* Observations to Estimated Satellite-Derived Vegetation Phenological Parameters

5.1 Introduction

Parameters of land surface phenology (LSP) represent the timing of reflectance changes that are driven by the activity of vegetation within the study area (Hanes *et al.,* 2014). Green up or SOS is closely related to budburst and leafing of vegetation (Delbart *et al.,* 2015). The increase in organic matter is quantified by an increase in a vegetation index values as the photosynthetic tissue increases within a pixel (Delbart *et al.,* 2015). However, observations of EOS using satellite-derived data are more complex and there is no distinct agreement among researchers on the most an appropriate model structure for observing the end of season and autumn senescence (Schaber and Badeck, 2003; Pouliot *et al.,* 2011). Leaf drop has been observed to be consistent annually, which could suggest that senescence is controlled by photoperiod (Lee *et al.,* 2003; Richardson *et al.,* 2006).

Characterising the relationship between *in situ* phenophase events and LSP remains challenging, and to assess LSP the estimates are often 'validated' with *in situ* observations, systematic photography or climatology models. The comparison of *in situ* observations to satellite-derived vegetation phenology can be used to assess the effectiveness of a range of LSP processing techniques including smoothing methods to derive the green-up and senescence data from VI time-series and the several techniques that can be used to assess the timing of SOS and EOS (White *et al.,* 2009). All parameters estimated from remote sensing studies are derived inversely from the spectral reflectance; therefore, the accuracy of these estimates needs to be assessed.

Satellite-derived estimates of vegetation phenology are aggregates of the varying spectral properties of several vegetation types (and their reflectance) to the pixel level. Therefore, relating satellite-derived estimates to *in situ* observations of individual plants is ideally best done when the species observed are representative of the surrounding community up to the scale of the pixel size (Delbart *et al.,* 2015). For pixels with heterogeneous land cover, diverse species or distinct vegetation phenological differences from the observed *in situ* species the comparison can be complex. For pixels containing agricultural land or managed land the comparison is problematic (Delbart *et al.,* 2015).

Conflicting definitions of both spring and autumn and the exact timing of events are apparent in both *in situ* and satellite-derived studies. A universal standard for defining spring and autumn events would allow a comparison of observation results across the globe, a succinct review of annual ecological variation, and the effect of climate change on different ecosystems to be assessed.

This aim of this chapter was to compare *in situ* phenophase observations to satellite-derived vegetation phenological estimates of SOS and EOS in the UK and to determine the relationship between the timing of LSP SOS and EOS and phenophase events utilising citizen science data. A combination of statistical methods is utilised to characterise the relationship between the observed events and estimated LSP parameters, including descriptive statistics, conventional regression and geographically weighted regression modelling.

5.2 Data and Methodology

For this assessment three separate data sources were used; *in situ* phenophase observations of deciduous tree species from Nature's Calendar, composites of Medium Resolution Imaging Spectrometer (MERIS) Terrestrial Chlorophyll Index (MTCI), and the Land Cover Map 2007 (LCM2007) produced by the CEH. The study period covers from 1st January 2005 to 30th April 2011, to account for the additional months required when using Fourier smoothing to estimate EOS. The six years were chosen to account for extremes within the UK weather and climate, and the effects that this may have on LSP estimates.

5.2.1 Nature's Calendar

The *in situ* data used were derived from the Woodland Trust's citizen science dataset, Nature's Calendar. The species included from the Nature's Calendar dataset are shown in table 5-1. The data were quality checked and data points were discarded due to issues with geographic location and data error as in Chapter 4 (e.g. incorrect assessment of phenophase event). The *in situ* phenophases analysed were; (1) budburst (BB), (2) first leaf (FL), (3) first tint (FT), (4) first leaf fall (FLF), and (5) full tint (FuT).

Table 5-1 *In situ* species observations used within this research (Woodland Trust, 2016).

Latin Name	Common Name
Fraxinus excelsior	Ash
Fagus sylvatica	Beech
Acer campestre	Field Maple
Aesculus hippocastanum	Horse Chestnut
Quercus robur	Oak (*Penduncula*te)
Quercus petraea	Oak (*Sessile*)
Betula pendula	Silver Birch
Acer pseudoplatanus	Sycamore

5.2.2 MERIS Satellite Sensor Data

The Medium Resolution Imaging Spectrometer (MERIS) is a sensor launched by the European Space Agency (ESA) on board the Envisat Earth Observation Satellite. MERIS, a passive imaging spectrometer, has a 68.5° field-of-view that measures the solar radiation reflected by the Earth in 15 spectral bands (Table 5-2) at 300 m spatial resolution (ESA, 2006). The MERIS sensor spectral bands sample visible, near-infrared (NIR) and narrow bands (390 nm to 1040 nm) that improve the spectral assessment of vegetation (Boyd *et al.,* 2011). MERIS completes full coverage of the Earth every 3 days (Verstraete *et al.,* 1999). MERIS is a full-resolution geophysical sensor for ocean, land and atmosphere studies with high radiometric accuracy (Curran and Steele, 2005). MERIS data is available in three products, with three processing levels; level 1B, 2 and 3. For this research, MERIS level 2 Full Resolution Full Swath (MER_FRS_2P) data with a spatial resolution of 300 m were used. The Level 2 product is derived from level 1B and is pre-processed for geolocated geophysical data, surface radiance and reflectance, latitude, longitude, altitude and topographic corrections, sun azimuth, sun elevation, view azimuth, and view elevation.

There are two VI that have been developed using MERIS data; the MERIS global vegetation index (MGVI) (Gobron *et al.,* 1999) and the MERIS Terrestrial Chlorophyll Index (MTCI) (Dash and Curran, 2004). MTCI was utilised in this research as it is related directly to the canopy chlorophyll content. The onset of spring equates to an increase in chlorophyll content, and autumn senescence leads to a decrease in foliage chlorophyll.

Table 5-2 MERIS spectral bands and associated applications.

MDS Nr.	Band centre (nm)	Bandwidth (nm)	Applications
1	412.5	10	Yellow substance and detrital pigments
2	442.5	10	Chlorophyll absorption maximum
3	490	10	Chlorophyll and other pigments
4	510	10	Suspended sediment, red tides
5	560	10	Chlorophyll absorption minimum
6	620	10	Suspended sediment
7	665	10	Chlorophyll absorption and fluorescence reference
8	681.25	7.5	Chlorophyll fluorescence peak
9	708.75	10	Fluorescence reference, atmospheric corrections
10	753.75	7.5	Vegetation, cloud
11	760.625	3.75	Oxygen absorption R-branch
12	778.75	15	Atmosphere corrections
13	865	20	Vegetation, water vapour reference
14	885	10	Atmosphere corrections
15	900	10	Water vapour, land

Chlorophyll strongly absorbs energy in the wavelength bands between 0.45 and 0.67 µm, the Photosynthetically Active Region (PAR). The area of the spectrum that drives photosynthesis are between 0.6 -0.7 µm, red and near infrared wavebands (Lillesand and Kiefer, 1994). At 0.7 µm the reflectance of healthy vegetation increases dramatically, and between 0.7 µm and 1.3 µm, leaves typically reflect 40 – 50% of the radiated energy. The dramatic increase in reflectance of vegetation in the NIR waveband is referred to as the red edge

(Carter and Spiering, 2002). MTCI utilises the spectral reflectance in the red edge wavelengths, and therefore should detect the spectral signature of different vegetated land cover types, for instance broadleaf, coniferous and grasslands, as different species have a different range of spectral reflectance. Healthy vegetation and malnourished vegetation or vegetation in drought conditions, also shows a different spectral reflectance to healthy vegetation.

MTCI is a ratio of the difference in reflectance between band 10 and band 9 and the difference in reflectance between band 9 and band 8 of the MERIS standard band setting.

The MTCI VI is formulated as follows:

$$\mathrm{MTCI} = \frac{\mathrm{R_{Band10}} - \mathrm{R_{Band9}}}{\mathrm{R_{Band9}} - \mathrm{R_{Band8}}} \tag{1}$$

(R_{Band10}, R_{Band9}, and R_{Band8} are wavebands 753.75nm, 708.75nm and 681.25nm)

MTCI VI does not have the same levels of limitations as NDVI, such as saturation at high biomass (Dash and Curran, 2007). In addition, MTCI is less affected by noise from the atmosphere and soil background, and there is no overall bias such that the noise within MTCI data is assumed to be white with a zero mean value (Dash *et al.,* 2008; Atkinson *et al.,* 2012). Each composite is referred to by a composite number (CN). 10 day composites of the MERIS MTCI data were created with a 250 m spatial resolution using a flux conversion algorithm. The compositing algorithm calculates the arithmetic mean of the input measurements, with the additional option for a weighting to be applied to the measurement. First, drop-outs were eliminated through an averaging process within a temporal neighbourhood prior to, and following, a drop-out from 1 week to 2 months to; thus, fill the gaps within the time-series.

Fourier analysis is used commonly to smooth time-series satellite-based data. By approximating complicated time-series as the sum of sinusoidal waves at multiple frequencies, Fourier analysis can be used to interpret vegetation growth cycles. Fourier uses one model parameter, the number of harmonics, to smooth noisy data and can be applied effectively with a few lines of software code (Atkinson *et al.,* 2012). However, limitations include requiring a long time-series and equally spaced observations, and also difficulty when applied to irregular or asymmetric data, due to dependence on symmetric sine and cosine functions.

Fourier-based models may also generate false oscillations in the VI time-series (Chen *et al.,* 2004).

For each year within the study, an additional 4 months from the following year was added to the dataset (e.g., January 2005 to April 2006). This is due to Fourier analysis requiring a full sinusoidal curve to detect the start and end of season. Then the dataset was smoothed using Fourier analysis, and the LSP parameters (SOS and EOS) were estimated using the method from Dash *et al.,* (2010). Discrete Fourier transformation (DFT) decomposed the complex waveforms into a series of sinusoids, thus removing noise. The noise fluctuations are removed and the harmonics are then interpreted as seasonal variation of VI value (Wagenseil and Samimi, 2006). The Discrete Fourier Transform is formulated as:

$$F(u) = \frac{1}{N} + \sum_{t=0}^{N-1} VI\left((t) * e^{-2\pi ut/T}\right) \tag{2}$$

where u is the number of Fourier components, *t* is the composite number, VI(*t*) is the input VI value in the time-series, *T* is the number of composites and here *T* is equal to *N*, the number of data in the time-series.

The first two harmonics in Fourier transform models account for 50-90% of the variability in the VI time-series, and may not represent the vegetation phenological cycle. In this study, as previously used successfully in Dash *et al.,* (2010) and Jakubauskas *et al.* (2001), the first four harmonics were used to extract SOS and EOS. From the extracted SOS and EOS estimates the Julian day of year (DOY) was calculated as the median of the days within each composite.

5.2.3 Comparison Methodology

In the UK, the area of land dominated by broadleaf vegetation equated to only 6% of the total land cover (Morton *et al.,* 2011). When the pixels defined as dominant broadleaf land cover were intersected with the *in situ* observations from Nature's Calendar there were a significantly reduced number of remaining phenophase observations across the study period. As stated previously, Nature's Calendar is a citizen science initiative and has observational hotspots across the UK. Typically citizen observations are carried out close to where people live, in parks, gardens, or forests or grasslands which are often next to agricultural or urban land cover (Delbart *et al.,* 2015). This is echoed in the Nature's Calendar database; there is an increase in number of observations in areas classed as dominant agricultural land, improved grassland and residential, and in the South East of England, in comparison to Northern England and Scotland (Figure 4-1). Therefore, depending on the size of the pixel intersected with the *in situ* observation the estimates of SOS or EOS may not reflect the observation, due to the aggregation of land cover over the pixel.

To combat the spatial limitation of *in situ* observations within areas defined as broadleaf land cover and the interference of managed land cover types (e.g. agricultural and improved grassland), only the areas dominated by natural land covers were chosen. To identify the land cover types across GB the LCM 2007 1 km percentage aggregate class was used to identify areas of semi-natural grassland, broadleaf woodland, coniferous woodland and mountain bog and heathland with >50% coverage (Morton, 2011). The pixels were reclassified to select pixels with 50% to 100% coverage and were extracted as representative homogeneous pixels.

Figure 5-1 Black shading shows areas dominated by broadleaf woodland, coniferous woodland, semi-natural grassland and mountain, heath and bog (>50%) (Morton, 2011).

The *in situ* point observations were then intersected with the assessments of SOS and EOS from MERIS MTCI data for each individual year and subsampled to each land cover type. To compare the relationship of the DOY of satellite-derived estimated SOS and EOS and observed *in situ* observations a range of techniques were used, including descriptive statistics, interpolation, conventional regression and geographically weighted regression (GWR). The summary statistics of each species were first estimated, including the mean, median, and standard deviation. Conventional regression outputs between the observed *in situ* phenophase events and the estimated SOS or EOS, including the coefficient of determination (r^2), the adjusted-r^2 and associated p-value. A *t-test* was used to assess the significance of the difference between the means of the *in situ* observations and the satellite-derived estimates.

Across the UK there is a large amount of spatial variation in phenophase events, even for the same species, due to the influence of land cover, latitude and elevation. Therefore, by implementing GWR, as opposed to conventional regression techniques, the spatial relationship between *in situ* and satellite-derived estimates can be assessed further.

Geographically weighted regression (GWR) is a local spatial statistical technique used to analyse spatial non-stationarity in the relationship between variables, where data varies from one location to another (Fotheringham *et al.,* 2002). It takes into account local constraints and has shown to be a more effective way of analysing remotely sensed data (Roy and Yuan, 2007). GWR expresses the spatial variation in the relationship between predicted variables and a set of covariates through spatial variation in the regression coefficients and the coefficient of determination. It can be particularly helpful in revealing relationships where missing variables exist, as may be the case here (Brunsdon *et al.,* 1998). The ARCMap GWR was applied using a fixed kernel bandwidth and utilising the *corrected* Akaike Information Criterion (AICc) to assess goodness-of-fit (Hurvich *et al.*, 1998). The variable bandwidth approach accounts for the spatial variation and clustering of observations across the UK. The choice of bandwidth is important for GWR as is reduces bias, and with an increase in bandwidth there is increase in bias. As remote sensing is an abundant source of spatial data GWR can be a valuable technique to assess this non-stationarity and find relationships that would otherwise remain hidden.

The relationship between two variables using GWR is expressed by the equation:

$$\gamma = \alpha(\theta) + \beta(\theta)x + \varepsilon \tag{3}$$

Diagnostic measures such as the corrected AICc, local standard errors, local measures of influence, and a local goodness-of-fit can be applied. The AICc method takes into account the degrees of freedom when measuring model performance and can be helpful when comparing different regression models. The model with the lower AICc value provides a better fit to the observed data. AICc is not a strict measure of goodness-of-fit, but can be used to determine the better fitting model in a relative sense. The AICc is also used to determine the optimal bandwidth value, utilising the bandwidth with the lowest AICc value. AICc is expressed as follows:

$$AICc = 2n\,log_e\,(\hat{\sigma}\,) + n\,log_e\,(2\pi) + n\left\{\frac{n + tr(S)}{n - 2 - tr\,(S)}\right\} \tag{4}$$

where *n* is the number of observations in the dataset, $\hat{\sigma}$ is the estimate of the standard deviation of the residuals, and *tr(S)* is the trace of the hat matrix.

5.3 Results

5.3.1 Species-Specific Variability in Phenophase Events

The mean budburst DOY from the Nature's Calendar data for each species reveals that the difference between the earliest, *Aesculus hippocastanum,* and the latest, *Fraxinus excelsior*, budburst is 26 days (Table 5-3). However, within those species there is a range of observed variability of 122 days for *Aesculus hippocastanum* and 144 for *Fraxinus excelsior.* As stated previously, the correlation to satellite-derived estimates and *in situ* data can be affected due to the dominant species within the study area and the species used for *in situ* comparison (Beck *et al.,* 2007). The number of species observations varies greatly across the study period, with *Aesculus hippocastanum* budburst observed 8,598 times, and *Quercus petraea* 1,712 times. It is noted that the variability in budburst DOY and the greater number of observations may affect the correlation with SOS estimates.

For first leaf, the species with the mean earliest first leaf event was *Aesculus hippocastanum* (98 DOY), with *Fraxinus excelsior* later in the season (123 DOY).

The range of first leaf within these species is less than budburst, with 105 days for *Aesculus hippocastanum* and 109 days for *Fraxinus excelsior* (Figure 5-2). The observed mean first leaf DOY for *Fagus sylvatica* and *Quercus robur* are both 114, and for *Betula pendula* and *Acer pseudoplatanus*, 105 and 106. The similarities in first leaf DOY for these species could highlight that the controlling factors for temperature, precipitation and photoperiod are similar.

Table 5-3 *In situ* species mean DOY and standard deviation for phenophase events for 2005 – 2010 across the UK.

	Budburst		**First Leaf**		**First Tint**		**First Leaf Fall**		**Full Tint**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Fraxinus excelsior	113	14.36	124	11.30	277	16.27	295	15.65	294	13.72
Fagus sylvatica	106	12.97	115	10.16	265	19.72	298	18.50	300	15.41
Acer campest.	91	13.78	109	11.55	270	18.81	300	17.91	298	15.94
Aesculus hippocas.	86	12.34	98	11.67	253	19.22	288	18.54	284	17.01
Quercus robur	106	12.41	115	11.13	274	18.41	307	20.30	309	15.49
Quercus petraea	107	13.42	117	11.94	274	20.47	306	20.19	306	15.82
Betula pendula	96	12.60	106	10.24	264	19.31	294	21.84	296	16.98
Acer pseudop.	94	14.67	106	11.66	267	19.40	293	19.71	294	16.62

For autumn phenophase events, first tint, first leaf fall and full tint, *Aesculus hippocastanum* has the earliest DOY for each event. *Aesculus hippocastanum* also has the greatest range in observational dates, 161 days for first tint, 212 days for first leaf fall and 173 days for full tint. The degree of divergence for these phenophase events could be due to observer error or location-specific controlling events (local weather, latitude and elevation). The species with the latest date for first tint is *Fraxinus excelsior* with a mean of 277 DOY. For first leaf fall and full tint, *Quercus robur* has the latest observed DOY with 307 (3rd November) and 309 (5th November). The range between the mean observed first tint DOY is 24 days, for first leaf fall, 19 days, and for full tint, 25 days. As with the spring phenophase events the dominant observed species and the dominant vegetation within the aggregated pixel will impact the relationship between SOS and EOS and the chosen phenophase.

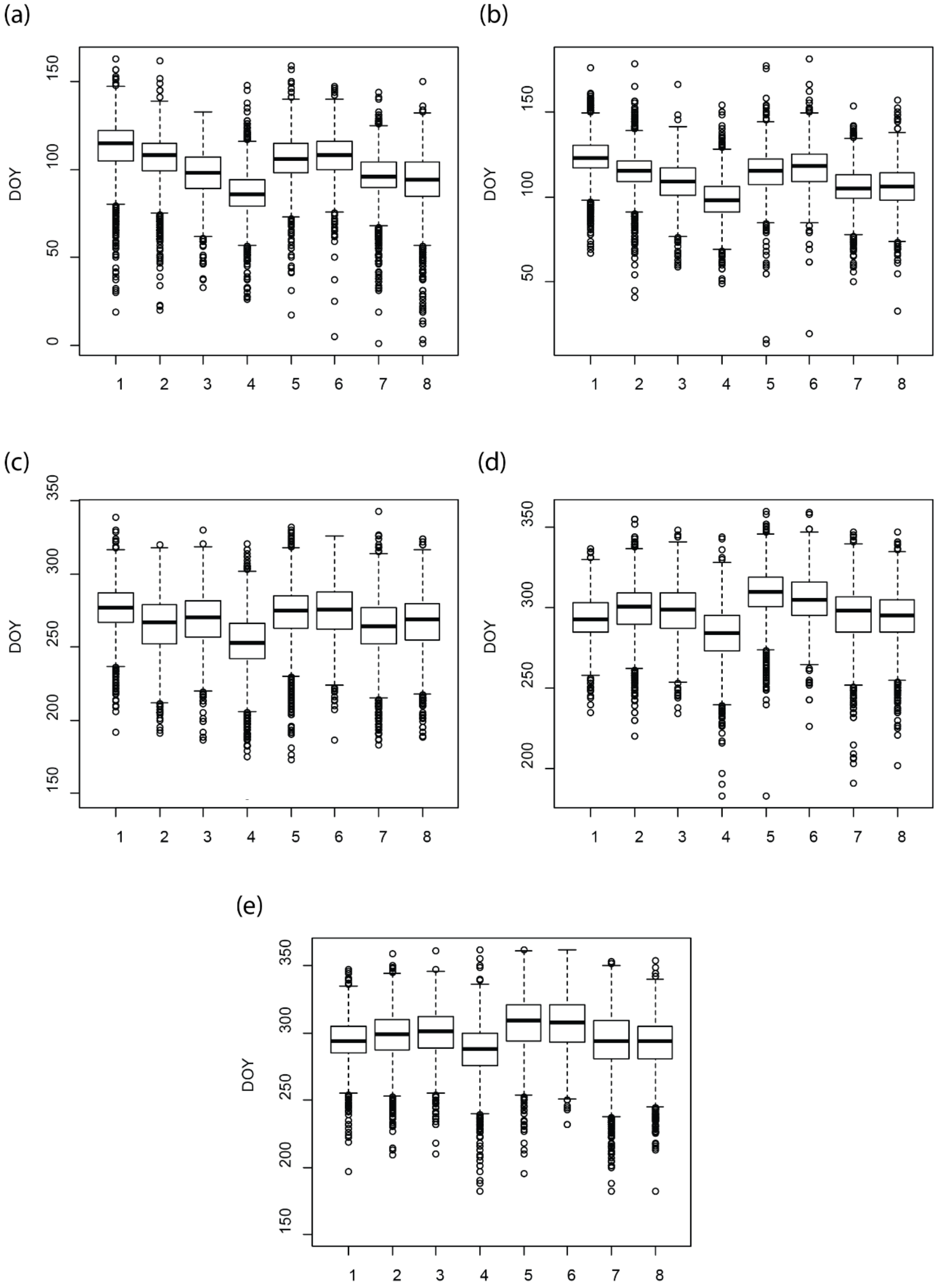


Figure 5-2 *In situ* species variability in DOY for each phenophase for (a) Budburst, (b) First Leaf, (c) First Tint, (d) Full Tint and (e) First Leaf Fall. Species: (1) *Fraxinus excelsior* (Ash), (2) *Fagus sylvatica* (Beech), (3) *Acer campestre* (Field Maple), (4) *Aesculus hippocastanum* (Horse Chestnut), (5) *Quercus robur* (Oak Penduncolate), (6) *Quercus petraea* (Oak Sessile), (7) *Betula pendula* (Silver Birch), and (8) *Acer pseudoplatanus* (Sycamore).

5.3.2 Interpolation

Spatial variability in phenophase events across the UK arises due to variation in the latitude, elevation and dominant land cover types across the UK (Figure 5-3, 4, 5, 6, 7). SOS occurs later in the year in northern and high elevation areas of the UK, predominantly in Scotland, across the Pennines, Wales and in several localised areas of the South of England. As highlighted in the descriptive statistics (Table 5-4) the satellite-derived estimates of SOS are earlier in comparison to the *in situ* observations of BB and FL. The dominant land cover type of arable and improved grassland across much of southern England highlights the large discrepancy between SOS DOY and spring phenophase DOY, as spring growth occurs much earlier due to land management techniques.

The spatial variance of BB and FL across the UK also shows the latitudinal effects on the DOY of phenophase events for all species. For the individual species of deciduous trees, there is a notable difference in the timing of BB and FL spatially (Figure 5-3, 5-4).

Comparison of EOS to first tint, first leaf fall and full tint phenophase events is known to be problematic, as the estimate of satellite-derived EOS has several limitations. The FT, FLF and FuT phenophase *in situ* observations occur much earlier than satellite-derived EOS estimates in the north and highland regions (Fig. 5-5, 6, 7). In southern and central areas satellite sensor derived EOS shows an earlier EOS. This is predominately in areas of dominant arable and improved grassland which are predominantly located in the South have an earlier EOS than natural unmanaged land cover areas.

There is less spatial variance in the autumn phenophase DOY between the individual species. As discussed in chapter 4, the majority of species for autumn showed a small, negative correlation for the autumn phenophase events, highlighting that autumn phenophase events are only partially controlled by latitude and elevation.

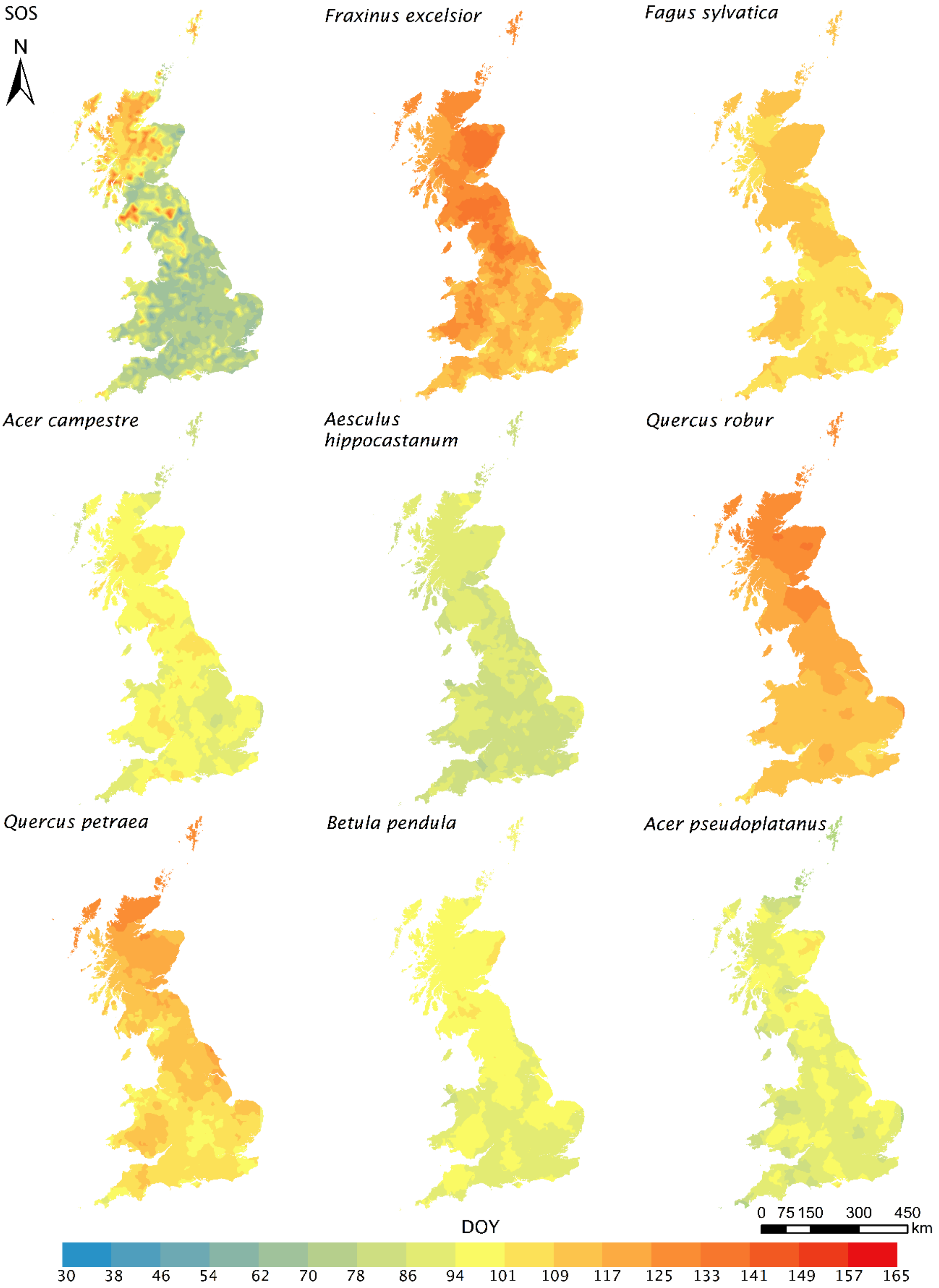


Figure 5-3 Smoothed satellite-derived SOS estimates and kriging interpolation of observations for budburst (BB) for each of the eight broadleaf species.

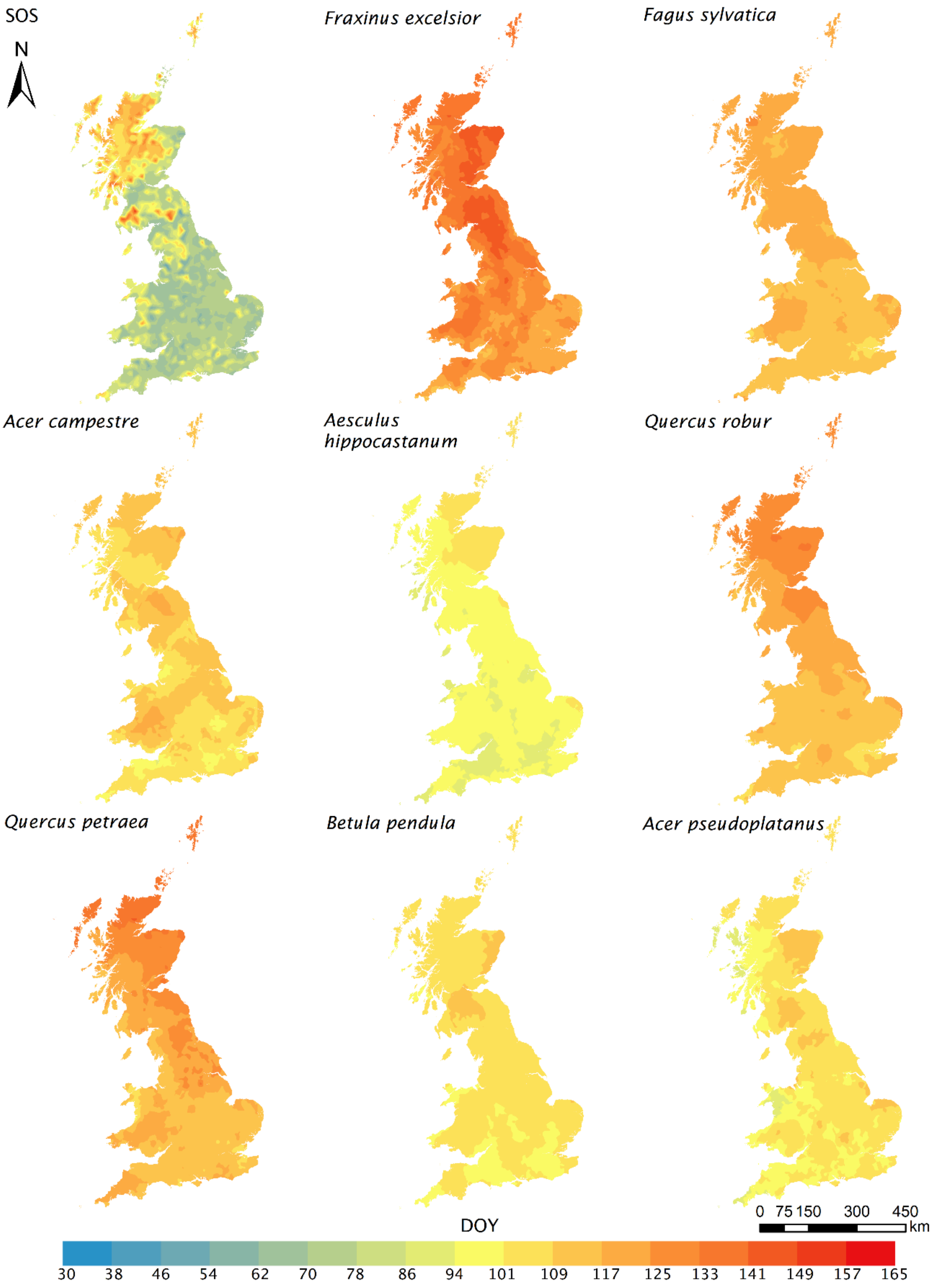


Figure 5-4 Smoothed satellite-derived SOS estimates and kriging interpolation of observations for first leaf (FL) for each of the eight broadleaf species.

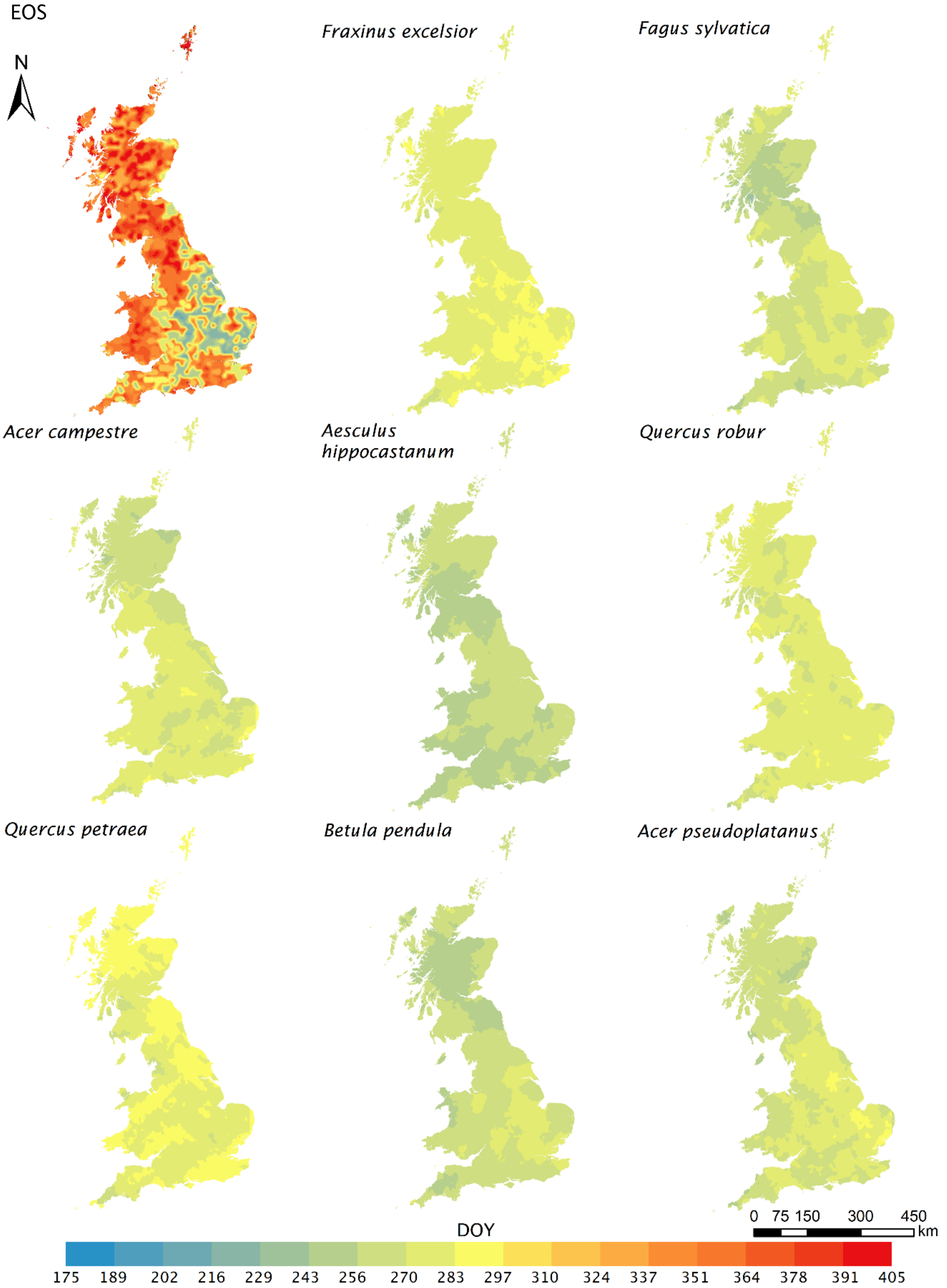


Figure 5-5 Smoothed satellite-derived EOS estimates and kriging interpolation of observations for first tint (FT) for each of the eight broadleaf species.

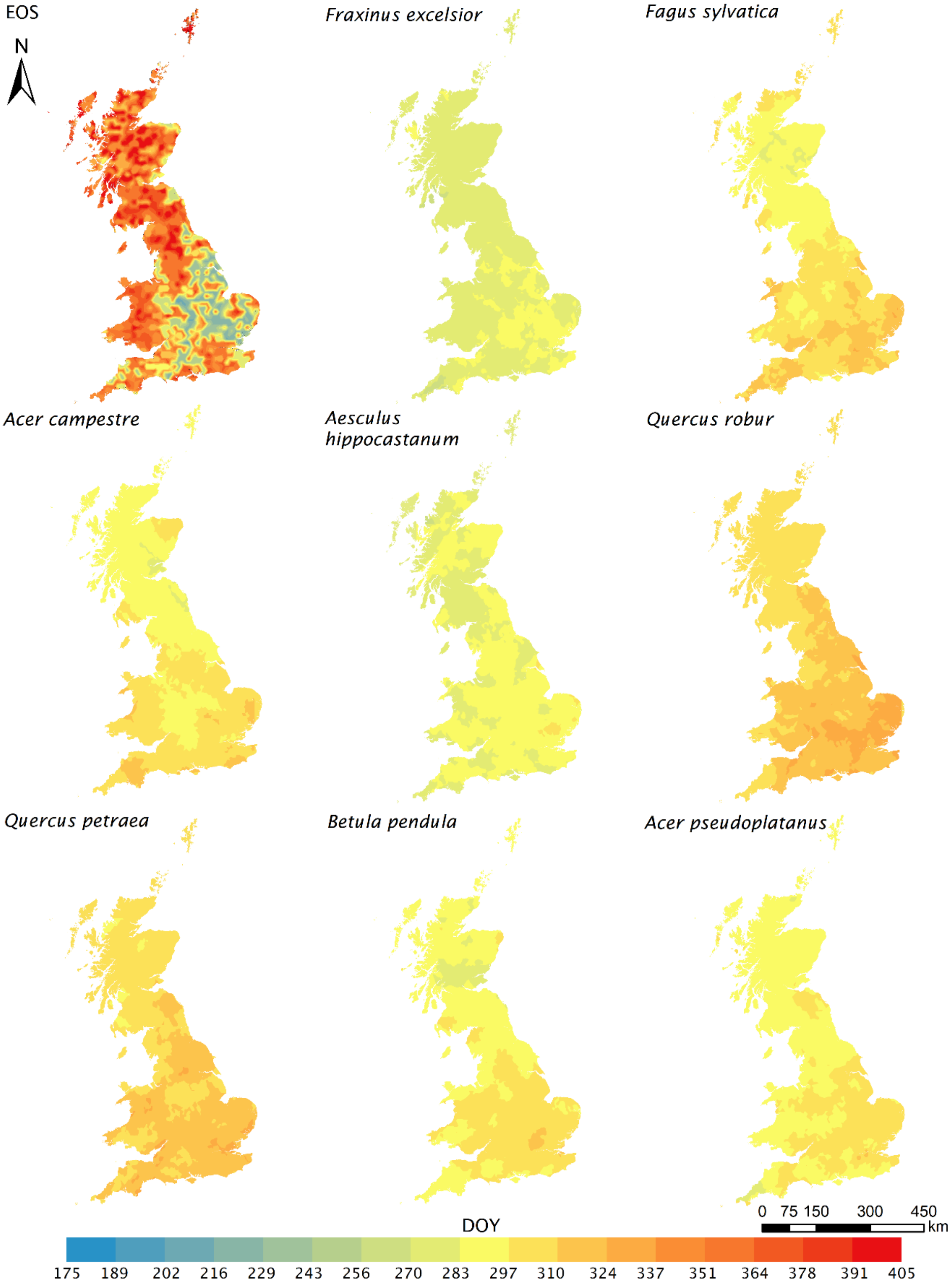


Figure 5-6 Smoothed satellite-derived EOS estimates and kriging interpolation of observations for full autumn tint (FuT) for each of the eight broadleaf species.

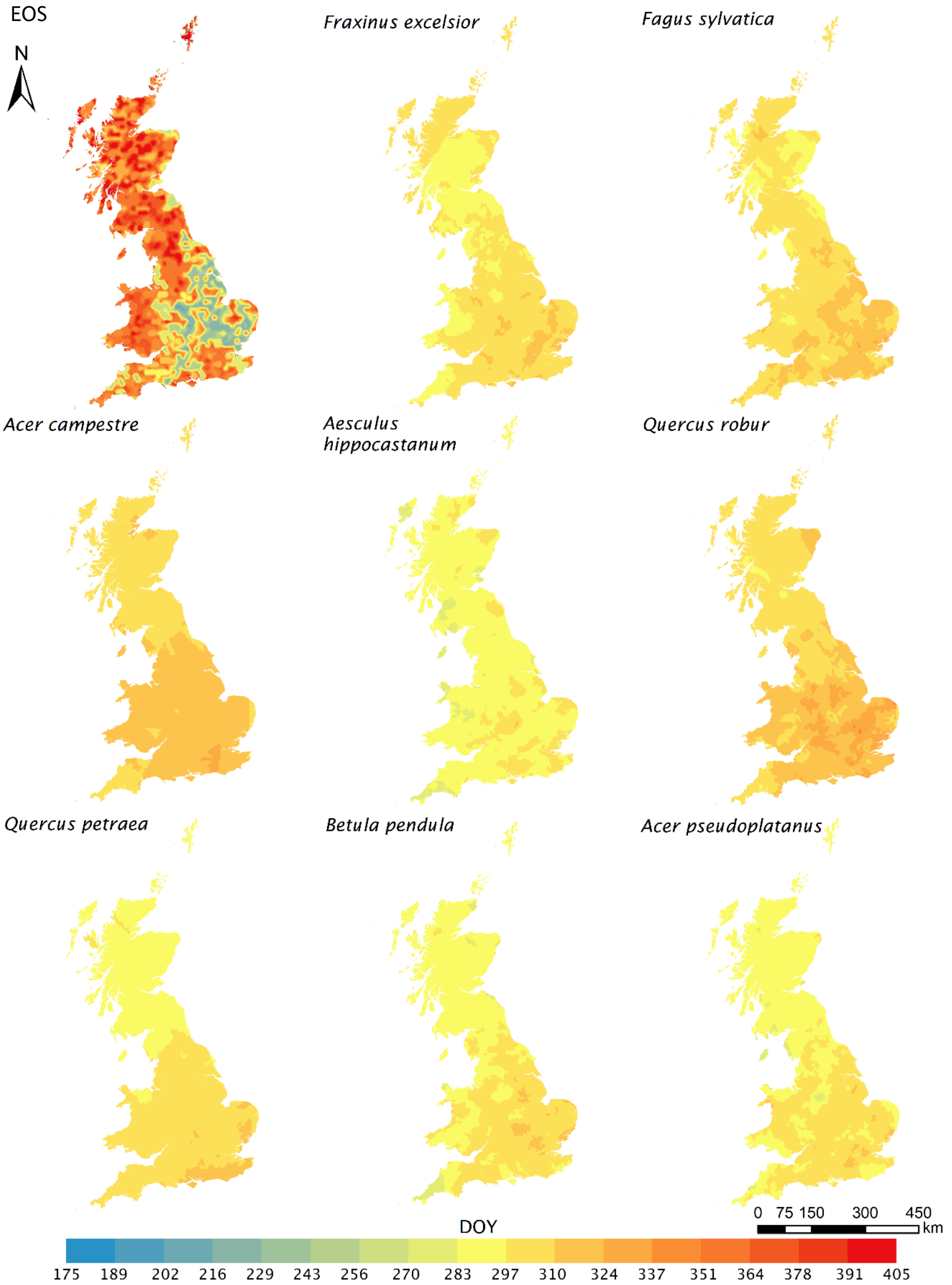


Figure 5-7 Smoothed satellite-derived EOS estimates and kriging interpolation of observations for first leaf fall (FLF) for each of the eight broadleaf species.

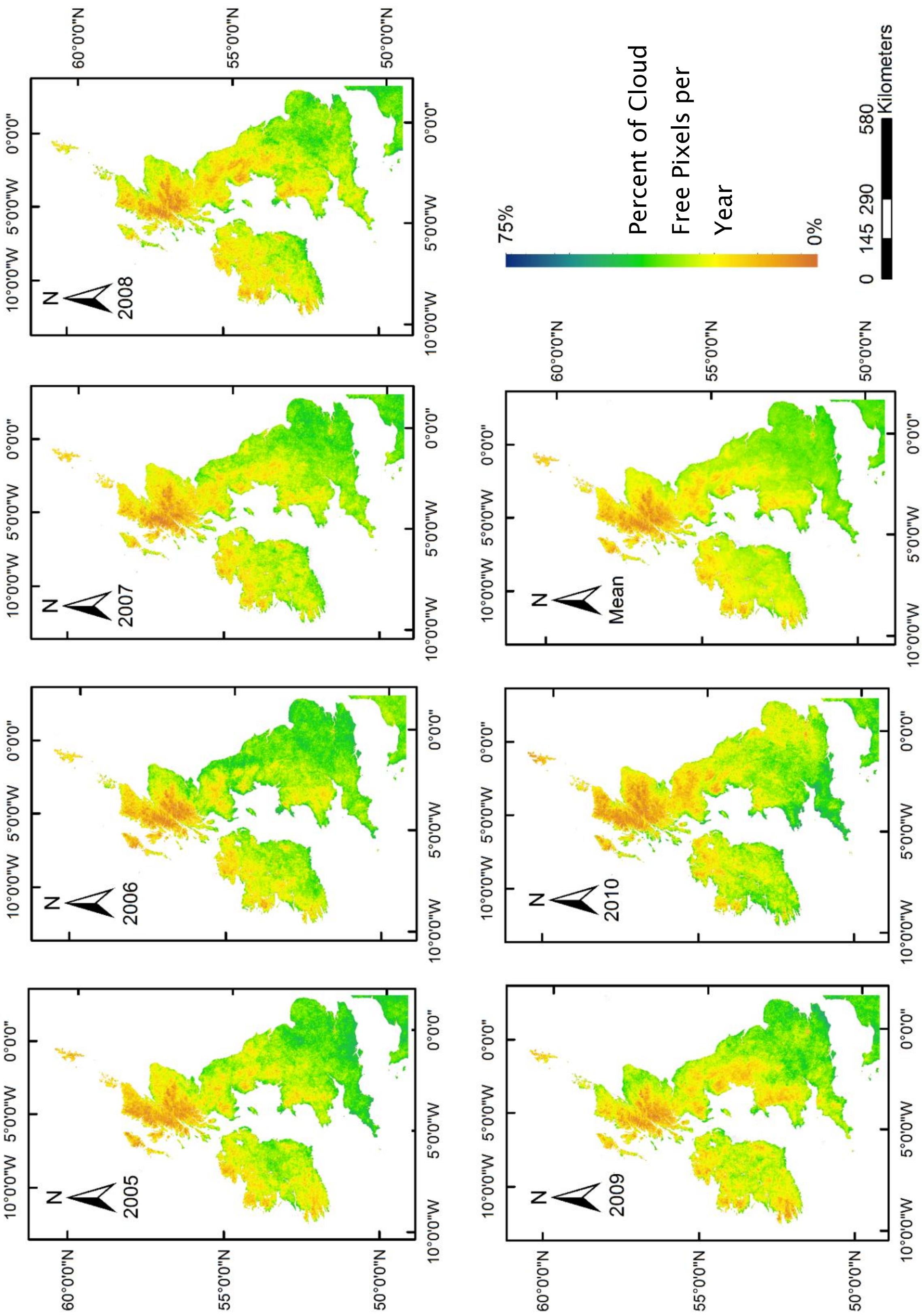


Figure 5-8 Percentage of cloud free days per year derived from MERIS satellite imagery.

The estimation of EOS through satellite-derived techniques is commonly limited due to cloud cover, causing data gaps within the time-series. The percentage of cloud cover was calculated for each year within the study period. Cloud cover particularly affects Northern and Western areas of the UK (Figure 5-8). The limited numbers' of cloud free images across these areas will affect the estimation of EOS as there is a reduced number of MTCI values with which to estimate the vegetation phenological parameters. One of the known limitations in using Fourier transformation is the requirement of a long time-series and equally spaced observations. As the UK, particularly Northern regions including Scotland and Northern England, is known to have persistent cloud cover during winter the influence of cloud cover should be noted within this study. The use of the 'gap filling' technique attempted to minimise the effects of cloud cover, however, in areas with 30% or less cloud free pixels per year the estimation of EOS has been delayed.

5.3.3 Descriptive Statistics

The descriptive statistics (Table 5-4) highlight the difference in both the satellite-derived SOS and EOS estimates and the relative phenophase events for all species of broadleaf species for each year within the study, thus, highlighting the annual variability in phenophase events across the UK. The satellite sensor derived estimates of SOS and EOS were intersected with the observed point *in situ* data for each year. The mean SOS estimates were earlier in comparison to both BB and FL observations for each year. In comparison, EOS satellite-derived estimates are much later in comparison to first tint, first leaf fall and full tint.

For the period 2005 to 2010, the mean SOS DOY estimate varies between days 64 and 88, whereas the BB DOY is between days 93 and 101, and FL is between days 105 and 116. For EOS DOY estimates for 2005 to 2010 there is a range of between days 326 to 368. However, the observed in situ phenophase DOY varies from days 261 to 272 for FT, 288 to 304 for FLF and 292 to 304 for FUT.

Table 5-4 Descriptive statistics for *in situ* phenophase events and estimated satellite-derived DOY per year.

Phenophase Event	Satellite Mean DOY	*In situ* Mean DOY	Satellite Median DOY	*In situ* Median DOY	Satellite SD	*In situ* SD
2005						
Budburst	81	96	75	97	44.20	12.11
First Leaf	82	108	85	108	43.84	10.66
First Tint	369	272	385	273	58.53	13.36
First Leaf Fall	356	303	385	302	68.59	16.77
Full Tint	354	301	385	300	68.85	17.15
2006						
Budburst	71	101	75	105	33.58	15.65
First Leaf	71	116	75	117	35.08	9.673
First Tint	333	270	365	274	65.05	18.24
First Leaf Fall	330	304	365	307	66.48	16.41
Full Tint	328	304	355	306	67.64	14.80
2007						
Budburst	78	94	75	96	34.29	12.54
First Leaf	79	105	75	105	33.20	9.445
First Tint	330	263	345	264	66.56	16.73
First Leaf Fall	327	293	345	294	66.29	15.98
Full Tint	326	293	340	294	66.92	14.18
2008						
Budburst	88	93	85	93	27.17	11.01
First Leaf	88	111	85	112	26.97	11.27
First Tint	356	264	365	266	48.51	16.57
First Leaf Fall	355	293	365	294	49.06	15.44
Full Tint	355	296	365	296	49.06	12.80
2009						
Budburst	66	94	65	94	38.96	11.33
First Leaf	65	105	65	105	38.13	9.75
First Tint	362	261	385	262	72.81	15.85
First Leaf Fall	360	289	385	290	74.04	16.46
Full Tint	359	290	385	291	74.63	14.40
2010						
Budburst	84	101	85	102	30.43	11.05
First Leaf	85	112	85	112	31.27	9.576
First Tint	346	265	365	268	48.50	17.48
First Leaf Fall	344	293	365	296	49.87	17.17
Full Tint	344	296	360	297	49.89	13.10

5.3.4 Conventional Linear Regression

Utilising conventional linear regression, there was little-to-no relationship between the *in situ* observations and satellite-derived estimates for the DOY of spring and autumn events across all years within the study period (Table 5-5). One single point observation may not reflect the dominant species or land cover for its related pixel at the selected spatial resolution. In particular, when a pixel represents a mosaic of land cover types or in areas with high species diversity this comparison is known to be highly challenging (Delbart *et al.,* 2015).

The results indicate that the mean lag in days between SOS and BB is smaller than with FL. The largest mean lag between phenophase and SOS is for *Fraxinus excelsior* with 26.9 days lag for BB and 37 days for FL. The RMSE is between 32.7 and 41.8 for this species and MAE is between 28.3 and 37.9. *Aesculus hippocastanum* has the smallest mean lag between observed phenophase and SOS with -0.24 days for budburst and 9.91 days for first leaf. This species also has the smallest RMSE and MAE. However, the r^2 and p values indicate only a small relationship.

For EOS there are fewer intersected observations for EOS and associated phenophase events in comparison to SOS observations, due to the smaller number of observations undertaken by the public during autumn. Using conventional regression techniques highlights that there is no significant relationship between EOS estimates and *in situ* phenophase observations (Table 5-5). The observed phenophase events for *Quercus robur* have the smallest mean lag between observed autumn phenophases and estimated EOS DOY, with 105 days difference for first tint, 73 days for first leaf fall and 72 days for full tint. *Acer pseudoplatanus* first tint has the greatest mean lag between observation DOY and estimated EOS, with 141 days difference. In addition, there is a 101 mean lag difference between first leaf fall and EOS. The comparison between full tint and EOS for *Aesculus hippocastanum* has the largest mean lag with 99 days difference. The vast divergence between species specific *in situ* autumn phenophase observations and the satellite-derived EOS estimates highlights the difficulties in comparing the relationship between observational techniques.

Table 5-5 Relationship between species-specific phenophase events and satellite-derived SOS. *N* (number of observations). Mean lag negative value indicates satellite estimates are later than observed phenophase.

Phenophase Event	N	Mean lag	r^2	Adjusted r^2	p– value	t-value	RMSE	MAE
Fraxinus excelsior								
Budburst	72	26.9	0.0166	0.0025	0.28	11.5	32.7	28.3
First Leaf	80	37	0.0036	-0.011	0.63	15.0	41.8	37.9
Fagus sylvatica								
Budburst	81	19.40	0.0247	0.0124	0.16	8.04	30.2	26
First Leaf	76	16.59	0.0001	-0.013	0.91	12.7	32.2	28.6
Acer campest.								
Budburst	23	3.39	0.11	0.068	0.12	0.835	22.2	17.1
First Leaf	24	18.79	0.01	-0.027	0.54	5.79	23.5	20.5
Aesculus hippocas.								
Budburst	102	-0.24	0.12	0.002	0.27	-0.11	20.65	16
First Leaf	94	9.91	0.002	-0.007	0.6	4.45	23.13	18.7
Quercus robur								
Budburst	65	18.3	0.025	0.009	0.2	7.51	25.64	18.32
First Leaf	80	23	0.001	-0.011	0.77	9.64	30.96	26.03
Quercus petraea								
Budburst	41	23.04	0.001	-0.023	0.78	7.52	30.38	26.75
First Leaf	40	31.8	0.026	0.0008	0.31	11.9	36.54	33.87
Betula pendula								
Budburst	85	7.7	0.01	0.007	0.2	3.01	23.17	19.49
First Leaf	99	13.9	0.003	-0.006	0.56	6.02	27.45	13.97
Acer pseudop.								
Budburst	68	10.5	0.001	-0.013	0.73	4.14	23.76	19.11
First Leaf	70	17.9	0.001	-0.013	0.76	7.93	25.76	17.97

Table 5-6 Relationship between species specific phenophase events and satellite-derived EOS. *N* (number of observations). Mean lag negative value indicates satellite estimates are later than observed phenophase.

Phenophase Event	N	Mean lag	r^2	Adjusted r^2	p-value	t-value	RMSE	MAE
Fraxinus excelsior								
First Tint	51	108.23	0.007	-0.013	0.553	-21.18	113.6	108.2
First Leaf Fall	65	86.15	0.032	0.16	0.153	-18.21	95.31	88.61
Full Tint	43	91.23	0.03	0.006	0.266	-15.8	99.6	91.32
Fagus sylvatica								
First Tint	85	114.4	0.00005	-0.012	0.948	-25.41	121.7	115.46
First Leaf Fall	62	84.32	0.012	-0.004	0.387	-16.32	94.3	87.09
Full Tint	67	80.22	0.004	-0.01	0.056	-15.2	91.67	84.07
Acer campest.								
First Tint	31	106.5	0.089	0.057	0.102	-13.44	117.15	110.32
First Leaf Fall	24	86.79	0.007	-0.037	0.689	-8.83	99.53	93.87
Full Tint	26	73.88	0.123	0.078	0.078	-8.44	88.48	81.96
Aesculus hippocas.								
First Tint	39	121.3	0.002	-0.024	0.771	-16.46	129.86	122.26
First Leaf Fall	58	89.56	0.001	-0.016	0.789	-17.79	97.61	91.51
Full Tint	61	99.06	0.003	-0.013	0.664	-20.57	105.68	99.68
Quercus robur								
First Tint	120	105.54	0.016	0.007	0.165	-26.41	115.07	107.09
First Leaf Fall	53	73.28	0.015	-0.003	0.372	-12.11	84.09	76.86
Full Tint	51	72.88	0.05	0.03	0.114	-11.23	88.2	79.27
Quercus petraea								
First Tint	33	111.32	0.003	-0.028	0.748	-14.37	117.32	111.32
First Leaf Fall	27	80.51	0.018	0.012	0.088	-11.89	89.29	83.63
Full Tint	25	81.28	0.094	0.055	0.134	-10.39	92.06	83.92
Betula pendula								
First Tint	55	114.9	0.056	0.038	0.08	-18.85	125.13	116.47
First Leaf Fall	49	96	0.001	-0.019	0.08	-16.87	104.01	96
Full Tint	62	92.61	0.026	0.01	0.207	-17.45	102.61	94.93
Acer pseudop.								
First Tint	50	141.1	0.022	0.002	0.29	-18.46	145.48	141.1
First Leaf Fall	48	101.5	0.001	-0.02	0.78	-11.89	106.5	101.5
Full Tint	37	88.02	0.06	0.033	0.143	-12.89	98.83	90.35

5.3.5 Geographically Weighted Regression

The relationship between *in situ* phenophase observations to satellite-derived vegetation phenological estimates is difficult to assess using conventional regression due to several factors, including the comparison of pixel to point estimates. The utilisation of GWR allows spatial non-stationarity in the regression parameters, as described above. The results of GWR highlight the relationship between individual species observations and satellite-derived SOS and EOS estimates. As in global regression, the (locally varying) coefficient of determination (r^2) explains the proportion of the variance in one variable that is predictable from another (at that location).

The local r^2 values were larger in comparison to the results utilising conventional regression techniques (Tables 5-5 and 5-6). FL has greater relationship with satellite sensor-derived estimates of SOS (Table 6) than for BB. For *Fraxinus excelsior* and *Acer pseudoplatanus* first leaf r^2 is greater than 0.5, indicating the satellite-derived estimates have a large local relationship with the observed *in situ* data.

The GWR analysis of the EOS estimates and the observed phenophase events highlights that full tint has the largest relationship with the satellite-derived estimates in comparison to FT and FLF (Table 5-8). The species with the largest correlations were *Fraxinus excelsior*, *Quercus robur* and *Acer pseudoplatanus*. The r^2value of 0.455 for *Quercus robur* indicates the largest relationship with the satellite sensor estimates. However, the results are still not statistically significant. One of the reasons for this may be due to the limitations of estimating EOS through satellite-derived techniques.

Table 5-7 GWR results for *in situ* observations and SOS satellite- sensor derived estimates.

Phenophase Event	r^2	Adjusted r^2	Bandwidth	AICc
Fraxinus excelsior				
Budburst	0.423	0.356	209877	1466
First Leaf	0.542	0.428	124685	1359
Fagus sylvatica				
Budburst	0.273	0.165	172830	1688
First Leaf	0.454	0.371	172830	1477
Acer campest.				
Budburst	0.141	0.1003	6111970	470
First Leaf	0.152	0.046	250651	485
Aesculus hippocas.				
Budburst	0.235	0.155	180233	2082
First Leaf	0.447	0.358	132172	1903
Quercus robur				
Budburst	0.293	0.236	286393	1336
First Leaf	0.424	0.358	177648	1598
Quercus petraea				
Budburst	0.295	0.211	329507	847
First Leaf	0.362	0.287	344373	789
Betula pendula				
Budburst	0.354	0.272	161757	1763
First Leaf	0.324	0.293	355259	2017
Acer pseudop.				
Budburst	0.464	0.42	322110	1409
First Leaf	0.595	0.526	179268	1418

Table 5-8 GWR results for *in situ* observations and EOS satellite-sensor derived estimates.

Phenophase Event	r^2	Adjusted r^2	Bandwidth	AICc
Fraxinus excelsior				
First Tint	0.44	0.351	192679	1086
First Leaf Fall	0.065	0.0501	8689031	1373
Full Tint	0.43	0.375	333546	915
Fagus sylvatica				
First Tint	0.02	-0.001	670350	1848
First Leaf Fall	0.3	0.214	219719	1344
Full Tint	0.34	0.245	175908	1480
Acer campest.				
First Tint	0.123	0.067	735610	658
First Leaf Fall	0.05	-0.016	783698	521
Full Tint	0.188	0.116	597316	547
Aesculus hippocas.				
First Tint	0.01	-0.016	1572820	829
First Leaf Fall	0.028	0.01	8689031	1243
Full Tint	0.102	0.053	454203	1308
Quercus robur				
First Tint	0.194	0.144	175908	2591
First Leaf Fall	0.034	-0.005	775380	1153
Full Tint	0.455	0.368	196791	1099
Quercus petraea				
First Tint	0.001	-0.03	9026975	731
First Leaf Fall	0.041	0.003	8643881	589
Full Tint	0.15	0.113	8599366	554
Betula pendula				
First Tint	0.082	0.064	9094266	1220
First Leaf Fall	0.024	0.003	8645541	1070
Full Tint	0.096	0.058	580423	1357
Acer pseudop.				
First Tint	0.385	0.265	182642	1092
First Leaf Fall	0.144	0.079	470782	1055
Full Tint	0.234	0.177	587872	811

5.4 Discussion

The accurate assessment and characterisation of vegetation phenological events is important to assess the impacts of long-term climate changes (White *et al.,* 2003; Sparks *et al.,* 2000; Badeck *et al.,* 2004). Vegetation indices, such as MTCI, are an indication of the 'greenness' within the canopy of each pixel (Curran and Steven, 1983). LSP enables the monitoring of global vegetation dynamics to be assessed at a global level, including in harsh biomes. Satellite-derived pixel-based estimates are necessarily aggregates of the reflectance due to several species, and the influence on reflectance that these multiple species have compared to a single species or a species type is unknown (Maignan *et al.,* 2008). The species present in the study area can affect the estimation of vegetation phenology parameters; e.g., start of season (SOS) and end of season (EOS) (Beck *et al.,* 2007).

There are several uncertainties and biases that may affect satellite-derived vegetation phenological estimates, including pixel resolution, temporal resolution, vegetation phenology extraction method and atmospheric contamination (Schott, 2007; Hamunyela *et al.,* 2013; Bradley *et al.,* 2007). Therefore, by comparing LSP estimates to *in situ* observations the accuracy of estimates, the relationship between LSP SOS and EOS and the related phenophase events, and the controlling factors for vegetation development can be assessed. However, in this study the influence of cloud cover has impacted the assessment of EOS. Data gaps caused by cloud can to large biases of approximately two weeks or more for EOS, and the estimation of EOS is related to the decrease in MTCI values which can be related to extended periods of cloud covered pixels, which do not relate to LSP parameters (Reed *et al.*, 1994b; Hmimina *et al.,* 2013).

Several previous researchers have compared *in situ* observations to LSP within Europe. However, no national comparison for the UK has been undertaken utilising citizen science data (Badeck *et al.,* 2004; Studer *et al.,* 2007; Maignan *et al.,* 2008; White *et al.,* 2009; Hamunyela *et al.,* 2013). Country-wide comparisons such as this one, are difficult due to several controlling factors affecting phenophase events. Typically, studies concentrate on a single restricted study site within a defined area (Liang *et al.,* 2011; White *et al.,* 2014). The *in situ* observations are collected at regular intervals, with a high spatial density by experts. Therefore, comparing the two datasets has fewer limitations than when utilising citizen science initiatives. Whereas, the strength of this research is the spatial extent of the comparison of *in situ* observations and LSP SOS and EOS has been assessed for the whole of the UK.

This research highlights several of the issues in the comparison of satellite-derived estimates to *in situ* observations. The comparison is problematic in areas dominated by managed arable and improved grassland species (Debart *et al.,* 2015). Within the UK areas of arable land and improved grassland are predominantly in South and Central England and SOS occurs much earlier in comparison to the natural land cover areas of broadleaf woodland, coniferous woodland, semi-natural grassland and mountain, heath and bog, due to the management of the land, use of pesticides and species present. There is a distinct increase in the number of *in situ* observations within these areas, mainly as there is a high density of population in the adjoining areas (Figure 4-1).

The exclusion of areas of land classed as managed arable and improved grassland species increased the relationship between the Nature's Calendar *in situ* data for broadleaf vegetation species and satellite-derived estimates, as the relationship is affected by the aggregation of vegetation (and its reflectance) (Delbart *et al.,* 2015). However, within the UK, the managed land cover areas account for 50% of the land cover, which reduced the number of suitable data points available.

The standard deviation of satellite-sensor derived SOS and EOS DOY is larger in comparison to that of the *in situ* data. This could be due to the temporal compositing of the data and the aggregation of different land covers within each of the 250 m pixels. The *in situ* observations are for single tree events. Therefore, if the observation was within an area that is dominated by another species, the satellite estimate may be much earlier or later within the time-series.

Citizen science datasets are valuable assets with which to assess country-wide vegetation phenological trends at the species level. However, the sporadic nature of these data causes several issues for comparison with satellite-derived estimates. With an increase in public contributions, the spatial density of observation points would increase and assist with the comparison of datasets. In addition, the influence of outliers would be minimised. As with many citizen science vegetation phenological networks, autumn phenophase events have fewer observations in comparison to spring events; this is apparent with the Nature's Calendar dataset. The number of individual species phenophase observations varies greatly across the study period. *Aesculus hippocastanum* budburst events were observed 8,598 times, whereas *Quercus petraea* budburst events were observed only 1,712 times. It is noted that the variance in budburst DOY and the greater number of observations may affect the correlation with SOS estimates. *Quercus robur* is the most observed species for first tint events with 9,574 individual observations across the study period. For first leaf fall, *Betula pendula* has the greatest number of observations with 4,087 and for full tint *Aesculus hippocastanum* with 4,179 observations.

The number of valid observations used was significantly reduced when intersected with the satellite-sensor derived estimates of SOS and EOS and the subset of only natural land cover areas. The species with the most observations was *Aesculus hippocastanum* with 102 for budburst comparison with SOS and *Quercus Robur* with 120 data points for the comparison of first tint and EOS.

Anomalies in the species phenophase events exist within the Nature’s Calendar database. For example, for budburst several observations dating budburst between the 5th and 26th January occur, and for first leaf dates exist between the 20th January and the 2nd February. This could be due to observational error by the public or one single tree indicating budburst and first leaf much earlier than the surrounding populous.

RMSE values were smallest for the comparison of budburst and SOS (20.65 to 32.7). Mean lag, MEA and RMSE were smallest for the comparison of *Aesculus hippocastanum* with -0.24 difference between the two datasets. Fraxinus excelsior observations for first leaf have the largest mean lag, MEA and RMSE in comparison to SOS, with 37 days variability. In comparison to SOS, the correlation between autumn phenophase events and EOS is smaller. First tint comparisons with EOS have the largest mean lag (ranging from 105 to 141), and high RMSE and MEA.

As highlighted, the relationship between *in situ* phenophase and satellite-derived vegetation phenological estimates is difficult to assess, in particular at a country-wide scale utilising citizen science datasets. Previous research states that the relationship between LSP SOS estimates and spring *in situ* observations are better than for EOS, which is noted in this research (Maignan *et al.,* 2008). There are several obstacles, particularly when using conventional regression techniques, not least due to the fine-scale spatial variability of vegetation (and other land cover) distribution(s) and its vegetation phenological response across the UK. Assessing broadleaf species separately and utilising GWR assisted in assessing the relationship between observed phenophases and satellite-derived estimates.

GWR has been utilised in previous vegetation phenological research as it utilises the spatial relationships between variables (Maselli, 2002; Foody, 2003; Foody and Dash, 2010; Yuan, *et al.,* 2013; Comber and Brundson, 2015). As reflected in this research, GWR is a useful method to account for the spatial variability of vegetation phenology data. GWR weights each data point by its distance from the regression point. The closer a data point to the regression point, the more weight it receives. This means that a data point closer to the regression point is more weighted in the local regression than are data points located further away. In areas with varying land cover types, such as this study area, where each type responds differently to climate and environmental seasonal changes a single linear relationship can be inappropriate. GWR enables the parameters to vary locally, and in this research provided a more useful assessment of the relationship between satellite-derived estimates and *in situ* observations. Linear regression provides a single estimate for the relationship over the entire study area, whereas GWR enables each point to be assessed individually (Foody, 2003; Zhang *et al.,* 2004; Yuan, *et al.,* 2013).

The results indicated that *Fraxinus excelsior*, *Quercus robur* and *Acer pseudoplatanus* have a larger relationship with the satellite-derived estimates of both SOS and EOS. SOS estimates had the largest correlation with *in situ* observations of FL. *Fraxinus excelsior* and *Acer pseudoplatanus* FL r^2 is greater than 0.5, indicating the satellite-derived estimates are related with this observed dataset. For EOS full tint observations have a larger relationship with EOS. *Quercus robur* has the largest r^2 value of 0.455. However, the relationship between other species autumn observations and EOS is relatively small.

5.5 Conclusion

This chapter has highlighted the difficulties in assessing the relationship between *in situ* phenophase observations and satellite-derived vegetation phenological estimates. The additional challenges of utilising a nationwide citizen science dataset were evaluated, including the varying spatial density of observations located in urban and managed land areas. There are several obstacles, particularly when using conventional linear regression techniques due to the spatial variability of multiple factors at fine spatial scales across the UK. Assessing broadleaf species separately and utilising GWR to assess the local relationship between each parameter assisted in assessing the relationship between observed phenophases and satellite-derived estimates.

In future, indicators and controlling factors would need to be included to account for the spatial non-stationarity in the relations between satellite-derived and *in situ* phenophase events. This could include a diverse assessment of all environmental metrics associated with temperate vegetation phenology, including elevation and climate indicators. However, an increase in observational points located in areas dominated by broadleaf woodland, coniferous woodland, heath land, and semi-natural grassland, would need to be collated in order for this to be completed on a national scale. The Nature's Calendar is a public source dataset, and therefore, requirements on the spatial coverage and periodic sampling of vegetation collected by the public is extremely difficult to regulate.

Chapter 6 Controlling Factors of Vegetation Phenophases in the UK

6.1 Introduction

Vegetation phenological observations have been obtained via *in situ* observations (Sparks and Carey, 1995), satellite sensor imagery (Pouliot *et al.,* 2011; Guyon *et al.,* 2011) and digital camera photography techniques (Richardson *et al.,* 2007; Ahrends *et al.,* 2009). Long-term records have been invaluable to assessing changes to the annual cycle of vegetation development and the impact of climate change (Reed *et al.*, 1994a). The utilisation of multiple techniques allows for a comparison of the phenophase events that are detected across all resolutions, and a greater understanding of environmental and climate controls to be inputted into GCM (Figure 6-1).

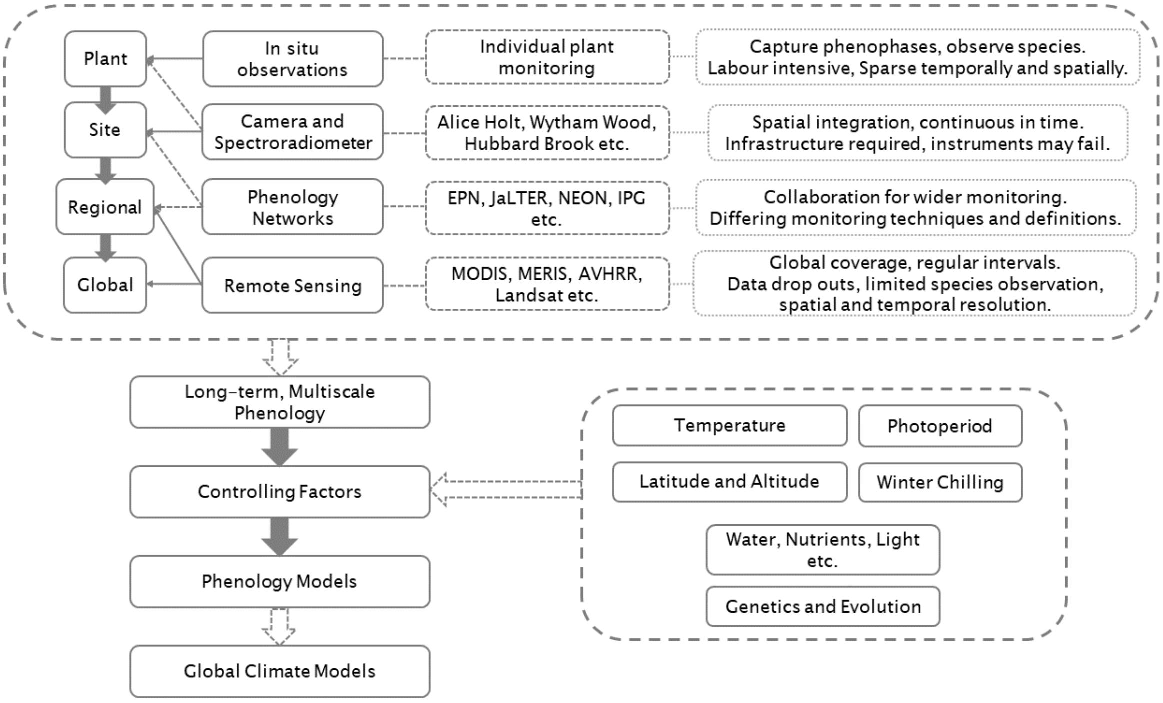


Figure 6-1 Relationship between observation techniques, including the advantages and limitations of each techniques, controlling factors, and environmental models.

Vegetation phenology is sensitive to annual variation in weather and climate and, therefore, is an effective indicator of long-term climate change and ecosystem responses to increased temperatures (Reed *et al.*, 1994a; Zhou *et al.,* 2001; Badeck *et al.,* 2004; Arora and Boer, 2005; Cleland *et al.,* 2007; Parry *et al.,* 2007; Thackeray *et al.,* 2016). Long-term vegetation phenological records have shown that spring events are occurring earlier (Menzel *et al.,* 2006; Doi and Katano, 2008; Thompson and Clark, 2008; Chen and Xu, 2012). Changes in the timing of autumn vegetation phenology of temperate forests are not as well documented as changes in spring vegetation phenology. The majority of research has reported delays in leaf colouring and leaf fall related to increases in temperatures during late summer or early autumn (Estrella and Menzel, 2006; Doi and Takahashi, 2008; Delpierre *et al.,* 2009).

The UK Climate Projections (UKCP09) has projected that by 2080 the UK experience increases in mean summer temperature of up to 4.2°C in the south and up to 2.5°C in the north (Jenkins *et al*., 2009). In addition to increases in winter temperatures of between 1.5°C to 2.5°C. Although annual precipitation has not significantly changed, there has been an increase in precipitation during winter and a decrease during summer over the last 50 years. For precipitation, the projections vary across the country but continue with this trend, with increases in winter projected for the western side of the UK and decreases across Scotland. Southern England will be particularly effected by a notable decrease in precipitation in summer (up to a 40% decrease). The IPCC Climate Change 2014 report projects that there will be an increase in extreme events including droughts and increased rainfall across Europe. Since 1950 there have been an increase in high temperature events across Europe and the IPCC projects that there will be an increase in the mean number of heat waves by 2100 (Pachauri *et al*., 2014).

Annual changes in spring and autumn vegetation phenology have been reflected in satellite remote sensing data across the globe (Gitay *et al.,* 2002; Jeong *et al.,* 2011). However, the delay in autumn vegetation phenology due to climate change is less pronounced and more homogenous than for spring (Parry *et al.,* 2007). As spring vegetation phenology events are occurring earlier, and autumn vegetation phenology occurring later, this has led to an extension in the growing period. The extension in the annual growing period occurs as the environmental factors required for plant growth (e.g. temperature, precipitation, and photoperiod) reach a threshold for plant development earlier in the year and are sustained for a prolonged period, therefore, delaying dormancy.

The repetitive cycle of dormancy and growth correlates with annual environmental conditions (Nitsch, 1957; Cooke *et al.,* 2012). Perennial species of vegetation in temperate regions match their growth and dormancy in order to adapt and survive seasonal climate changes (Singh *et al.,* 2017). For spring phenophase events (e.g. bud burst, flowering and first leaf) chilling requirements, photoperiod and temperature are the dominant environmental factors controlling the timing of spring in temperate ecosystems (Körner and Basler, 2010; Basler and Körner, 2012). Strong photoperiod control may limit the degree to which first leaf can advance. In addition, when chilling requirements are not met, first leaf may be delayed (Zhang *et al.,* 2007; Morin *et al.,* 2009; Korner and Basler, 2010; Migliavacca *et al.,* 2012). Vernalization is the requirement of species to experience cold winter temperatures or frost prior to flowering (Henderson *et al.,* 2003). Therefore, if no frost occurs due to increased winter and spring temperatures this may hinder plant growth. For autumn, it is assumed that photoperiod is the main controlling factor (Basler and Korner, 2012). However, autumn controlling factors are not as well understood as for spring. Shorter photoperiod length and declining temperatures occur parallel to changes in leaf biochemistry and physiology before the annual dormancy of winter (Hänninen and Tanino, 2011).

Photoperiod increases and decreases on a seasonal basis due to the Earth's position in relation to the Sun. This cycle does not vary, however, precipitation and temperature increase and decrease due to changing climatic conditions. This may lead to asynchrony between historically paired environmental cues to changes in the season (Visser and Booth, 2005; Hänninen and Tanino, 2011). For vegetation located in northern regions, such as the UK, this may constrain the responses of increased LOS to a warming climate (Saikkonen, *et al.,* 2012). The impact of asynchrony is dependent on the species present and the local population. For several deciduous species of tree, photoperiod is expected to be the dominant force of senescence and development into annual dormancy (Hänninen and Tanino, 2011). However, for understory species, bushes and flowers, higher temperatures later in the year may mean a longer growing season without the competition of canopy tree species.

The flowering of certain species is dependent on photoperiod (Bernier, 1988). Select species may not flower until a certain photoperiod length has been reached over successive days (Bernier, 1988). Several studies have focused on the molecular mechanisms for plant growth (Ellis *et al.,* 2010; Jiménez *et al.,* 2010). The variation in vegetation phenology between species and populations are due to plant genetic properties and evolutionary traits with respect to vegetation phenology. Each individual species response to environmental changes is due to the genetic traits of each species and the ability to adapt. The genetic traits may result in a tendency for earlier growth, or increase sensitivity to environmental conditions.

Vegetation phenological divergence allows species to be exposed to different environmental characteristics and, therefore, could lead to new adaptations (Muller, 1978). Early emerging understory species are exposed to increased sunlight in comparison to species that emerge later in the season. However, early emerging species have a lower chance of survival due to their susceptibility to frost and freezing conditions, which may damage plant development. Richardson and O'Keefe (2009) state that the budburst of most understory species occurs earlier than for dominant canopy species, suggesting the understory vegetation uses the strategy of 'vegetation phenological escape'. However, the period of escape was limited to a few days for the majority of the understory species. Coexisting tree species are known to leaf out at alternating times (Lechowicz, 1984), which indicates that their climatic triggers are different. There is also variability between young and adult plant species in autumn.

Variations in climate and differing environmental conditions affect the development of different species. Higher latitudes and elevation delay SOS and advance EOS of several species, compared to low latitudes and low elevation. At higher latitudes vegetation phenology may be more sensitive to climate change due to increased warming compared to lower latitudes (Parmesan, 2007; Oberbauer *et al.,* 2013; Pachuri *et al.,* 2014; Prevéy *et al.,* 2017). This is primarily due to changes in temperature between locations. In addition, at high latitudes, flowering timing is correlated to the timing of snowmelt (Forrest *et al.,* 2010). The variation among species could indicate that the dominant controlling factors are not necessarily temperature, but a combination of factors.

The comparison of understory, canopy and satellite-derived vegetation development is an area of research that requires further analysis. *In situ* observations are taken from the ground, and do not necessarily represent upper canopy changes. Near-surface techniques can observe vegetation from below and above the canopy, depending on the strategy used by researchers. The relationship between the observational strategies needs to be considered, as they are each affected by different properties. For example, understory and canopy leaf structure differ due to the light environment that they are exposed to. The light conditions through the seasons vary throughout the strata depending on the development and senescence of the canopy, and on the changing zenith angle and solar irradiance. With the utilisation of web cameras suspended above the canopy, the images can cover a relatively large area within a single woodland. The cameras can be scheduled to take photographs on a periodic basis, leading to good temporal coverage. The spatial extent is limited in comparison to satellite imagery, however, it does bridge the spatial extent from *in situ* to satellite, as single trees can be observed in addition to the surrounding species.

The controlling factors of vegetation phenological development requires further assessment because future climatic changes may affect the timing of species growth and senescence. In addition, the comparison between observation techniques and the determination of SOS and EOS should be considered to fully assess vegetation phenology detection techniques. The aim of this chapter was to better understand the relationship between vegetation phenological data and the controlling factors that correlate to seasonal vegetation phenological variations. *In situ*, near-surface, satellite sensor datasets were compared to provide a measure of impact of scale of observation to three important controlling factors; temperature, precipitation and sunshine hours, for both spring and autumn phenophase events.

6.2 Study Area

For this analysis two separate study sites were chosen, both located in Southern England (Figure 6-2), Wytham Wood, Oxfordshire, and Alice Holt, Hampshire. Both of these sites have been documented and assessed for several environmental strategies due to the continuous observation that has taken place at each site by the CEH, Oxford University and the Forestry Commission. The site-specific *in situ* and near-surface data collected at each site differs due to the varying temporal coverage of photographic and eddy covariance observation techniques. However, a dataset of *in situ* and climatic data is present at both sites (Nature's Calendar). The study period runs from January 2005 to December 2012.

Figure 6-2 Location of Wytham Wood and Alice Holt.

6.2.1 Alice Holt

Alice Holt is an area of ancient woodland, working forest and woodland park located within the South Downs National Park on the border of Hampshire and Surrey, South East England (51°10'N 0°50'W) (Figure 6-3). The forest is at the North West corner of the Western Weald, situated between the chalk escarpments of the North and the South Downs, and covers an area of approximately 850 ha.

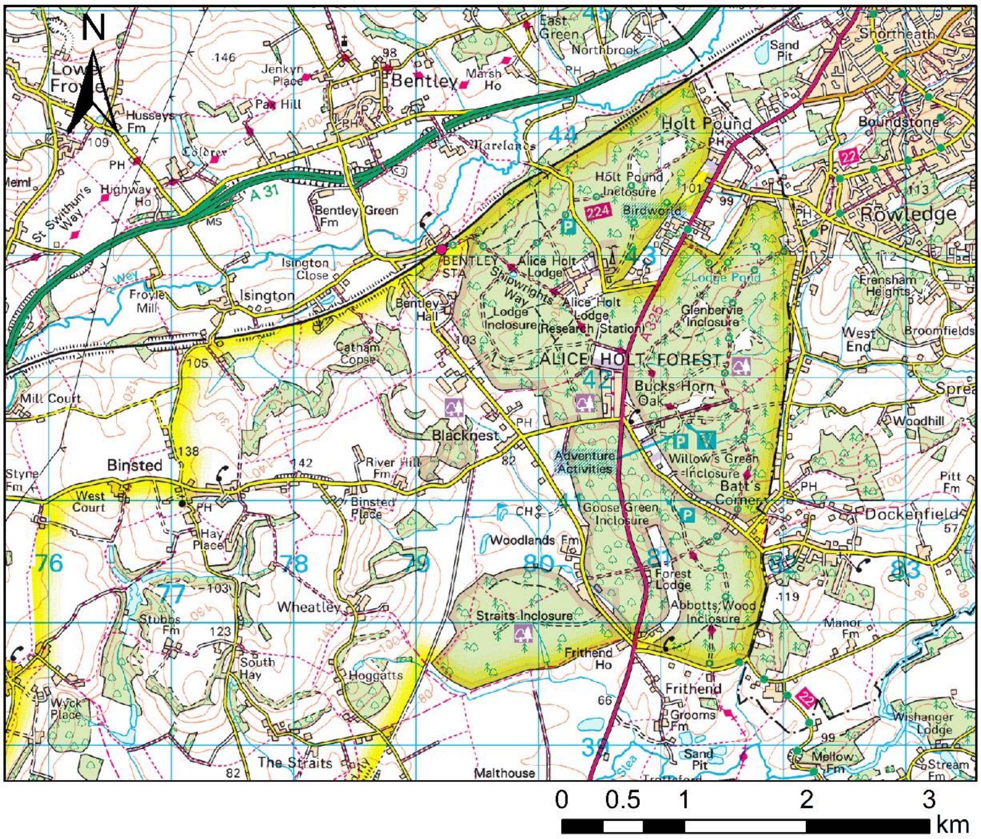


Figure 6-3 Ordnance Survey map of Alice Holt (1:50 000).

The climate at Alice Holt is typical of Southeast England, with an average monthly temperature range from 22.5°C maximum to -0.5°C minimum, with an annual average of 10°C. The mean annual rainfall is 782 mm (Forest Research, 2015). Alice Holt was once a predominant ancient oak forest; however, due to forestry and timber production, several coniferous species have been planted. There are several broadleaf and coniferous species found within Alice Holt forest (Table 5 - 1). The ages of the broadleaf woodland species vary between younger plantations from between 1930 and 1995 and 200 years old. The site has been managed by the Forestry Commission since 1924, with a research station established in 1946. The forest contains sections of Site of Special Scientific Interest (SSSI) on the North West side which are of interest for nature conservation and is a member of several national and European environmental monitoring initiatives (e.g. UK Environmental Change Network (ECN), FutMon).

Table 6-1 Species record at Alice Holt in 2012. Areas of coverage less than 1 ha are included in mixed others (hornbeam, wild cherry, Norway maple, sycamore, poplar, grand fir, Sitka spruce) (Forest Research, 2015).

Species	Scientific Name	Area (ha)
Broadleaf:		
Oak	*Quercus robur, Q. petraea*	271
Beech	*Fagus sylvatica*	19
Birch	*Betula pendula*	23
Ash	*Fraxinus excelsior*	9
Sweet Chestnut	*Castanea sativa*	4
Mixed/Others		50
Coniferous:		
Corsican pine	*Pinus nigra* var.*maritima*	184
Scots pine	*Pinus sylvestris*	43
Norway spruce	*Picea abies*	22
Western hemlock	*Tsuga heterophylla*	25
Larch	*Larix* spp.	20
Douglas fir	*Peudotsuga menziesii*	25
Cypress	*Cupressus* spp.	6
Western Red cedar	*Thuja plicata*	7
Mixed/Others		2

6.2.2 Wytham Wood

Wytham Wood is an area of ancient semi-natural woodland 5 km North West of Oxford owned by the University of Oxford (51°46’N 1°20’W) (Figure 6-4). The site is surrounded by a meander of the River Thames and covers an area of approximately 415 ha. The mixed deciduous woodland covers 385 ha, with an area of organic mixed farmland covering 370 ha (Cole *et al.,* 2015). The elevation of this site varies from 60 m at the flood plain of the River Thames, to 165 m at the peak of Wytham Hill.

Wytham Wood is split into three woodland classifications; ancient, secondary and plantation, in addition to areas of semi-natural grassland and scrub. The ancient woodland is an area that has been continually covered in trees since the prehistoric ‘wild wood’. The secondary woodland, an area of natural woodland, has expanded over pasture or cultivated land in the last 200 years. Both the ancient and secondary woodland are not managed today. The oldest beech plantations are around 200 years, with the majority around 50 to 60 years old. The farmland includes areas of arable land, hedgerows, wetland and grassland. The grassland is managed under the Upper Thames Tributaries Environmentally Sensitive Area Scheme and Countryside Stewardship.

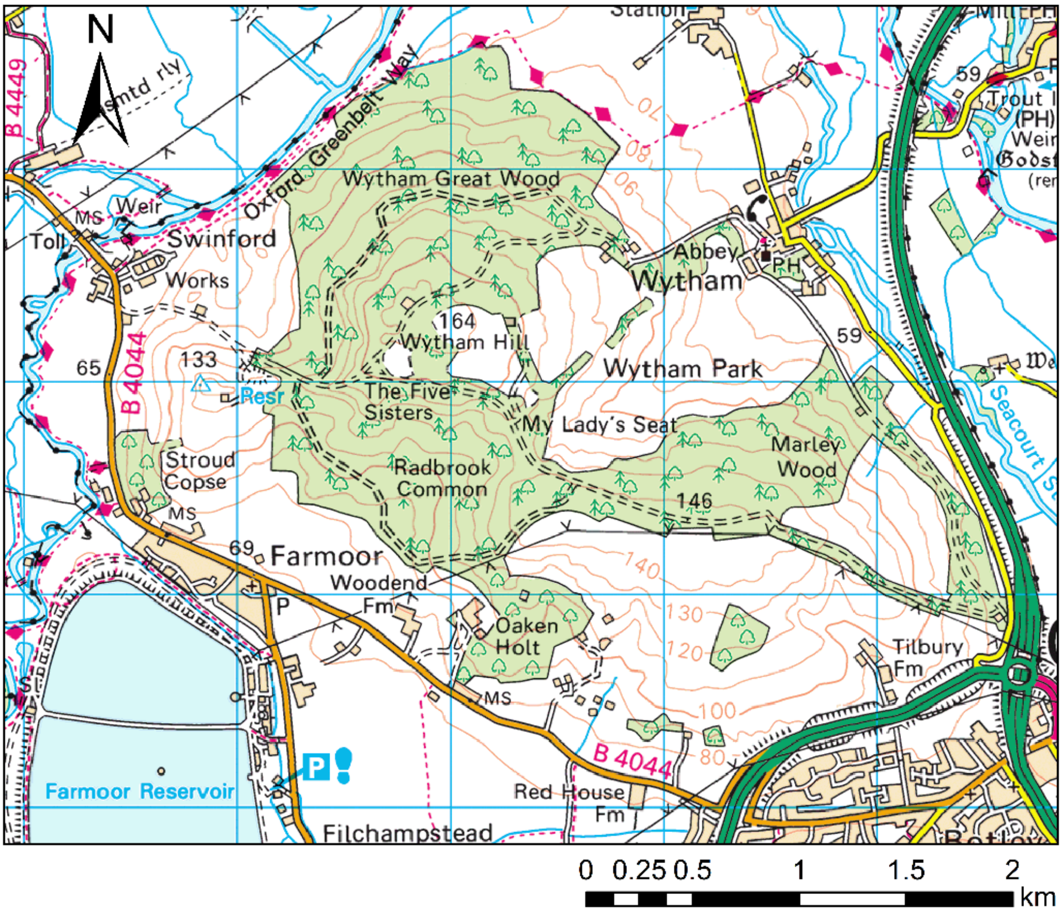


Figure 6-4 Ordnance Survey Map of Wytham Wood (1:50 000).

The mean annual temperature at the site is 9.9°C with a mean annual rainfall of 745 mm. The broadleaved woodland canopy is primarily oak (*Quercus robur*), ash (*Fraxinus excelsior*), sycamore (*Acer pseudoplatanus*), and beech (*Fagus sylvatica*), with an understory of hawthorn (*Crataegus momgyna*), hazel (*Corylus avellana*), elder (*Sambucus niger*), and field maple (*Acer campestre*) (Perrins, 1965). The estate has been owned by Oxford University since 1943, and has been the location of several pioneering ecological studies. Wytham was a flagship site for NERC’s Terrestrial Initiative in Global environmental Research (TIGER) programme and since 1992, has been studied by the ECN for terrestrial monitoring.

6.3 Data and Methodology

Several data sources were utilised in this research (Table 6-2). Table 6-2 highlights the observation method, study area (Wytham Wood or Alice Holt), and temporal coverage of each dataset. The datasets that were used have been provided by several organisations including the CEH, Forestry Commission, the Woodland Trust and the Met Office.

Table 6-2 Observation method, study site and coverage (site and time-series).

Study Area	Data	Data Type	Coverage
Both Sites	Nature's Calendar	*In situ*	2005-2012
	Met Office Climate Data	Climate	2005-2012
	MODIS	Satellite	2005-2012
Alice Holt	Canopy RGB	Near-surface	2010-2012
Wytham Wood	Understory Camera	Near-surface	2005-2012
	CROPSCAN	Near-surface	2010-2012
	Canopy Webcam	Near-surface	2012

6.3.1 Nature's Calendar

The Nature's Calendar dataset provided by the Woodland Trust has been discussed in detail in Chapter 4.2.1. The data were spatially subsampled for each study site across all years for the species and observed phenophase shown in Table 4-1. However, due to the sporadic sampling of the data points within Nature's Calendar the spatial radius surrounding each site was increased as there were few data points located within each study site. Some species did however have no observations within the increased radius of the sampling area (Appendix B – M). Observations of first leaf (FL), bud burst (BB), first flower (FF), first tint (FT), first leaf fall (FLF) and full tint (FuT) were selected for several species located within Wytham Wood and Alice Holt. The mean DOY for each phenophase were calculated, with the species specific mean DOY available in Appendix B-M.

6.3.2 MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a satellite sensor on board the Terra and Aqua satellites. MODIS acquires data in 36 discrete spectral bands ranging from 0.405 and 14.385 μm. The sensor has global coverage every one to two days, and acquires data at 250 m, 500 m and 1 km spatial resolution. MODIS was chosen for this section of research for a continuous comparison to the *in situ* and near surface data from 2005 to 2012, as the MERIS sensor was lost on the 12th April 2012.

MODIS satellite sensor imagery were collated for the duration period of the study (2005 to 2012) from the USGS Earth Explorer (EE) (https://earthexplorer.usgs.gov/). The MODIS data was subsampled to only the pixels that covered the Nature's Calendar data points for a direct comparison of SOS and EOS per study site.

The MODIS VI's are intended to provide consistent monitoring of global vegetation and continuity following the NOAA-AVHRR (Justice *et al.,* 1998; Huete *et al.,* 2002; Justice *et al.,* 2002). The MOD13Q1 Normalised difference vegetation index (NDVI) and the Enhanced vegetation index (EVI) data were utilised. The data are produced in 16 day composite periods at a spatial resolution of 250 m as a gridded level 3 product. NDVI and EVI are two of the most commonly used indices and accompany one another to improve the detection of vegetation changes and extraction of vegetation phenological parameters (Huete *et al.,* 2002). NDVI is sensitive to changes in chlorophyll, whereas EVI is responsive to changes in the canopy structure (Gao *et al.,* 2000).

NDVI is formulated as follows:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \tag{1}$$

EVI is formulated as follows:

$$\mathrm{EVI} = 2.5\frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{C_1RED} - \mathrm{C_2BLUE} + \mathrm{L})} \tag{2}$$

where NIR, RED, and BLUE are atmospherically-corrected surface reflectances, and C_1, C_2, and L are coefficients to correct for atmospheric condition. L=1, $C_1 = 6$ and $C_2=7.5$.

To extract the vegetation phenological parameters, the satellite sensor imagery for each year were layer stacked using ENVI. Both datasets included data gaps due to cloud cover, and therefore, due to the 16 day composite window the missing values were replaced using a moving window average based on the two nearest neighbours. The dataset was smoothed using Fourier analysis, and the LSP parameters (SOS and EOS) were extracted. The Julian day of year (DOY) was calculated as the median of the days within the assigned composite.

6.3.3 Alice Holt Data

6.3.3.1 Photography

The photographic canopy record was collected by the Forestry Commission using a commercial webcam 'Net Cam' mounted on an eddy covariance tower at a height of 26 m. The NetCam SC 5MP (StarDot Technologies, Buena Park, CA, USA) had a field-of-view of 47° facing a south westerly direction (Figure 6-5). The colour balance was set to red 256, green 180 and blue 256 and exposure set to auto. The photographs were taken at half hour intervals between 12:00 and 13:30 GMT. The images were processed using the methodology from Mizunuma *et al.,* (2013). By utilising images acquired nearest to 12:00 GMT, shadowing and BRDF effects were minimised (Richardson *et al.*, 2009).

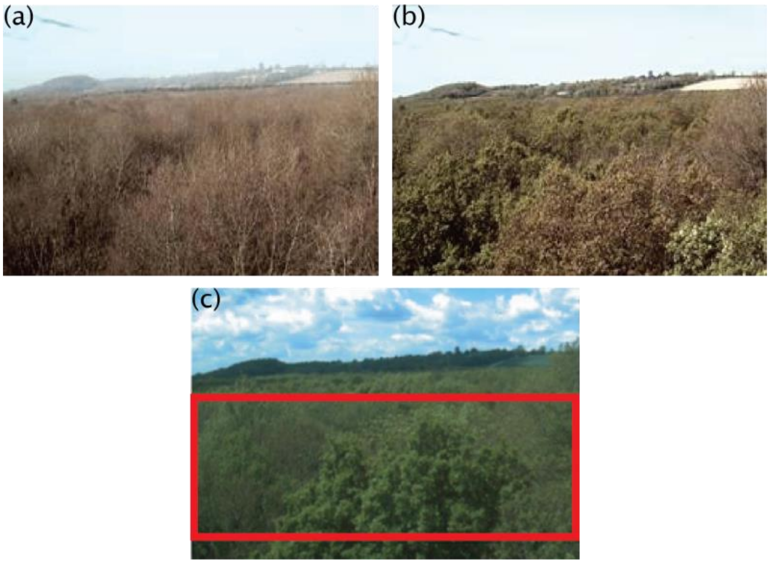


Figure 6-5 Example of photograph taken using Net Cam and the selected ROI of the canopy (a) winter, (b) autumn, (c) summer and ROI at Alice Holt.

An ROI was utilised to exclude the influence of the sky and background vegetation. The ROI includes the canopy of surrounding vegetation, with the crowns of oak trees present (Figure 6-5).

To quantify the change in greenness within the time-series of the photographs two VI were utilised, the green chromatic coordinate (GCC) (Petach *et al.,* 2014) and the excess green index (EGI) (Woebbecke *et al.*, 1995). EGI is thought to be more effective in minimising the effects of variation of illumination (Sonnentag *et al.*, 2012). To quantify canopy greenness GCC is used widely to assess the changes in canopy greenness and vegetation phenology parameters. GCC is formulated as follows:

$$\mathrm{GCC} = \frac{GREEN}{(\mathrm{RED} + GREEN\ + BLUE)} \tag{3}$$

EGI is formulated as follows:

$$\mathrm{EGI} = 2\mathrm{GREEN} - \mathrm{RED} - \mathrm{BLUE} \tag{4}$$

6.3.4 Wytham Wood Data

6.3.4.1 Photography

The photographic record of the understory of Wytham Wood was taken on a weekly basis with a Fujifilm FinePix F30 digital camera, with a focal length of 8 mm. The location of the record is within the ECN Target Sampling Site (TSS) located on the Northern side of Wytham Wood (U.K. National Grid Reference SP45 09, altitude 65m). The TSS is within the ancient woodland, which includes hazel (*Corylus avellana*) and oak (*Quercus robur*). The soil is deep heavy clay (Denchworth series) and becomes waterlogged in winter. The field-of-view shows the multi-stemmed hazel stools with an oak to the left-hand side. To the left of centre there is a willow (*Salix caprea*) leaning across the picture, with a small hawthorn (*Crataegus monogyna*) tree behind. The grass is mainly tufted hair-grass (*Deschampsia cespitosa*) and Wood false-brome (*Brachypodium sylvaticum*) (Figure 6-6).

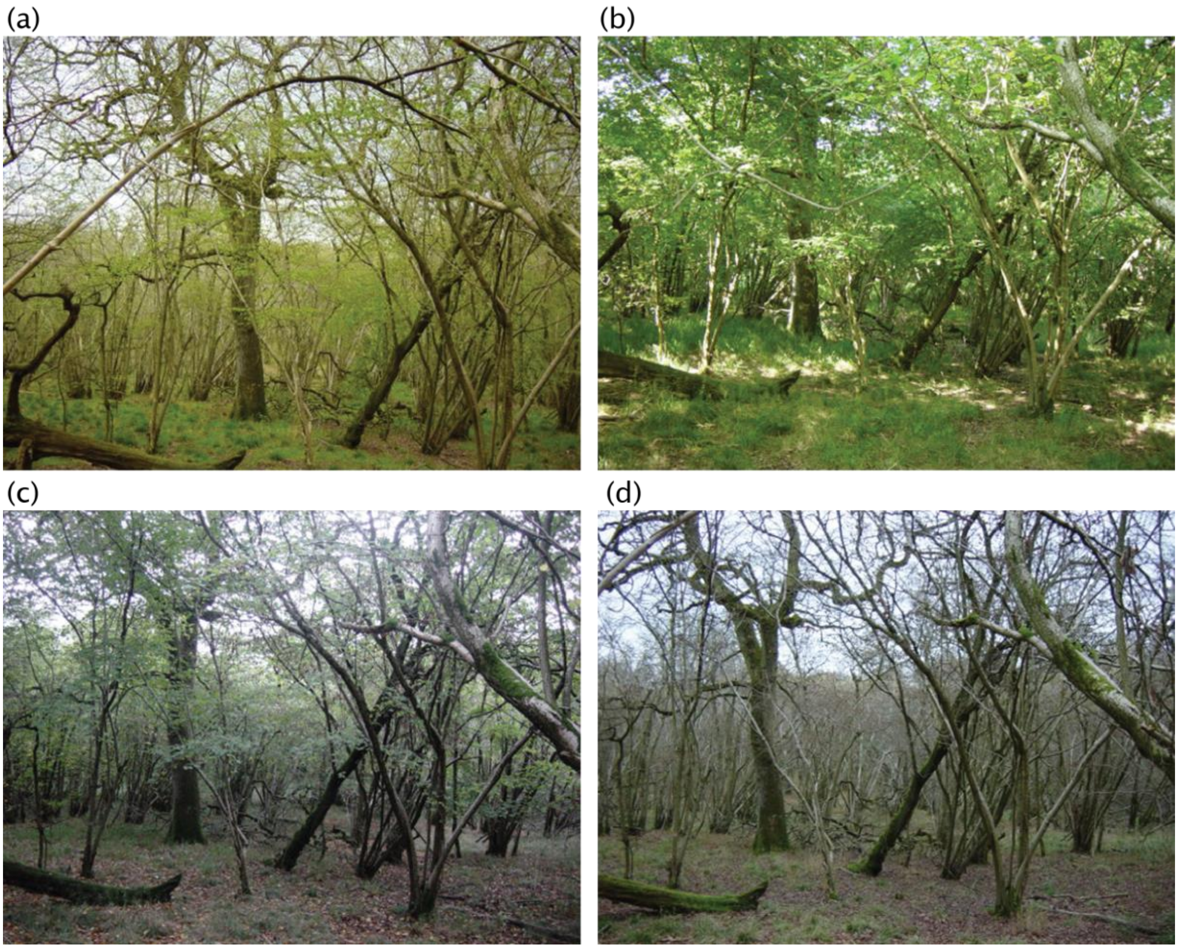


Figure 6-6 Example of understory digital camera photography (a) spring, (b) summer, (c) autumn, (d) winter at Wytham Wood.

Figure 6-7 ROI used for understory photography at Wytham Wood.

To extract the RBG spectral values from the photographs, firstly a ROI was selected (Figure 6-7). The ROI selected the areas of vegetation within the image, removing the influence of the sky and foreground (grass and bare ground). A script was formulated in IDL to process and analyse the series of digital image files. Images were sequentially read and the analyses of the levels of each RGB channel were conducted within the ROI. This extracted the RGB digital values for each colour channel. EGI and GCC VI were calculated for each extracted RGB digital value (Eq. 3 and 4).

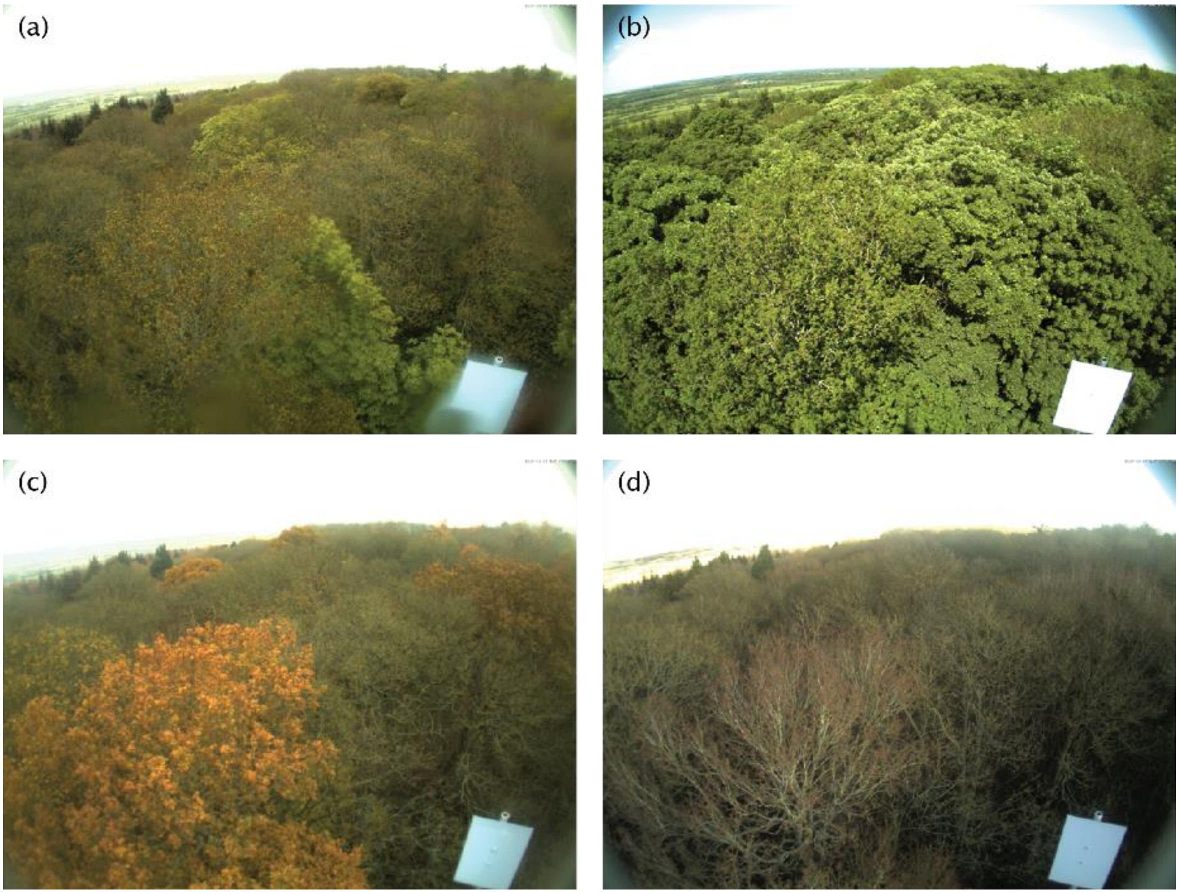


Figure 6-8 Example of canopy digital camera photography (a) spring, (b) summer, (c) autumn, (d) winter at Wytham Wood.

The canopy photographs were taken on a daily basis using a Mobotix m24m 'security' camera (Figure 6-8). The camera was mounted on a flux tower providing a horizontal view approximately 6m above the tree canopy for 2012 only. Similarly to the understory camera photographs, the images were sequentially read and the analyses of the levels of each RGB channel were selected within the ROI, and both EGI and GCC were calculated (Figure 6-9).

Figure 6-9 ROI used for canopy photography at Wytham Wood.

There are several methods used to extract vegetation phenological parameters, including visual observation methods to visually assess SOS from digital camera photography (Fisher *et al.,* 2006, Ahrends *et al.,* 2008, Ahrends *et al.,* 2009) and sigmoid-shaped logistic functions (Richardson *et al.,* 2006, Richardson *et al.,* 2007). To extract the phenological parameters of SOS and EOS for all records of digital photography at both Alice Holt and Wytham Wood, a delayed moving average (DMA) method was utilised. Reed *et al*., (1994) first proposed the DMA method, and it has been utilised in several vegetation phenological studies utilising satellite imagery (Schwartz *et al.,* 2002; Schwartz and Hanes, 2009). The DMA was chosen as it is designed to detect the first sustained positive change in the VI signal during spring and is shown to be comparable to *in situ* observations (Schwartz *et al.,* 2002). However, there are limitations to using DMA, as it is shown to detect an earlier SOS in comparison to other methods and is be sensitive to sensitive to the window size chosen (Schwartz *et al.,* 2002).

The DMA method determined the SOS and EOS based on the intersections of the original VI curve and the moving average curve (the sliding mean of previous n values). When the values from the original VI departs from (becomes greater than) the value of the moving average, this is labelled as the SOS. The transition to EOS follows a similar, but reverse pattern. The LOS was determined by the length between the SOS and EOS. DMA is not suitable for locations where there are multiple growing seasons or vegetation that is strongly influenced by rainfall, therefore, it was suitable to be utilised for these two study areas, as UK forested areas do not have multiple growing seasons and are not known to be predominately controlled by precipitation.

6.3.4.2 CROPSCAN

CROPSCAN MSR16R multispectral radiometers were placed within Wytham Wood by the CEH which observed an oak (*Quercus robur*) and a sycamore (*Acer pseudoplatanus*). The data period is over 2 years of this study period between 2010 and 2012. The CROPSCAN radiometers measured 16 wavelengths from Blue to SWIR (400 -1500 nm) and were placed at a height of approximately 17 m. The narrow band filters certain bands in the visible and NIR electromagnetic spectrum. This allows the reflectivity of the vegetation species within the field-of-view to be assessed. The data were collected at regular intervals throughout each day between 10:00 and 16:00. To assess the variance of greenness CROPSCAN-derived NDVI was used (Eq. 1).

6.3.5 Controlling Factors

The Met Office historical station datasets were utilised due to the proximity of their location to the study areas, Oxford and Heathrow. Even though both study sites are located in the South of England, the reason that two separate stations were utilised is to account for minor localised variations in climatic conditions between the two sites, and to remove the spatial restriction of national datasets such the Central England Temperature (CET). However, the Met office historical station at Heathrow is 40 km away from Alice Holt. The data consist of; mean daily maximum temperature, mean daily minimum temperature, days of air frost, rainfall and sunshine hours.

The Oxford observation station is located at 51° 45' N, 1° 15" W and 63 m above mean sea level. The Heathrow site is located at 51° 28'N, 0° 26' W and 25 m above mean sea level.

The vegetation phenological data collated and analysed at each site were first analysed to compare the assessment of spring phenophase events and SOS, and autumn phenophase and EOS. The controlling factors assessed in this study were chosen as they are most recognised to control SOS and EOS of temperate vegetation phenology; temperature (Rutishauser *et al.,* 2009), precipitation (Peñuelas *et al.,* 2004) and sunshine hours.

Annual mean phenophase event DOY were correlated with the three mean monthly (month of onset, and the two previous months) values for temperature, precipitation and sunshine hours. The largest correlation coefficients of the three months were classed as a measure for the responsiveness to each controlling factors for the phenophase events, SOS and EOS. The linear regression values of the onset days per year were analysed for each monitoring technique per site (Wytham Wood and Alice Holt). For each phenophase the mean DOY were calculated and the regression coefficients were analysed to provide a measure for the temperature sensitivity. In addition, for each phenophase the *t* value (Student's t distribution), standard error, and the *p* value, a measure of the statistical probability of fit to the regression line, were calculated.

The CROPSCAN data did not include a full year of coverage. Thus, the SOS and EOS could not be analysed. However, the NDVI time-series was included for comparison to the satellite and digital photography time-series.

6.4 Results

6.4.1 Alice Holt Vegetation Phenology

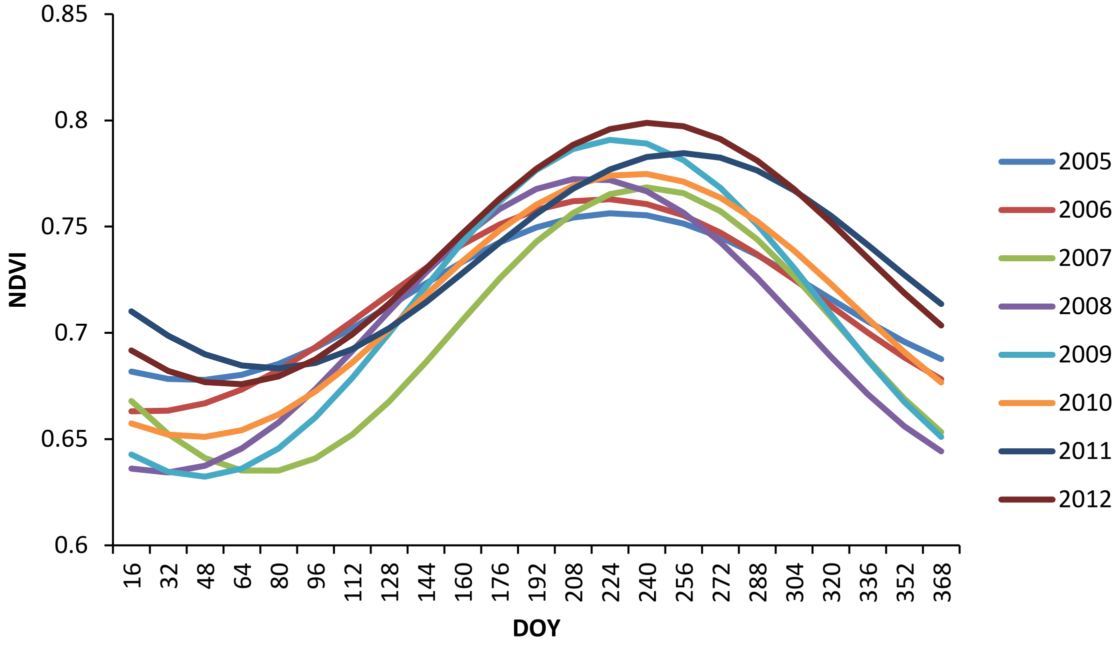
The mean DOY of all species located at Alice Holt per year from the subsampled Nature's Calendar data is shown in table 6-3. Budburst has a mean DOY of 89 across all years (30 March). The mean LOS between BB and FLF is 206 days. For autumn phenophase events, there is mean DOY of 267 for FT (24 September). The data show that 2005 and 2011 are the years in which the earliest BB occurs, with BB occurring later in 2006, 2007 and 2010. For autumn, FT occurs earliest in 2009, with FLF occurring earliest in 2008. The individual species mean DOY (Appendix 2 and 3) shows the range of emergence and senescence across all species available within the study region radius.

Table 6-3 Nature's Calendar Alice Holt mean DOY for each phenophase observed. BB (Budburst), FF (First Flower), FL (First Leaf), FT (First Tint), FLF (First leaf fall), FuT (Full Autumn Tint).

	BB	FF	FL	FT	FLF	FUT
Mean	89	104	101	267	295	293
2005	83	101	99	264	297	272
2006	100	123	110	277	303	306
2007	95	97	98	261	285	291
2008	87	99	105	261	267	292
2009	86	93	93	259	286	279
2010	93	112	108	268	299	297
2011	82	96	93	260	293	287
2012	89	104	99	279	295	295

The time-series of both the NDVI and EVI values for Alice Holt is a stereotypical curve for broadleaf woodland, with a distinct SOS influx and EOS decrease (Figure 6-10). The NDVI and EVI time-series show the difference in NDVI and EVI values, due to the choice in VI.

EVI indicates an earlier emergence of spring in comparison to NDVI, in addition to an earlier EOS (Table 6-4). EVI is stated to be more precise than NDVI and is also more responsive to canopy structural variations (Huete, *et al.*, 2002). The LOS is between 218 and 272 days for NDVI and 228 and 274 days for EVI, indicating a substantial range in the LOS between the years observed. In relation to the *in situ* data, 2006 and 2010 are also the years in which SOS occurs later (20th April 2010 and 22nd April 2006). The mean DOY SOS for both NDVI and EVI are earlier than the BB and FL DOY; 5 days for NDVI and 13 days for EVI in comparison to the *in situ* observations of BB.



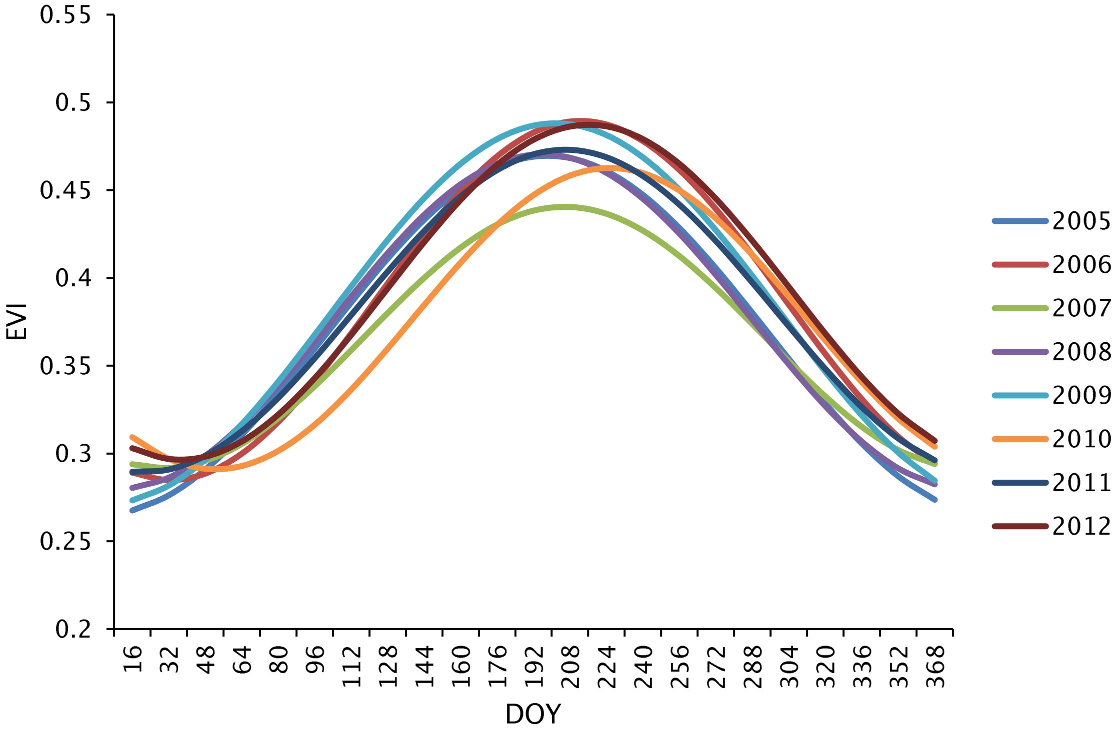


Figure 6-10 Fourier smoothed NDVI (top) and EVI (bottom) MODIS time-series at Alice Holt.

EOS occurs later than mean observational dates for *in situ* autumn observations of FT, FLF and FUT. The NDVI mean DOY for EOS across all years is 37 days later than FLF, and 35 days later for the EVI EOS estimate.

Table 6-4 Alice Holt MODIS NDVI and EVI SOS, EOS and LOS mean DOY for each year, and a total mean for the study period.

	NDVI			EVI		
	SOS	EOS	LOS	SOS	EOS	LOS
Mean	84	332	247	76	330	254
2005	72	328	272	72	328	256
2006	112	328	216	88	328	240
2007	72	344	272	70	344	274
2008	72	328	256	72	330	258
2009	72	328	256	68	328	260
2010	110	328	218	72	328	240
2011	88	328	240	88	328	240
2012	88	344	256	68	332	264

The canopy photographic record at Alice Holt was available only for 3 years within this study period, 2010 to 2012. The EGI and GCC time-series shows a dramatic increase in vegetation during spring, with a decline into autumn senescence following (Figure 6-11). The peak and maturity of the vegetation occurs early within the time-series between DOY 122 (2nd May) and 156 (6th June).

There are slight reflectance differences between GCC and EGI, however the assessments of SOS and EOS, show no variation in the mean SOS, EOS and LOS for this dataset (Table 6-5). The data for 2012 shows a distinct late emergence of vegetation which is in direct conflict to the *in situ* observations of BB, and satellite derived NDVI and EVI.

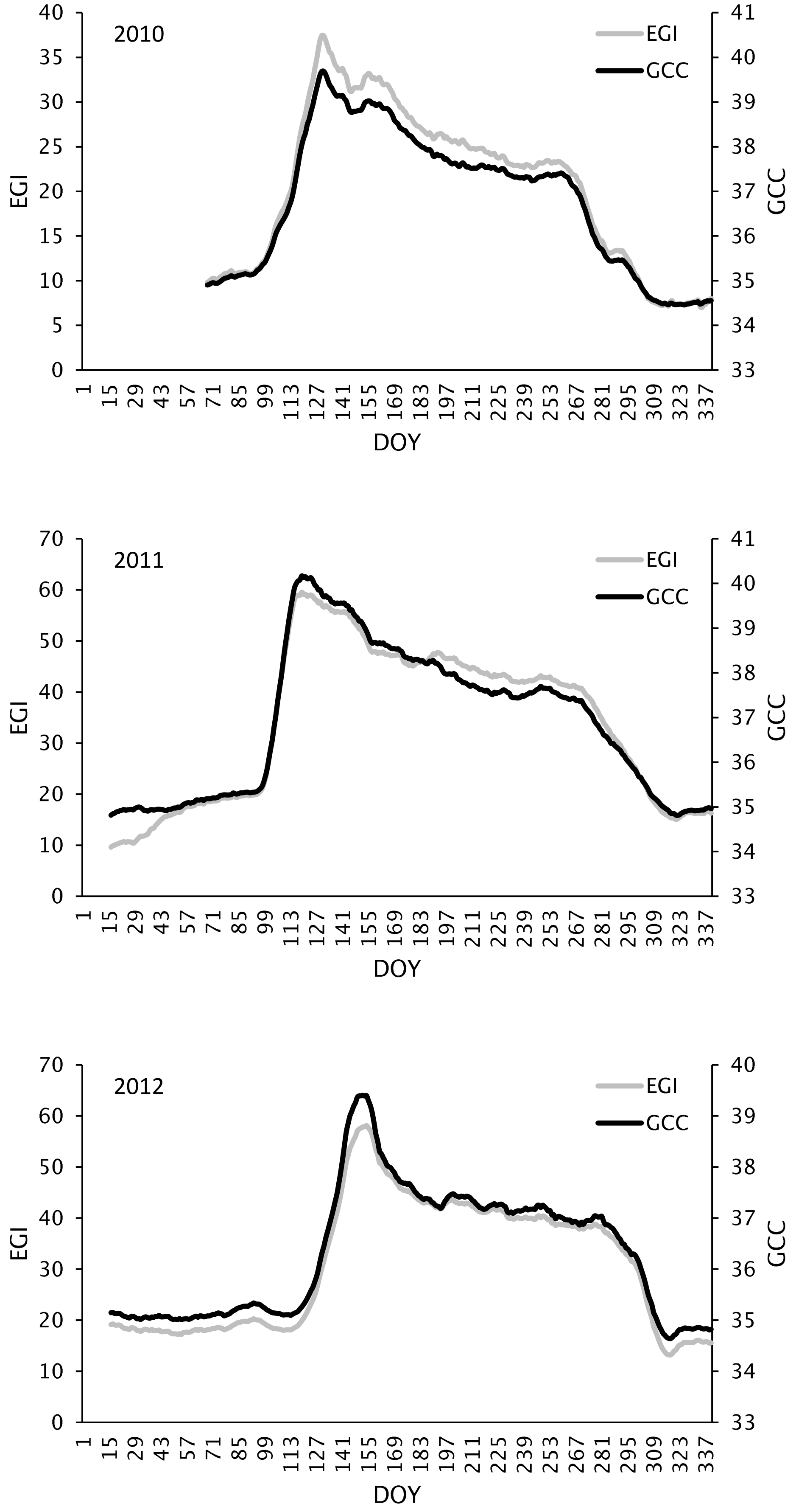


Figure 6-11 Smoothed EGI and GCC time-series from canopy photography at Alice Holt for 2010, 2011 and 2012.

Table 6-5 Mean DOY estimates of SOS, EOS and LOS from canopy photography at Alice Holt.

	EGI DOY			GCC DOY		
	SOS	EOS	LOS	SOS	EOS	LOS
Mean	105	305	200	105	305	200
2010	100	299	199	100	299	199
2011	101	306	205	101	306	205
2012	114	312	198	114	312	198

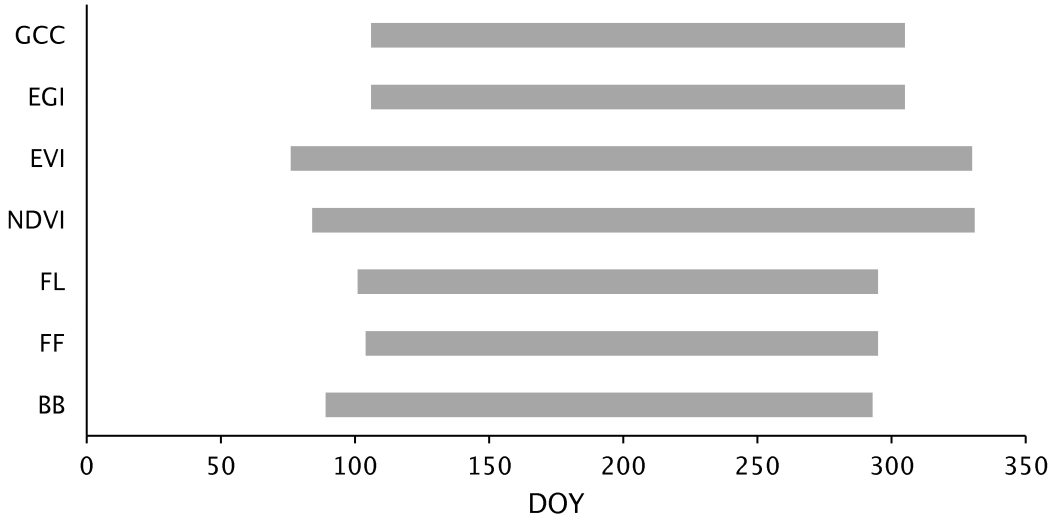


Figure 6-12 Mean length of season (LOS) for each observation technique at Alice Holt. To assess the LOS for the Nature's Calendar data, the mean DOY of first leaf fall (FLF) was utilised as the EOS DOY.

In comparison with all three observational techniques there are variations in the DOY of occurrence for SOS and EOS (Figure 6-12). The satellite sensor derived SOS and EOS for both NDVI and EVI have recorded a longer period of growth than the alternative observational methods, due to an earlier spring and late EOS estimate. The canopy RGB EGI and GCC show the latest occurrence of DOY for spring canopy growth (15th April). Thus highlighting the variances in estimates of vegetation phenological parameters depending on the observational technique utilised.

6.4.2 Wytham Wood Vegetation Phenology

The Nature's Calendar highlighted that BB occurred earlier in 2007, 2008, 2009 and 2011, in comparison to 2006 and 2010 here, (Table 6-6), with a difference of up to 10 days in BB emergence. FF and FL also echo the results from Alice Holt, showing that both phenophase events occurred later in 2006 and 2010. The EOS phenophase events show that FT occurred later in 2005 and 2006. FLF also occurred later in 2006 in comparison to the other years assessed.

Table 6-6 Nature's Calendar Wytham Wood mean DOY for each phenophase observed. BB (Budburst), FF (First Flower), FL (First Leaf), FT (First Tint), FLF (First leaf fall), FuT (Full Autumn Tint).

	BB	FF	FL	FT	FLF	FUT
Mean	86	106	95	263	291	296
2005	83	110	93	270	299	298
2006	92	113	107	268	304	305
2007	82	90	89	263	290	294
2008	87	101	96	257	289	293
2009	82	102	92	254	282	287
2010	92	112	103	261	284	294
2011	82	99	92	259	290	299
2012	85	104	93	263	294	300

Table 6-7 MODIS NDVI and EVI SOS, EOS and LOS mean for each year, and a total mean for the study period at Wytham Wood.

	NDVI			EVI		
	SOS	EOS	LOS	SOS	EOS	LOS
Mean	75	328	252	80	333	253
2005	72	312	240	88	328	240
2006	72	328	256	72	344	272
2007	72	328	256	72	328	256
2008	72	330	258	88	344	256
2009	72	328	256	72	328	256
2010	88	344	256	88	344	256
2011	84	328	244	88	328	240
2012	72	328	256	72	322	250

In conflict to the Alice Holt assessment of SOS estimate from MODIS NDVI and EVI, SOS assessments for Wytham Wood show that EVI estimates a later SOS and EOS by 5 days later (Figure 6-13). The mean EVI LOS is comparable to the NDVI estimate of LOS with only one day difference (Table 6-7).

In relation to the *in situ* observations, 2010 also indicated a later SOS. The majority of NDVI SOS DOY dates are earlier than the *in situ* observations with up to 20 days difference between the Nature's Calendar observations for BB and SOS. However, as the results of EVI are later than the NDVI DOY, there is up to 13 days difference between SOS and BB reported in the Nature's Calendar data.

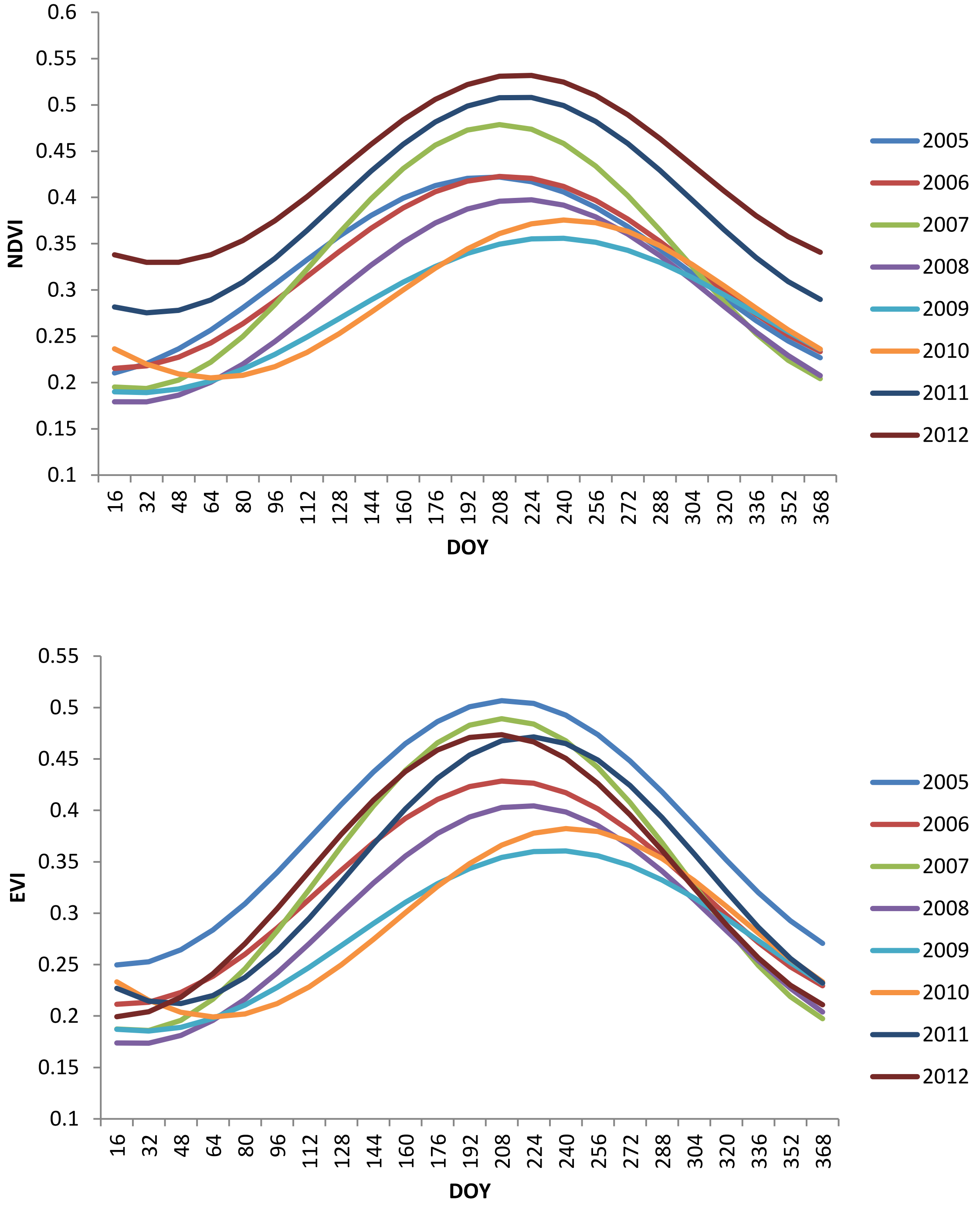


Figure 6-13 Fourier smoothed NDVI (top) and EVI (bottom) MODIS time-series at Wytham Wood.

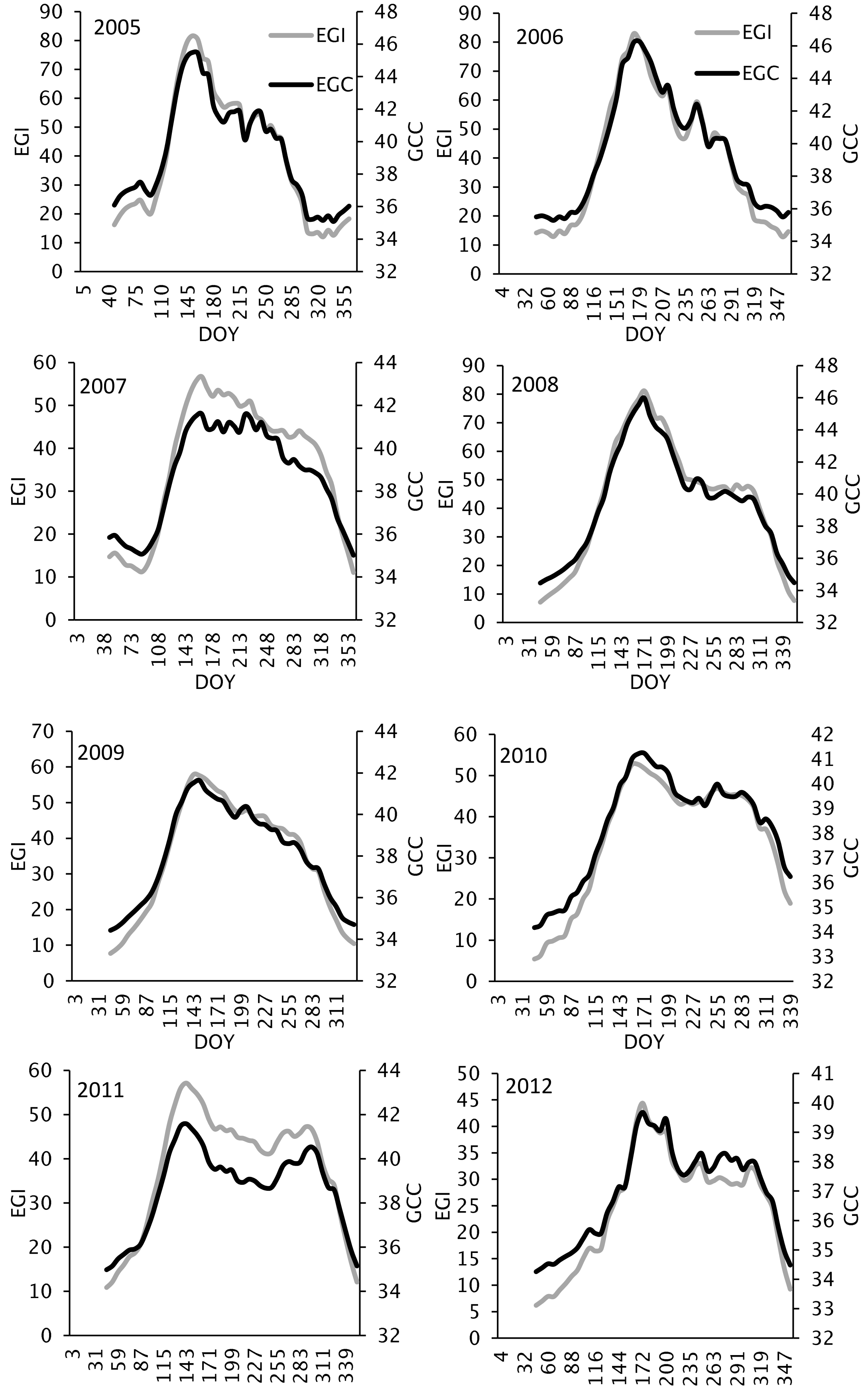


Figure 6-14 Smoothed EGI and GCC time-series from understory photography at Wytham Wood per year (2005-2012).

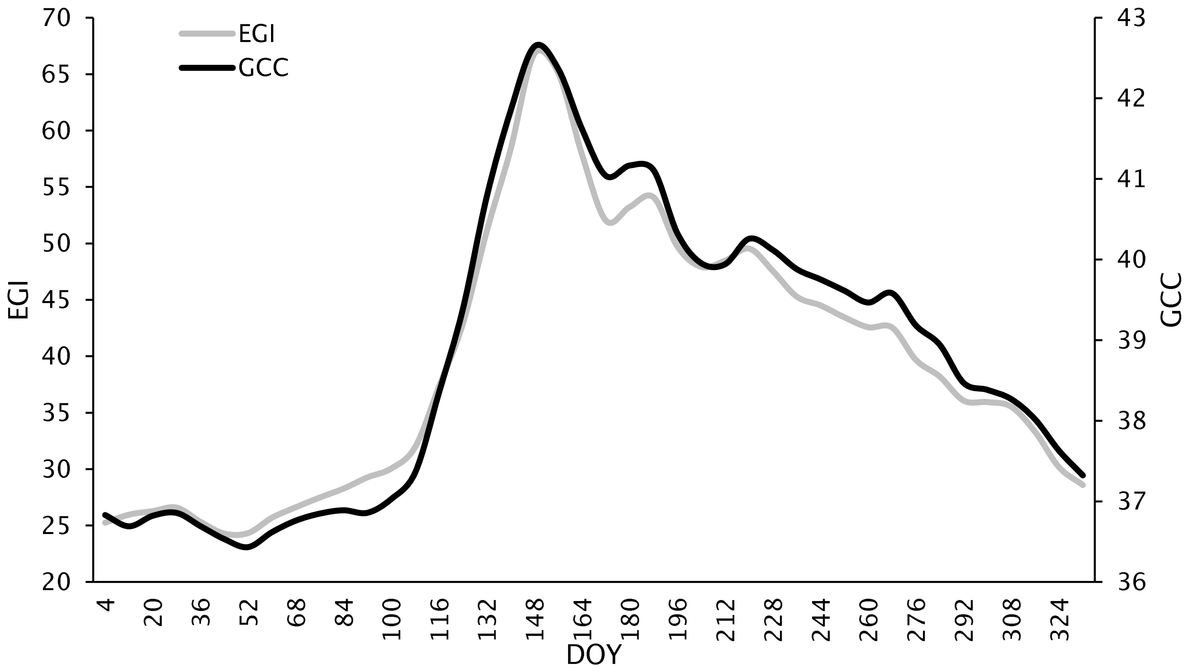


Figure 6-15 Smoothed GCC and EGI time-series derived from Wytham Wood canopy photographs for 2012.

In comparison to the understory and canopy camera data, the understory canopy detects the emergence of species earlier than the canopy camera (Figure 6-14 (2012), Figure 6-15), therefore, highlighting an earlier increase in understory vegetation growth. For 2012, this resulted in a 26 day difference in SOS (Table 6-8). Although the CROPSCAN data do not comprise a full year of coverage (no data prior to March), the increase and decline in NDVI is notable for 2010 and 2012 (Figure 6-16). The date of decline in EGI and GCC in 2011 is comparable to the 2011 understory for both the oak and sycamore CROPSCAN measurements.

Both EGI and GCC detected the spectral signature of the vegetation present. The time-series of EGI and GCC highlight the sharp increase in vegetation growth in spring, and the maximum VI value occurring early in the summer months (Figure 6-15). Senescence has a more gradual decline in both EGI and ECC in both the understory and canopy.

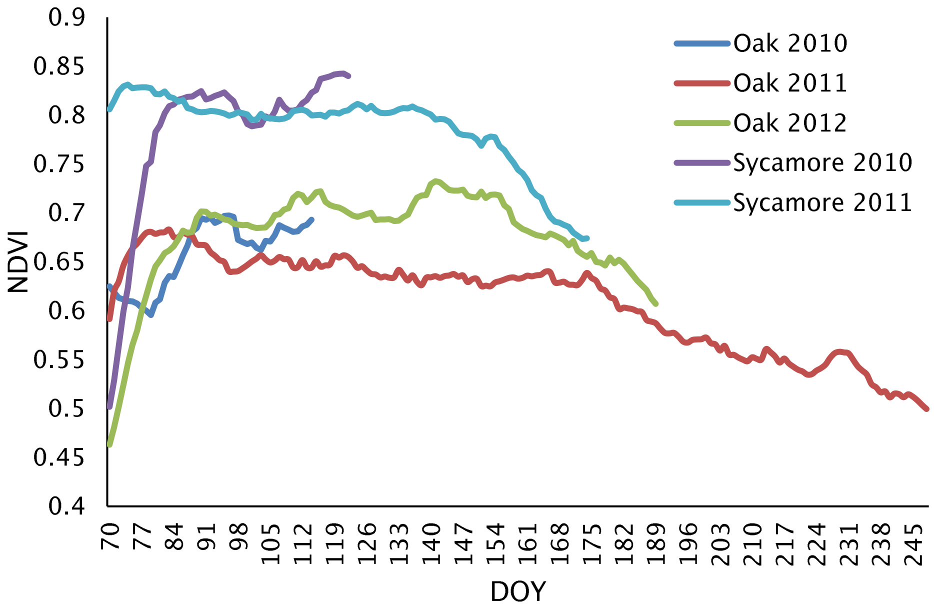


Figure 6-16 Time-series of CROPSCAN NDVI for 2010, 2011 and 2012 for Oak and Sycamore at Wytham Wood.

Table 6-8 Mean DOY SOS, EOS and LOS estimates from understory and canopy photography at Wytham Wood.

	EGI DOY			GCC DOY		
	SOS	EOS	LOS	SOS	EOS	LOS
Mean	93	342	249	94	342	248
2005	96	313	217	96	313	217
2006	95	326	231	95	326	231
2007	87	361	274	95	361	266
2008	89	345	256	93	345	252
2009	91	343	252	91	343	252
2010	97	349	252	95	349	254
2011	89	355	266	89	355	266
2012	82	354	272	82	354	272
2012 (Canopy)	108	332	224	108	332	224

The SOS estimate from the understory camera data show again that 2010 is one of the years studied in which SOS occurred latest (DOY 97, 95) (Table 6-8). The difference between DOY of the *in situ* observations for BB is 8 days between the understory estimates, in comparison to 22 days between the 2012 *in situ* BB DOY and canopy SOS. EOS, is shown to be detected much later, and is more comparable to satellite sensor EOS estimates, in particular for 2005, 2006, and 2010, where there is between 1 and 5 days difference.

For Wytham Wood, the comparison between SOS, EOS and LOS between observation techniques, highlights that satellite-derived vegetation phenology detected the longest growing period (Figure 6-17). The understory camera mean DOY for SOS is comparable to the mean DOY of FL from Nature's Calendar, indicating that understory cameras are an efficient method to detect the emergence of leaves in spring. The *in situ* data from Nature's Calendar has the shortest growing season. However, this may be due to the phenophase observation, as the first leaf to fall may not be a true reflection of the vegetation population.

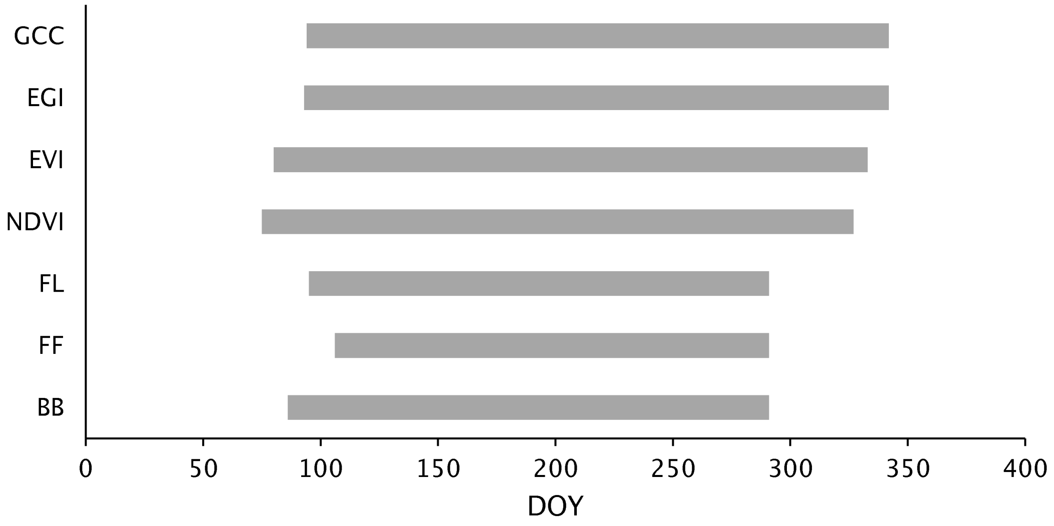


Figure 6-17 Mean length of the season (LOS) for each observation technique at Wytham Wood. To assess the LOS for the Nature's Calendar data, the mean DOY of first leaf fall (FLF) was utilised as the EOS DOY.

6.4.3 Controlling Factor Results

6.4.3.1 Alice Holt Controlling Factors

The results indicate that BB has a strong negative correlation with temperature *(r* = -0.65) (Table 6-9). FF shows the most significant relationship with temperature, in comparison to all other phenophase events and controlling factors (r^2 =0.71). Precipitation shows no relationship with the timing of spring phenophase events from the *in situ* observations from Nature's Calendar. However, for FuT the relationship is more apparent than for sunshine hours (r^2= 0.26).

FT and FLF autumn phenophase events show a significant positive correlation with temperature (*r* =0.72, *r* = 0.74). This is greater than the correlation to sunshine hours for the same phenophase events (*r* =0.54, *r*= 0.56). This highlights that temperature is the dominant controlling factor for both spring and autumn phenophase events at Alice Holt.

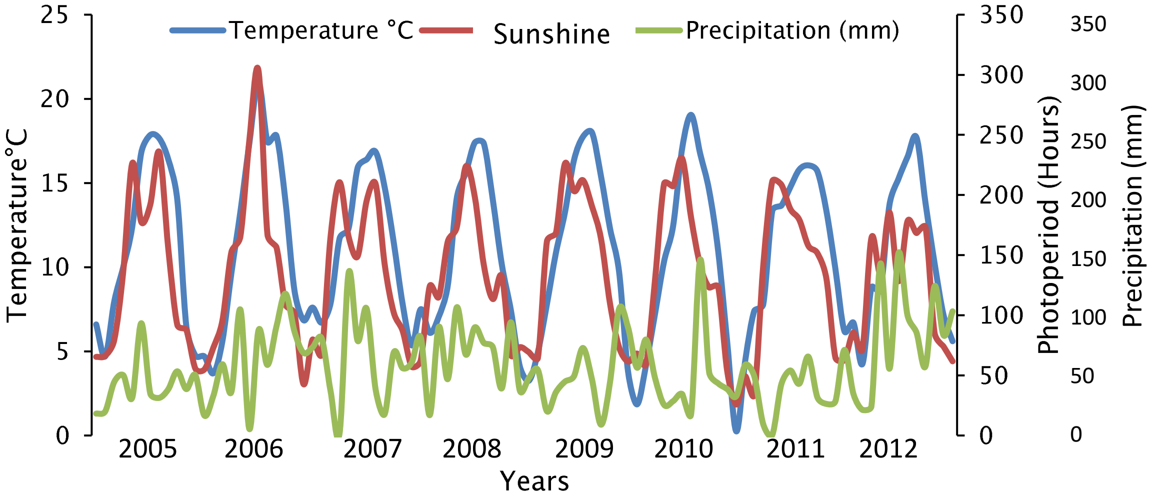


Figure 6-18 Alice Holt Monthly mean temperature, sunshine hours, precipitation (Met Office Heathrow Station Observations).

Table 6-9 Correlation coefficient (r) of the Nature's Calendar Alice Holt data. BB (Budburst), FF (First Flower), FL (First Leaf), FT (First Tint), FLF (First leaf fall), FuT (Full Autumn Tint). SE (Standard Error).

		BB	FF	FL	FT	FUT	FLF
Temperature	r	−0.65	−0.84	−0.25	0.72	0.55	0.74
	t	11.75	1.58	8.50	−10.79	5.93	−10.85
	SE	0.45	0.26	0.41	0.57	0.05	0.41
	p	0.00	0.00	0.00	0.00	0.00	0.00
Precipitation	r	−0.1	−0.1	−0.2	0.14	0.50	0.41
	t	−1.36	1.91	2.85	1.32	5.16	4.37
	SE	0.06	0.05	0.04	0.09	0.05	0.05
	p	0.18	0.55	0.00	0.19	0.00	0.00
Sunshine	r	−0.5	−0.5	−0.34	0.54	0.38	0.56
	t	7.86	12.90	5.42	0.07	−3.67	-6.79
	SE	0.02	0.03	0.02	-6.75	0.06	0.05
	p	0.00	0.00	0.00	0.00	0.00	0.00

SOS and EOS estimates from the NDVI VI show a greater negative correlation to temperature than the comparable EVI data (Table 6-10). The results from MODIS NDVI and EVI EOS DOY, also highlight the absence of a relationship of phenophase event to precipitation (r <0.1). For SOS the sensitivity of vegetation to increased temperatures is greater than for EOS. The relationship with sunshine hours is weaker than with temperature for both SOS and EOS (r^2 <0.32).

The canopy photograph-derived EGI and GCC, produced a strong correlation between temperature and EOS (r=0.96). For SOS, sunshine hours is the dominant controlling factor, (r=−0.93), in comparison to temperature (r= −0.71). The results for precipitation, do show that for SOS, there is sensitivity to rainfall amount and increase in vegetation growth (r^2= 0.367), whereas for EOS there is none (r^2= 0.1).

Table 6-10 Regression analysis of the MODIS EVI and NDVI Alice Holt data.

		NDVI		EVI	
		SOS	EOS	SOS	EOS
Temperature	*r*	-0.72	0.52	-0.52	0.47
	t	2.62	-0.585	1.50	-0.14
	SE	2.57	0.038	0.6	0.029
	p	0.03	0.585	0.183	0.74
Precipitation	*r*	-0.43	0.1	-0.18	0.01
	t	-1.19	0.261	-0.45	0.041
	SE	0.266	0.10	0.144	0.077
	p	0.277	0.802	0.65	0.69
Sunshine	*r*	-0.5	0.41	-0.25	0.4
	t	1.44	-0.676	0.64	-1.08
	SE	0.169	0.184	0.094	0.131
	p	0.198	0.524	0.53	0.32

Table 6-11 Regression analysis of the canopy EGI and GCC.

		EVI		GCC	
		SOS	EOS	SOS	EOS
Temperature	*r*	-0.71	0.96	-0.71	0.96
	t	-1.01	-4.10	-1.01	-4.10
	SE	2.91	0.765	2.91	0.765
	p	0.049	0.152	0.049	0.152
Precipitation	*r*	-0.60	0.1	-0.60	0.1
	t	3.84	-0.10	3.84	-0.10
	SE	0.053	0.252	0.053	0.252
	p	0.161	0.34	0.161	0.34
Sunshine	*r*	-0.93	0.76	-0.93	0.76
	t	-3.89	-0.73	-3.89	-0.73
	SE	0.066	0.203	0.066	0.203
	p	0.159	0.59	0.159	0.59

6.4.3.2 Wytham Wood Controlling Factors

For Wytham Wood, the results indicate that FF has a significant negative correlation with temperature (*r* = -0.84) (Table 6-12). Autumn phenophase events, FT, FuT and FLF also show the greatest sensitivity to temperature change (*r*=0.78, *r*=0.79, *r*=0.81). Precipitation shows a slight relationship with the timing of spring phenophase event (r^2<0.0670). The results show that vegetation is related to sunshine hours for FF (*r*=-0.72), with a strong negative relationship. For FT (*r*=0.73) and FLF (*r*=0.75), the results highlighting a strong positive relationship with sunshine hours.

The relationship between MODIS NDVI and EVI DOY is more significant for SOS in comparison to EOS for all controlling factors (Table 6-13). SOS shows a greater sensitivity to sunshine hours as opposed to EOS, with a greater negative relationship (NDVI *r*=-0.58, EVI *r*=-0.62). This relationship is stronger than the relationship to temperature (*r*=-0.39, *r*=-0.48). Precipitation shows a moderate relationship with SOS, however, there is no relationship apparent with EOS.

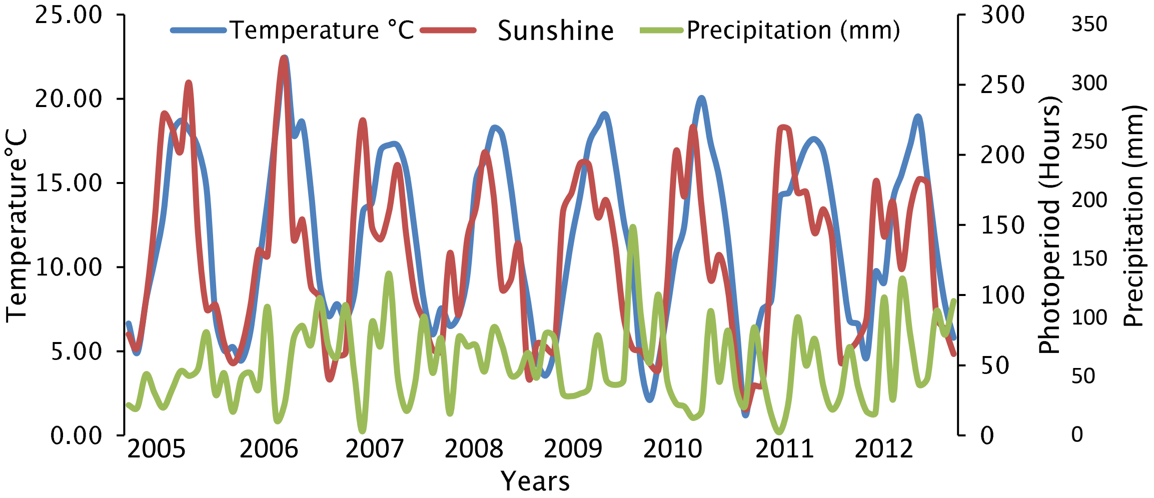


Figure 6-19 Wytham Wood monthly mean temperature, sunshine hours and precipitation (Met Office Oxford Observation Station).

Table 6-12 Regression analysis of the Nature's Calendar Wytham Wood data. BB (Budburst), FF (First Flower), FL (First Leaf), FT (First Tint), FLF (First leaf fall), FuT (Full Autumn Tint). SE (Standard Error).

		BB	FF	FL	FT	FUT	FLF
Temperature	*r*	−0.55	−0.84	−0.60	0.78	0.79	0.81
	t	18.14	16.09	18.34	−30.47	−27.65	−31.03
	SE	0.289	0.14	0.26	0.23	0.182	0.19
	p	0.00	0.00	0.00	0.00	0.00	0.00
Precipitation	*r*	−0.14	−0.15	−0.14	0.17	0.17	0.25
	t	1.66	6.83	3.99	4.42	3.88	5.89
	SE	0.025	0.02	0.023	0.027	0.028	0.03
	p	0.09	0.00	0.00	0.00	0.00	0.00
Sunshine	*r*	−0.52	−0.72	−0.50	0.73	0.65	0.75
	t	16.39	12.63	15.64	0.018	−18.146	−24.87
	SE	0.014	0.011	0.016	−26.15	0.025	0.022
	p	0.21	0.00	0.00	0.00	0.00	0.00

Table 6-13 Regression analysis of the MODIS EVI and NDVI Wytham Wood data.

		NDVI		EVI	
		SOS	EOS	SOS	EOS
Temperature	*r*	−0.39	0.35	−0.48	0.41
	t	−0.306	−0.31	−0.62	1.11
	SE	2.522	3.01	3.20	2.30
	p	0.06	0.079	0.05	0.30
Precipitation	*r*	−0.3	0.08	−0.24	0.1
	t	−0.77	0.02	0.63	0.09
	SE	0.143	0.09	1.90	0.152
	p	0.46	0.84	0.55	0.52
Sunshine	*r*	−0.58	0.62	−0.64	0.44
	t	−0.46	−1.98	−2.08	−0.52
	SE	0.071	0.137	0.07	0.18
	p	0.06	0.09	0.08	0.19

Table 6-14 Regression analysis of the EGI and GCC understory data.

		EVI		GCC	
		SOS	EOS	SOS	EOS
Temperature	r	-0.71	0.63	-0.7	0.63
	t	-2.50	0.17	-2.44	0.17
	SE	1.37	2.19	1.28	2.19
	p	0.04	0.86	0.05	0.86
Precipitation	r	-0.34	0.14	-0.57	0.14
	t	0.91	0.41	2.23	0.41
	SE	0.10	0.15	0.079	0.15
	p	0.39	0.68	0.06	0.68
Sunshine	r	-0.72	0.14	-0.64	0.14
	t	-2.63	-0.42	-2.05	-0.42
	SE	0.038	0.27	0.03	0.27
	p	0.68	0.00	0.08	0.68

The understory camera-derived EGI and GCC estimates of SOS show a strong negative relationship with temperature and sunshine hours (Table 6-14). The EVI estimate of SOS has a stronger relationship that temperature. For EOS temperature is the dominant controlling factor, whereas the relationship to sunshine hours is small. However, as this dataset observes the understory, the amount of light cascading through the canopy may be the reason for this. The results for precipitation, do show that for SOS, there is sensitivity to rainfall, whereas for EOS the sensitivity to rainfall is small (r^2=0.1).

6.5 Discussion

6.5.1 Comparison of Observation Technique

For this assessment three dominant observation techniques were utilised; Nature's Calendar citizen science observations, digital camera photography and MOD13Q1 EVI and NDVI data. Nature's Calendar is a valuable resource for the assessment of the timing of phenophase events, and for a comparison to near-surface and satellite-sensor data. Near surface observation techniques taken from both above and under the canopy, also serve to compare and 'bridge the gap' between observation methods and the vegetation phenophase being detected and contributed to the importance of understory influence to satellite observation. The spatial and temporal differences of each data set were considered and by subsampling the MODIS pixels to pixels what contained observation points from Nature's Calendar a direct pixel-to-point comparison could be accomplished. However, the 16 day composite period of the MODIS EVI and NDVI dataset was much greater than the three times daily near surface photograph data. By utilising an 8 day window for DMA the increased noise of daily illumination variations was minimised.

The relationship between satellite sensor-derived DOY for SOS and EOS and other vegetation phenological observation technique is challenging to investigate, primarily due to the spatial scale of observations, heterogeneous land cover and species diversity, and temporal coverage of observations (Fisher and Mustard, 2007; Hufkens *et al.,* 2012). The increase in VI value is related to the increase in photosynthetic tissue. At both sites, the DOY of SOS was earlier, EOS was later, and the growing season was longer when assessed by the MODIS data in comparison to the other datasets. SOS has been stated to be closely related to the BB, FL and FF of vegetation (Delbart *et al.,* 2015). When comparing the mean of BB and SOS, SOS detects growth earlier. Therefore, it could be concluded that a minor increase in vegetation could account for the earlier assessment of SOS. The Nature's Calendar dataset is compiled of observations points collected in a sporadic fashion, which is the nature of citizen science datasets, however the satellite imagery is representative of the vegetation community. As the MOD13Q1 is compiled of 16 day composites, it is a likely conclusion that the understory vegetation development is mostly likely the reason for this discrepancy (Burrows, 2003; Ahl *et al.,* 2006).

At both sites, the three autumn phenophase events from the Nature's Calendar data (FT, FLF, FUT) occurred earlier than EOS assessments from the digital camera photography and MODIS data. Although both spectral techniques showed a decline in vegetation, the comparable DOY for both metrics of EOS were not matched with the *in situ* observation for autumn. The chlorophyll content and digital channel spectral properties of the vegetation are still present during FT, FLF and FUT. Therefore, the comparison of EOS and autumn phenophase events is difficult to assess.

By utilising both canopy and understory digital camera photography at Wytham Wood, the relationship between satellite sensor EOS DOY and vegetation was characterised to a greater degree. It is known that the emergence of several understory species occurs earlier than in the canopy, however, this may only be a few days (Richardson and O'Keefe, 2009). As expected, the canopy EGI and GCC estimates of SOS showed a later SOS and earlier EOS than the understory estimates. Across both sites the RBG digital channel spectral properties were able to assess the rapid increase in vegetation during spring and the slow senescence of autumn. Thus, highlighting, the difference between spring and autumn vegetation development.

Satellite sensor observations are primarily stated to observe the changes in spectral reflectance of the canopy and the influence of the understory is rarely discussed. In a few previous studies the influence of understory vegetation in satellite-sensor estimates is shown (Kaelke *et al.,* 2001; Burrows, 2002; Ahl *et al.,* 2006). The mean DOY estimate of EOS from MODIS NDVI and EVI, were comparable to the EOS estimate of digital camera EGI and GCC VI of the understory vegetation at Wytham Wood. The agreement in DOY of SOS between near-surface and satellite-sensor derived estimates is shown in previous studies (Hmimina *et al.,* 2013; Klosterman, *et al.,* 2014). Thus highlighting that near-surface observations are a valuable resource in determining the physiological phenomenon that are determined by satellite-sensor estimates. As reflected in Klosterman, *et al.,* (2014) the observations of FL were closely related to the digital camera derived estimates of SOS. The understory digital camera estimates of EOS were later than both the satellite-sensor and *in situ* observations indicating a tendency of understory camera estimates to represent the final stages of leaf senescence. With the comparison of satellite-sensor and digital camera estimates it is worth noting that the species observed within the ROI may not be fully representative of the species observed in satellite pixels. This is expected, as the canopy ROI in both sites do not have the same spectral coverage as a 250 m pixel.

The changes recorded and estimated as SOS and EOS by remote sensing techniques are not in full agreement. In addition, there is still yet to be an agreement on the most appropriate remote sensing technique to observe the EOS and to compare to ground reference data (Pouliot *et al.,* 2011). Understanding the relationship between *in situ* observations and satellite sensor data is imperative for the assessment of global vegetation phenological monitoring and models. The primary advantage of utilising remote sensing techniques, as opposed to *in situ* data, is that with more recent satellite sensors data are collected at a high temporal frequency, with increasing spatial resolution at a global scale. Therefore, understanding the relationship of the *in situ* vegetation develop detected by satellite sensors, and examining the exact ground level trigger for the variation in the signal is vital (Schwartz and Reed, 1999).

Citizen science initiatives are important for measuring and assessing long-term vegetation phenological trends. This research highlights that citizen science datasets can be utilised for a comparison to near surface and satellite sensor data. The utilisation of digital cameras is a relatively new technology, and one that has been effective in monitoring vegetation phenology (Richardson *et al.,* 2009). With the use of web cameras vegetation phenological observations can be taken at on a periodic basis at a high temporal frequency. By utilising the relative brightness of the RGB channels, canopy and understory vegetation changes can be detected easily. One of the limitations when utilising digital camera photography is that the RBG levels are susceptible to variations in scene illumination (Nagai *et al.,* 2011). Therefore, the viewing angle and ROI must be appropriately selected to minimise these effects and to limit the extremes in RGB values.

6.5.2 Comparison of Controlling Factors

Vegetation phenology is sensitive to annual variation in weather and climate. The variability of seasonal weather conditions across the study period is known, as seen in the results, as 2005 SOS occurred earlier, whereas for 2010 SOS occurred later due to variations in climate conditions. The temperatures in January and early spring in 2005 were higher than the long-term CET average, whereas for 2010, the winter of 2009, was below the CET average, and this continued into early spring of 2010 (Figure 3-3, 6-18, 6-19). In the UK, January 2010 was the coldest January since 1963. This extreme weather event did impact the SOS for that year, as SOS occurred which was found in the satellite-derived vegetation phenological data, digital camera-derived data and the *in situ* observations for 2010.

The changes in the timing of autumn vegetation phenology are not as well-known as spring vegetation phenology. There is little agreement in the literature for the controlling factors of autumn leaf senescence (Estrella and Menzel, 2006). There are a greater number of research predominately centring on the assessment of spring phenophase events, the relationship to temperature and vegetation phenological trends, in comparison to EOS. Leaf senescence and leaf fall is important for determining heterotrophic respiration dynamics, therefore accurately assessing the EOS is vital for the correct assessment of net ecosystem carbon exchange (Knohl *et al.,* 2003; Davi *et al.,* 2006).

The delay in FT and FLF is stated to be related to prolonged higher temperatures during summer and autumn (Estrella and Menzel, 2006; Doi and Takahashi, 2008; Delpierre *et al.,* 2009). For autumn, photoperiod is understood to be the dominant controlling factor for senescence, as leaf fall occurs consistently at the same time annually, which suggests that senescence is controlled by photoperiod (Lee *et al.,* 2003; Richardson *et al.,* 2006). However, the decline in temperatures during autumn, occur simultaneously to the decrease in photoperiod. Therefore, the controls of senescence and dormancy are most likely to be a combination of both environmental factors, as shown in this research. Similarly to spring development where the increase in temperature occurs parallel to the increase in daily photoperiod length.

Previous research has shown that the relationship between senescence and temperature is relatively weak (Chmielewski and Rotzer, 2001; Menzel 2002; Sparks and Menzel 2002). However, this research highlights that the relationship of several of the assessments of EOS were driven by temperature. For both sites, a similar conclusion can be made in regards to the controlling factors for vegetation development and senescence. However, given the spatial distance between both sites they both have similar climates.

Photoperiod and temperature are the primary environmental factors that control the development and senescence of temperate plant species (Körner, 2007). The break of dormancy of several temperate species has stages, predormancy, endodormancy and ecodormancy (Basler and Körner, 2014). For many temperate deciduous species endodormancy is released when the required ‘chilling period’ is reached in addition to photoperiod increasing (Malyshev *et al.,* 2018). Budburst is sensitive to photoperiod, as it can prevent early budburst occurring when the plant would be sensitive to further frosts (Malyshev *et al.,* 2018). Once the ‘chilling’ requirement is reached the plant then enters ecodormancy where the bud breaks and can respond to increases in temperature and photoperiod length. Buds can stay in an ecodormant state until the additional environmental factors trigger plant growth. The results show that BB was not as sensitive to temperature or sunshine hours as FF and FL. This is primarily due to plant physiology and ecodormancy stage, as although temperature accelerates bud development, ‘chilling period’ and photoperiod control the release from endodormancy. For EOS as the chlorophyll content depletes, due to reduced photoperiod length, the ‘greenness’ of leaves also reduces. The autumn colourisation of leaves (orange and red) is due to the increased production of anthocyanins during senescence (Lee *et al.,* 2003). Autumnal cessation is known to be controlled by photoperiod, however, the simultaneous reduction in temperature is an additional factor for plant dormancy. The autumn phenophase events, FT, FuT, and FLF, had the greatest relationship to temperature at both Wytham Wood and Alice Holt.

Between the three observational techniques utilised, satellite, digital camera photography and *in situ observations,* there were variances in the overall assessment of the dominant controlling factors for SOS and EOS. At Alice Holt the MODIS derived estimates of SOS and EOS showed a greater correlation with temperature. For estimates utilising NDVI showed a greater sensitivity in comparison to EOS. In contrast to the Nature’s Calendar data, there was a relationship between precipitation and SOS. In contrast, the MODIS Wytham Wood estimates showed a slightly increased sensitivity to sunshine hours for SOS and EOS, in comparison to temperature. This may be due to concentration of differing species present at both sites.

The camera-derived EGI and GCC SOS at Alice Holt showed the correlation to sunshine hours was greater than temperature and precipitation. However, for Wytham Wood, there was a little variation in correlation between the two environmental factors. For EOS, the EGI and GCC estimates at both sites indicated that senescence had a stronger relationship to temperature. The overall results indicate that precipitation has little relationship with autumn phenophase events of temperate vegetation species, and the relationship to SOS is weaker than the additional two factors. This could be related to the highly variable nature of precipitation through the year across the UK (Figure 3-4).

Focussing on three environmental factors was useful in the assessment of the sensitivity of vegetation phenology to temperature, precipitation and sunshine hours. The comparison of the relationship between observational techniques is also an interesting addition. For example, the degree of sensitivity between NDVI and EVI for both SOS and EOS varied. The results show that vegetation phenological changes for both SOS and EOS were a reaction to temperature change.

Variation in the onset and senescence of vegetation causes changes to a variety of ecosystem processes including surface albedo, primary productivity and a possible increase in competition between species. The UK, like much of the Northern Hemisphere is predicted to have a continued increase in temperatures throughout the year, with wetter, milder winters, and warmer summers with lower rates of precipitation (Osborn and Hulme, 2002; Way and Montgomery, 2015). The changes to the UK climate are expected to affect vegetation in northern regions to a greater degree than southern areas (Holden and Adamson, 2002; Kendon *et al.,* 2015). Therefore, by understanding the controlling factors for plant development and senescence the future predictions of changes to vegetation development can be assessed.

6.6 Conclusion

This analysis has assessed the relationship between temperature, precipitation and sunshine hours with vegetation phenological observations and by monitoring technique. Precipitation shows no overall relationship to the Nature's Calendar *in situ* phenophase events, apart from FuT at Alice Holt.

The most notable conclusion from this assessment is the sensitivity of EOS phenophase metrics to temperature, as the MODIS derived estimates at Wytham Wood and digital camera estimates at both sites, indicated that the senescence of temperate vegetation is more sensitive to declining temperatures than the shortening in day length.

In order to continue the focus on controlling factors for temperate vegetation in the UK, further research could expand to include the degree in which 'chilling periods', frosts and growing degree days control budding and spring vegetation growth. Previous research states that prolonged periods of chilling accelerate bud growth. However, the data processed for 2010 (notable cold winter) shows a delayed SOS. Therefore, further environmental influences and species-specific adaptations to climate variation should be assessed in future research.

Chapter 7 Sensitivity of Satellite-Derived Vegetation Phenological Parameters to Spatial Resolution and Temporal Compositing Period

7.1 Introduction

Accurate and precise estimations of vegetation phenological parameters are required to detect and quantify subtle inter-annual trends (Pouliot *et al.,* 2011; Kandasamy and Fernades, 2015) and, from there, to increase the understanding of the effects of global climate changes on vegetation phenology. The individual processing steps applied to satellite-derived data need to be considered, as they each impact on the distribution of the output(s) of vegetation phenological parameters (e.g. SOS and EOS) (Schott, 2007). This includes the choice of satellite-sensor data, spatial resolution, composite period, correction and smoothing technique, which may affect calculations of vegetation phenological parameters. The magnitude of this is dependent on the specific choice of technique applied, as each processing technique has its own limitations and biases. With the launch of new sensors with higher spatial and spectral resolutions, such as the ESA Sentinel missions and the NOAA WorldView-3 satellite sensor, research has focused upon achieving a greater accuracy from satellite imagery (Kross *et al.,* 2011).

The estimates of vegetation phenological parameters, such as SOS and EOS, from remote sensing data may vary due to the techniques used to transform the data (Gahegan and Ehlers, 2000). Several studies concentrate on a single study area, using a single type of imagery and a single methodology, which makes it difficult to assess the most appropriate satellite imagery, preprocessing techniques and methodology to extract vegetation phenological parameters (Foody and Atkinson, 2002). In global vegetation phenology studies this is increasingly difficult due to the spatial extent and numerous biomes of vegetation assessed in each study. The satellite-sensor variables that relate to vegetation phenology parameter estimation include, variable temporal and spatial coverage, different measurement protocols within study networks, unknown measurement of accuracy and the different vegetation phenological stages measured (White *et al.,* 2009).

Constructing high quality VI datasets with a low noise ratio is vital in vegetation phenology studies (Jonsson and Eklundh, 2002; Chen *et al.,* 2004). Researchers have utilised several methods to aggregate over time or space to reduce satellite noise, errors and negative bias, as using raw data to assess vegetation phenology trends risks tracking non-random satellite noise (Savitzky and Golay, 1964; Moulin *et al*., 1997; Moody and Johnson, 2001; Jonsson and Eklundh, 2002; White and Nemani, 2006; Fisher and Mustard, 2007). The sensitivity of LSP estimates of SOS and EOS to changes along the processing chain has not been fully evaluated for remotely sensed vegetation phenological studies. The choice of VI, compositing period and model fitting technique can propagate to the estimates of vegetation phenology parameters (White *et al.,* 2009). The two input parameters that are the focus of this research are spatial resolution and composite period. Coarse spatial resolution is assumed to be one of the main sources of uncertainty in estimating vegetation phenology, but the effect of composite period on vegetation phenology detection is relatively unknown (Zhang *et al.,* 2009).

Satellite sensors are limited when detecting vegetation phenological events due to spatial resolution and soil background characteristics (Reed *et al*., 1994a). Pixels are not a true geographical object and one pixel can cover a large geographical area (Duveiller and Defourny, 2010). Aggregation methods over time or space have been used to reduce satellite noise, errors and negative bias (Marceau *et al.,* 1994). The original data are processed through spatial and/or temporal filtering techniques to detect the dominant signal from a time-series of observations, and to avoid non-random satellite noise (Fisher and Mustard, 2007). Aggregation of spatial coverage can cause a decrease in the degree of precision, as the spectral properties of a pixel are the approximate mean (Goodchild, 1994). The utilisation of coarse spatial resolution data limits the spatial variability that is detectable within remotely sensed imagery, meaning that changes in a small sub-pixel area of the study region may go unnoticed and not be fully represented (Fisher and Mustard, 2007). Whereas, with an increased spatial resolution it is possible to monitor vegetation dynamics in greater detail reducing the aggregation of the spatial reflectance of the area.

One concern with the analysis of time-series data is the period over which imagery is collected to build a composite (Foody and Dash, 2010). Many studies require a short compositing period, which may be useful when assessing vegetation phenological events, such as onset of greening. However, this may not be possible due to the requirement of at least one clear observation of the Earth's surface during the composite period (Foody and Dash, 2010). Composite periods restrict the precision with which vegetation phenological parameters can be estimated from remotely sensed data. For example, a coarse composite period may produce an earlier or delayed estimate compared to a shorter composite window (Dungan, 2002). Several earlier studies evaluated the sensitivity of vegetation phenological parameter estimation to composite period (Pouliot *et al.,* 2011; Kross *et al.,* 2011). Pouliot *et al.,* (2011) suggested a compositing period of between 7 to 11 days is appropriate to minimise random error and provide the best estimates of SOS. However, the most commonly used composite period for vegetation phenology studies is between 8 to 16 days. This is due to the effects of geometric registration, view angle, sun angle, atmosphere and cloud cover (Zhang *et al.,* 2009; Reed *et al*., 1994a). Daily data have a greater temporal resolution than composited data. However, daily data is affected heavily by increased noise and data dropouts, which can affect the estimates of vegetation phenology parameters (Testa *et al.,* 2015).

The sensitivity of estimates of vegetation phenological parameters due to choice of spatial resolution, and the spatial aggregation of satellite pixels, requires further assessment to provide greater assurance about the variability of satellite-derived estimates (Ahl *et al.,* 2006). Sensitivity analysis refers to the study of divergence in the output of a model related to sources of variance in the model input(s). Sensitivity analysis is conducted for several reasons; to determine which input parameters contribute the most variability in the output, which parameters are insignificant, if parameters interact which each other, and if the outputs can be explained (Iooss and Lemaître, 2015). The variability associated with an input parameter is propagated to the output(s) and can result in a large correlation between an input parameter and a variation of the output (Hamby, 1994). In models with multiple input parameters, sensitivity analysis assesses the main driver for variation in the output(s), and are an informative analysis on the influence of model inputs or parameters (Hamby, 1994). The emphasis of a sensitivity analysis depends on the context and the questions that are being asked within the assessment, but centres on addressing changes to 'optimal' metrics and the effects this has on parameter output values.

The sensitivity of estimated vegetation phenological parameters to choice of spatial resolution and composite period can be assessed by varying inputs systematically and observing the effect on parameter estimates. The aim of this research was to assess the sensitivity of satellite-derived vegetation phenological parameters, SOS and EOS, in day of year (DOY) units, to choice of spatial resolution and composite period per dominant land cover type.

7.2 Data and Methodology

7.2.1 Study Area and Land Cover Classes

For this research, the study period was from January 2005 to April 2011. The 1 km aggregate, dominant LCM2007 produced by the Centre of Ecology and Hydrology (CEH) was used to define the dominant vegetated land cover types across the UK; broadleaf woodland, coniferous woodland, arable, improved grassland, semi-natural grassland and mountain, heath and bog, to account for the variations in the time series of LSP for each land cover type.

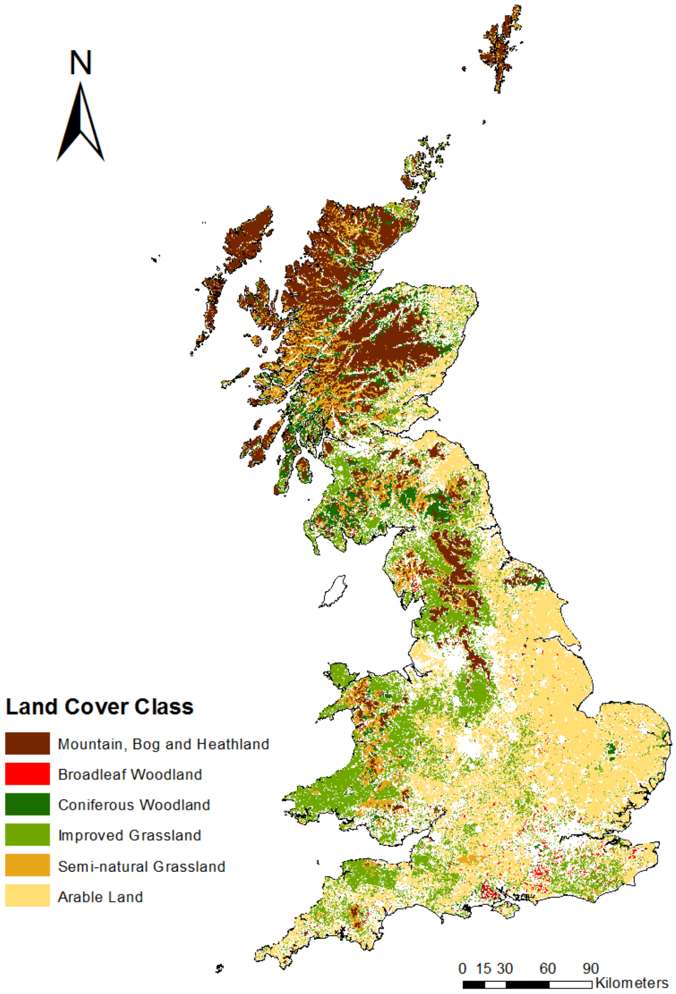


Figure 7-1 Areas defined as >50% coverage for each land cover type from LCM2007 Dominant Aggregate 1 km Class cover.

The aggregate percentage cover of each land cover was reclassified to 50-100% of the dominant vegetation land cover type within each pixel (Figure 7-1). The 50% threshold was chosen to reduce the number of heterogeneous pixels for this assessment. The reclassified LCM was then converted to shape files and used to mask the estimated MERIS MTCI vegetation phenological parameters for SOS and EOS. The subsampling by land cover type is necessary due to the individual distinct time-series between and timing of SOS and EOS of the species present in each dominant land cover type (Bradley and Mustard, 2008). The spatial variation of the land cover classes across the UK has been discussed previously in section 3-3. Table 7-1 includes further details regarding the land cover classes and the spatial coverage of the areas defined as >50% dominant land cover.

Table 7-1 Land Cover classes as described by the 1 km aggregate dominant LCM 2007 classes, including broad habitat description, spatial coverage, species and management occurring in each class (Morton *et al.,* 2011).

Aggregate Class	Coverage (km^2)	Broad Habitat	Species and management
Broadleaf Woodland	1723	Broadleaved, Mixed and Yew Woodland	Willow (*Salix),* Alder (*Alnus glutinosa),* Sessile oak (*Quercus petraea*), Penduculate oak (*Quercus robur*), Beech (*Fagus*),Ash (*Fraxinus*), Silver birch (*Beula pendula*), Downy birch (*Betula pubescens*).
Coniferous woodland	10501	Coniferous Woodland	Douglas fir (*Pseudotsuga menziesi)*, Sitka Spruce (*Picea sitchensis)*, Scots Pine (*Pinus sylvestris)*, Juniper (*Juniperus)*, Yew (*Taxus baccata)*, Larch (*Larix).*
Arable	58812	Arable and Horticulture	Cropland, including perennial crops, woody crops, intensively managed commercial orchards, commercial horticultural land, nurseries, commercial vegetable and flower plots, freshly-ploughed land, annual leys, rotational set-aside and fallow.
Improved Grassland	40908	Improved Grassland	Managed pastureland, mown for silage, recreation or amenity purposes. Grasses include *Lolium* and white clover (*Trifolium repens*).
Semi Natural Grassland	17059	Rough, Neutral, Calcareous and Acid Grassland, and Fen, Marsh and Swampland	Bracken (*Pteridium aquilinum*) the heath family (ericoids) or dwarf gorse *Ulex minor* reedbeds (*Phragmites australis*).
Mountain, Heath and Bog	33663	Dwarf Shrub Heath, Bog, Montane Habitats and Inland Rock	Wetland, peat forming and ombrotrophic mire. Bog areas are ericaceous, herbaceous and mossy swards

7.2.2 MERIS MTCI

The methodology used for MERIS MTCI in Chapter 5 was utilised for this research to smooth the data and extract the vegetation phenological parameters of SOS and EOS. MERIS MTCI composites were created for periods of 4, 8, 10 and 16 days. The 250 m composites were resampled using Matlab, to represent average values at coarser spatial resolutions of 500 m, 1 km, 2 km, 4 km, and 8 km. The composites were layered such that the 16 day composite contained 32 layers, 10 day composite 50 layers, 8 day composite 62 layers and the 4 day composite 122 layers. Each composite represents either a 4, 8, 10 or 16 day period and is indexed by composite number (CN). The Julian day of year (DOY) was calculated as the median of the days within the assigned composite. The variance of estimated SOS and EOS due to the sensitivity to variation in spatial resolution and composite period was assessed using the mean DOY over the spatial dataset and the overall variance within each output.

7.2.3 Methodology

Across all chosen spatial and composite periods for across each subsampled land cover type the mean and standard deviation of the SOS and EOS estimates were calculated. The vegetation phenological parameters used in this study are SOS and EOS. The sensitivity of this approach is based on the response of estimates of SOS and EOS as a continuous function of the varying spatial resolution and composite period. A schematic diagram of the methodology can be seen in Fig. 7-2.

The simplest and most commonly used form of a sensitivity analysis is the one-at-a-time (OAT) approach which assesses individual sensitivity in output(s) to alterations in the value of one input metric (Crosetto *et al.,* 2000; Saltelli *et al.,* 2000). Importantly, OAT techniques do not explore input interactions and are limited to the nominal value sensitivities (Crosetto *et al.,* 2000). However, this screening method allows quick exploration of the model and evaluation of influential parameters (Iooss and Lemaître, 2015). The approach here assesses the variation of the output of vegetation phenological parameter when the input metrics of composite period and spatial resolution are altered on an OAT basis. The effect of the variation of a single metric on the output, while all other metrics are fixed at nominal values, enables the influence of the metric on the sensitivity of the vegetation phenological parameters to be assessed. This simplistic approach concentrates on the two parameters that are known to influence the estimates of SOS and EOS. By utilising commonly used values for composite period and spatial resolution, this enables the most influential input parameter to be screened. For this research, the OAT approach was chosen to assess the sensitivity of SOS and EOS to choice of spatial resolution and compositing period. The most commonly used values for spatial resolution and composite have been utilised for this research.

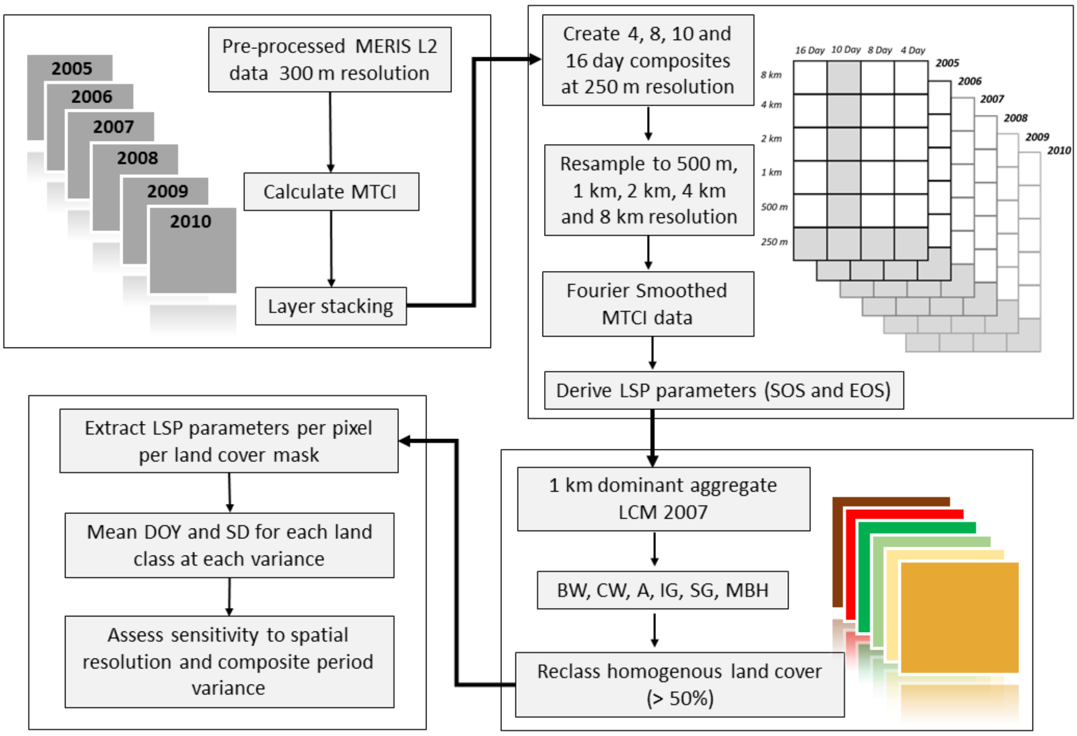


Figure 7-2 Schematic diagram showing the research methodology utilised in this research (BW – Broadleaf Woodland, CW – Coniferous Woodland, A – Arable, IG – Improved Grassland, SG – Semi-Natural Grassland and MGH – Mountain, Bog and Heathland).

7.3 Results

7.3.1 Spatial Distribution of SOS and EOS

The spatial distribution of the estimated vegetation phenological parameters were found to be affected by the latitudinal and elevation variation across the UK, as shown in previous chapters (Chapter 4 and 5). This is evident in all of the maps produced, irrespective of the spatial resolution and composite period, particularly within the Northern latitudes and the Highlands of Scotland, the Pennines and Snowdonia. Across these areas of high latitude and/or elevation the estimates all show a later SOS (Figure 7-3). The areas showing the earliest SOS occur in the areas of improved grassland and arable land. These areas are managed as pasture, silage production or recreation, and are expected to have an earlier SOS in comparison to the natural unmanaged areas of the UK. Interestingly, the estimates of SOS from the finest spatial resolution (250 m) exhibit a later SOS in comparison to the coarsest spatial resolution (8 km). The estimates of SOS from the course composite period data (16 day) indicate a later estimation of SOS in comparison to the shorter composite period (4 day) estimates.

For EOS, the estimates across the UK highlight that Northern latitudes and elevated regions have a later EOS than the lowland regions (Figure 7-4). However, as lowland areas in the South and East of England are predominantly arable, EOS is expected to be earlier within the season primarily due to the harvesting of crops. The vegetation species across the Northern latitudes are predominately heathers and coniferous woodland, which are dominated by evergreen species, making EOS more difficult to estimate. In addition, Northern and high latitude regions of the UK have a large proportion of cloud cover and rain during the autumn and winter months. Therefore, the number of cloud free pixels available will be significantly reduced in comparison to Southern regions. Therefore, even with the inclusion of the gap filling methodology to combat the issue of no data pixels, the effects may coincide with a later estimated EOS.

In comparison to SOS, the shorter composite period (4 day) estimates a later EOS in comparison to the coarse composite period (16 day) estimates. However, similar to spatial resolution, the sensitivity is dependent on the land cover within specific areas. Across the UK, the estimates show that in lowland Southeast areas a finer spatial resolution exhibits a later EOS, and in Northern upland regions finer spatial resolution exhibits an earlier EOS. Across the UK the estimates of SOS and EOS are sensitive to both a variation in spatial resolution and composite period. However, the degree of sensitivity to these depends on the dominant land cover within the area.

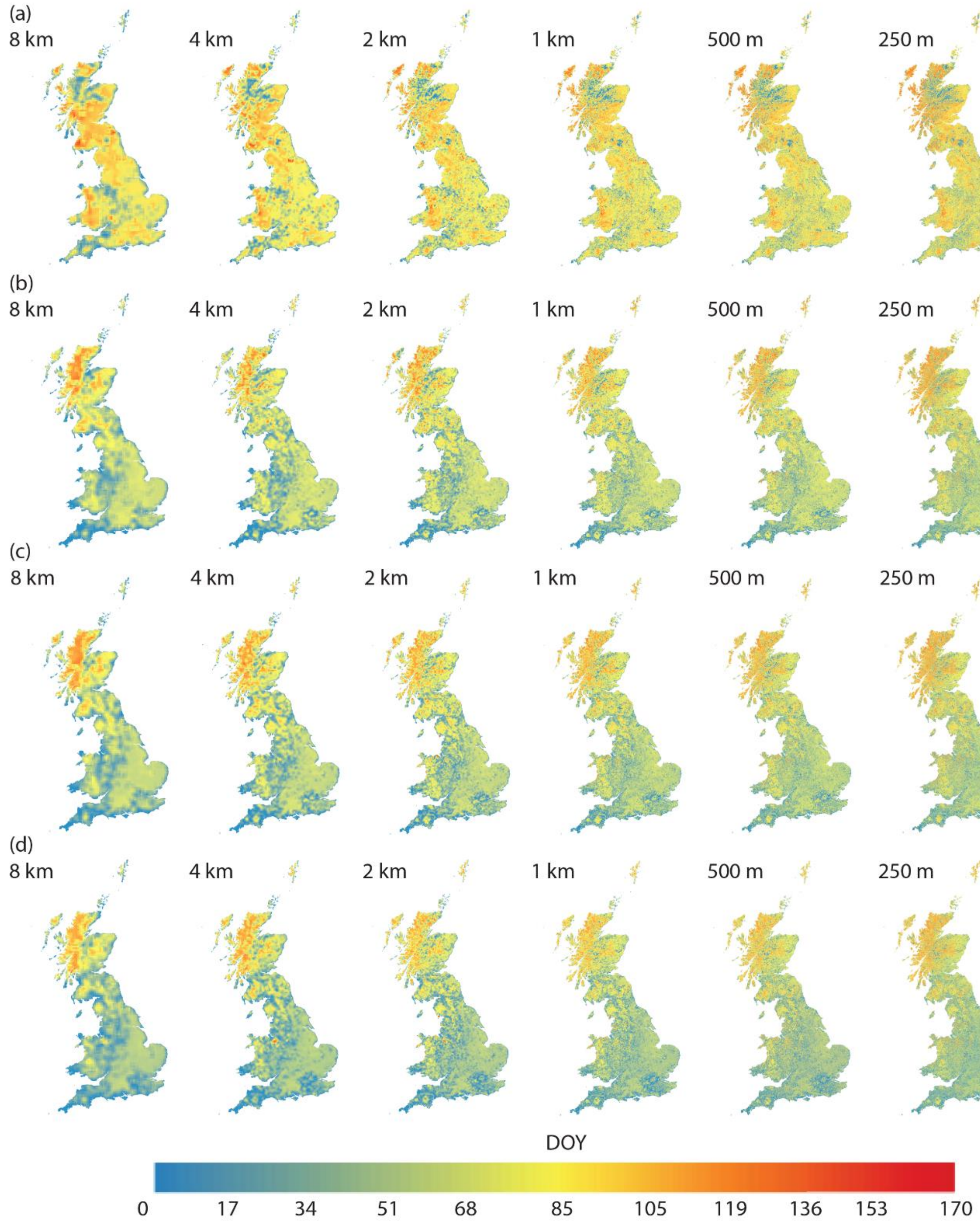


Figure 7-3 Mean MERIS MTCI SOS estimates for 2005-2010 across the chosen spatial resolutions. (a) 16 day composite (b) 10 day composite (c) 8 day composite and (d) 4 day composite.

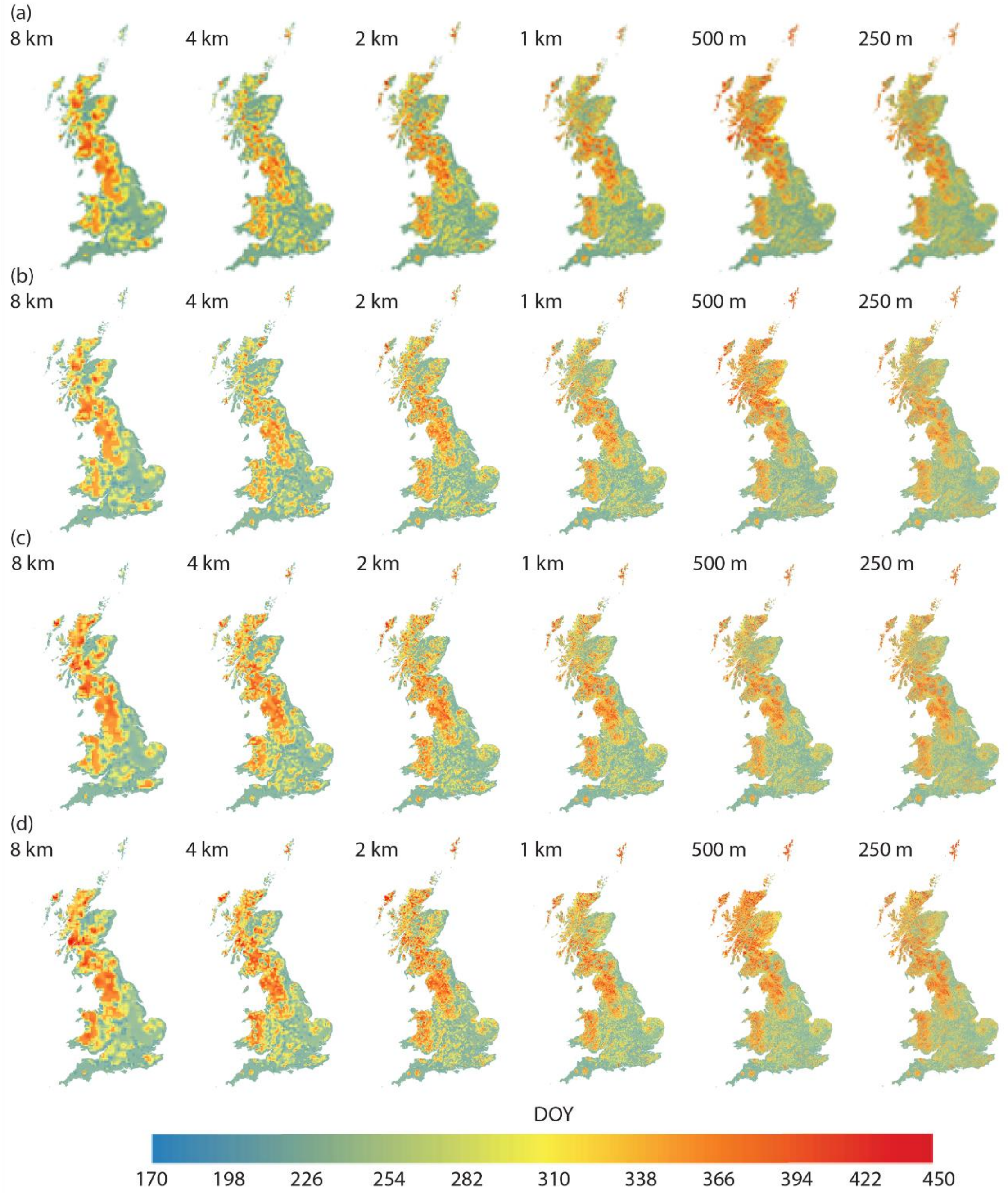


Figure 7-4 Mean MERIS MTCI EOS estimates for 2005-2010 across the chosen spatial resolutions. (a) 16 day composite (b) 10 day composite (c) 8 day composite and (d) 4 day composite.

7.3.2 Time-Series for Specific Vegetation Types

Within the time-series data there are fluctuations the value of MTCI depending on the spatial resolution of the data. For each of the dominant land cover classes there is distinct variation in the time-series and reflectance values (Figure 7-5). The time-series of the MTCI value for broadleaf woodland areas is a stereotypical curve for vegetation phenological studies, with a distinct SOS increase and EOS decrease. The time-series show that within each composite period input, the 8 km resolution data showed the smallest values of MTCI during the peak of season (between 2.5 and 3.3). However, there is a fluctuation between the largest MTCI values as for the 16, 8 and 4 day composites the 500 m resolution data showed the largest values (between 3.8 and 4.2), and for the 10 day composite the 250 m data showed the largest MTCI values.

The increase in MTCI in arable, highlighting the SOS, occurs much earlier than the other land classes as does the decrease in MTCI, highlighting the EOS. Following this initial trough there is a second peak. This is most likely due to the harvesting of crops during the autumn, other plant species, a second crop growing season within these areas and weed growth on ploughed fields.

For areas classed as coniferous woodland and improved grassland there is an indication of a SOS and EOS. However, through the time-series for the different spatial resolutions there are distinct peaks and troughs. Since both of these land cover classes are predominately evergreen areas, the time-series will vary depending on the non-evergreen species present within the pixels. For the improved grassland areas, these areas are managed pastureland, mown for silage, or in non-agricultural contexts for recreation and amenity purposes, and are expected to have a high level of productivity and little winter senescence.

Areas classed as mountain, heath and bog and semi-natural grassland have the largest value for MTCI predominantly for the 8 km and 4 km resolutions. These areas highlight a distinct increase in MTCI for the SOS and a slow decline for the EOS. As discussed previously, as these areas are located within Northern regions and areas of higher elevation clear pixels with no cloud coverage were less common than in areas of the South. Therefore, the slow decline for EOS is as expected.

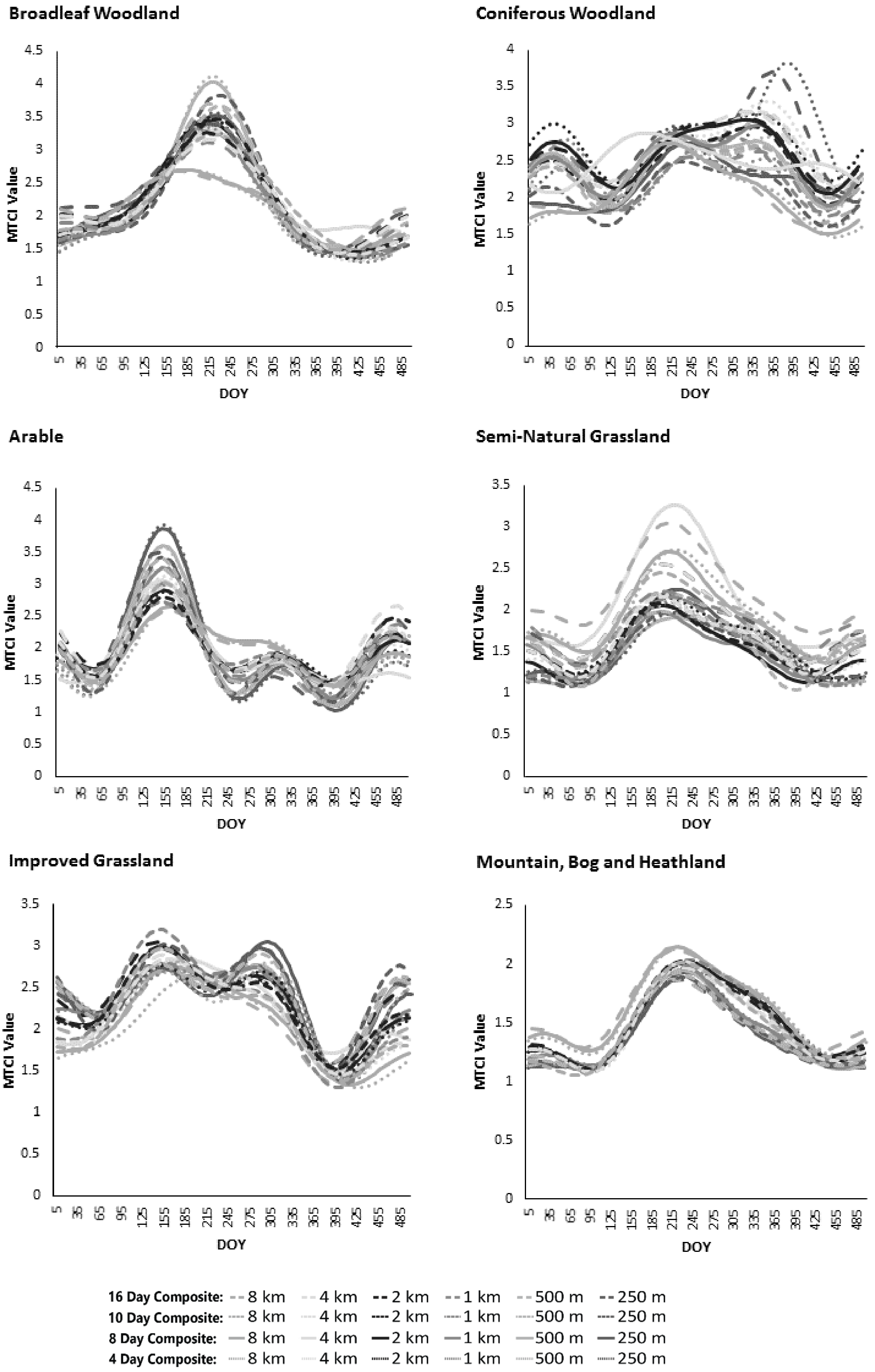


Figure 7-5 Time-series of mean MTCI values for each land cover class (2005-2010).

7.3.3 LSP Parameters for Specific Vegetation Types

Table 7-2 shows the results of the estimates of mean SOS DOY across all chosen composite periods and spatial resolutions for each land cover class across the study period. Variation in SOS exists depending on the type of vegetation within the classified pixels. Pixels classed as coniferous woodland, semi-natural grassland and mountain, bog and heath all indicate a later SOS in comparison to the other vegetated land classes, ranging between 129 and 80 DOY depending on the spatial resolution. This is predominately due to the location of these land cover types, as they are located in the northern latitudes and higher elevated areas. Arable land and improved grassland areas have the earliest SOS ranging between 44 and 87 DOY. The coarse 16 day composite estimated a later SOS compared to the 4 day composite.

The largest range of SOS mean DOY occurs in the areas classed as coniferous woodland (45 days). In addition, the variability due to the sensitivity of vegetation phenological parameters to both composite period and spatial resolution is between 27 and 29 days. This is most likely due to the detection of SOS in areas predominantly dominated by evergreen species, as evergreen trees do not have a sharp increase in greenness during spring (Jönsson *et al.,* 2013). The latest SOS, from the 16 day composite 250 m dataset, is estimated as 129 DOY (8th May), and the earliest SOS estimate is 84 DOY is from the 4 day composite at 8 km resolution. All estimates for the coniferous woodland class are in the assumed time-frame of spring (March – May).

The earliest estimate of SOS within the chosen land classes for the UK is the for the improved grassland areas, with a range of 43 days from 44 (13th February) to 87 DOY (27th March). The range of estimates due to the sensitivity of LSP and spatial resolution is between 3 and 7 days, with an increase in estimates occurring in the 4 day composite datasets. The areas classed as arable have the least sensitivity to spatial resolution depending on composite period, with no variability shown in the 10 day composite datasets, and 5 day variance in the 8 day composite dataset. The LSP parameters showed the greatest sensitivity to variance in composite period with up to 37 days range with a range of estimates between 50 DOY and 87 DOY.

Table 7-2 Mean SOS DOY estimates and the standard deviation for the each land class across the UK for 2005 – 2010.

		16 Day Composite		10 Day Composite		8 Day Composite		4 Day Composite	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Broadleaf Woodland	8 km	92	17.90	75	19.45	68	23.29	58	21.05
	4 km	93	20.18	76	22.61	68	24.42	59	26.62
	2 km	94	22.53	78	24.49	73	27.33	62	26.23
	1 km	96	24.29	82	25.05	79	24.82	64	27.53
	500	96	26.93	84	25.94	81	26.81	69	27.68
	250	96	27.25	82	28.32	83	23.30	72	25.70
Coniferous Woodland	8 km	101	30.28	98	37.84	92	38.49	84	43.11
	4 km	107	33.17	104	41.86	97	37.74	95	33.98
	2 km	112	38.50	116	37.40	104	42.02	99	38.33
	1 km	122.	42.49	121	38.82	114	44.33	107	47.12
	500	128	45.82	126	39.79	119	47.30	110	48.41
	250	129	48.61	127	40.0	119	48.95	111	50.05
Arable	8 km	86	18.99	69	14.52	63	16.73	51	18.58
	4 km	86	22.98	69	13.87	60	18.03	53	17.16
	2 km	86	26.74	69	14.94	65	16.27	53	17.37
	1 km	86	32.60	69	16.70	64	18.91	54	18.65
	500	87	33.41	69	18.78	64	21.22	53	21.32
	250	87	34.64	69	20.94	65	22.92	50	23.25
Semi-Natural Grassland	8 km	101	24.34	93	26.61	88	29.76	75	35.19
	4 km	102	24.73	95	26.15	91	27.33	81	33.70
	2 km	102	24.17	94	25.11	91	27.34	80	32.25
	1 km	104	22.16	93	24.98	90	28.06	80	31.60
	500	102	24.43	93	26.00	90	29.02	80	32.55
	250	102	33.36	93	27.23	89	35.19	80	32.71
Improved Grassland	8 km	87	23.74	65	25.27	58	28.82	44	30.60
	4 km	86	24.54	63	26.92	60	29.70	44	32.21
	2 km	85	26.27	63	28.96	56	32.38	43	33.69
	1 km	84	30.46	63	32.53	57	36.13	45	37.10
	500	84	32.41	64	35.81	59	39.71	49	39.98
	250	84	34.94	66	38.84	61	42.02	51	41.35
Mountain, Bog and Heath	8 km	112	21.34	104	24.93	101	26.08	90	34.26
	4 km	111	24.59	107	23.97	104	26.67	92	33.62
	2 km	113	24.42	108	23.27	104	24.62	95	31.79
	1 km	116	22.56	109	23.35	105	25.70	96	32.26
	500	116	25.51	109	24.74	106	27.18	96	33.81
	250 m	116	26.03	109	25.99	105	28.47	98	35.95

The mountain, bog and heathland class had the least sensitivity to spatial resolution and composite period with 26 days variability in mean SOS. The range of SOS due to composite period is between 18 and 22 days and between 5 and 8 days due to sensitivity in variability of spatial resolution. The areas of semi-natural grassland have a range of 29 days between estimates, with between 26 and 21 days due to composite period, and 2 and 6 days due to spatial resolution. The pixels classed as broadleaf woodland have a total variability of 38 days due to the sensitivity of LSP to variance in spatial resolution and composite period. The sensitivity of composite period is between 24 and 34 days whereas the sensitivity due to spatial resolution is between 15 and 4 days.

The estimates of EOS for each land cover type are shown in Table 7-3. The mean EOS DOY estimates for areas of the UK classed as arable land is estimated to occur between 251 to 297 DOY, mid-September and mid-October, depending on the sensitivity to spatial resolution and composite period. This correlates with the assumed EOS for arable lands, as they are managed and harvested between September and October. Senescence is expected to occur much earlier in arable lands than natural non-managed land. One of the main observable limitations with the estimation of EOS using satellite-derived techniques is that EOS does not occur within the assumed senescence of autumn, September to November, (245 to 335 DOY) for broadleaf woodland, coniferous woodland, semi-natural grassland, improved grassland and mountain, bog and heathland areas. The latest estimate for EOS DOY occurred in the mountain, bog and heathland (378 to 397), semi-natural grassland (371 to 392) and coniferous woodland areas (382 to 398).

The greatest range, and therefore sensitivity, to spatial resolution and composite period variation, occurred within the arable land class with 46 days. The variability due to spatial resolution is between 8 and 36 days, whereas for composite period it is between 17 and 43 days, indicating that LSP EOS parameters have a greater sensitivity to composite period.

Table 7-3 Mean EOS DOY estimates and the standard deviation for the each land class across the UK for 2005 – 2010.

		16 Day Composite		10 Day Composite		8 Day Composite		4 Day Composite	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Broadleaf Woodland	8 km	351	49.16	347	62.78	340	67.28	337	66.28
	4 km	356	42.60	361	51.16	354	59.07	350	57.61
	2 km	362	36.95	373	45.89	360	55.29	361	55.37
	1 km	367	35.32	371	46.71	368	49.12	369	43.34
	500 m	368	31.35	377	44.86	369	48.80	370	37.15
	250 m	367	32.26	374	45.65	367	48.49	369	37.30
Coniferous Woodland	8 km	385	39.17	390	49.02	395	50.89	398	53.63
	4 km	384	39.79	390	52.02	384	55.90	395	55.77
	2 km	383	43.09	392	52.30	388	55.73	394	58.00
	1 km	384	44.55	392	53.30	388	58.09	396	63.67
	500 m	386	48.10	390	56.83	386	61.25	392	68.18
	250 m	382	45.02	386	56.12	382	63.58	385	71.01
Arable	8 km	297	65.35	280	66.28	279	65.00	287	66.40
	4 km	295	64.93	275	63.83	277	64.82	282	63.19
	2 km	293	64.43	274	63.63	272	61.22	279	61.79
	1 km	288	64.13	272	62.69	271	61.47	276	60.66
	500 m	293	63.19	271	62.24	271	61.24	276	61.12
	250 m	294	62.86	272	62.76	272	61.62	251	76.12
Semi-Natural Grassland	8 km	377	38.22	381	50.75	386	51.44	392	52.17
	4 km	380	36.39	382	48.82	386	51.05	389	53.18
	2 km	379	36.59	380	48.98	383	51.81	386	53.80
	1 km	377	37.93	377	49.58	380	51.85	381	54.71
	500 m	375	38.53	374	50.50	377	52.91	379	55.47
	250 m	372	39.91	371	50.58	372	53.45	374	55.05
Improved Grassland	8 km	349	46.01	348	59.22	346	65.05	353	65.84
	4 km	348	45.60	345	59.40	344	63.48	350	66.25
	2 km	347	45.06	335	57.47	340	66.64	345	68.37
	1 km	347	46.69	338	63.85	337	68.07	340	70.34
	500 m	345	44.97	333	66.21	332	69.63	333	70.58
	250 m	344	45.84	331	66.70	330	70.29	329	70.71
Mountain, Bog and Heath	8 km	389	39.24	394	48.69	397	50.67	397	52.60
	4 km	388	39.59	391	51.85	396	53.46	395	56.22
	2 km	389	39.15	389	53.21	388	55.91	392	58.11
	1 km	386	42.38	385	55.04	386	57.18	387	60.10
	500 m	384	43.82	383	52.98	383	58.54	385	61.12
	250 m	380	45.71	380	53.16	378	59.08	380	60.83

In comparison to the SOS estimates, coniferous woodland had the smallest range in outputs with 16 days in total. The sensitivity due to in spatial resolution is between 3 and 13 days, and 4 to 12 days due to composite period, thus highlighting no discernible variances in order to determine which input parameters contribute the most variability in the output. The mountain, bog and heathland class had the least sensitivity to composite period with between 2 and 8 days difference, whereas the sensitivity due to spatial resolution is between 8 and 19 days. Broadleaf woodland, semi-natural grassland and improved grassland LSP EOS estimates have a greater sensitivity to variation in spatial resolution to composite period. For broadleaf woodland there is a total range in outputs of 40 days, with between 4 and 14 due to composite period, and 16 to 33 due to spatial resolution. Semi-natural grassland had a total range of 21 days, 3 to 15 due to composite period, and 8 to 18 due to spatial resolution. Finally, for improved grassland, there were a 5 to 24 day range due to spatial resolution and 5 to 15 due to composite period.

7.3.4 Sensitivity of LSP Parameters to Variability in Spatial Resolution and Composite Period

The distribution of SOS and EOS estimates for each land cover class are shown in Figure 7-6 There was an increase in divergence of EOS estimation in comparison to the SOS across all land cover types. For estimating SOS, the dramatic increase in MTCI values indicates an increase in canopy chlorophyll, and thus, is less complex to estimate a precise estimate of the arrival of spring within the time-series. In contrast, EOS occurs gradually over an extended period within the time-series, which causes difficulties in estimating remotely sensed LSP EOS. The results indicate an increase in sensitivity due to an increase in spatial resolution (250 m) in comparison to the coarse composite period (8 km). In addition, there is an increase in sensitivity with shorter composite period (4 day), in comparison to the 16 day composite.

There are visible trends for both SOS and EOS estimates depending on the land cover and sensitivity of LSP to composite period and spatial resolution (Figure 7-7). For SOS for each land cover type the coarse composite period estimates a later SOS in comparison to the shorter 8 and 4 day composites. However, for EOS there a less visible trend depending on composite period. For broadleaf woodland, coniferous woodland and semi-natural grassland, the shorter composite period (4 and 8 days) estimate a later EOS than the 16 day composites.

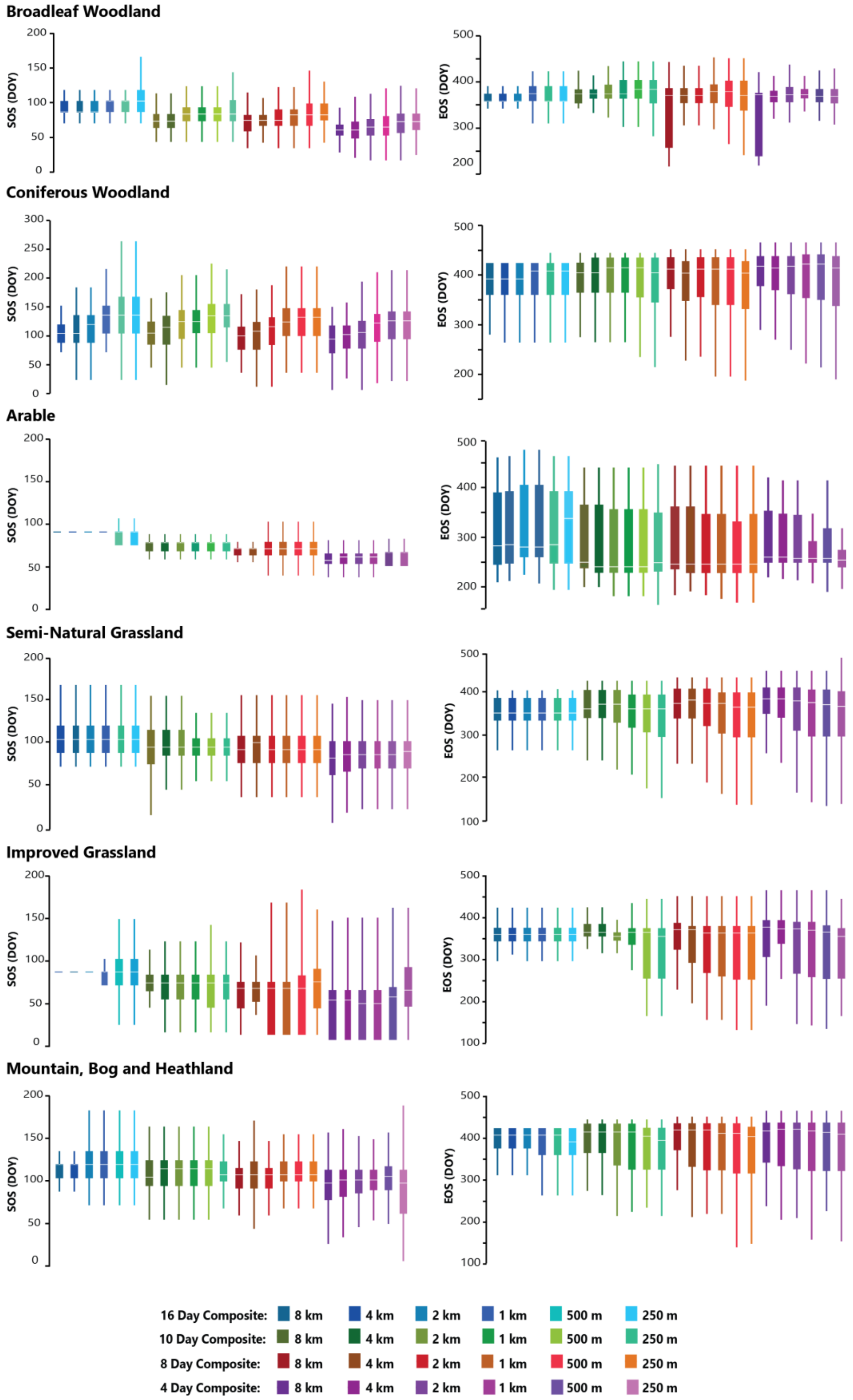


Figure 7-6 Boxplot highlighting the SOS and EOS DOY estimates for each land cover class across the chosen spatial resolution and composite period variables.

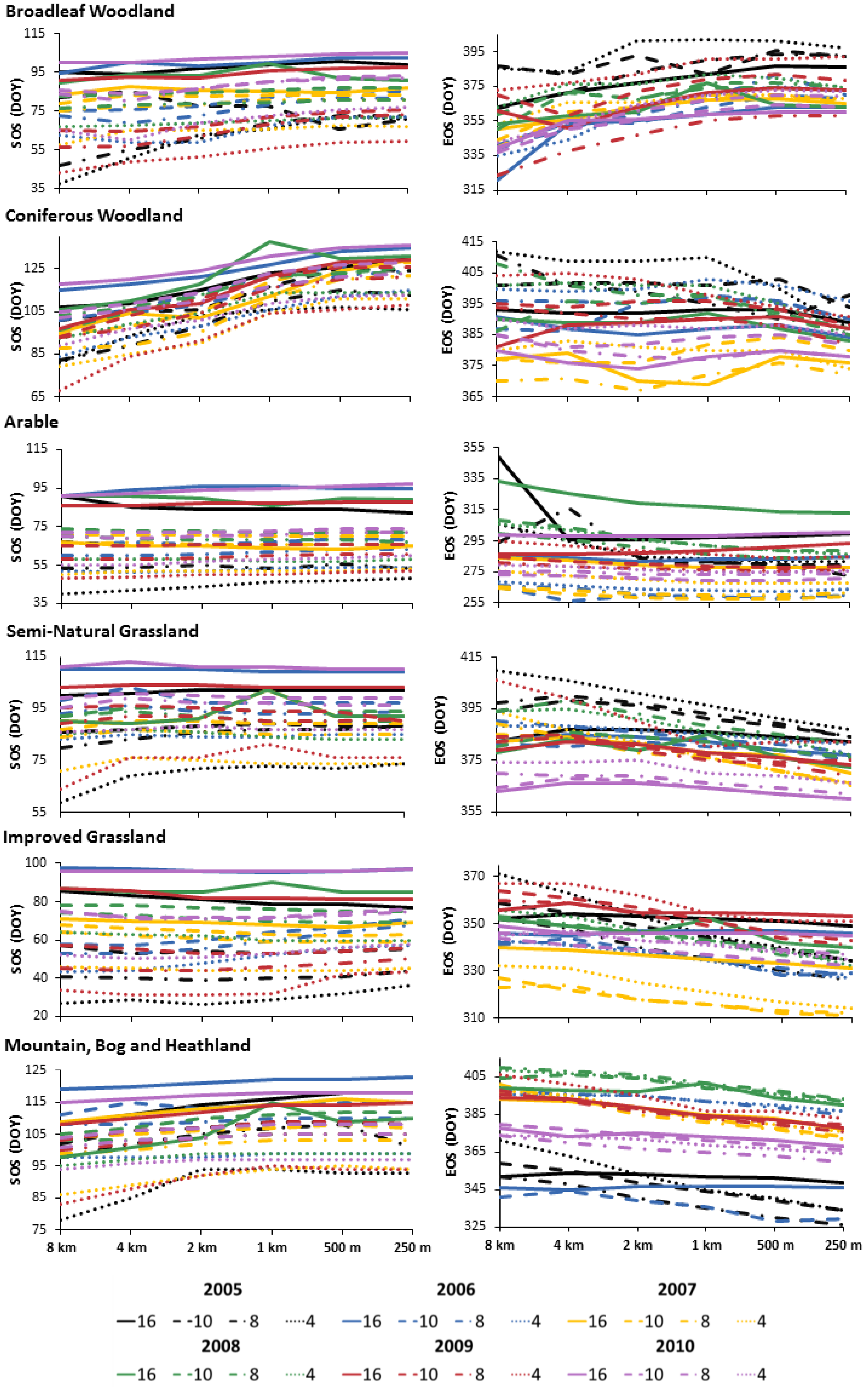


Figure 7-7 The estimated mean SOS and EOS DOY for each land cover class, spatial resolution and composite period. The line highlights the trend of earlier or later estimates.

For broadleaf woodland, there is a later trend for SOS with an increase in spatial resolution and longer composite period. For EOS both the 16 day composites and 250 m spatial resolution datasets estimate a later EOS. Coniferous woodland also showed a later trend in the estimation of SOS due to an increase in spatial resolution and composite period. The results of SOS estimates for arable, semi-natural grassland, improved grassland and mountain bog and heathland, all indicate a slight later trend with an increase in spatial resolution. However, the greatest sensitivity is due to the variance in composite period. A later EOS estimate occurs for coniferous woodland, semi-natural grassland, and mountain, bog and heathland areas with the 4 day composite dataset estimate, and the 250 m spatial resolution datasets estimate an earlier EOS.

7.4 Discussion

The purpose of this research was to examine the sensitivity of LSP estimates of SOS and EOS to spatial resolution and composite period. The simplistic nature of the sensitivity analysis used does not allow for the assessment of interactions between the factors within the model. However, this linear approach does highlight the sensitivity of outputs as a function of variation in spatial resolution and composite period, one at a time. With a mean range of up to 45 days for the estimated SOS and up to 46 days for EOS, due to the changes in the two input parameters, this highlights the potential inaccuracy of current vegetation phenological estimations (Ioos and Lemaître, 2015).

Depending on the chosen land cover type, there was a 26 to 45 day variance in SOS DOY due to the variation in chosen input value for spatial resolution and composite period, and a 16 to 45 variance for mean EOS DOY. Overall, remotely sensed SOS estimates were found to be more sensitive to variation in composite period, as less variation occurred between spatial resolution estimates across all land cover types (Ioos and Lemaître. 2015). For SOS, the coarser spatial resolution (8 km) datasets estimated an earlier SOS, whereas a later SOS occurred in the coarser composite period datasets (16 day). Excluding the coniferous woodland land cover class, the sensitivity to spatial resolution was greater in the 4 day composite with between 4 and 14 days variance in comparison to 1 and 4 day variance in the 16 day composite datasets.

LSP is influenced by several factors that affect the estimations of SOS and EOS including; atmospheric contamination, snow cover, bidirectional viewing, and cloud cover. This study highlights the limitations in the detection of EOS from satellite-sensor data, and shows that the estimates for EOS for natural unmanaged land classes do not occur within the assumed senescence of autumn, September to December. The influence of data gaps in determining LSP EOS estimates, which for the UK is predominately due to increased cloud cover over northern regions. Arable and agricultural land is predominately located in southern England, which had a greater number of cloud free pixels during the study period. Figure 5-8 showed the percentage of cloud free pixels over each year within the study period (2005 to 2010). Obtaining cloud-free coverage during vegetation phenophase events is important for an accurate estimate of SOS and EOS, as cloud contamination biases data values downward (Reed *et al.*, 1994b). In upland and northern regions there were as few as 20% cloud free pixels obtained during each study year.

The influence of data gaps caused by cloud can propagate to large biases of approximately two weeks or more for the determination of LSP EOS (Hmimina *et al.,* 2013). The estimation of EOS is related to the decrease in MTCI values and in some cases can be related to extended periods of cloud covered pixels, which do not relate to LSP parameters (Reed *et al.*, 1994b). The use of ‘gap filling’ data drop-outs using an averaging process eliminated the gaps within the time-series, thus allowing for the LSP SOS and EOS parameters to be estimated. The smoothing of the MTCI values did minimise the effects of the cloud cover contamination and produced a time-series for each land cover type. However, even with using this technique the effect of few cloud free pixels over a substantial period within the time-series caused the EOS estimates to be falsely delayed with incorrect estimates of EOS. The influence of several extended periods of data gaps within the time-series caused a delay of over two weeks within this study. The methodology used here to ‘gap fill’ data drop outs could be improved further to gain a more accurate estimate of EOS.

General trends can be drawn out from this research. The estimates of EOS for arable land, did occur within the agreed time frame for autumn senescence and harvest within the UK. There are visible trends that can be seen from this research. The estimation of EOS for arable land has a greater sensitivity to composite period. In comparison to the SOS estimates, coniferous woodland highlights no discernible variances to determine which input parameters contribute the most variability in the output. For the remaining land cover classes LSP EOS estimates have a greater sensitivity to variation in spatial resolution than composite period. This highlights the variability in sensitivity due to the land cover class and the difficulty in estimating EOS through satellite-derived techniques.

Aggregation of spatial resolution and composite period limits the spatial variability in vegetation phenology that is detectable (Fisher and Mustard, 2007). The earlier SOS estimates for the 8 km datasets highlighted that the species and areas of land that had a later SOS were not represented in the 8 km pixels. The sensitivity due to composite period highlighted that a later SOS occurred in the coarser composite period datasets. Coarse spatial resolutions were assumed to be one of the main sources of uncertainty and bias within LSP estimation. However, the results indicate that composite period has a greater influence over variation in SOS estimates.

The earlier increase in MTCI equating to earlier estimates of SOS in the coarse spatial resolution and shorter composite period datasets could be due to the influence of the understory vegetation. Typically the growth of understory in spring occurs earlier than the canopy to benefit from the additional availability of sunlight and resources (Riegel *et al.,* 1992). Understory vegetation is known to impact the reflected signal from the canopy (Eriksson *et al.,* 2006), and pixels will have a lower greenness value if the understory is cured, rather than green or sparse (Burgan and Hartford, 1993). The sensitivity of these estimates due to the influence of the understory vegetation on SOS and EOS estimates is an additional factor to be considered. In addition, phenophase variation due to differing species within each pixel may also impact the estimation of SOS and EOS. Species with earlier budburst events such as *Aesculus hippocastanum*, may not be fully represented in a pixel dominated by species that occur later in the season such as *Aesculus hippocastanum.* For LSP estimates, the phenophases of the dominant vegetation influence the estimation of SOS and EOS and, therefore, the precision may decrease due to the size of the pixel and the length of composite period utilised in each study.

There are known limitations with using this simplistic sensitivity analysis; it does not account for any relationship between the input variables, the variation in output variables is conditional on the linear behaviour of the model, and it only assesses the selected input(s). However, it enables the assessment of specific input parameter(s) and can identify non-influential inputs before using more complex sensitivity methods.

Given the large number of possible variants across all steps within the remote sensing processing chain and the range of available methodologies, including choice of satellite sensors, vegetation indices and filtering techniques, the sensitivity of phenological parameters and the relationship of input parameters within the modelling process requires further and more in-depth assessment (Ahl *et al.,* 2006; Schott 2007).

For assessing SOS Pouliot *et al.,* (2011) suggested a compositing period of between 7 to 11 days is appropriate to minimise random error. For EOS a shorter composite period may produce a more accurate assessment. However, in regions with greater cloud cover, such as GB, obtaining cloud free pixels is a priority. For the comparison of satellite sensor data to other data sources, such as *in situ* or near surface, the temporal window of observations should be considered. The influence of spatial resolution and the aggregation of land cover limits the variability in vegetation phenology that is detectable. For instance in this study, although the LCM2007 was utilised to determine the various land cover types and extract the regions of interest, the mean accuracy of the dataset is only 83%. Therefore, the aggregation of differing land cover types will have influenced the assessment of SOS and EOS. With an increased spatial resolution there is a reduction in the aggregation of MTCI values over each pixel. Satellite sensors such as Sentinel-2 and NOAA WorldView-3 have a much finer spatial resolution, compared with MERIS and MODIS. Sentinels resolution is 10 m, 20 m and 60 m dependant on the spectral band being utilised, and World View is increased further to 31 cm for panchromatic resolution, 1.24 m multispectral resolution and 3.7 m short wave infrared resolution. Therefore the increase in spatial resolution has the potential of increasing the accuracy of SOS EOS estimates, particularly for small study areas. In addition a higher degree of accuracy in the land cover type would increase the accuracy of the assessment of SOS and EOS for each natural land cover type and increase the understanding of the biophysical events being detected by remote sensing techniques.

7.5 Conclusion

This research highlights the sensitivity of satellite-derived vegetation phenological parameter estimates to variation in input variables within the processing chain and, in particular, to variation in the choice of spatial resolution and composite period. As spatial resolution and composite period are two of the initial parameters chosen in LSP research, it is vital to gain an accurate assessment of their influence on estimates of vegetation phenological parameters. Overall, remotely sensed vegetation phenological parameters were found to be more sensitive to variation in composite period, as less variation occurred between spatial resolution estimates than across all composite periods for both SOS and EOS. With up to 45 days in the range of estimates of SOS and 46 days for EOS, the results indicate the possible inaccuracy of current vegetation phenological estimates.

For SOS, a coarser spatial resolution (8 km) led to an earlier SOS, whereas a coarser composite period (16 day) led to a later SOS. For EOS, the results were dependant on the land cover class. There are known limitations in the detection of EOS from satellite-derived data. This is one area where LSP studies need to improve to provide precise estimates of the length of the growing season.

As highlighted above, the simplistic nature of the sensitivity analysis used does not allow for the assessment of interactions between the factors within the model. However, this linear approach does highlight the variability of outputs as a function of variation in both spatial resolution and composite period. Future research should include variants across all steps within the remote sensing processing technique, including the choice of satellite sensors, vegetation indices and filtering techniques, to determine the sensitivity of vegetation phenological parameters.

Chapter 8 Discussion

Terrestrial ecosystems play an important role in nutrient cycling, pollination, hydrology, atmospheric and climate cycles, and a reduction in biodiversity within ecosystems may have a diverse negative effect on ecosystem services. The UK Natural Ecosystem Assessment in 2009-2011 (Watson *et al.,* 2011) assessed that 30% of the UK's 'ecosystem services' were degraded or in a state of decline. The cause of this degradation is due to urbanisation, intensive agricultural practices, pollution and climate change (Sier *et al.,* 2016). Vegetation is an important factor within land surface processes and land-climate feedbacks, as exchanges of water, soil nutrients and $C0_2$ are driven by solar radiation, temperature, soil moisture and air humidity (Lorenz *et al.,* 2013). Future changes to UK vegetation phenology is dependent on the expansion of urban areas, the impact of the loss of natural land, increase in managed land areas, and environmental changes (e.g. increase in temperature and extreme weather events).

The aim of this research was to characterise UK vegetation phenology, evaluate and compare current vegetation phenology monitoring techniques and identify the controlling factors for vegetation phenophases. The characterisation of phenology is a crucial step in understanding the impacts of climate change and anthropogenic stresses on vegetation, and leads to a greater understanding of environmental and climate controls to be inputted into GCMs (White *et al.*, 2003; Sparks *et al.,* 2000; Badeck *et al.,* 2004). This research utilised several observation techniques from multiple scales, spatially and temporally, including citizen science data, near-surface photography, and remote sensing imagery to detect phenophase events at a national and site-specific level in the UK. The utilisation of several observational techniques allows for a comparison of the phenophase events that are detected by each method. This is particularly useful for the utilisation of remote sensing imagery and the comparison of VI time-series to *in situ* vegetation growth stages.

8.1 Nature's Calendar and Citizen Science Initiatives

In situ observations undertaken for scientific research are usually limited in both temporal and spatial extent (Zhang *et al.,* 2009). Therefore, this has led to an increase in the number of citizen science initiatives utilised for scientific research (Schwartz *et al.,* 2013; Dunkley, 2016). Voluntary citizen science initiatives provide a way to extend environmental observations to populated areas (Cohn, 2008; Conrad and Hilchey, 2011). Citizen science initiatives have therefore influenced the scale of vegetation phenological research being carried out and the relationship between members of the public and professionals (Dickinson, *et al.,* 2010).

Nature's Calendar is the largest *in situ* observational network containing more than 3 million observations from across the UK. Several of the observational records available within this dataset are historical records provided by the public and compiled by the Woodland Trust. The UKPN was launched as an online project in autumn 2000. Following a collaboration with the BBC television series, 'Springwatch', there was an increase in public interest and number of records obtained. The historic records have been previously utilised to assess trends between temperatures and spring phenophase events (Thompson and Clark, 2008). The dataset has also been utilised to assess the association between earlier budburst and light pollution, which has shown that budburst occurs up to 7.5 days earlier in brighter areas (Somers-Yeates, *et al.,* 2016).

Citizen science datasets are valuable for the assessment of country wide vegetation phenological observations at the species level. However, the sporadic nature of these data causes several issues for comparison with satellite-derived estimates. One main concern when utilising citizen science data is the skill and accuracy of the observer, in comparison to professionals (Dickinson *et al.,* 2010). This may lead to increased error or bias within the dataset, especially as few citizen science initiatives offer training to the participants. The accuracy of the data is partially down to the training and advice given to volunteers prior to recording, which makes it quite challenging to provide a robust dataset for validating satellite-sensor observations.

The heterogeneous nature of observational points, and gaps of observations, requires the data acquired by citizen science initiatives to be quality checked. Particularly for observation points at the beginning or end of the time-series of observations. With an increase in public contributions, the spatial density of observation points would increase and assist with the comparison of datasets. In addition, the influence of outliers would be minimised. In several citizen science vegetation phenological networks, autumn phenophase events have fewer observations in comparison to spring events; this is apparent with the Nature's Calendar dataset, as within this assessment there were 275,424 observations for spring and 117,789 observations of autumn phenophase events. For example, *Aesculus hippocastanum* budburst events were observed 8,598 times, and for full tint a total of 4,179 observations.

One of the main limitations in using Nature's Calendar is that volunteers can record within 6 miles (9.65 km) of a single postcode, which equates to a spatial area of 113.09 miles^2 (292.92 km^2). This is one of the prime drawbacks of using citizen science data for scientific research. To increase the locational accuracy of the observations it would be highly beneficial for volunteers to utilise a GPS device to record the exact location of each single observation. However, this may deter observers who are unable to use a 'smart' device such as a modern mobile phone.

Additional factors that relate to the accuracy of observations obtained via the public should be included and evaluated. The age of observers is an important factor that relates to the quality of data recorded, as typically older volunteers with at least two years of university education produce more accurate observations in citizen science data (Delaney *et al.,* 2008; Dickinson *et al.,* 2010). In addition, there are known 'first year effects', as observers produce a greater accuracy of observations over time (Sauer *et al.,* 1994*;* Kendall *et al.,* 1996; Bas *et al.,* 2008; Jiguet, 2009; Schmeller *et al.,* 2009). It has been reported that Nature's Calendar is seeing a decline in the number of observations collated, and a decline in the number of 'expert' recorders that submit more than 50 observations per year (Sparks *et al*., 2014).

The advancements in technology, the internet and smart phones, has made it easier for recorders in the field. (Silvertown, 2009; Burke *et al.,* 2006). As smartphones are becoming more powerful, easier to use, and relatively cheaper to purchase, there have been several applications and websites created to collate citizen science data, such as iSpot (https://www.ispotnature.org/), iNaturalist (https://www.inaturalist.org/), iNature and CitSci. These initiatives are aimed at helping the public identify nature, upload data and be involved in citizen science research.

In the UK, the Natural History Museum have created a guide for citizen science networks on behalf of the UK Environmental Observation Framework, which discusses the main aspects for implementing a citizen science project. This is in partnership with the Biological Records Centre, Centre for Ecology and Hydrology, Natural Environmental Research Council and the Joint Nature Conservation Committee. As there has been an increase in citizen science initiatives, there is an additional fear that with increasing popularity, vegetation phenological studies may reach a saturation point, be duplicated, or compete with one another (Whitfield, 2001). Therefore, guides such as this may assist in mitigating these concerns. The future of citizen science is also likely to benefit from the condition that research funders, such as the National Science Foundation in the USA and the Natural Environment Research Council in the UK, now include the additional factor of science outreach (Silvertown, 2009).

The *in situ* observations collated from Nature's Calendar enabled for species specific analysis to be undertaken. The timing of BB, FL, FF, FT, FLF and FuT per species were assessed. Coexisting tree species are known to leaf out at alternating times. Earlier emerging species, such as *Betula*, budburst 3 weeks or more earlier than later emerging species, such as *Quercus* and *Fraxinus* (Lechowicz, 1984). However, this assessment indicated a difference of up to 17 days between the mean budburst of these species. However, across all species, the range in the mean timing of budburst was up to 48 days (Table 4-5).

For first leaf, the tree species with the earliest mean of first leaf was *Aesculus hippocastanum* (98 DOY), with *Fraxinus excelsior* later in the season (123 DOY). Across all species, there was a range of up to 50 days between the first leafing of vegetation. The phenophase showing the largest range in timing between species was first flowering. *Corylus avellana* flowers a full 100 days before *Rosa canina*, the latest plant to flower of the species observed. These results indicate the range in genetic properties of species, and their adaptations to environmental controls for spring vegetation growth periods. It has been observed that select species may not flower until a certain photoperiod length has been reached over a number of successive days (Bernier, 1988; Bernier *et al.,* 1993; Bernier and Périlleux, 2005), and that flowering timing is also correlated to the timing of snowmelt (Forrest *et al.,* 2010).

The range in occurrence of autumn phenophase was much lower between the species observed. This varied between 24 days for FT, 26 days for FLF and 20 days for FLF. Thus, highlighting the similarly of the controls for autumn phenophase between the species observed. For autumn, it is assumed that photoperiod is the main controlling factor (Basler and Korner, 2012), and therefore, a limit to which autumn can be delayed.

8.2 Satellite-Derived Estimates

Accurate estimates of vegetation phenology parameters through satellite sensors is necessary to detect and quantify inter-annual trends up to a global scale (Poiliot *et al.,* 2011; Kandasamy and Fernades, 2015). Vegetation indices, such as MTCI and NDVI, are an indication of the ‘greenness’ of the canopy (Curran and Steven, 1983) and are an effective measure of vegetation phenology (White and Nemani, 2006; Reed *et al.,* 2009; Dunn and de Beurs, 2011; Jones *et al.,* 2011). As discussed there are several different strategies available to assess vegetation phenology using satellite imagery. This includes the choice of satellite sensor, preprocessing techniques, and methodology for assessing the time-series and extraction of vegetation phenology parameters (Foody and Atkinson, 2002; Ahl *et al.,* 2006). The individual processing steps applied to satellite-derived data impact on the distribution of the output(s) (Schott, 2007; Gahegan and Ehlers, 2000). In this assessment, two factors of the processing steps were assessed, composite period and spatial resolution.

The composites of satellite imagery is necessary due to data gaps caused by the spatial coverage of sensors and cloud cover. However, composite period can restrict the precision with which vegetation phenological parameters can be estimated (Dungan, 2002; Fisher and Mustard, 2007). Spatial resolution is another factor that can influence the detection of LSP, as coarse spatial resolution may not detect small variants across heterogeneous land cover types (Fisher and Mustard, 2007; Iooss and Lemaître. 2015).

This study showed that there was a mean range of up to 45 days SOS estimates and up to 46 days for EOS, due to the sensitivity of LSP to changes in spatial resolution and composite period. Depending on the land cover type, there were 26 to 45 days difference in SOS, and 16 to 45 days for EOS. Overall, remotely sensed SOS estimates were found to be more sensitive to variation in composite period, which differs from the previous research which highlights spatial resolution to be most influential (Zhang *et al.,* 2009; Duveiller and Defourny, 2010). For SOS, coarse spatial resolution estimated an earlier SOS, whereas, coarse composite period estimated a later SOS. For EOS, coarse composite period and coarse spatial resolution estimated an earlier EOS.

The subsampling of land cover type to assess the sensitivity of LSP to composite period and spatial resolution was important, particularly for areas classed as agricultural land. Agricultural land cover is extensive across the world, and has distinctive phenological properties in comparison to natural unmanaged land (Zhang *et al.,* 2006). This was shown in this research due to the notable spatial variation of SOS and EOS between dominant land cover classes across the UK. As 25% of the UK land cover is classed as being agricultural, it was important to individually assess the time-series of each dominant land cover type (Morton *et al.,* 2011).

The relationship between satellite sensor derived estimates of SOS and EOS to phenophase observations is difficult, due to spatial scale of observations, heterogeneous land cover and species diversity, and temporal coverage of observations (Fisher and Mustard, 2007; Hufkens *et al.,* 2012). The comparison is vital to understand and assess biotic responses to climate change (Studer *et al.,* 2007). Usually research comparing *in situ* observations to LSP studies concentrate on a single restricted study site within a defined area (Liang *et al.,* 2011; White *et al.,* 2014). The *in situ* observations are collected at regular intervals with a high spatial and temporal density by experts. Therefore, comparing the two datasets has fewer limitations than when utilising citizen science initiatives, as discussed previously due to the inaccuracies associated with public observations.

The influence of data gaps in determining LSP EOS estimates, which for the UK is predominately due to increased cloud cover over northern regions, is known to be larger than LSP estimates of SOS. This can propagate to large biases of approximately two weeks or more for the determination of LSP EOS (Hmimina *et al.,* 2013). The use of 'gap filling' data drop-outs using an averaging process eliminated the gaps within the time-series, thus allowing for the LSP SOS and EOS parameters to be estimated. When determining LSP EOS, there are additional influencing factors that should be considered. For example, the contribution of marcescence (e.g. leaves tint, but do not fall), which is common in deciduous woodland areas, and freshly fallen leaves. All of these contributing factors may influence the slow decline of VI, and partially explain the overestimation of LSP EOS (Nagler *et al*., 2000). The overestimation of LSP derived EOS is shown in this research, as excluding the assessments of EOS for agricultural land (where cloud cover and leaf litter was minimal), the satellite-derived estimates were later than the observed *in situ* phenophases and assumed senescence of species present.

The comparison of *in situ* phenophase events and LSP parameters is problematic due to the spatial resolution of satellite sensors, as vegetation and land cover are heterogeneous the exact meaning of LSP parameters is unclear. For the characterisation of vegetation phenology increased spatial resolution is generally preferred to coarse spatial resolution imagery (Zhang *et al.,* 2006). Utilising coarse spatial resolution satellite imagery, such as 8 km AVHRR, can prove difficult, particularly in areas with several plant species and varying elevation, which can be a source of error (Fisher *et al.,* 2007; Maignan *et al.,* 2008). In addition, the influence of microclimates (e.g. urban heat islands) on vegetation phenology may be lost (Fisher *et al.,* 2007). Therefore, for the comparison of LSP parameters and *in situ* observations the 250 m resolution imagery was utilised. In addition, as previous research states a composite period of 7 to 11 days provides the best estimate of SOS (Pouliot *et al.,* 2011; Kross *et al.,* 2011), a composite period of 10 days was chosen to assess the correlation between the two datasets.

The spatial variance of vegetation phenology was highlighted through the interpolation of *in situ* observations and the correlation between phenophase events and latitude. One of the main obstacles in the comparison of *in situ* and LSP parameters is the spatial variability of the data. Conventional regression techniques were shown to not be as effective as GWR for the comparison of *in situ* broadleaf species phenophase events and LSP parameters. GWR can reveal local patterns in the spatial distribution of parameter estimates of SOS and EOS as it recognises that the regression model can vary across the spatial extent of the dataset. GWR was shown to be useful in the comparison of events, as across the UK the MERIS MTCI SOS estimates were shown to have correlation with observations of FL. This was particularly strong with observation of *Fraxinus excelsior* and *Acer pseudoplatanus* (r^2 >0.5), indicating the satellite-derived estimates were correlated with the Nature's Calendar data. This result was in agreement with several recent papers that have shown that regional satellite leaf out (FL) data can be accurately matched with *in situ* ground data observations (Delbart *et al.,* 2005; Fisher and Mustard, 2007). However, other research has suggests that the onset of greenness corresponds closely with the start of budburst (Zhang *et al.,* 2006).

For EOS, the observations of the full tint of deciduous species had a larger correlation with EOS in comparison to first tint and first leaf fall. *Quercus robur* has the largest r^2 value of 0.455. However, the relationship between other species autumn observations and EOS is relatively small. Both the MODIS NDVI and EVI, and MERIS MTCI estimates for SOS detected spring growth earlier than all *in situ* observations, and a later EOS than the observed *in situ* autumn observations for FT, FLF and FUT. Thus, highlighting the difference between the detection of spectral increase in vegetation and the changes in vegetation that is observed at the ground level, and the need of further research to be undertaken into the sensitivity of LSP to changes in individual processing steps utilised in remote sensing studies (Schott, 2007).

8.3 Digital Camera Photography

Digital cameras have been successfully utilised to assess vegetation phenology. The number of studies utilising digital cameras has increased in recent years due to the reduction in cost of equipment and the increased need for real-time imaging at a high spatial resolution (Richardson *et al.,* 2007; Ahrends *et al.,* 2008; Richardson *et al.,* 2009; Ahrends *et al.,* 2009; Kurc and Benton, 2010; Ide and Oguma, 2010; Graham *et al.,* 2010). Digital camera photography proved to be an effective measure of vegetation phenology in this research, with data utilised from both digital camera and web camera datasets. There was a degree of noise within the RGB digital channels due to the varying illumination present within the photographic record, which is a known issue when utilising digital camera photography for vegetation phenological research (Sonnentag *et al.,* 2012). In addition, the possible impact of the choice in camera could not be assessed (Sonnentag *et al.,* 2012) as three different cameras were used with varying capabilities, including number of megapixels; ‘Net Cam’, Fujifilm FinePix F30 digital camera and a Mobotix m24m 'security' camera. One notable difference between the photographic records is that the clarity and resolution of the understory photography images were notably greater than both of the canopy photograph series. This was particularly apparent when the photographs from the canopy were affected by rain on the camera lens, which caused a reduced value of EGI and GCC for that image.

The understory photographic record at Wytham Wood could only be compared for a single year against the canopy record due to data availability. The 2012 understory and canopy photography comparisons indicate that understory vegetation growth occurs 26 days before the canopy. Richardson and O’Keefe (2009) state that records show understory species emerge earlier, due to understory vegetation using the strategy of ‘vegetation phenological escape’, which is typically limited to only a few days. However, this research shows that a greater degree of ‘vegetation phenological escape’ between the results obtained in the digital camera photography datasets.

The results do show that the SOS estimates from the RGB digital channels were later than the *in situ* observations for BB at both Wytham Wood (7 days) and Alice

Holt (16 days). However, for FL at Alice Holt, there was only a 1 day difference between the *in situ* observation and the SOS estimate. For EOS, the RGB digital channels produced a delayed estimate of EOS in comparison to FT, FLF and FuT observations. However, similar to the LSP estimates of SOS and EOS, the influence of marcescence and freshly fallen leaves may partially explain the overestimation of LSP. A simplistic visual inspection of the photographs of autumn for each photographic time-series does show that during autumn these factors may have influenced the estimates of EOS (Figure 6-5, 6-6 and 6-8).

8.4 Vegetation Phenology Trends and Controlling Factors

Across the Northern Hemisphere observations of vegetation phenology have shown a trend of earlier spring onset and a prolonged growing season (Studer *et al.,* 2007; Guyon *et al.,* 2011). The advancement of spring onset ranges from 1.4 to 3.8 days per decade over the last 50 years (Studer *et al.,* 2007). The advancement in spring is related to an increase in winter and spring temperatures. This is particularly noticeable in upland areas, where the changes in temperature are affecting species at an increased rate (Gottfried *et al.,* 2012; Pauli *et al.,* 2012; Chapman, 2013). Fitter and Fitter (2002) utilised first flowering data collected over 47 years to highlight vegetation response to climate change, and concluded that, average first flowering date of 385 British plant species advanced by 4.5 days over a 10 year period, in comparison to the previous four decades.

Several researchers have utilised long-term records of *in situ* phenophase events, and state that only observations covering 20 to 30 years should be utilised to assess vegetation phenological trends (Menzel, 2003). This study covered a period of only 8 years (2005 to 2012), therefore, a trend analysis of UK vegetation phenology was not suitable in this research. A degree of temporal stability is required in order to assess the national trend between climate change, advancing spring and delay of autumn, and this was not possible with the temporal coverage of this assessment. However, the relationship between temperature, precipitation, sunlight hours, latitude and elevation, and phenophase events were able to be assessed.

There were seasonal climate anomalies (e.g. extreme weather events) within the study period. The majority of these climate extremes occurred during January, February and December. This was particularly apparent in the deviation of temperature from the long-term average of the CET. For example, the mean monthly temperature in December 2009 was 1.9°C lower, 2.8°C lower for January 2010 lower, and 5.7°C lower for December 2010. However, in contrast the mean monthly temperature of January for 2005, 2008, 2007 and 2012 were between 1.2°C and 2.8°C above the long-term mean. There was also a high degree of variation in temperatures across both spring and autumn, particularly during 2011. The variation of annual seasonal temperatures and the timing of the relating phenophase event was observed in this research. This was most notable in 2010, where the results showed a later SOS in comparison to years where the winter temperatures were not significantly lower than the long-term CET average.

Throughout this research the latitudinal and elevation variation in the timing of vegetation phenological events has been observed. This also mirrors the land cover present across the UK, with northern and mountainous regions land cover predominately consisting of semi natural grassland, woodlands and heathland, in comparison to central and southern areas consisting predominately of managed grassland and arable land. There is a distinct borderline that runs horizontally across the UK, with the northern and higher elevation areas showing a later BB, FL, and FF, in addition to an earlier occurrence of FT, FuT and FLF.

For the spring phenophase events, BB, FL and FF, latitude has a greater influence on the start of season for all species studies, in comparison to elevation. For FL, the species with the largest relationship with latitude *(r* >0.7) were *Quercus robur*, *Fraxinus excelsior*, *Aesculus hippocastanum* and *Quercus petraea*, which are all deciduous tree species. For FF, the majority of species showed a large or moderate positive correlation (r^2 >0.5), excluding *Tussilago farfara* and *Corylus avellana*. However, for autumn phenophase events, FT, FLT and FuT, the relationship with latitude was weaker. *Sambucus nigra, Crataegus monogyna* and *Aesculus hippocastanum* show no significant correlation, which is noted in previous studies (Menzel *et al.,* 2001). The relationship between elevation and phenophase events is weaker than latitude. Upland areas in the UK cover 40% of the land area and are generally defined as areas above 250 to 300 m elevation (Orr *et al.*, 2008). Several of areas of upland have been designated as areas of outstanding natural beauty or National Parks, such as the North Pennines. However, this relationship may have been affected by the reduced number of observations above 500 m elevation, due to the spatial limitation of utilising citizen science vegetation phenological data.

From the assessment of controlling factors at Alice Holt and Wytham Wood, the results indicated that precipitation shows no overall relationship to the Nature's

Calendar *in situ* phenophase events, apart from FuT at Alice Holt. Both sunshine hours and temperature were shown to have a strong correlation to spring phenophase events, predominately FF and FL. The end of dormancy is stated to be controlled by 'chilling' requirements, photoperiod and temperature (Visser and Both, 2005; Peñuelas and Filella, 2009). Temperature is considered to be the dominant factor for FF (Chuine *et al.,* 2010), which was shown to have the greatest relationship at both Alice Holt and Wytham Wood. The influence of 'chilling degree days' was not assessed. However, previous research that utilised the long-term Marsham dataset to determine the influence of temperature and cold temperatures shows that both factors play a strong role in the phenology of all species (Sparks and Carey, 1995; Roberts *et al.,* 2015).

The most notable result of the controlling factors is the relationship of EOS and temperature. EOS was shown to have a greater overall relationship to temperature than to sunlight hours, which is assumed to control senescence (Basler and Korner, 2012). This result contradicts some previous research that showed a weak relationship between these metrics (Chmielewski and Rotzer, 2001; Menzel, 2002; Sparks and Menzel, 2002). However, previous studies utilised long-term datasets with a substantially larger number of observations. Whereas, this analysis covered a period of 8 years, and for particular year's observations of autumn phenophase events were not recorded. Cooke *et al.*, (2012) determined a positive slope for the regression of phenology on autumn temperatures, which was shown here.

The long-term dataset from the Woodland Trust has been utilised alongside GWR to account for the spatial variability of observed phenophase dates of first flowering of three tree species (Comber and Brunsdon, 2014). Previous research indicates that changes in the timing of phenophase events can be linked to changes in land use, in particular the influence the 'urban heat island'. The increase in urban land has been shown to be a predictor of phenological change, with an advance of 1.2 and 0.57 days for flowering per 10% increase in urban land use (Comber and Brunsdon, 2014). As discussed previously, the Nature's Calendar data is limited spatially due to preferential sampling near to highly populated areas (Figure 4-1), as there is a distinct increase in the number of observations recorded in close proximity to urban areas, in comparison to rural. Therefore, the use of GWR for the comparison of the Nature's Calendar *in situ* broadleaf species phenophase observations and LSP parameters accounted for this influence. In addition, as the UK population and urban areas are expected to continually increase, future research should further investigate the link between the ‘urban heat island’ and both spring and autumn phenophase events.

Chapter 9 Conclusion

9.1 Conclusion

The assessment of vegetation phenology is a valuable resource to assess the impact of climate change and changes to terrestrial ecosystems. Assessing vegetation sensitivity to environmental factors enables researchers to identify and model global ecosystem changes. In temperate environments, such as the UK, warming temperatures are related to changes in the timing of spring and autumn phenophases in vegetation. The advancement of spring, and elongated growing season affects ecological processes, agriculture, human health and the economy (Peñuelas and Filella, 2009). Shifts in vegetation phenology are also related to changes in vegetation population dynamics, competition between species and changes to the vegetation communities.

Climate scenarios have estimated that the South of England will have an increased occurrence of drought events. Natural land areas with low soil moisture capacity will be particularly affected by an increase in these events. In addition, a decline in frost events, which has already been noted, will have a knock-on effect to certain species that require a ‘chilling period’ in order to trigger plant growth.

In the UK there are several anthropogenic factors that impact vegetation phenology including intensive agricultural practices, animal grazing, air pollution and urban sprawl. During the 20th century there was a sharp increase in agricultural and managed land in the UK (Dallimer *et al.*, 2009). This coincided with a loss in diversity of species and a decrease in woodland, heathland and moorland areas. Natural areas such as heathland and moorland are important to the population of the UK for drinking water supplies, air quality and carbon storage (Orr *et al.,* 2008). Across the UK there has been an increase in the spatial extent of urban areas due to the increase in population. The increase in population is also combined with an increase in single person households and, therefore, increasing the pressure for further residential properties to be built. In addition to a loss in natural land cover, the impact of ‘urban heat islands’ on vegetation phenology is known to increase the growing season of surrounding vegetated areas (Zhang *et al.,* 2004; Wilby and Perry, 2006).

By assessing current vegetation phenology across the UK this enables future assessments to be completed on the effects of both the environmental and anthropogenic factors on vegetation phenology. Previously, UK vegetation phenology studies have concentrated on single locations or single phenophase events, predominately those occurring in spring (e.g. SOS, budburst, first leaf and first flower) (Collinson and Sparks, 2004; Collinson and Sparks, 2008; Boyd *et al.,* 2011). This assessment aimed to characterise current UK vegetation phenology at a national scale and to assess the relative controlling factors for species present. This research utilised several monitoring techniques at varying spatial scales, including *in situ* citizen data, near-surface digital camera photography and satellite-sensor imagery, and addressed the practicality of each monitoring technique, their limitations and advantages.

For this research the national citizen science vegetation phenological database currently available within the UK, Nature's Calendar, was used to characterise the spatial variation of vegetation species phenophase events. The dataset enabled a national assessment of vegetation phenology to be undertaken at a fine spatial resolution. Due to the latitudinal and elevation variability across the UK, the observations from Nature's Calendar were compared to these two controlling factors for national variability in vegetation phenology. Both metrics are effectively proxies for climatic variation, and the results showed that there is a relationship between latitude and elevation. However, latitude showed a greater relationship to spring phenophase events in comparison to autumn.

The relationship between *in situ* observations and satellite-sensor derived estimates of SOS and EOS is a complex task, particularly when using citizen science data, with varying spatial covering. However, with the utilisation of GWR, this indicated that SOS estimates were shown to have the closest relationship with observations of FL. In comparison, EOS has the strongest relationship with full tint, however, the strength of this is species dependent. The use of remotely sensing imagery to establish the relationship between *in situ* vegetation phenology events enables a greater understanding of the assessment of local, regional and global assessments of SOS and EOS estimates. This is particularly useful in areas with a low population density or that are inaccessible and, therefore, are areas where *in situ* observations are unable to be gathered. However, with the range of satellite sensors, pre-processing, and smoothing methodologies available the choices along the processing chain of remotely sensed imagery need to be carefully acknowledged. The results from the sensitivity of composite period and spatial resolution gave an insight in to the possible variability of outputs depending on only two of the many factors associated with satellite imagery.

In temperate environments, such as the UK, there is a large correlation between vegetation growth (and dormancy) and temperature (Lang, 1987; Kramer *et al.,* 2000; Heide and Prestrud, 2005). For EOS, the collective agreement among many researchers is that photoperiod is the dominant controlling factor for vegetation. The results in fact indicated that temperature is the strongest relationship between both SOS and EOS of vegetation. Therefore, the decrease in chlorophyll in plants and dormancy is more sensitive to declining temperatures. However, this conclusion is limited to the temporal extent of the study period.

Finally, the most important conclusion from this research is that it provides a baseline in which national vegetation phenology for the UK can be assessed further. With increasing stresses on the vegetative landscape of the UK, including climate and anthropogenic factors, it is important to fully characterise and assess the controlling factors for vegetation growth and senescence. The results show that latitude and temperature are two of the dominant factors for vegetation phenology, which is an important factor to consider in regards to northern regions, such as Scotland, where vegetation is more sensitive, and less likely to adapt to a changing climate. This will particularly affect areas where species could lose suitable climate space due to the upland spreading of competitive species and with an increase in drought events, there will be an increase in tree mortality (Trivedi *et al.*, 2008; Adams *et al.*, 2009).

9.2 Limitations and Recommendations

There were limitations within this assessment that have been discussed throughout, including the spatial density of Nature’s Calendar data. There were ‘hot spots’ of observations in areas in close proximity to high populated areas. Therefore, areas with a low population density, such as highland areas in Scotland and Northern England, and Wales, had fewer observational points. Therefore, the possible effect of the ‘urban heat island’ should be noted in regards to the influence on the assessment of the timing of phenophase events. In addition, observations of broadleaf vegetation species were in areas classed as arable, improved grassland and urban, and thus, may not be representative of the aggregate spectral reflectance in satellite pixels and the resolution utilised within this research (>250 m).

The inaccuracies and biases present when utilising a citizen science database have been discussed. This includes, temporal biases for the preference of collection day of the week and incorrect observations present within the data.

Another limitation within this research relates to the study area, due to the percentage of cloud free satellite imagery across the UK within the time-series. Satellite imagery is affected by cloud cover, which results in data gaps. These issues were addressed with the use of gap filling methodology, however, for areas of Scotland there was a high percentage of cloud cover throughout the year.

A recommendation for future work from this research would be to extend the current assessments of the relationship of vegetation phenology to controlling factors for each monitoring technique, with the additional inclusion of growing degree days and chilling period, in order to predict the future responses of vegetation phenology to the current predictions of climate change. This would be particularly valuable at a national scale across all species and land cover types to evaluate changes in LOS, GPP, NPP and carbon storage for vegetation, as well as the implications to agricultural practices, particularly for plant species that require a chilling period.

Appendices

Appendix A Timing of Budburst (BB), First leaf (FL), First flowering (FF), First tint (FT), Full tint (FuT), First leaf fall (FLF) of species observed in Nature's Calendar compiled through several horticultural agencies (RHS etc).

Latin Name	BB	FL	FF	FT	FuT	FLF
Alnus glutinosa	April	April	–	–	–	–
Fraxinus excelsior	April/ May	April/May	–	Oct	Oct	Oct
Fagus sylvatica	April	April	–	Sept	Oct	Oct
Prunus spinosa	–	–	March/April	–	–	–
Hyacinthoides non-scripta	–	–	April/May	–	–	–
Dactylis glomerata	–	–	June	–	–	–
Tussilago farfara	–	–	March/April	–	–	–
Cardamine pratensis	–	–	April	–	–	–
Rosa canina	–	–	May	–	–	–
Sambucus nigra	March/ April	March/April	June	Sept	Oct	Oct
Larix decidua	March/ April	March/April	–	–	–	–
Acer campestre	April	April	–	Sept/Oct	Oct	Oct
Alliara petiolata	–	–	April	–	–	–
Crataegus monogyna	March	March/April	April/May	Sept/Oct	Oct	Oct
Corylus avellana	–	–	March	Late Sept	Late Sept	Nov
Aesculus hippocastanum	March/ April	March/April	April	Sept	Oct	Oct
Ranunculus ficaria	–	–	March/April	–	–	–
Syringa vulgaris	–	–	May	–	–	–
Alopecurus pratensis	–	–	April	–	–	–
Quercus robur	April/May	April/May	April/May	Sept/Oct	Oct/Nov	Nov
Quercus petraea	April May	April/May	April/May	Sept/Oct	Oct/Nov	Nov
Leucanthemum vulgare	–	–	May/Sept	–	–	–
Sorbus aucuparia	April	April/May	May	Sept	Oct	Oct
Betula pendula	April	April	April/May	Sept	Oct	Oct
Acer pseudoplatanus	April	April	–	Sept	Oct	Oct
Phleum pratense	–	–	June	–	–	–
Anemone nemorosa	–	–	March/April	–	–	–
Holcus lanatus	–	–	June	–	–	–

Appendix B Alice Holt mean DOY budburst (BB) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Alnus glutinosa	–	115	85	–	–	107	85	100
Fraxinus excelsior	82	114	114	116	93	105	90	92
Fagus sylvatica	–	106	106	88	92	106	94	114
Sambucus nigra	62	59	64	69	51	56	55	70
Larix decidua	–	98	82	93	93	103	86	94
Acer campestre	–	118	102	108	108	98	97	89
Crataegus monogyna	75	81	74	60	73	84	63	65
Aesculus hippocastanum	80	93	85	81	83	89	83	81
Quercus robur	103	115	101	103	94	108	99	77
Quercus petraea	118	95	–	107	79	103	76	89
Sorbus aucuparia	–	95	–	–	–	80	76	100
Betula pendula	–	109	109	97	95	107	87	93
Acer pseudoplatanus	–	101	102	–	–	110	78	87

Appendix C Alice Holt mean DOY first leaf (FL) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Alnus glutinosa	99	109	97	104	100	106	108	107
Fraxinus excelsior	127	123	118	120	113	114	114	120
Fagus sylvatica	109	121	103	108	104	109	103	114
Sambucus nigra	70	74	59	57	68	80	68	57
Larix decidua	92	109	88	100	92	103	90	94
Acer campestre	91	110	98	102	99	116	103	110
Crataegus monogyna	74	99	73	65	75	89	76	82
Aesculus hippocastanum	94	109	88	93	87	96	85	85
Quercus robur	111	123	104	114	109	115	105	110
Quercus petraea	113	122	83	120	107	119	112	–
Sorbus aucuparia	107	111	99	108	92	110	95	109
Betula pendula	100	111	101	98	99	107	96	99
Acer pseudoplatanus	97	110	97	105	94	102	96	103

Appendix D Alice Holt mean DOY first flower (FF) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Prunus spinosa	76	97	68	58	81	94	71	75
Hyacinthoides non-scripta	94	112	94	100	92	107	98	96
Dactylis glomerata	–	152	–	–	–	157	135	139
Tussilago farfara	47	100	56	–	71	85	80	78
Cardamine pratensis	106	107	102	88	93	106	87	89
Rosa canina	–	153	128	145	146	151	128	150
Sambucus nigra	147	148	117	147	123	127	123	143
Alliara petiolata	103	119	105	111	103	109	99	96
Crataegus monogyna	116	129	111	123	120	128	112	127
Corylus avellana	45	–	31	20	17	36	20	12
Aesculus hippocastanum	120	127	112	125	111	125	110	119
Ranunculus ficaria	53	80	63	47	66	79	63	55
Syringa vulgaris	117	127	109	125	112	119	98	115
Alopecurus pratensis	–	143		129	–	143	113	148
Quercus robur	–	–	116	132	115	–	116	121
Quercus petraea	–	–		126	–	124	–	117
Leucanthemum vulgare	132	140	121	137	138	138	113	134
Sorbus aucuparia	–	134	113	117	–	109	111	135
Betula pendula	–	123		117	–	109	102	93
Phleum pratense	–	123	105	123	116	125	103	142
Anemone nemorosa	78	99	82	87	77	90	89	80
Holcus lanatus	–	–	132	–	–	170	155	152

Appendix E Alice Holt mean DOY first tint (FT) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	287	283	271	271	270	267	263	282
Fagus sylvatica	275	272	266	259	259	261	258	276
Sambucus nigra	262	257	257	254	246	245	252	268
Acer campestre	278	270	259	261	246	260	258	276
Crataegus monogyna	264	269	266	263	251	262	256	280
Corylus avellana	292	281	272	254	257	263	240	278
Aesculus hippocastanum	250	252	255	240	241	243	241	252
Quercus robur	274	273	280	262	264	263	271	282
Quercus petraea	–	273	262	–	261	280	290	274
Sorbus aucuparia	268	284	256	259	254	264	276	276
Betula pendula	263	261	264	261	255	271	265	258
Acer pseudoplatanus	268	254	262	252	251	264	257	272

Appendix F Alice Holt mean DOY first leaf fall (FLF) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	–	296	283	–	288	302	293	302
Fagus sylvatica	–	297	276	–	–	302	299	296
Sambucus nigra	–	298	294	268	268	287	276	270
Acer campestre	–	306	–	–	291	303	306	297
Crataegus monogyna	–	322	287	–	–	296	305	–
Corylus avellana	324	322	296	–	280	297	–	314
Aesculus hippocastanum	297	298	276	267	–	288	275	294
Quercus robur	298	303	–	–	305	303	308	303
Quercus petraea	–	–	297	–	–	308	–	–
Sorbus aucuparia	–	317	–	–	–	306	286	–
Betula pendula	270	303	286	–	266	304	289	299
Acer pseudoplatanus	–	303	284	–	–	306	299	296

Appendix G Alice Holt mean DOY full tint (FuT) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	–	315	–	–	268	305	271	–
Fagus sylvatica	–	316	289	–	287	289	283	289
Sambucus nigra	–	303	–	–	266	–	–	–
Acer campestre	–	317	–	–	274	300	297	292
Crataegus monogyna	–	322	276	–	–	303	299	–
Corylus avellana	–	322	293	–	–	301	–	307
Aesculus hippocastanum	283	288	285	–	274	282	274	292
Quercus robur	–	317	–	292	289	295	301	294
Quercus petraea	–	316	307	–	–	306	–	–
Sorbus aucuparia	–	298	–	–	–	303	279	–
Betula pendula	260	303	289	–	284	298	296	295
Acer pseudoplatanus	–	299	297	–	–	300	288	294

Appendix H Wytham Wood mean DOY budburst (BB) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Alnus glutinosa	89	96	82	90	84	95	84	71
Fraxinus excelsior	112	117	111	102	109	104	105	111
Fagus sylvatica	97	110	95	103	100	100	95	116
Sambucus nigra	55	64	64	76	61	73	51	42
Larix decidua	79	–	79	95	81	103	87	87
Acer campestre	81	99	79	91	89	104	92	102
Crataegus monogyna	67	84	61	48	65	84	64	74
Aesculus hippocastanum	83	93	78	83	77	85	84	85
Quercus robur	102	115	99	107	99	103	100	96
Quercus petraea	96	117	84	105	102	115	–	113
Sorbus aucuparia	89	105	97	95	78	97	91	94
Betula pendula	82	99	92	87	88	98	91	90
Acer pseudoplatanus	89	95	86	98	86	94	86	94

Appendix I Wytham Wood mean DOY first leaf (FL) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Alnus glutinosa	99	109	97	104	100	106	108	107
Fraxinus excelsior	127	123	118	120	113	114	114	120
Fagus sylvatica	110	120	103	108	104	109	103	114
Sambucus nigra	70	74	59	82	68	80	68	57
Larix decidua	92	109	88	100	92	103	90	94
Acer campestre	91	110	98	102	99	116	103	110
Crataegus monogyna	74	99	73	65	75	89	76	82
Aesculus hippocastanum	94	109	88	93	87	96	85	86
Quercus robur	111	123	104	114	109	115	106	110
Quercus petraea	113	122	83	120	107	119	112	-
Sorbus aucuparia	107	111	99	108	92	110	95	109
Betula pendula	100	111	101	98	99	107	96	99
Acer pseudoplatanus	97	110	97	105	94	102	96	103

Appendix J Wytham Wood mean DOY first flower (FF) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Prunus spinosa	64	98	55	64	79	91	82	75
Hyacinthoides non-scripta	101	118	99	104	99	114	101	93
Dactylis glomerata	138	154	140	134	132	138	130	142
Tussilago farfara	81	86	72	44	81	85	80	78
Cardamine pratensis	105	112	98	106	105	114	110	112
Rosa canina	146	152	139	148	147	151	125	151
Sambucus nigra	133	153	129	142	135	146	123	138
Alliara petiolata	109	115	108	109	101	112	98	119
Crataegus monogyna	115	127	105	116	108	126	108	117
Corylus avellana	25	–	17	24	34	46	26	40
Aesculus hippocastanum	119	126	109	112	115	122	110	119
Ranunculus ficaria	61	81	51	50	60	85	72	57
Syringa vulgaris	122	124	108	120	112	121	102	114
Alopecurus pratensis	130	131	117	129	121	130	112	137
Quercus robur	123	123	110	118	117	128	110	117
Quercus petraea	119	131	108	–	107	–	–	–
Leucanthemum vulgare	131	138	116	133	135	139	119	138
Sorbus aucuparia	128	133	119	126	121	132	113	132
Betula pendula	109	116	109	106	106	104	106	111
Phleum pratense	161	160	126	136	142	155	147	163
Anemone nemorosa	94	99	86	81	82	92	87	89
Holcus lanatus	159	160	149	141	142	147	152	132

Appendix K Wytham Wood mean DOY first tint (FT) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	287	283	271	262	270	267	263	274
Fagus sylvatica	275	272	266	271	259	261	258	265
Sambucus nigra	262	257	257	259	246	245	251	255
Acer campestre	278	270	259	254	246	260	258	263
Crataegus monogyna	264	269	266	263	251	262	256	263
Corylus avellana	292	281	272	254	257	263	240	269
Aesculus hippocastanum	250	252	255	240	257	243	241	247
Quercus robur	274	273	280	262	241	263	271	272
Quercus petraea	–	273	262	–	264	280	290	271
Sorbus aucuparia	268	284	256	259	261	264	276	265
Betula pendula	263	261	264	261	255	271	265	262
Acer pseudoplatanus	268	254	262	252	251	264	257	260

Appendix L Wytham Wood mean DOY full tint (FuT) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	295	312	293	287	288	300	299	299
Fagus sylvatica	307	315	301	301	299	303	310	300
Sambucus nigra	276	274	283	281	274	282	258	304
Acer campestre	291	306	291	298	276	290	309	271
Crataegus monogyna	286	308	299	301	287	297	289	274
Corylus avellana	305	304	297	302	297	296	278	307
Aesculus hippocastanum	288	288	293	280	271	267	280	297
Quercus robur	327	316	305	298	303	307	311	308
Quercus petraea	–	320	303	–	302	298	307	–
Sorbus aucuparia	300	306	288	291	286	295	318	307
Betula pendula	300	310	900	295	285	296	308	296
Acer pseudoplatanus	305	315	293	302	292	300	294	295

Appendix M Wytham Wood mean DOY first leaf fall (FLF) per species. Missing values show no observations for that species within the study year.

Species	2005	2006	2007	2008	2009	2010	2011	2012
Fraxinus excelsior	300	299	288	286	286	279	307	290
Fagus sylvatica	304	312	295	297	292	293	303	299
Sambucus nigra	279	288	283	269	274	270	229	278
Acer campestre	310	302	285	266	272	269	285	290
Crataegus monogyna	284	305	293	299	283	289	286	292
Corylus avellana	299	313	295	288	286	290	285	294
Aesculus hippocastanum	289	296	279	284	275	278	278	283
Quercus robur	323	323	311	300	288	290	285	305
Quercus petraea	308	281	294	-	289	298	315	295
Sorbus aucuparia	290	310	283	282	290	280	323	288
Betula pendula	304	307	289	293	280	290	291	293
Acer pseudoplatanus	296	301	291	284	269	283	285	287

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