Direct and Lagged Effects of Extreme Warm Temperatures on Forest Phenology in Europe using Envisat Meris Terrestrial Chlorophyll Index (MTCI) Time Series Data

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by

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Abstract

Recent global warming affects temperate and boreal forest by way of lengthening their growing season. This study aims to investigate if direct increase in forest phenology and productivity translates into lagged effects in subsequent phenological year. The study thus identify and map areas in Europe that experienced extreme warm spring and autumn temperatures between 2002-2012; to extract the phenological and productivity variables of natural forest vegetation in these extreme warm areas from Envisat-MERIS remotely sensed multi-temporal data set; and to investigate direct and lagged effects of extreme warm spring and extreme warm autumn events. The study used 8-day and 10-day composite Meris Terrestrial Chlorophyll Index (MTCI) in addition to Globcover Land Cover classification map, daily mean temperature data sets (1961-1990 and 2003-2011) from European Climate Assessment and Dataset (ECAD). The study applied standard anomaly plus certain conditions to define warm temperature areas in Europe. A point of inflection based method in Discrete Fourier Transformation (DFT) was applied to extract onset of growth (OG) and end of senescence (EOS) for the phenological variables; and integrated MTCI (I-MTCI). For direct positive effect of extreme warm spring on spring productivity, needle-leaved deciduous forest showed statistically significant increase in productivity whiles broad-leaved deciduous forest and mixed forest did not. For lagged effect of extreme warm spring on autumn productivity, the study found no statistical significance difference in forest productivity for all the forest types. In the case of direct positive effect of extreme warm autumn on autumn productivity, needle-leaved deciduous showed marginal significance increase in productivity. But broad-leaved deciduous forest, needle-leaved evergreen forest and mixed forest all showed no statistical significance in direct positive effect. On the side of lagged effect of extreme warm autumn on spring productivity of the following phenological year, mixed forest showed statistically significance for positive lagged effect in its productivity. However, broad-leaved deciduous forest; needle-leaved deciduous forest; and needle-leaved evergreen forest showed no statistically significance in lagged effect.

Key words: Direct effect, Lagged effect, MTCI, Extreme warm spring temperatures, Extreme warm autumn temperatures, Onset of growth, End of senescence, Integrated MTCI

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Chapter 1: INTRODUCTION

1.1 Background

The world today is exposed to unusual increases in air temperature; and these warming temperatures are directly or indirectly affecting plants and animals ecosystems. One important medium by which the global warming temperatures reveal themselves is through the variations in the timing of temperate and boreal natural vegetation growth and development. To this end, several methods and techniques have been rolled out to continuously observe changes in forest vegetation in terms of their growth and development. This essentially enables the measurement of ecosystem productivity in the face of extreme warm global temperatures. It is argued that extreme warming temperatures unusually shift temperate and boreal tree phenology (Menzel and Fabian, 1999;Schwartz et al., 2006;Cleland et al., 2007); and thus these transitions in the phenological variables depending on the season they occur play significant role in determining forest greenness (productivity). In other words, if extreme temperatures occur in spring or autumn; it may impact tree directly or /and indirectly in terms of the quantum of forest greenness in the growing seasons. Because spring seasons activates the productive time length in temperate and boreal forest phenology; it has gained the attention of many researchers and they have therefore researched into the consequences of warm spring on the tree phenology and productivity (Richardson et al., 2010). However, in this work, the impacts of warm autumn events on tree phenology and productivity (leaf greenness) are considered in addition to warm spring. The findings of this study should equip forest managers, policy makers, planners and other stakeholder with spatial information by which they can conserve terrestrial ecosystems(Dash et al., 2010; Richardson et al., 2010). Further, the outcome of this study can serve as input data to run regional climate models.

Vegetation phenology, which falls under the broad term land surface phenology (LSP) has been described as the seasonal pattern of variation in plant cover observed from remote sensing technology; and it thus serves as a surrogate measure of global change (Piao et al., 2006; White et al., 2009; Tan et al., 2011). The phenology of plants extends from observing the onset of growth and photosynthesis in the spring and senescence and abscission of vegetation in the fall (Cleland et al., 2007 ; Morisette et al., 2009) .

Monitoring changes in plant growth and development through time is essential to gather information in sustaining system earth. This is to say that vegetation phenology is at the heart of ensuring effective cyclical flow of carbon, water and energy between vegetation and the atmosphere (Peñuelas & Filella, 2001; Kaufmann et al., 2008; Piao et al., 2008) . It therefore stands to reason that it is possible for a small shift in the normal vegetation phenology to throw the ecosystem and climate system out of sync (Schwartz & Reiter, 2000; Piao et al., 2006; Menzel et al., 2006) . And when this happens terrestrial life forms may be affected. For instance, in the event of advanced spring, carbon sequestration may be unusually high which can affect the normal ways by which terrestrial life forms interact and function in the ecosystem (Peñuelas and Filella, 2001; Walther et al., 2002) . As a result of current experiences of earth warming, many research efforts have been thrown into mapping and estimation of vegetation phenology at local, regional and global scales (Jeganathan et al., 2010; Boyd et al,2011) . The mapping and quantification of phenological variables is essential since shifts in plant phenology have bearing on climate change, the structure and functioning of the ecological system and the earth carbon cycling (Cleland et al., 2007). This study concentrates on natural forest vegetation predominant in Europe so as to have a broader perspective of changes in leaf amount of these various vegetation types as they grow through the temperate seasons of the year. The natural vegetation, for the purposes of this study, specifically refers to broad leaved deciduous forests; needle leaved evergreen forests; needle leaved deciduous forest; and mixed forest. Satellite remote sensing is applicable to extracting the phenology of forest canopy. To this end, the study retrieved onset of growth(OG) and end of senescence (EOS) of these temperate-boreal vegetation types (Schwartz et al., 2002; Verstraete et al., 2008; Jeganathan et al., 2010). Onset of growth (OG) is a plant phenological metrics which defines the dates of leaf appearance of the vegetation as a result of the resumption of intense photosynthetic activity (White et al., 2009) ; and mainly occur in the spring season of the temperate regions. And the other phenological parameter of this study is called the end of senescence (EOS). The end of senescence marks the end of the disappearance of green foliage of plants.

Observing the phenology of plants provides the opportunity to identify the impacts of climate change (Menzel, 2002). Vegetation phenology is closely connected to the climate (Cleland et al., 2007); and as a result, temperature may influence the timing of plant phenology (Cleland et al., 2007). For example, Badeck et al. (2004)

in their work, *Responses of spring phenology to climate change*, suggest that the climate is responsible for an earlier spring onset and longer growing season in plant phenology. Therefore, it is possible to conclude that incessant analyses of inter-annual phenology is an important way to monitor native forest responses to global-scale climate variability (Fisher and Mustard, 2007).

1.2 Research Problem

Europe, like the rest of the temperate regions of the world, has its vegetation growing and peaking up in spring and summer respectively; declining in autumn and resting in winter. Tracking the growth and development dynamics of temperate vegetation is essential in understanding the impacts of climate on terrestrial life-forms (Reed et al., 1994; Chuine & Beaubien, 2001; Morisette et al., 2009). The seasonal appearance and disappearance of plant foliage cannot be underestimated since it regulates biophysical relationship that exists between land and atmosphere such as albedo and water and energy exchanges (Wilson & Baldocchi, 2000;Molod et al., 2003). For instance, as a result of global warming the timing of the growing seasons of temperate vegetation have unusually lengthened and has thus increased photosynthetic activity which now determines how much of CO_2 and H_2O the atmosphere holds (White et al., 1997; Schwartz, 1999;Cleland et al., 2007; Richardson et al., 2010). Even though there is some merits in lengthening plant growth by way of providing increased atmospheric carbon sink (Lucht et al., 2002; Whitehead, 2011; Marchetti et al., 2012); however, exceptionally longer photosynthetic duration may reduce surface albedo and hence cause terrestrial warming (Betts, 2000). Furthermore, vegetation phenology sets the tone for competition and interactions (via the complex food chain and food web processes) among plant and animal species in the ecosystem. For humans, the seasonal changes in vegetation inures ecosystem services such as food; fibre; medicine and beautiful landscape for recreation (Badeck et al., 2004; Kauserud et al., 2012)

In spite of these importance the timing of plant phenology brings to the biosphere, recent temperature anomalies in intermediate and high latitude Europe have been responsible for early onset of growth and late end of senescence (Roetzer et al., 2000; Walther et al., 2002; Parmesan & Yohe, 2003; Mimet et al., 2009).

Extreme climatic variables stemming from climate change has the tendency to influence forest composition and ecosystem productivity (Hufkens et al., 2012). Mabuchi et al., (2009) in their work

Numerical Investigation of Climate Factors Impact in East Asian Terrestrial Ecosystem observed a high anomalous surface temperature which happened in the cold seasons and therefore generated huge increases in gross primary production in that ecosystem.

Further, a simulated extreme warm winter conditions carried out in Sweden showed that bud development of Vaccinium myrtillus will be delayed up to 3 weeks in the following spring and these warming winters will also decrease flower production by more than 80% (Bokhorst et al., 2008).

Another result of climatic variable anomaly in frost event following early spring leaf out across northeastern United States, decreased annual gross ecosystem productivity by 7-14 % at high elevation forest areas and satellite remote sensing confirmed this damage by the frost event (Hufkens et al., 2012).

With the changes anomalous temperatures bring to bear on vegetation phenology; it has thus become imperative to investigate the extent to which anomalous warm temperatures in spring and autumn phenology directly affect forest greenness (productivity) and also to investigate if this direct effect translates into lagged effect in subsequent spring or autumn phenology.

1.3 Research Objectives

The main objective of this study is to investigate if direct impact of extreme warm events in one phenological phase translates into lagged effect on subsequent phenological phase.

1.3.1 Specific objectives

i. To identify and map areas in Europe that experienced extreme warm spring and autumn temperatures between 2002 and 2012
ii. To extract phenological and productivity variables of forest vegetation in these extreme warm areas from Envisat-MERIS remotely sensed multi-temporal data set
iii. To investigate direct and lagged effects of extreme warm spring and extreme warm autumn

1.4 Research Questions

i. Where in Europe experienced extreme warm spring and autumn between 2002 and 2012?

ii. How are the forest phenology and productivity variables extracted?

iii. To what extent does direct positive effect of extreme warm events translate into lagged effect?

1.5 Research Design

1.5.1 Data sets

The study uses mean temperature climatic data set sourced from the European Climate and Assessment Dataset (ECAD). Besides, in this study, radiometric sourced vegetation index product called MERIS Terrestrial Chlorophyll Index (MTCI) collected by the Envisat platform of the MERIS sensor which was flown over Europe in the mid-periods of 200-2012 to generate 8-day and 10-day composite time series data were used. In this study, only data collected form the years 2003-2011 were resorted to. This is because of the need for complete year data files for the study. Finally, the study made use of the GlobCover Land Cover classification v2.2 product to identify the vegetation types and their spatial location in Europe.

1.5.2 Sampling method

Since the area coverage of natural vegetation types in Europe is continuously large the study collected samples of these natural vegetation. An MTCI pixel size (~1km^2) is used as the threshold for selecting these samples. It thus means that the size of a vegetation type sampled should be at least 1km^2. To this end, samples of broad leaved deciduous forest; needle leaved evergreen forest; needle leaved deciduous forest; and mixed forest were collected.

1.5.3 Statistical method

In this work, standardized anomaly test was used to determine anomalous temperature areas in Europe between 2003-2011 years. For descriptive statistics of the phenological and productivity variables extracted in this study, median was applied in order to curtail the influence of outliers since samples from different locations were grouped into similar latitudes for analysis. However, for the purposes of determining the extent of difference between mean values of phenological and productivity variables for normal and anomalous events, the study applied Student's one-tailed t-test analysis (Student, 1908). Also, this is because the sample sizes for all the forest types are less than thirty.

1.6 Conceptual models

In the light of evaluating the relationship between forest phenology and forest productivity (in terms of amount of leaves synthesized), the study dwells on certain theories to investigate its objectives.

In the case of extreme warm spring conditions (anomalous spring event), the study expects that temperate and boreal forest would generally experience earlier onset of growth and thus increased forest productivity. This is because the extreme warm temperature might step up the rate at which microbes in the soil convert dead organic matter to inorganic forms for the trees (nitrogen mineralization); and this in the end might increase tree photosynthetic activity since more nitrogen is made available (Richardson et al., 2009). In similar vein, early start of growth as a result of unusual warm spring could facilitate greater growth of tree foliage which may lead to increased trapping of solar radiation for further canopy photosynthetic activity (Jolly et al., 2004). But having looked at the positive sides where warm spring temperatures may lead to direct and immediate increase in forest productivity, the study conversely theorized that if the intensity of the warm spring is high then the study expects late senescence of leaves in autumn because of extension in growing season length. This is because the study anticipates there would be some degree of heat from the preceding extreme spring available in autumn to ensure extension of productivity into autumn.

In extreme warm autumn cases, the study theorizes again that mineralization would be active and trees could still continue with carbon assimilation (Pastor et al., 1984; Larcher, 1995); and this may delay start of senescence in autumn. A delay in start of senescence therefore suggests increased annual greenness in forest ecosystems. However, it is expected in this study that the warm autumn may lead to early or late spring in the following production year.

By these conceptual models, the study recognizes three possible lagged effects in forest greenness when there is direct positive effect. They are no lagged effect; positive lagged effect; negative lagged effect (Figures 2, 3, 4, 5, 6, and 7). No lagged effect is when the total forest greenness for normal spring or autumn is equal to total forest greenness for anomalous spring or autumn. Positive lagged effect is when the total forest greenness for anomalous season is greater than total greenness for normal season. Contrarily, if total forest greenness for anomalous season is short of total greenness for normal season then there is negative lagged effect

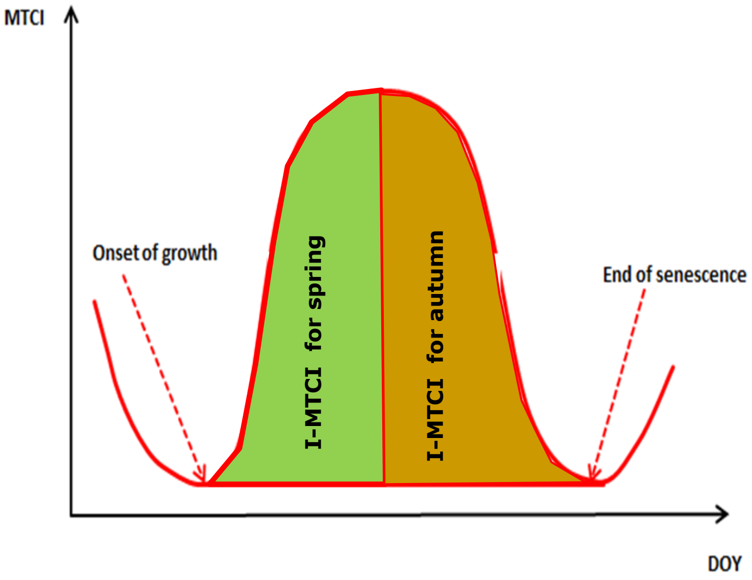

Figure 1. Normal phenological profile

This is a representation of a normal phenological profile derived from MTCI values over time series, day of year (DOY). The onset of green variable marks the beginning of forest growth whiles the end of senescence defines the time forest growth ceases. Integrated MTCI (I-MTCI) connotes the summation of all the MTCI values of the area under the curve; hence it is named I-MTCI for spring and I-MTCI for autumn to measure forest productivity for spring and autumn seasons respectively.

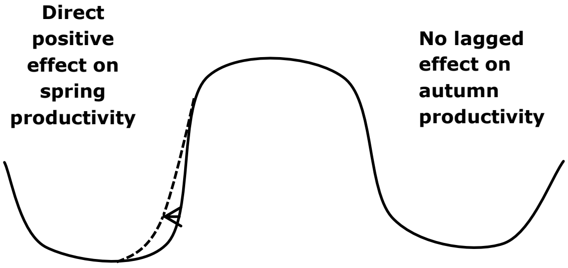

Figure 2. Extreme warm spring: No lagged effect model

This model theorizes that earlier OG in spring, as a result of extreme high temperatures, ensures direct positive effect on spring productivity which in turn may not have any lagged effect on autumn productivity. The broken lines show anomalous spring productivity whiles the arrow depicts a shift from normal spring productivity to anomalous spring productivity; thus connoting direct positive effect on spring productivity.

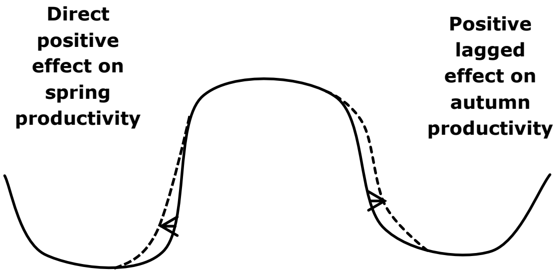

Figure 3. Extreme warm spring: Positive lagged effect model

This conceptual representation indicates that direct positive effect in spring forest productivity as a result of anomalous warm spring season might lead to positive lagged effect in autumn productivity. The arrow at the right hand shows a shift from normal autumn productivity to anomalous autumn productivity in the positive direction connoting increase in autumn forest productivity when compared to normal.

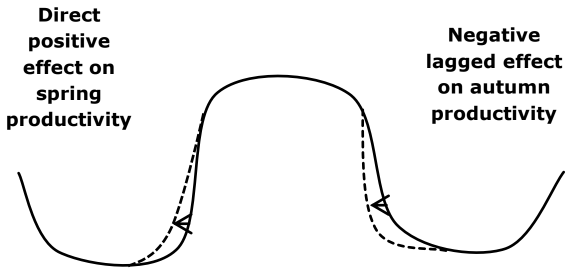

Figure 4. Extreme warm spring: Negative lagged effect

This conceptual representation indicates that direct positive effect in spring forest productivity as a result of anomalous warm spring season might lead to negative lagged effect in autumn productivity. The arrow at the right hand shows a shift from normal autumn productivity to anomalous autumn productivity in the negative direction connoting decrease in autumn forest productivity when compared to normal.

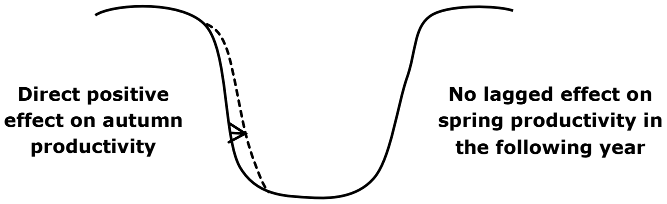

Figure 5. Extreme warm autumn: No lagged effect

This model theorizes that delayed EOS in autumn, as a result of extreme high temperatures, ensures direct positive effect on autumn productivity which in turn may not have any lagged effect on subsequent spring productivity. The broken lines show anomalous autumn productivity whiles the arrow depicts a shift from normal autumn productivity to anomalous autumn productivity; thus connoting direct positive effect on autumn productivity but without any lagged effect on spring productivity

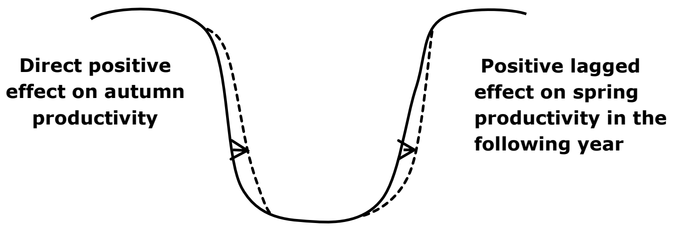

Figure 7. Extreme warm autumn: Positive lagged effect model

This conceptual representation indicates that direct positive effect in autumn forest productivity as a result of anomalous warm autumn events might lead to positive lagged effect in spring productivity. The arrow at the right hand shows a shift from normal spring productivity to anomalous spring productivity in the positive direction connoting increase in spring forest productivity when compared to normal.

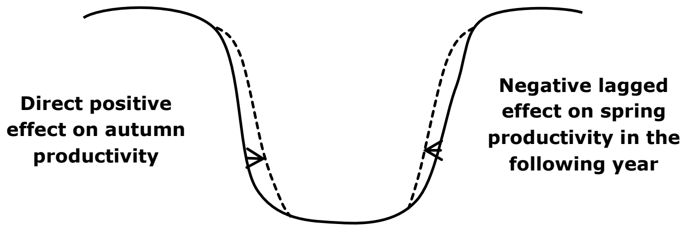

Figure 6. Extreme warm autumn- Negative lagged effect

This conceptual representation indicates that direct positive effect in autumn forest productivity as a result of anomalous warm autumn events might lead to negative lagged effect in spring productivity. The arrow at the right hand shows a shift from normal autumn productivity to anomalous autumn productivity in the negative direction connoting decrease in autumn forest productivity when compared to normal.

Chapter 2: LITERATURE REVIEW

2.1 Role of temperature to vegetation phenology in Europe

Endogenous factors such as phytohormones; and environmental variables such as light (photoperiod) and temperature have been regulating growth and development in plants (Schnelle, 1955; Larcher, 1995). In temperate and boreal Europe, seasonal alterations in light and temperature cues have been regulating the various annual phenophases. A school of thought gives substantial credence to the influence of photo-periodism in the regulation of growth and development of some ecotypes (Pauley and Perry, 1954; Wareing, 1956; Howe et al., 1996). However, other scientists agree that temperature modifies important phenological events in trees tagged as dependent on photoperiod for development (Mølmann et al., 2005; Fracheboud et al., 2009; Tanino et al.,2010). Unlike temperature, the influence of photoperiod in regulating bud unfolding is restricted to few species such as beech (*Fagus sylvatica*) (Heide, 1993; Vitasse and Basler, 2013); thus in many other species the role of photoperiod in timing of bud break out is not clear (Hanninen and Kramer, 2007; Chuine et al., 2010) . In order words, no research findings have shown that photoperiod is more influential than temperature in the determination of leaf colouring (Delpierre et al., 2009), leaf unfolding or flowering in tree species; even including beeches which are sensitive to photoperiod. Conversely, studies done earlier by some scientists espouse the idea that for either temperate or boreal tree plants, leaf unfolding is highly sensitive to temperature at both endodormancy (the type of dormancy induced by internal conditions of the plants) and ecodormancy (dormancy instigated by external, environmental conditions) phases (Chuine et al., 2003;Hanninen & Kramer, 2007). Air temperature is thus the most crucial external cue in determining the seasonal onset and cessation of tree growth in Europe especially when it comes to spring phenology (Schwartz et al., 2006). Sequence of optimal temperature range ensures optimal growth of plants by indirectly supplying energy for metabolic processes and development; and also directly regulate the development of plants via the processes of thermoinduction; thermoperiodism and thermomorphism (Larcher, 1995) . Similar to all growth processes, temperature variations have direct relationship with photosynthetic activity of plants (Michelsen et al., 1996;Methy et al., 1997;Ormrod et al., 1999;Higuchi et al., 1999). For example, temperature is significantly needed at the stage of CO_2 fixation and eventual making of photosynthates. A chain of different reactions is involved in photosynthetic processes. First of all, the pigments in the plant's chloroplasts intercept energy from the sun; transported through electron transport chain and then converted into chemical energy. The chemical energy is then made use of by temperature-dependent reactions known as Calvin cycle (or dark reactions) to fix CO_2 and eventually makes sugars. Some work have been done to understand the common relationship that exists between temperature and photosynthesis (Kolari et al., 2007; Estrella et al., 2009). For example, warmer temperatures have been responsible for a corresponding increased plant growth in the northern high latitudes(Myneni et al., 1997; D'Arrigo et al., 2008). Even though there is no established linear relationship existing between tree phenology and warming temperatures (Morin et al., 2009; Morin, Roy, Sonie, & Chuine, 2010) , however, dendrochronology research carried out have supported the hypothesis that there is increased growth in events of warmer springs and autumns in mid and high latitude zones(McKenzie et al.,2001; Bunn et al.,2005). Conversely, warmer temperatures experienced in high latitude regions since 1950 have generally indicated unexpectedly lower growth in many species in the Northern Hemisphere (Briffa et al., 1998; Lloyd & Fastie, 2002; D'Arrigo et al., 2004; D'Arrigo et al., 2008) . To this end, many plausible reasons have been offered by scientists to explain such divergence; and one of these explanations is the evidence that warm summers in the high latitude regions are exceeding the optimal temperature for growth in tree plants (Way and Oren, 2010)

Generally, plants need a prerequisite optimal temperature range of approximately 0^0C to 40^0C to induce photosynthetic activity (Went, 1953). However, plants in Europe like other temperate regions need an optimal temperature range of approximately 0^0C to 10^0C for germination to commence (Larcher, 1995). Further, in temperate regions, some of its woody plants such as Picea, Pinus and Fagus take off growth processes if hitherto opened up to conditions of low temperatures for several weeks (Halevy, 1989; Dahanayake & Galwey, 1998). Tree species in mid and high latitudes are active for two quarters of the year (spring and summer) and dormant in the latter part of autumn to winter. It is therefore the role of temperature to activate photosynthetic activity of the trees after a rest period in winter. This phenomenon is as a result of forcing temperatures (Nienstaedt, 1974; Larcher, 1995). On the other hand, after the photosynthetic phase, the trees in temperate and boreal climates assume a dormant period (Hanninen et al., 1990; Partanen et al., 1998). This dormancy period is necessary for the plant life and thus its success in turn affects the following photosynthetic phase (Junttila and Hänninen, 2012). In the dormancy period, air temperatures are supposed to decrease to ensure the chilling requirement (Myking & Heide, 1995; Guilbault et al., 2012) plant ecosystem needs. Therefore, the alternation of chilling and forcing temperatures regulates the active and inactive photosynthetic rhythm of terrestrial woody plants in Europe. However, in real life situations, temperatures may go higher or lower than the required optimal temperature range conducive for normal plant growth and development. And when this happens at greater intensity and longer duration, plants may be opened up to irreversible injury which may harm the photosynthetic system (Joslyn & Diehl, 1952; Berry & Bjorkman, 1980; Lafta & Lorenzen, 1995) .

2.2 Recent changes in the world's climate

Over the years many research activities have been carried into studying the climate; it is now generally remarked by scientists that the earth is presently experiencing unusual warming. For the past century the earth has experienced about 0.6 ^{o}C warming in its climate which was pronounced in the years between 1910 and 1945 as well as since 1976 (IPCC, 1996). However the global warming experienced since 1976 is said to be about two times intense than what the earth experienced in its past 1000 years(IPCC, 2001). Further, scientists have predicted the world's temperatures to go up by 1.1^{0}C–6.4^{0}C by 2100 as a result of the growing greenhouse gases in the atmosphere and alterations in how the earth's surface reflect energy; and thus forest biomes in high latitudes may warm by approximately 10^{0}C (IPCC, 2007). Indeed, greenhouse gases (GHG) emission, primarily as a result of human activities, have been the major culprit for the unusually high temperatures Europe, like the rest of the world, experiences (IPCC, 1996;Christidis et al., 2012). However, the variability in Europe's climate is naturally affected by the North Atlantic Oscillation (NAO) phases; and since 1980s the strong NAO phase has been responsible for the warming temperatures in Europe(Hurrell and VanLoon, 1997), however, anthropogenic GHG forcing has been stimulating the NAO (Ulbrich and Christoph, 1999). Yan et al., (2002) therefore examined the trend of extreme temperatures in Europe using daily temperature series data.

With the abnormal increase in global temperature averages, it is obvious that terrestrial ecosystem would have direct brunt of the associated consequences. Many works have been done to investigate the impacts of global warming on plant phenology (Chmielewski and Rötzer, 2001; McCarty, 2001; Badeck et al., 2004; Prieto et al., 2009) . In Europe, the study of effects of extreme warming temperatures on terrestrial ecosystems which for the purposes of this work is narrowed down to forest phenology and productivity has been severally researched and documented (IPCC, 2001; Walther et al., 2002; Parmesan & Yohe, 2003; Root et al., 2003). One obvious way to detect the responses of terrestrial land forms to extreme warming temperatures is to monitor the processes of vegetation phenology (Walther et al., 2002).

Forest biomes in intermediate and high latitude Europe have been responding to the warming temperatures since the early part of the 1960s as a result of research findings which show that onset of spring growth starts approximately 6 days earlier whiles offset of growth in autumn is delayed by approximately 5 days; and hence the length of annual growing season has been extended up to about 11 days (Menzel & Fabian, 1999).

2.3 Field observation of vegetation phenology in Europe

The general interest in phenology dates back to days of early civilization when people realized changes in their environment regarding plant development; however, lack of systematic data collection by then did not encourage the study of phenology as a discipline (Schwartz, 2003).

Since the early part of 750 AD, Japan have collected and documented phenological data on a cherry plant in the royal court of Kyoto and thus been credited as having the longest record on plant phenology; however Europe have got the most in-depth and extensive culture in recording phenological events (Menzel, 2002). This is because Europe has got long series of continuous phenological information. These collectors of phenological events in Europe are mainly a group of volunteers or experts interested in nature. Individual phenology data collecting groups have been knitted into a network of phenology groups at international (European) or national or regional and local levels. The earliest phenological network was formed by Linne (1750-1752) in Sweden (Schnelle, 1955); it was Europe-wide and was thus put under the administration of the Societas Meteorologica Palatina at Mannhein (1781-1792) (Reed et al., 2003).

In 1957, Schnelle and Volkert constituted the International Phenological Gardens (IPGs) to enable Europe compare phenological data by monitoring phenological events of genetically identical plants. The IPGs area coverage stretches from 42 to 69^0N and from 10^0W to 27^0E; which is obviously made up of dissimilar climatic types (Reed et al., 2003).

In a related development, phenology groups also exist at the national level as national networks. Generally, many of these national networks are run by National Weather Services (Schnelle, 1955). The data generated by these national groups are both internally and externally used for research in areas including ecology, forestry and climate and climate change impacts assessment (Reed et al., 2003).

Beyond the international (European) and national networks, phenology observation groups exist at local or regional levels; this is to facilitate research peculiar to such fine scale.

Even though at a point, ground data collection of phenological variables went into oblivion. Recently, the impacts of climate change have resulted in the renaissance of phenology study in Europe; and this has thus gets the attentions of European governments. For example, in 2001 a body known as European Phenology Network (EPN) was put together with an aim to " improve monitoring, assessment and prediction of climate induced phenological changes and their effects in Europe" (Reed et al., 2003). EPN wants to ultimately make popular the use of phenological observation and research, and to encourage European member states to apply phenological data to study the impacts of climate change and suggest ways by which Europe can adapt to these impacts. The activities and programmes of the EPN are financed by the European Commission.

Phenology study is seen as an indirect way to measure the impacts of climate change. And since plant growth and development in Europe is mainly tied to the seasonal cycles of photoperiods and temperature (Schwartz et al., 2006); it is possible to investigate the impacts of extreme temperatures on the phenological cycle of forest vegetation across Europe.

The International Phenological Gardens (IPG) in Europe collects ground observation data on plant phenology. And recent studies into the IPG data show increase in the length of growing season across Europe (Menzel, 2003). Chmielewski & Rotzer (2002), in their work "annual and spatial variability of the beginning of growing season in Europe in relation to air temperature changes", applied IPG phenological data covering 1969-1998 to investigate the beginning of growing season of some tree species across Europe as a function to mean air temperature changes.

Based on phyto-phenological national databases in Europe for the period 1951-1998, changes in spring phenology was observed (Ahas et al., 2002). Further, Menzel et al., (2006) applied in situ observed phenological variables from twenty-one (21) European national databases to study the responses of species to global warming. They concluded that species' phenology responds to the unusual warming of the continent Europe.

Clearly, direct observation of vegetation phenology which precedes satellite monitoring of phenology provides in-depth information on each and every individual species at fine temporal resolution. However, the ground-based observation of phenology is fraught with limited spatial coverage and lack of objectivity. This problem of limited spatial coverage therefore makes it difficult for researchers to apply field data for broad studies of biome-scale responses to changing climate (Ricotta and Avena, 2000); Schwartz et al., 2002; (White et al., 2005)

2.4 Remote sensing vegetation phenology

The development of satellite remote sensing technologies has led to the collection of data on vegetation dynamics from space. This is to say the design of space-crafts which host a number of sensors has brought a paradigm shift in the way earth resources are monitored. And therefore for well over three decades data churned out by satellite-based remote sensing technology have contributed enormously to the study of vegetation phenology (Reed et al., 1994; Reed et al., 2009; Zhao et al., 2012). By the advancement in remote sensing technologies, terrestrial resources including vegetation are observed at different temporal and spatial scales (Ricotta & Avena, 2000; Elmore et al., 2005; Fisher et al., 2006; Hoepfner & Scherer, 2011 ; Bobée et al., 2012; O'Connor et al., 2012) . In other words, the strengths of satellite-based remote sensing such as repeated sampling and synoptic coverage have made it possible for vegetated lands to be monitored at landscape levels (Jeong et al., 2011); and this is commonly known as land surface phenology (De Beurs & Henebry, 2004; Ganguly et al., 2010). To date many satellites have been put in space; and these satellite-based sensors have generated voluminous multi-temporal data on the seasonal rhythm of vegetation. Therefore, in land surface phenology, phenological information are derived from time series data churned out by space-borne satellite sensors; and thus related to climatic variations (Tan et al., 2008). Even though space-borne satellite observation of terrestrial vegetation has expanded the frontiers of environmental science; however, in certain conditions and times it picks information on non-vegetated surface instead of vegetated (signal-to-noise ratio). And this challenge may stem from atmospheric conditions such as cloud cover; bidirectional reflectance distribution function (BRDF); changes in soil background; navigation and calibration problems (Piao et al., 2003; Atkinson et al., 2012).

To vividly measure and characterize the seasonal rhythm of temperate vegetation, scientists have developed spectral vegetation indices. A pioneer of these vegetation indices is the normalized difference vegetation index (NDVI), which is essentially a ratio of the difference between reflectance or radiance from the near-infrared and red wavelengths of sensors to their sum (Tucker, 1979; Myneni et al.,1995), have extensively been used to extract phenological information .

The National Oceanic and Atmospheric Administration platform which hosts the Advanced Very High Resolution Radiometer (NOAA/AVHRR) in space since the early part of 1980, tracks terrestrial resources which include vegetation phenological processes. Therefore the NOAA/AVHRR as a pioneering satellite remote sensing; its data culminated in the generation of satellite-based normalized difference vegetation index (NDVI). The NOAA/AVHRR NDVI time series data sets, which preceded the other vegetation indices time series, generated from recent radiometric measurements have been applied to quantifying plant phenology. Numerous works on mapping and quantification of vegetation phenology have been done using NOAA/AVHRR data sets. For example, plant phenology as a function of climate in twenty year time length was mirrored by the application of NOAA/AVHRR land surface parameter data set (Stöckli and Vidale, 2004). Julien & Sobrino (2009) fitted double logistic function to global inventory mapping and monitoring studies (GIMMS) Normalized Difference Vegetation Index (NDVI) to quantify start, end and length of growing season of global vegetation cover. In their study, they found out a global trend showing 0.38 days per year advance in spring season; a delay date of 0.45 days per year; and growing season increase of 0.8 days. And their correlation test in that work reveals strong spatial association between phenological metrics and climate variables.

Again, NDVI data from NOAA/AVHRR polar orbiting satellite and daily mean temperature data were used to study long term changes in growing season of temperate vegetation in the Northern hemisphere (Tateishi & Ebata, 2004; Jeong et al., 2011) . Karlsen et al. (2007) used GIMMS/NOAA AVHRR NDVI data set to map for each year in a twenty-one year long period, the annual spatial variability in onset of greening in Fennoscandia. And their results, generally, showed that 1°C increase in spring temperatures ensures advances of 5–6 days in spring green-up. The application of NOAA/AVHRR data to analyze global vegetation phenology reveals that satellite remote sensing is an important technology to map and monitor vegetation at both regional and global scales (Justice et al., 1985)

Beside NOAA/AVHRR, other remote sensing systems have calculated NDVI in a same manner as in the case of NOAA/AVRR to apply it to estimating spatial and temporal variations in vegetation activity. For example, MODIS (Beck et al, 2006), Système Pour L'Observation de la Terre (SPOT)-VEGETATION(VGT) (Atzberger & Eilers, 2011) and Indian Remote Sensing-Wide Field Sensors (WiFS) (Josh et al , 2006; Prasad et al., 2007)

It is has become imperative that beyond monitoring of vegetation phenology in response to climate change; studies are conducted to examine the environmental or ecological impacts the changes in plant phenology in response to climate change bring about (van Vliet and Schwartz, 2002)

Recent studies by Zhang et al. (2006), used MODIS data to produce global maps of these phenological variables- green up; maturity; senescence and dormancy for vegetation of the world that obviously revolve in sync with annual seasonal changes. Again, Zhang et al. (2006) identified vegetation phenological transition dates by using 2001 MODIS data and MODIS Land Surface Temperature(LST) data from the northern hemisphere between 35^0N and 70^0N.

Further, a study on the differences between rural-urban phenological transition dates and land surface temperatures have been carried out using data from the Moderate Resolution Imaging Spectroradiometer in urban areas larger than $10km^2$ in eastern North America

(Zhang et al., 2004). In Europe, a work was done to investigate the differences and trends of spring phenophases between urban and rural areas of some ten regions in Central Europe using data from phenology network stations of these regions (Roetzer et al., 2000). Besides, the application of in situ data set to tell apart rural and urban phenology; remote sensing data have been combined with its in situ counterpart to study the plant phenology in rural and urban environments (Mimet et al., 2009)

Other works on the impacts of warming climates on the phenology of natural vegetation have been carried out. In 2006-2007, the occurrence of mild winter and spring over western Europe was responsible for pervasive early vegetation green-up (Maignan et al., 2008)

Jolly et al. (2005) looked into the different ways vegetation grows at the Swiss Alps in the face of the extreme high summer temperatures that rocked Europe in 2003.

Also, recent climate changes have made researchers to build models to predict the possible impacts of climate change on the phenology of natural vegetation (Chmielewski et al., 2005)

Yu et al. (2010) examined the impacts of anomalous warming temperatures in winter and spring seasons on spring phenology of steppe and meadow over the Tibetan plateau. And their results showed that the extreme high temperatures in winter and spring led to delayed spring phenology in these vegetation types.

Prieto et al. (2009) subjected shrub and grass species of some selected sites in Europe to simulated warmer conditions. This is to test the hypothesis that predicted warmer temperatures forecasted by climate models will advance start of spring growth in the selected plant species. And they reported their results as: "although the acceleration of spring growth was the commonest response to warming treatments, the responses at each site were species specific and year dependent ".

2.5 Extraction of phenological metrics

Time series (8-day, 10-day or 16-day composite) of vegetation index products from optical sensors mounted in satellite-platforms provide the data sets to which phenological metrics are extracted. The phenological metrics derived from a time-vegetation index curve could be variedly named but mainly include onset of growth; peak of growth; end of growth and length of growing season. In Europe, like any other cool and temperate region, onset of growth variable is defined by the spring season; and the peak of growth is defined by the summer season. The end of growing season on the other hand is mainly defined by the onset of autumn season whiles winter characterizes the dormancy period of vegetation. Meanwhile the length of growing season (LGS) is a derivative metrics (the difference between onset of growth and end of growth seasons). Before these metrics are estimated, the raw data sets from satellite remote sensing undergo preprocessing stages.

Remote sensing technology faces challenges such as changes in illumination and viewing angles; cloudy atmosphere and snow cover; and these challenges introduce noise in radiometric data. Therefore, in satellite remote sensing of phenology, these sources of noise are either reduced or removed (data cleaning). In some cases, pixels whose quality is so poor are removed from the analysis. In other words, the quality of pixels is flagged as either good or poor (Dash et al., 2010)

It is rare to have data sets without noise (missing data) since optical sensors may experience line drop out. In land surface phenology, the gaps created in the data as a result of sensor noise such as sensor drop out are filled generally by interpolation methods (Dash et al., 2010).

To extract phenological metrics from cleaned and gap-filled (where there were missing data) temporal radiometric data, the data is smoothed. Many techniques have been used to fit smoothing function to temporal satellite sensor data; the commonly used techniques include discrete Fourier transform (DFT) (Menenti et al., 1993; Verhoef et al.,1996; Roerink et al., 2000; Jakubauskas et al., 2001; Moody & Johnson, 2001; Wagenseil & Samimi, 2006; Geerken, 2009) ; moving average(White et al., 2009) ; double logistic (Zhang et al., 2003) (Beck et al., 2006); median smoothing (Reed et al., 1994); curve fitting (Bradley et al.,2007); Savitzky-Golay (Chen et al., 2004); asymmetric Gaussian (Jonsson and Eklundh, 2002); wavelet decomposition (Sakamoto et al., 2005; Lu et al., 2007; Martínez & Gilabert, 2009) and the Best Index Slope Extraction(BISE) (Viovy et al., 1992). However, any of these smoothing methods if applied to time-vegetation index profile should not deviate from the nuances of the original data set.

After fitting a smoothing function to temporal satellite sensor data; they are now ready for phenological metrics to be extracted. Reed et al. (1994) catalogued all the individual algorithms which have been applied to quantitatively derive vegetation phenology into three broad streams- threshold-based methods, inflection point methods and trend derivatives methods.

The threshold method does work when they are fed with either a pre-determined or relative reference value; and are thus split into two types- global and local techniques. In the global threshold technique, a uniform vegetation index (eg. NDVI or MTCI) value is selected by the user to estimate the phenological parameters (eg. onset of growth and end of growth seasons) for the entire study site (Lloyd, 1990; Reed et al., 1994; White et al., 2009). In other words, the global threshold technique does not take cognizance of the various vegetation index values set as threshold for different cover types. The local threshold method on the other hand respects the various threshold values set to each and every single pixel in the study area (White et al., 1997); and thus use these local thresholds to quantify onset of growth and end of growth.

There is another threshold-based algorithm in seasonal midpoint NDVI (SMN). In this approach the midpoint value between lowest and highest NDVI or MTCI is selected as the threshold to estimate phenology variables, mainly onset of growth and end of senescence (White et al., 1997;Schwartz et al., 2002). Jonsson & Eklundh (2002) also defined onset of growth by taking the 10% distance between the lowest and highest NDVI as threshold. In this method the threshold can be fixed to the seasonal amplitude of a pixel and therefore, the changing characteristics of every pixel (Reed et al., 2003).

The inflection point algorithm has been used in many works. It is generally an algorithm that defines the phenological metrics by identifying where in the temporal curve (as result of plotting NDVI or MTCI against time) does a change from one linear stage to another takes place; and this change might be at decreasing to increasing or increasing to decreasing phases(Reed et al., 2003). The algorithm thus identifies the points with maximal curvatures to define the phenological metrics. For example, Zhang et al.(2003) applied this algorithm to define these phenological variables- green up, maturity, senescence, and dormancy.

Similar to the point of inflection and threshold-based approaches is the curve derivative technique; it also seeks to identify where in the curvature vegetation index data showcases change in gradient. Example of this approach is the delayed moving average(DMA) (Reed et al., 1994); where they compared NDVI values to the mean of the initial *n* observations to make out any deviations from what is supposed to be the normal trend. The DMA values in other words can be regarded as predicted values based on earlier observations (Reed et al., 2003). Reed et al., (1994) therefore set a change in trend to when NDVI values become greater than values predicted by the DMA; and they were able to extract twelve Phenological variables for each year by this approach.

The moving average technique operates differently from the threshold methods. In the moving average, a metric is derived when the vegetation index curve, as a function of time, intercepts with the moving average window either at upward or downward direction.

The function fitting method relatively has the complex techniques in asymmetric Gaussian function, polynomial function (Piao et al., 2006) and piecewise Logistic function. These are mathematical functions applied to temporally smoothed satellite sensor data to quantify phenological metrics.

2.6 Validation of phenological metrics

The ground observation technique and satellite remote sensing have provided a lot of data for phenology studies but many not validated (Fisher & Mustard, 2007). Groups such as the United States National Phenological Network (US-NPN) (United States Phenological Network, 2012) and European Phenology Network (Van Vliet et al., 2003) have created databases on land surface phenology (LSP). For phenological variables estimated from radiometric measurements to be trusted, there is the need to validate their accuracy (Reed et al., 2009). Liang et al., (2011) validated the LSP of MODIS Enhanced Vegetation Index (EVI) product using an intensive field observation. Their results reveal that EVI - derived start of spring season (SOS) was able to predict landscape phenology full budburst with an absolute error short of 2 days.

Besides validation of phenology variables by ground observation, there is now an approach of linking satellite phenology data with digital camera data. This application of digital camera to monitor LSP is known as near- surface remote sensing (Hufkens et al., 2012). Hufkens et al., (2012) validated MODIS based phenological data with vegetation phenology data from digital camera. Their results show a correlation between the phenological time series and metrics obtained from the digital camera and MODIS images. Nevertheless, they mentioned that spatial scale and representation have a strong influence on linking the relationship between digital camera data and radiometric data. Again, Fisher & Mustard (2007) compared phenology data collected from Landsat to that collected by MODIS; and both data yielded a correlation co-efficient, $r^2 = 0.6$, which is however, not too impressive. Ide and Oguma (2010) extracted green-up dates for wetland mixed deciduous forest and evergreen broadleaf forest using eight year daily images captured from digital camera.

Chapter 3: STUDY SITES, MATERIALS AND METHODS

3.1 Study sites

The study focuses on Europe which is defined by 30^0 N-70^0 N and 15^0 W-45^0 E. However the subsets of this geographic region that experienced anomalous warm spring, anomalous warm summer and anomalous warm autumn between the years 2002 and 2012 are the study sites (Figures 9 and 10). Europe as a continent of the world has vegetation types whose presence and distribution, to some extent, are predetermined by the type of prevailing climate. And the climate of Europe is basically temperate and boreal types which are largely influenced by maritime and continental air masses (Köppen et al., 1930). However, many of the vegetation types in Europe are managed by humans. Essentially, the vegetation of Europe is made up of temperate and boreal grasses, shrubs and trees.

3.2 Materials

3.2.1 Gridded surface temperature datasets and analysis

The study makes use of daily mean temperatures of periods 2003-2011 and 1961-1990. The 2003-2011 is the study period. This is because the MTCI data used for extraction of forest phenology and productivity variables has complete data within these years. The 1961-1990 is the long term temperature used to determine the standardized anomaly. The study selected 1961-1990 because it is the climate with best estimate per the World Meteorological Organization (WMO) quality assessment work (WMO, 1996). These E-OBS data files are as part of Europe's ENSEMBLE project (Haylock et al., 2008). They are high resolution gridded data sets of 0.25^0 x 0.25^0 per cell with a spatial coverage of 25° N-75° N x 40° W-75° E in a

NetCDF compressed format. And have WGS 1984 spatial referencing system (Haylock et al., 2008)

3.2.2 GlobCover Land Cover classification v 2.2 product

GlobCover Land Cover is a global land cover map collected by European Space Agency MERIS sensor hosted in its Envisat space-borne satellite at full resolution mode of 300m. This product was collected between December 2004 and June 2006. It is further characterized by a geographic coordinates in a Plate-Carrée projection (WGS84 ellipsoid). Also, have a spatial coverage in the neighbourhood of 90°N, 180°W to upper left corner and 90°S, 180° to the lower right corner (see http://due.esrin.esa.int/globcover). And the classification is based on the UN Land Cover Classification System (LCCS). This GlobCover Land Cover 2005-2006 product was used to identify the spatial locations of broad-leaved deciduous forest; needle-leaved deciduous forest; needle-leaved evergreen forest and mixed forest in Europe.

3.2.3 Envisat MTCI time series data

MERIS Terrestrial Chlorophyll Index characterizes terrestrial vegetation and it is collected by European Space Agency (ESA) Envisat MERIS sensor. The ESA Envisat platform carries the MERIS sensor; and they were jointly in space in the mid-years of 2002-2012. This ESA satellite system monitors the earth surface at fine spectral resolution; both full and reduced spatial resolution; and has three day repeat cycle. Dash & Curran (2007) in their work 'Evaluation of MERIS terrestrial chlorophyll index (MTCI)' detailed the geometric, spectrometric and radiometric properties of ESA Envisat MERIS system (Table 3).

The MTCI is thus set to make use of spectral reflectance in the red edge position to estimate chlorophyll content of vegetation cover (Dash & Curran, 2007; Boyd et al., 2012)

For the purposes of retrieving vegetation phenology, the study used Envisat MERIS Terrestrial Chlorophyll Index (MTCI) weekly and dekad series data spanning 2003 to 2011 which primarily cover the whole of Europe. In detail, per the MTCI data set used for this study, from 2003 to 2007 the MTCI is collected at an 8-day composite interval. And then from years 2008-2011 the MTCI is collected at 10-day composite interval. For each MTCI composite collection, whether 8-day or 10-day is considered as one (1) band. Thus, in a normal case, the 8-day composites collected until 2008, each year should have forty-six (46) bands (Table 1). And in the case of the 10-day composites, each year should have thirty-six bands. In this work, the MTCI data set is downloaded online (ftp://l3-server.infoterra.co.uk/pub/). However, two of the weekly composite MTCI data were truncated; and therefore treated as missing data. These missing weeks precisely occurred for 8th October 2003 – 15th October 2003 and 16th October 2003 - 23rd October 2003 collections. On the other hand, the dekad (10-day composite) of the MTCI; the truncated collection occurred for the date 16th September 2010 – 23rd September 2010. To this end, the study thus padded these missing data with zeros but later applied linear interpolations to gap fill these missing data. By inspection, these MTCI products are in latitude-longitude gridding and a GEOTIFF format. Additionally, when downloaded they come along with XML metadata file and a JPEG browse image.

The Envisat MERIS Terrestrial Index is a measure of chlorophyll richness of vegetation by the MERIS sensor. And it is a ratio expressed as:

$\frac{\mathrm{R_{band\ 10}} - \mathrm{R_{band\ 9}}}{\mathrm{R_{band\ 9}} - \mathrm{R_{band\ 8}}} = \frac{\mathrm{R_{753.75}} - \mathrm{R_{708.75}}}{\mathrm{R_{708.75}} - \mathrm{R_{651.25}}}$, where $R_{753.75}$, $R_{708.75}$ and $R_{681.25}$

refer to the bands 10, 9 and 8 respectively in the MERIS standard band setting (Dash and Curran, 2004). The higher the MTCI value the richer the chlorophyll content of the leaves of the vegetation type. And the lower the MTCI value the vegetation is as well low in chlorophyll content. The MTCI data is of WGS 1984 referencing system; have about 1km^2 spatial resolution and 30^0 N-70^0 N to -15^0 W-45^0 E area coverage.

Table 1. A year slice of the 8-day composite time series of MTCI data

The bold numbers are for the temporal bands and immediately to it are the dates to which the images are collected. The Julian days are the added-on days of the year, also known as day of year (DOY)

Composite band & Gregorian dates	Julian Days	Composite band & Gregorian dates	Julian Days	Composite band & Gregorian dates	Julian Days
1. 1-8 January	8	**17**. 9-16 May	136	**33**. 14-21 September	264
2. 9-16 January	16	**18**. 17-24	144	**34**. 22-29 September	272
3. 17-24 January	24	**19**. 25 May-1 June	152	**35**. 30 September-7 October	280
4. 25 January-1 February	32	**20**. 2-9 June	160	**36**. 8-15 October	288
5. 2-9 February	40	**21**. 10-17 June	168	**37**. 16-23 October	296
6. 10-17 February	48	**22**. 18-25 June	176	**38**. 24-31 October	304
7. 18-25 February	56	**23**. 26 June-3 July	184	**39**. 1-8 November	312
8. 26 February-5 March	64	**24**. 4-11 July	192	**40**. 9-16 November	320
9. 6-13 March	72	**25**. 12-19 July	200	**41**. 17-24 November	328
10. 14-21 March	80	**26**. 20-27 July	208	**42**. 25 November-2 December	336
11. 22-29 March	88	**27**. 28 July-4 August	216	**43**. 3-10 December	344
12. 30 March-6 April	96	**28**. 5-12 August	224	**44**. 11-18 December	352
13. 7-14 April	104	**29**. 13-20 August	232	**45**. 19-26 December	360
14. 15-22 April	112	**30**. 21-28 August	240	**46**. 27-31 December	365
15. 23-30 April	120	**31**. 29 August-5 September	248		
16. 1-8 May	128	**32**. 6-13 September	256		

Table 2. A year slice of the 10-day composite of MTCI data (2008-2011). MTCI data were collected at 8 day interval until 2008 when Envisat started collecting vegetation greenness data every 10 days. The bold numbers are for the temporal bands and immediately to it are the dates to which the images are collected. The Julian days are the added-on days of the year, also known as day of year (DOY)

Composite band & Gregorian dates	Julian Days	Composite band & Gregorian dates	Julian Days
1. 1-10 January	10	**19**. 30 June-9 July	190
2. 11-20 January	20	**20**. 10-19 July	200
3. 21-30 January	30	**21**. 20-29 July	210
4. 31 January-9 February	40	**22**. 30 July-8 August	220
5. 10-19 February	50	**23**. 9-19 August	230
6. 20-29 February	60	**24**. 20-29 August	240
7. 1-10 March	70	**25**. 30 August-8 September	250
8. 11-20 March	80	**26**. 9-19 September	260
9. 21-30 March	90	**27**. 20-29 September	270
10. 31 March-9 April	100	**28**. 30 September-9 October	280
11. 10-19 April	110	**29**. 10-19 October	290
12. 20-29 April	120	**30**. 20-30 October	300
13. 30 April-9 May	130	**31**. 31 October-9 November	310
14. 10-19 May	140	**32**. 10-19 November	320
15. 20-29 May	150	**33**. 20-29 November	330
16. 30 May-8 June	160	**34**. 30 November-9 December	340
17. 9-19 June	170	**35**. 10-19 December	350
18. 20-29 June	180	**36**. 20-29 December	360

3.2.4 Tools/software used

The general tools/softwares essentially used to see the completion of this work are ArcGIS; Envi; Google Earth; MATLAB and Excel. ArcGIS and Envi are used for geospatial analysis. Google Earth was basically used to validate the samples selected. The forest phenology and productivity variables are extracted by running the script in MATLAB which output it to excel for further analysis. All statistical analyses are done in Excel.

Table 3. Properties and descriptions of the Envisat MERIS sensor, (Dash and Curran, 2007)

Property	Description
Geometric	
Field-of-view	68.5^0 centered around nadir
Swath Width	1150 km
Localization accuracy	400 m(no use of landmarks)
Spatial resolution	Full resolution(FR)-300m;
	Reduced resolution (RR)- 1200 m
Spectral	
Band-to-band registration	< 0.1 FR pixel
Spectral range	390-1040 nm
Spectral sampling interval	1.25 nm
Spectral resolution	1.8 nm
Band transmission capacity	15 bands programmable in position and width
Radiometric	
Band width	Programmable from 1.25 nm up to 30 nm
Radiometric accuracy	< 2% in reflectance
Dynamic range	Up to bright clouds(100% reflectance)
Signal-to-noise ratio	1650:1 at 412.5 nm(for typical ocean signal)

3.3 Method

3.3.1 Defining anomalous temperature

In this study, the 2003-2011 and 1961-1990 gridded daily mean temperature data sets are also referred to as the study time and reference time respectively. The study sets out to identify areas in Europe that experienced anomalous warm spring and autumn events. Thus, the study needs mean temperature map for spring and mean temperature map for autumn of each year of the two periods (1961-1990 and 2003-2011). For this reason, the study by the application of ENVI 4.8 tool, each year of both study and reference periods are resized into spring and autumn seasons. There are missing data in both data sets; and therefore all missing data were masked out. Mean and standard deviation maps for spring and autumn seasons were created for the 1961-1990 reference data (30-year long mean and standard deviation maps for spring and autumn seasons each) whiles only mean map of spring and autumn seasons made for the 2003-2011 study data. With spring and autumn of the reference period having its mean and standard deviation and mean (spring and autumn) for the study period; a standardized anomaly statistic (Wilks, 1995) was applied to arrive at the anomalous warm spring and autumn events maps. In applying the standardized anomaly test, the study period means (spring mean and autumn mean) were used as the observation values (x). The spring and autumn means and standard deviations for the reference data were used as the mean and standard deviation parameters in estimating the standardized anomaly test for both spring and autumn events. Wilks (1995) computed standardized anomaly, z, by subtracting the sample mean of the batch from which the data are drawn, and dividing by the corresponding sample standard deviation; put as:

$$Z = \frac{X - \bar{X}}{S_{\bar{X}}}$$

where X is the mean observation of the study time, $\bar{X}$ and $S_{\bar{x}}$ are the mean and standard deviation of the reference time respectively.

The study sets a threshold to define extreme warm spring and autumn seasons in the nine year study period (2003-2011). In this threshold, a season is extremely warm if its standard anomaly exceeds 1.5 standard deviation of the mean reference period.

Otherwise, the season is considered normal (Figure 8). For the purposes of investigating direct and lagged effects the study was further controlled by certain conditions (Tables 4 & 5). The conditions are that if the season under consideration is anomalous then:

i. the preceding season must be normal
ii. the succeeding season(s) must be normal
iii. the same season must be normal in the following phenological year

Table 4. The set conditions for spring. The condition is that if the spring season of the year under consideration is extremely warm(anomalous) then autumn (of the preceding year); summer and autumn seasons of the same growing year under consideration; and the spring season in the following year should all have to be normal (not have experienced extreme warm temperatures).

	Normal Seasons		
Extreme warm season	preceding season(s)	succeeding season(s)	season in following year
spring 2004	autumn 2003	summer 2004 autumn 2004	spring 2005
spring 2005	autumn 2004	summer 2005 autumn 2005	spring 2006
spring 2006	autumn 2005	summer 2006 autumn 2006	spring 2007
spring 2007	autumn 2006	summer 2007 autumn 2007	spring 2008
spring 2008	autumn 2007	summer 2008 autumn 2008	spring 2009
spring 2009	autumn 2008	summer 2009 autumn 2009	spring 2010
spring 2010	autumn 2009	summer 2010	spring 2011

Table 5. The set conditions for autumn. The condition is that if the autumn season of the year under consideration is extremely warm (anomalous) then spring and summer seasons that preceded autumn (in the same growing year); and spring and autumn seasons of the following year should all be normal (not have experienced extreme warm temperatures).

	Normal Seasons		
Extreme warm season	preceding season(s)	succeeding season(s)	season in following year
autumn 2003	spring 2003 summer 2003	spring 2004	autumn 2004
autumn 2004	spring 2004 summer 2004	spring 2005	autumn 2005
autumn 2005	spring 2005 summer 2005	spring 2006	autumn 2006
autumn 2006	spring 2006 summer 2006	spring 2007	autumn 2007
autumn 2007	spring 2007 summer 2007	spring 2008	autumn 2008
autumn 2008	spring 2008 summer 2008	spring 2009	autumn 2009
autumn 2009	spring 2009 summer 2009	spring 2010	autumn 2010
autumn 2010	spring 2010 summer 2010	spring 2011	autumn 2011

At this point the study identified six (6) sites in Europe that experienced significantly unusual warm spring and autumn events in the period 2003-2011. These sites become the study sites for this work; and they are warm autumn 2003; warm autumn 2005 and warm autumn 2009. The others are warm spring 2004; warm spring 2007; and warm spring 2009 (Figures 9 and 10).

With the help of Global Land Cover v2.2 classification map from ESA Envisat MERIS sensor (http://due.esrin.esa.int/globcover/); we identified broad-leaved deciduous forest (BLDF); needle-leaved deciduous forest (NLDF); needle-leaved evergreen forest (NLEF); and mixed forest (MF) in these extremely warm areas of Europe in the years 2003-2011. BLDF are a result of reclassification. From the GlobCover map classes, classes 50 and 60 are merged into one class named broad-leaved deciduous forest; class 70 is left same as needle-leaved evergreen forest. Class 90 is considered as needled-leaved deciduous forest even though it originally has some stands of evergreen; and the study considered it as needle-leaved deciduous forest because it is more of deciduous than evergreen. Class 100 is mixed forest; and it is composed of broad-leaved and needle-leaved forests mainly. Further, in ArcGIS 10.1, we digitized for samples of these vegetation types using MTCI pixel size as a selection threshold (Figure 8). We chose this threshold because the study is interested in large homogenous (having the same vegetation type) areas for study areas. This means that if a vegetation type in a spatial location is not about 1 km^2 then it is not sampled; and the samples are representative. And also the study ensured that samples fall in only one extreme warm event (Figures 21 and 22). These forest type samples are used as region of interests (ROIs) over temporally stacked MTCI composite layers to extract the pixels that constitute each region of interest.

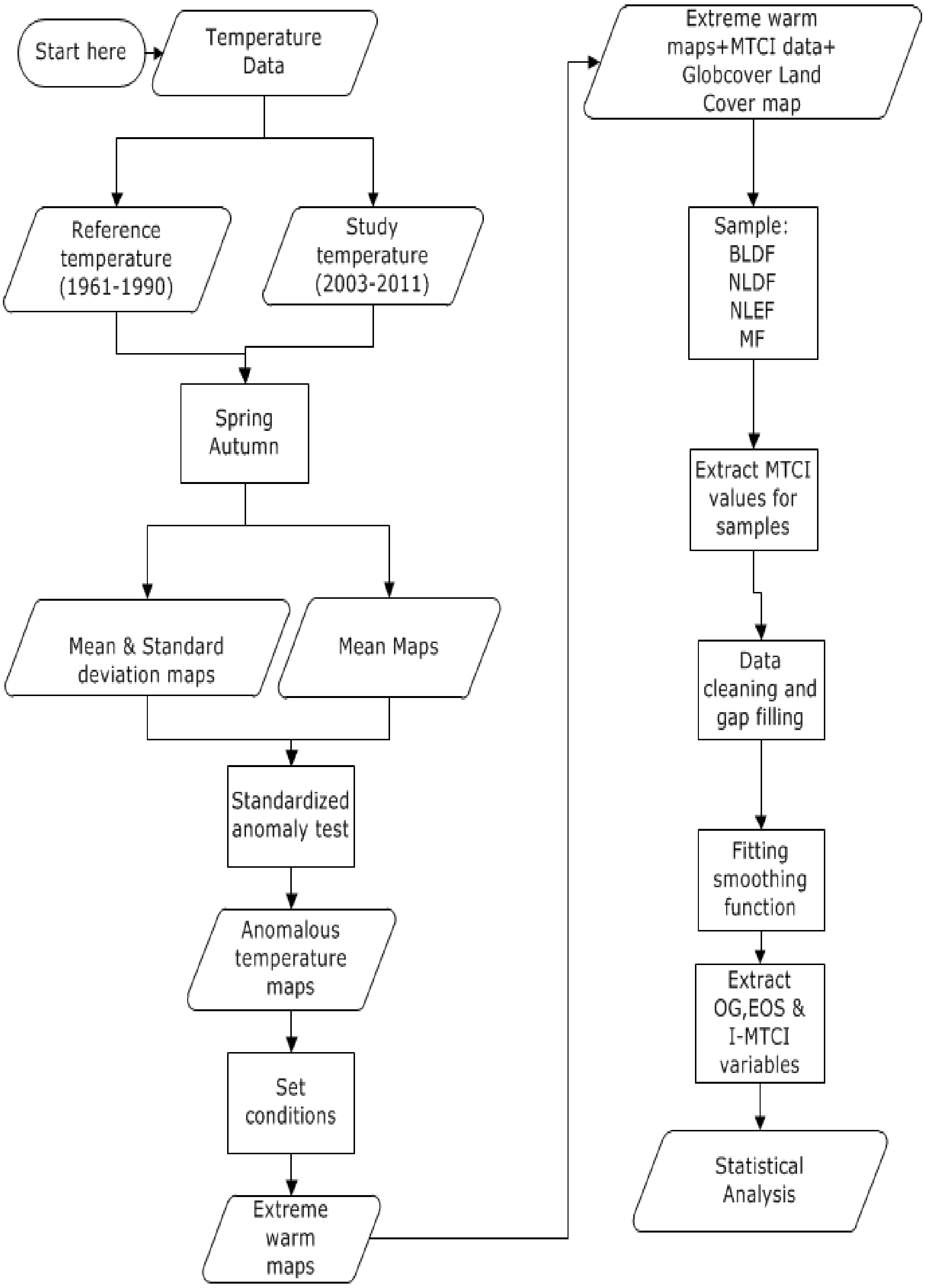

Figure 8. A summary of study work flow. The study basically identified and mapped warm spring and autumn areas in Europe;

then extracted phenological and productivity variables and finally estimated statistics

3.3.2 Data cleaning, flagging and gap filling

There are missing data for some of the pixels. For MTCI data, missing data are recorded as zero (0). These missing data might have arisen from sensor drop out or snow cover over tree canopy (especially in higher latitude Europe). To clean the data, first of all, all pixels that start with 10 or more consecutive weeks or dekads with missing data are discarded. This is done to preserve the true pattern of data collected by the space-based satellite sensor. For the rest of the missing data present in the qualified pixels, linear interpolation script run in MATLAB was applied to fill those missing data. In this script, first of all, the entire data file of each sample is considered at a time. And if there are more than eight (8) continuous missing data (zeros) in that sample then that sample is flagged as poor quality. Otherwise it is flagged as good. Further, the first or last six consecutive values starting or ending a yearly data files are checked to ensure they contain no more than six gaps; otherwise the start or end of this data file is flagged as not reliable. The algorithm continues to find the first and last valid points; and within these valid points a linear interpolation method is applied to iron out gaps within that range of values in the data file. A valid point is defined as a non-zero value in a considered range of values within the data file. When all these quality check algorithms are run then a three point temporal moving average was applied to the entire data file to smooth it.

3.3.3 Temporal based information extraction

In this work, an algorithm of the inflection point-based in Discrete Fourier Transformation was applied. This approach was selected because it is convenient to apply and does not depend on subjective threshold selection as in the case of threshold method. Also, the first four harmonics define the phenological metric of natural vegetation well (Reed et al., 1994; Dash et al., 2010). The algorithm used in this work is vividly described by Dash et al.(2010); and it thus applied in this work. However, in order to effectively define the phenological variables, the inflection point-based technique is utilized in addition to logical and continuity functions. Therefore, phenological metrics derived from the algorithm are onset of growth (OG) and end of senescence (EOS) (Figure 1). OG and EOS are basically the day of year (DOY) at which growth starts and ends. However, the algorithm works basically on deriving the OG and EOS by starting from the dominant peak in the time-MTCI profile to search for valleys.

The algorithm defines OG and EOS on valley point principle. It thus means that onset of growth is defined by the valley point that lies at the start of greening season. The end of senescence on the other hand is defined by the valley point that takes place at the offset of greening period. Even though nine yearlong stacked time series (2003-2011) were used in this study, the algorithm was still able to conveniently derive the phenological metrics by extending its temporal search activity into subsequent years to define their metrics as well. In other words, the algorithm functions by searching to define phenological variables year by year. And it does this by embarking on search activity from the obvious peak of annual phenological cycle and thus search for valleys at backward and forward directions of the dominant peak. Valley point found at the backward end as a result of change in derivative value from positive to negative then becomes the OG for that annual growing cycle. Similarly, the valley point that lies at the forward end defines the EOS. However, in cases where a supposed valley point has larger MTCI values as a result of local variations then the algorithm may be limited. To avoid this, peak MTCI and valley MTCI values are differenced out and the result is thus compared to the highest MTCI value. If the difference between the peak MTCI and valley MTCI values is more than twenty-percent of the highest MTCI value then the valley point qualifies to define a phenological date, else the algorithm continues running until a valid valley point is found.

The algorithm further estimated integrated MTCI (I-MTCI) (Figure 1) which measures the total greenness of the forest under the season; and thus used in this study as a surrogate measure to forest productivity. Integrated MTCI (I-MTCI) is an integration of all the MTCI values of the area that falls under the curve (MTCI axis against day of year axis (DOY); and it is dimensionless. However, a higher I-MTCI value indicates increase in forest productivity (greenness) and vice-versa (Figure 8). The study thus estimated I-MTCI for both spring and autumn events.

3.3.4 Statistical Analysis

Having obtained the variables; OG, EOS and I-MTCI for spring and autumn from the point of inflection based algorithm, the study estimated the median values for each of these variables for all pixels that form a region of interest for sampled forest types. The study used median in order to curtail the influence of outliers. For this study, there is always one year in the study period (2003-2011) to which extreme warm spring or autumn occurred, also known as anomalous year. And the rest of years (8 years) of which no extreme warm event occurred. This eight year period is referred to as normal years. For instance, if you pick extreme warm spring 2004 (anomalous year) then the rest of spring events in the study period 2003-2011 are said to be the normal years. To this end, the study estimated median value for both phenological and productivity variables for anomalous and normal years of each forest type. The anomalous medians are thus compared to the normal median in order to investigate phenology. To investigate direct and lagged effects, the study estimated the mean I-MTCI values for all regions of interest for each forest type in each extreme warm event. Like the phenology analysis, the mean I-MTCI values for normal phenological events are compared to the mean I-MTCI values of the anomalous phenological events(extreme warm spring and extreme warm autumn events) Further, the study performed one-tailed t-test for the phenological variables (OG and EOS) for each forest type under each extreme warm event. Similar analysis was done for the productivity variables (Figure 8).

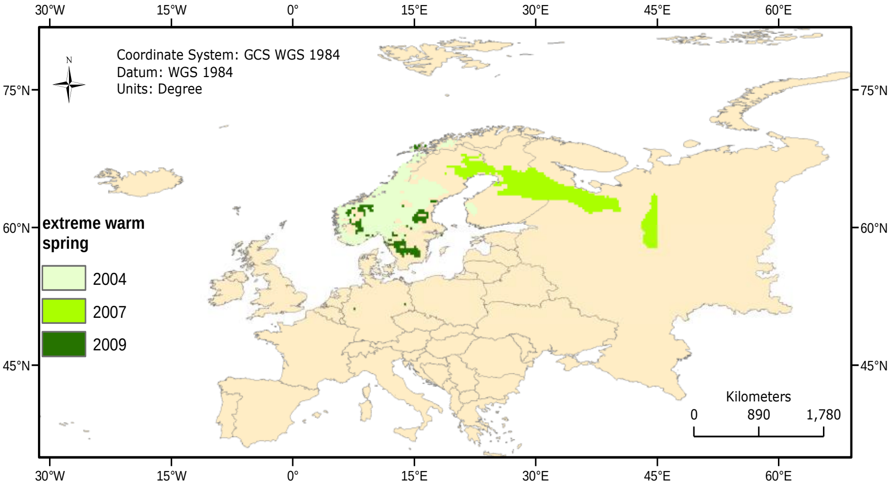

Figure 9. Areas in Europe that experienced Extreme warm spring. The extreme warn spring events happened in years 2004, 2007 and 2009. And these events extensively occurred in Russia, Finland, Sweden and Norway (boreal Europe)

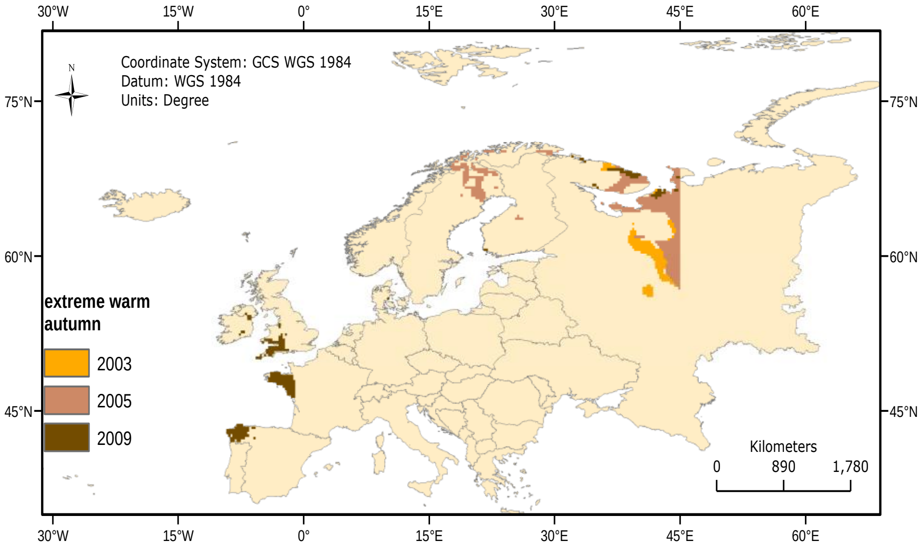

Figure 10. Areas in Europe that experienced extreme warm autumn events. These events happened in Spain, France and the United Kingdom. And also in Russia, Sweden and Norway. Largely, extreme warm autumns 2003 and 2005 overlapped same area.

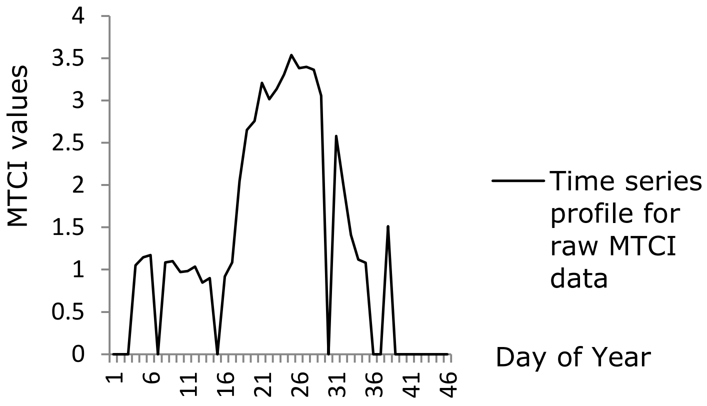

Figure 11. Profile for raw MTCI data. Before pre-processing and Discrete Fourier Transformation (DFT) algorithm is run on raw MTCI data; this is how MTCI-DOY profile for a year slice looks.

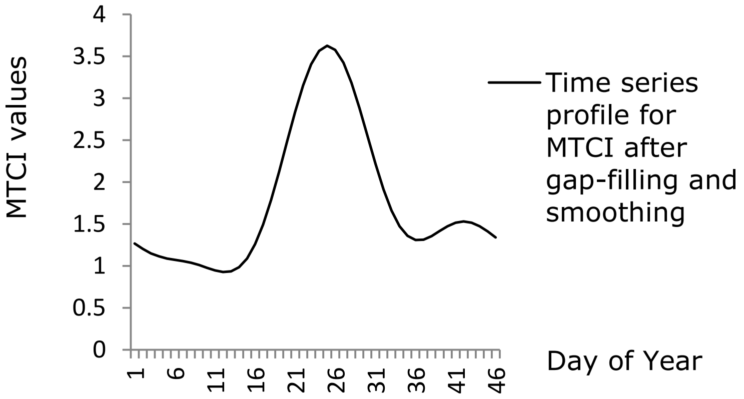

Figure 12. Profile for cleaned MTCI data. This is how a year slice of raw MTCI data looks after cleaning, gap filling and smoothing

Chapter 4: RESULTS AND ANALYSIS

4.1 Defining extreme warm seasons in Europe

With a standard deviation of more than 1.5 to the mean values for spring and autumn seasons, the study found extreme warm spring in the years 2004, 2007and 2009. The extreme warm spring occurred extensively in Scandinavia Europe (Norway, Sweden and Finland) and Russia (Figure 9). On the other hand, the extreme warm autumn events occurred in the years 2003, 2005 and 2009. Extreme warm autumn events predominantly happened in Russia, Spain, France and United Kingdom (Figure 10).

4.2 Data cleaning, flagging and gap filling

Figures (12 and 13) show the profiles of the MTCI values through time series before and after application of gap filling (linear interpolations) and smoothing (first four harmonics Discrete Fourier Transformation) techniques.

4.3 Phenology and productivity variables

4.3.1 Extreme warm spring events

Under extreme warm spring events, only broad-leaved deciduous forest, needle-leaved deciduous forest and mixed forest samples were used in the analysis. This is because there was no significant amount of needle-leaved evergreen forest present in these areas of Europe that experienced extreme warm spring. The sample sizes, N, for BLDF, NLDF and MF are 11, 23 and 13 respectively (Table 6). All the forest types show early onset of growth (OG) for the direct positive effect as anticipated in the conceptual models. Broad-leaved deciduous forest (BLDF) shows its normal onset of growth (OG) as 111±22 day of year (mean±SD) but as a result of the extreme warm spring events BLDF shows leaf flushing on 110±21 day of year. This thus suggests that

BLDF showed a day earlier for OG. Needle-leaved deciduous forest (NLDF) normally start growth in 132±8 day of year but as a result of the extreme warm spring events NLDF begin flushing in 120±14 day of year which is earlier than normal. NLDF thus started leafing out 12 days earlier than normal. Similarly, mixed forest (MF) show earlier OG because the normal OG is 132±4 day of year and experienced earlier OG in 129±3 day of year. MF started bearing leaves 3 days earlier. Obviously, BLDF; NLDF and MF all show earlier onset of growth consequent to the anomalous warm spring temperatures they experienced (Figure 13). However, for a one-tailed t-test, at $\propto=0.05$, only NLDF ($p=0.0007$) and MF ($p=0.02$) show statistical significant earlier OG date for the anomalous period with respect to mean OG date for normal spring phenology. The mean OG for BLDF in the anomalous spring events is not statistically significant earlier than normal mean OG (Table 6).

In end of senescence measurement, NLDF and MF delayed but BLDF shows earlier EOS (Figure 14). The normal EOS for BLDF is 309±20 day of year whiles its EOS for the extreme warm spring events is 303±17 day of year. BLDF therefore greened down three days earlier than normal. However, NLDF extended its EOS by seven days since its normal EOS is 304±15 day of year and anomalous EOS is 311±11 day of year. Similarly, MF delayed EOS by four days. MF normally ceases growth around 291±4 day of year, but due to the unusual warm spring events MF green down during 295±11 day of year. For a one-tailed t-test analysis, at $\propto=0.05$, with anticipation of anomalous EOS being dragged beyond normal EOS, the study found that BLDF ($p=0.23$), NLDF ($p=0.1$) and MF ($p=0.12$) lateness were not statistically significant (Table 7)

4.3.2 Extreme warm autumn events

Here in the extreme warm autumn events, needle-leaved evergreen forest (NLEF) is an addition to BLDF, NLDF and MF for analysis. And the sample sizes, N, for BLDF; NLDF; NLEF and MF are 13, 15, 11 and 8 respectively. With autumn events, the direct phenological metrics are EOS and OG of the following phenological year; whiles the OG determines the measure for lagged effect.

For the direct EOS metrics, all the forest types; BLDF, NLDF, NLEF and MF show late senescence (Figure 15). BLDF anomalously marks end of senescence in 291±8 day of year as against normal EOS date, 286±3 day of year. This shows that BLDF extended its EOS by five days. NLDF extended its EOS by eight days. The normal EOS for NLDF is 286±5 day of year; but NLDF ceased making leaves in 294±7 day of year. Similarly, NLEF continue its photosynthetic activity until 316±10 day of year. Meanwhile, NLEF normally ceases growth in 301±6 day of year. This therefore suggests that NLEF delayed EOS by 15 days. Further, MF delayed its EOS by ten days. The normal EOS for MF is 286±3 day of year; but it ceased greening in 296±8 day of year. In testing for late EOS, one-tailed t-test at ∝=0.05 was performed; the study found that all the forest types; BLDF (p=0.02), NLDF (p=0.001), NLEF (p=0.0002) and MF (p=0.008) significantly delayed EOS under the extreme warm autumn incidents (Table 8).

For onset of growth in the following phenological years, NLDF and MF showed early OG whiles BLDF and NLEF delayed their start of season (Figure 16). Needle-leaved deciduous forest starts the spring season in 139±4 day of year which contrasts its normal OG in 146±3 day of year. NLDF thus start leaf flushing 7 days earlier than normal. Mixed forest on the other hand started flushing 6 days earlier than normal. Averagely, MF begin leaf unfolding in 139±5 day of year. However, the occurrence of extreme warm autumn shifted its OG earlier than usual in 133±4 day of year. Relatedly, NLDF (p=0.001) and MF (p=0.03) are significantly earlier in their spring phenology (Table 9). Broad-leaved deciduous forest delayed OG by three days. BLDF is expected to leaf-out in 127±6 day of year but rather begin leaf unfolding in 130±4 day of year. Similarly, NLEF delayed OG by 7 days. NLEF normally grow leaves in 118±6 day of year but due to the anomalous warm temperatures in autumn it delayed its OG when it starts leaf unfolding in the subsequent spring season around 125 ± 4 day of year. The delayed OG due to the anomalous spring phenology is statistically significant for BLDF (p=0.01) and NLEF (p=0.0000014) (Table 9).

Table 6. Sample size, N, mean and standard deviation and the p-values for onset of growth variable for BLDF, NLDF and MF under extreme warm spring events

Forest type	Sample size, N	Mean±SD		p-value
		Normal OG	Anomalous OG	
BLDF	11	111±22	110±21	0.45
NLDF	23	132±8	120±14	0.0007
MF	13	132±4	129±3	0.02

Table 7. Sample size, N, mean and standard deviation and the p-values for end of senescence variable for BLDF, NLDF and MF under the extreme warm spring events

Forest type	Sample size, N	Mean±SD		p-value
		Normal EOS	Anomalous EOS	
BLDF	11	309±20	303±17	0.23
NLDF	23	304±15	311±17	0.10
MF	13	291±4	295±11	0.12

Table 8. Sample size, N, mean and standard deviation and the p-values for end of senescence variable for BLDF, NLDF, NLEF and MF under extreme warm autumn events

Forest type	Sample size, N	Mean±SD		p-value
		Normal EOS	Anomalous EOS	
BLDF	13	286±3	291±8	0.02
NLDF	15	286±5	294±7	0.001
NLEF	11	301±6	316±10	0.0002
MF	8	286±3	296±8	0.008

Table 9. Sample size, N, mean and standard deviation and the p-values for onset of growth variable of the following phenological year for BLDF, NLDF, NLEF and MF under extreme warm autumn events

Forest type	Sample size, N	Mean±SD		p- value
		Normal OG	Anomalous OG	
BLDF	13	127±6	130±4	0.01
NLDF	15	146±3	139±4	0.001
NLEF	11	118±6	125±4	0.0000014
MF	8	139±5	133±4	0.03

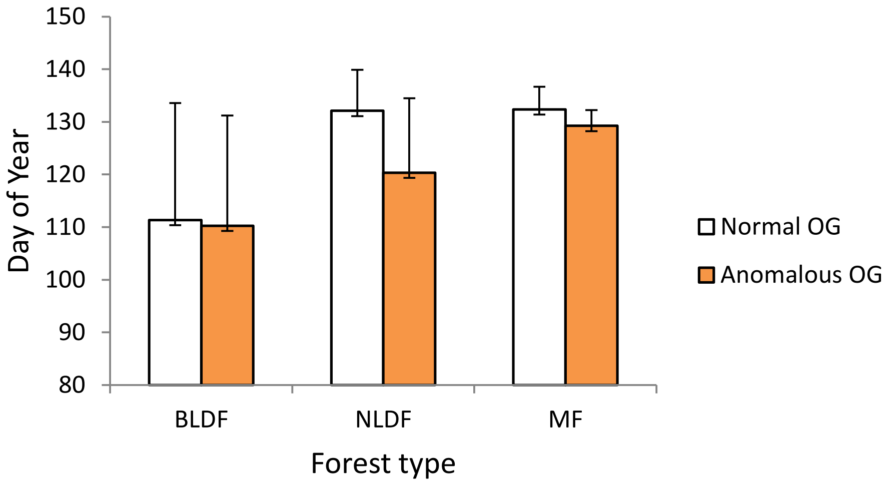

Figure 13. Extreme warm spring: Normal OG vs Anomalous OG. These bars represent the mean OG for normal and anomalous warm spring events for broad-leaved deciduous forest (BLDF), needle-leaved deciduous forest (NLDF) and mixed forest (MF). The error bars on top of each bar show the standard deviation.

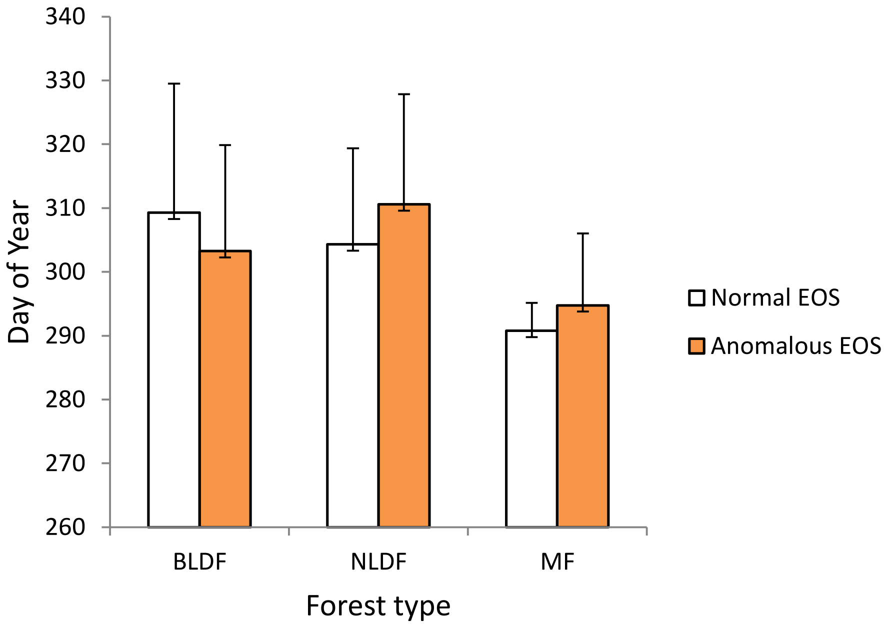

Figure 14. Extreme warm spring: Normal EOS vs Anomalous EOS These bars represent the mean EOS for normal and anomalous warm spring events for broad-leaved deciduous forest (BLDF), needle-leaved deciduous forest (NLDF) and mixed forest (MF). The error bars on top of each bar show the standard deviation.

Table 10. Extreme warm spring: Comparing mean I-MTCI for anomalous spring to normal spring. The p-value is used to determine significance level of the statistical difference between the mean I-MTCI for normal spring and I-MTCI for anomalous spring.

Forest type	Sample size, N	Mean±SD		p-value
		I-MTCI for normal spring	I-MTCI for anomalous spring	
BLDF	11	218±40	226±59	0.35
NLDF	23	148±25	173±43	0.01
MF	13	168±14	171±23	0.36

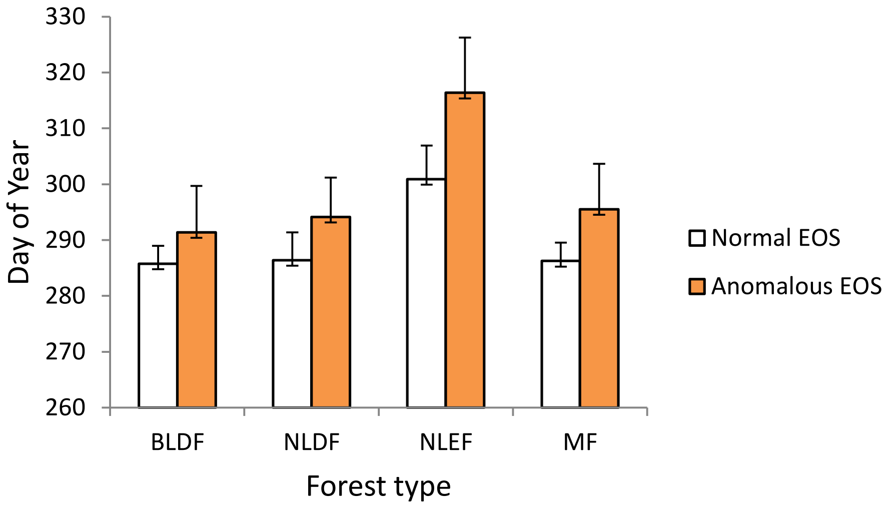

Figure 15. Extreme warm autumn: Normal EOS vs Anomalous EOS These bars represent the mean OG for normal and anomalous warm autumn events for broad-leaved deciduous forest (BLDF), needle-leaved deciduous forest (NLDF), needle-leaved evergreen forest (NLEF) and mixed forest (MF). The error bars on top of each bar show the standard deviation.

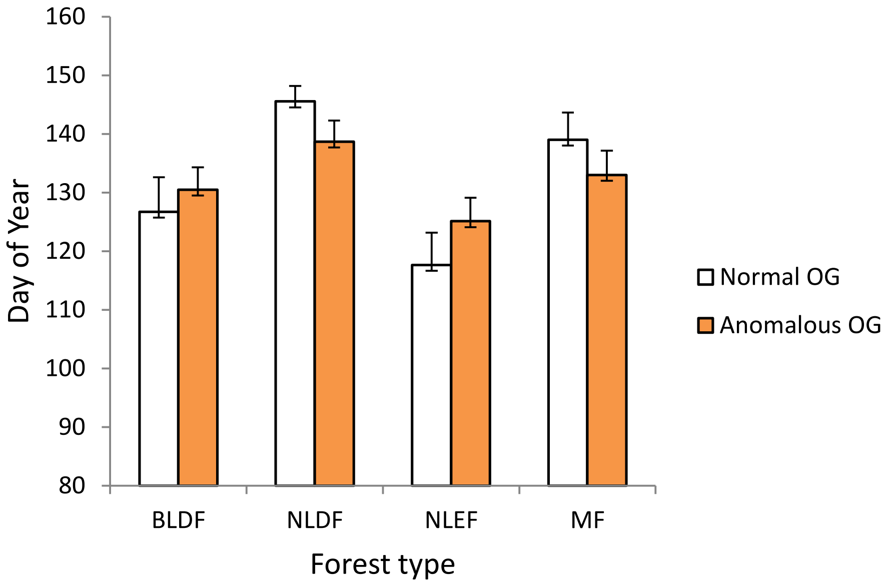

Figure 16. Extreme warm autumn- Normal OG vs Anomalous OG of following phenological year. These bars represent the mean OG for normal and anomalous warm autumn events for BLDF, NLDF, NLEF and MF. The error bars on top of each bar show the standard deviation.

4.4 *Investigating direct and lagged effects*

4.4.1 Extreme warm spring events

In normal spring, the total greenness of BLDF, NLDF and MF are 218±40; 148±25; and 168±14 respectively. However, as a result of the extreme high spring temperatures the total greenness of these forest types increased. Thus, the total greenness for BLDF is 226±59, an increase of 18 in mean I-MTCI; NLDF is 173±43, an increase of 25 in mean I-MTCI; and MF is 171±23, an increase of 3 in the mean I-MTCI. Clearly, there is increased difference in the mean I-MTCI values for when the forest types are under normal spring seasons and when they experienced anomalous warm temperatures. This is to say that BLDF, NLDF and MF all show direct positive effect on productivity as result of the anomalous warm events (Figure 17). However, at ∝= 0.05, it is only NLDF which demonstrates statistically significant (p=0.01) direct positive effect under extreme warm spring conditions. BLDF (p=0.35) and MF (p=0.36) shows no statistically significance for direct positive effect in spring productivity (Table 10).

In investigating if the early onset of growth leads to lagged effect in autumn productivity, the study found that BLDF shows negative lagged effect on autumn productivity. This is because its mean I-MTCI (206±28) is less than mean I-MTCI (230±50) for normal spring events.

Table 11. Extreme warm spring events- Investigating lagged effect. Sample size, N, Mean±SD of I-MTCI for normal and anomalous autumn seasons. And p-value for significance level of the statistical difference between the mean I-MTCI for normal spring and I-MTCI for anomalous spring**.**

Forest type	Sample size, N	Mean±SD		p-value
		I-MTCI for normal autumn	I-MTCI for anomalous autumn	
BLDF	11	230±50	206±28	0.10
NLDF	23	167±41	166±32	0.48
MF	13	168±14	175±18	0.15

The NLDF shows no lagged effect on autumn productivity. This is because normal I-MTCI mean value (167±41) and mean I-MTCI for anomalous warm spring events (166±32) are about the same. Meanwhile, MF shows positive lagged effect on autumn productivity since mean I-MTCI (168±14) for normal autumn productivity is less than the mean I-MTCI for autumn productivity in the anomalous autumn (Figure 18). Nevertheless, at ∝=0.05, the mean I-MTCI for normal autumn productivity and anomalous autumn productivity are not statistically significantly different for BLDF (p=0.1), NLDF (p=0.48) and MF (p=0.15) (Table 11)**.**

4.4.2 Extreme warm autumn events

In this test conditions, unlike the extreme warm spring events, four forest types are involved in the analysis- BLDF, NLDF, NLEF and MF. It is expected in this study that as a result of the unusual warm autumn seasons there should be direct positive effect on autumn productivity. Indeed, BLDF (199±25 for productivity in anomalous autumn as against 194±21 productivity in normal autumn); NLDF (141±10 for productivity in anomalous autumn as against 135±7 in normal autumn) and MF (156±16 for productivity in anomalous autumn as against 146±7 in normal autumn) experienced direct positive effect from the extreme warm events. However, the mean I-MTCI for NLEF (222±18) in anomalous autumn is not different from mean I-MTCI (222±22) for normal autumn phenology (Figure 19).

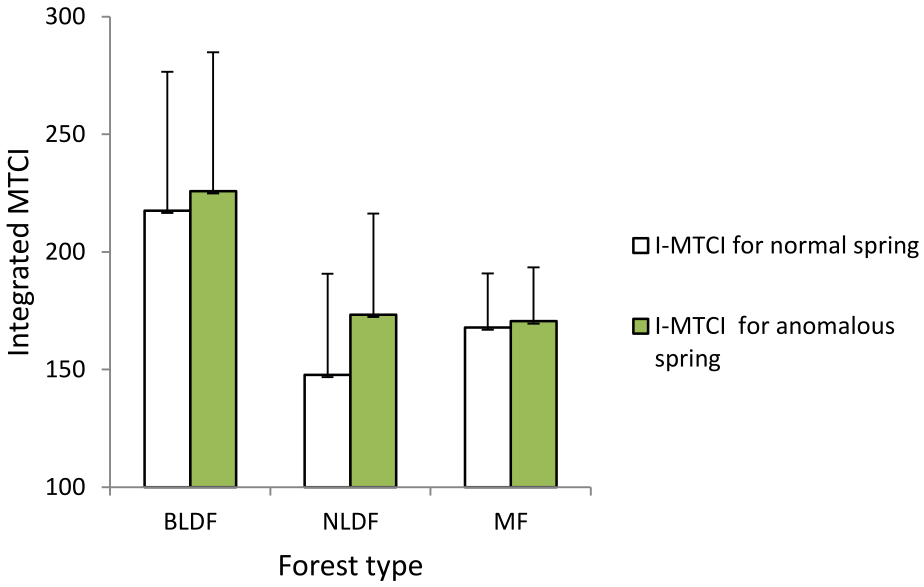

Figure 17. Extreme warm spring: investigating direct positive effect. The forest type and its mean integrated MTCI(the bars- the open bars are the mean I-MTCI when spring was normal and the green shaded bars are mean I-MTCI when spring was anomalous) The error bars show 1 standard deviation of the mean I-MTCI values. The mean I-MTCI for anomalous spring exceeds those of normal spring signifying direct increase in spring productivity.

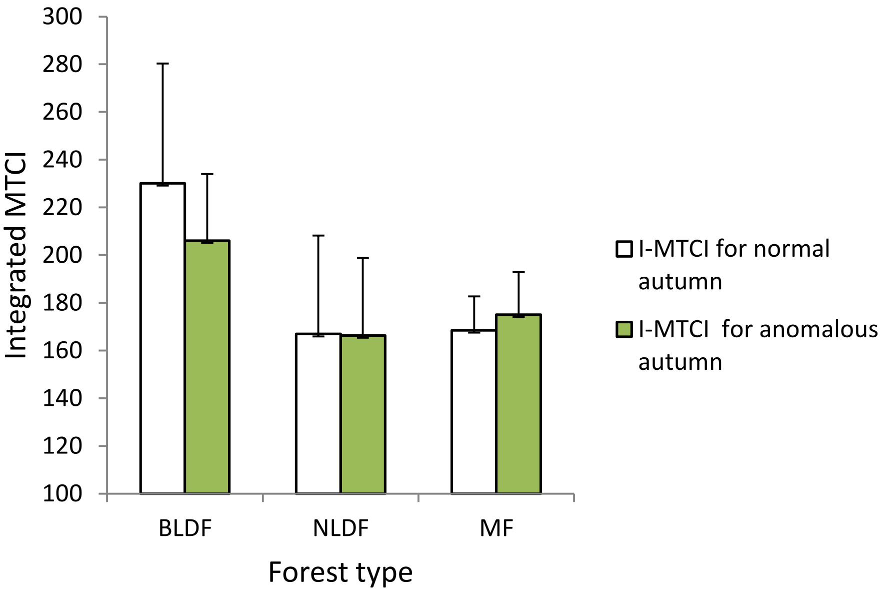

Figure 18. Extreme warm spring: investigating lagged effect. The forest type and its mean integrated MTCI(the bars- the open bars are the mean I-MTCI for when spring was normal and the green shaded bars are mean I-MTCI when spring was anomalous) The error bars show 1 standard deviation of the mean I-MTCI values. The mean I-MTCI for anomalous spring of BLDF and NLDF compare less to mean I-MTCI for normal spring. However, MF shows increase in mean I-MTCI for anomalous spring event.

Table 12. Extreme warm autumn: Investigating direct effect. Sample size, N, Mean±SD of I-MTCI for normal and anomalous autumn seasons; and p-value of the statistical difference between the mean I-MTCI for normal autumn and I-MTCI for anomalous autumn.

Forest type	Sample size, N	Mean±SD		p-value
		I-MTCI for normal autumn	I-MTCI for anomalous autumn	
BLDF	13	194±21	199±25	0.27
NLDF	15	135±7	141±10	0.03
NLEF	11	222±22	222±18	0.50
MF	8	146±7	156±16	0.06

Besides, at $\propto=0.05$, only NLDF ($p=0.03$) show significant direct increase (positive effect) in productivity as a result of the extreme warm autumn temperatures. BLDF ($p=0.27$) and MF ($p=0.06$) show direct positive productivity but are not significantly greater than mean I-MTCI when autumn temperatures are normal (Table 12).

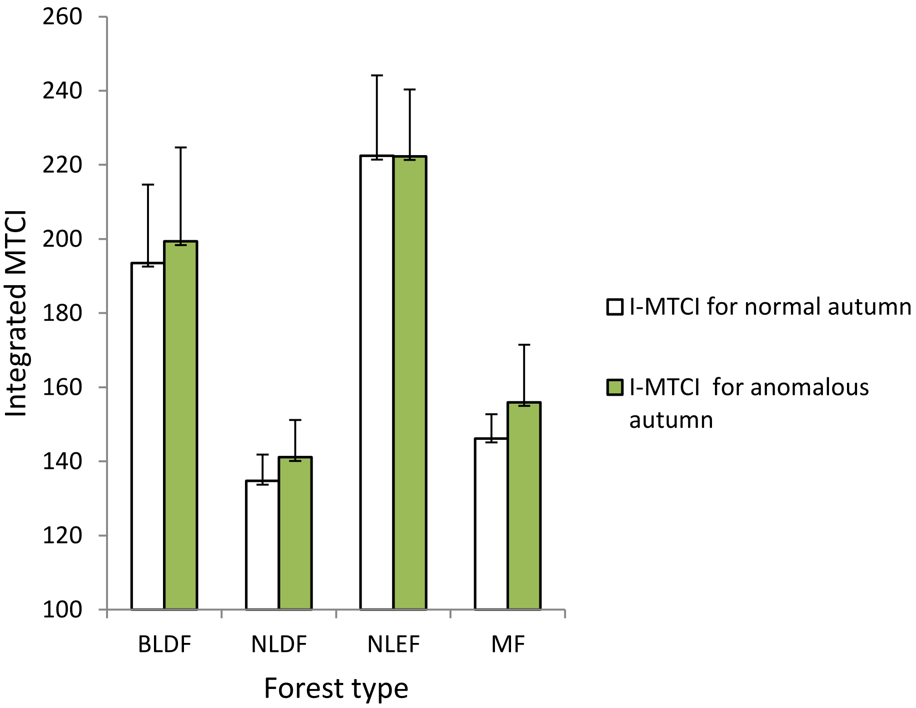

Figure 19. Extreme warm autumn: investigating direct positive effect. The forest type and its mean integrated MTCI(the bars- the open bars are the mean I-MTCI when spring was normal and the green shaded bars are mean I-MTCI when spring was anomalous) The error bars show 1 standard deviation of the mean I-MTCI values. Except NLEF, the mean I-MTCI for anomalous autumn exceeds mean I-MTCI for normal autumn signifying direct increase in autumn productivity for BLDF, NLDF and MF.

To determine if the direct positive effect ensures a carry-over effect on the next spring forest productivity, mean I-MTCI as a result of anomalous OG is compared to the mean I-MTCI for normal OG (Figure 20). And in this investigation, the study found that BLDF; NLDF and MF show increase in total greenness. Under normal spring phenology, BLDF; NLDF and MF show mean I-MTCI of185±16, 133±7 and 139±4 respectively. However, with the anomalous EOS in the autumn, BLDF (186±13); NLDF (136±7) and MF (148 ±8) experienced positive lagged effect in their sum of greenness (productivity). For NLEF, even though it did not show direct positive effect in autumn productivity, however, it experienced negative lagged effect in the following spring phenology. It thus means that the mean I-MTCI for NLEF (194±17) during normal spring phenology is higher than the mean I-MTCI for NLEF (185±15) under anomalous onset of growth.

As mentioned earlier on, BLDF;NLDF and MF experienced increase in productivity, however, for one-tailed t-test at $\propto$=0.05 significance level, only MF (p=0.007) show statistically significant positive lagged effect to the anomalous warm autumn events. BLD (p=0.42) and NLDF (p=0.13) do not show statistically significance in positive lagged effect. Conversely, NLEF (p=0.1) show negative lagged effect but this effect is not statistically significant (Table 13)

Table 13. Extreme warm autumn: Investigating lagged effect. Sample size, N, Mean±SD of I-MTCI for normal and anomalous autumn seasons; and p-value of the statistical difference between the mean I-MTCI for normal spring and I-MTCI for anomalous spring.

Forest type	Sample size, N	Mean±SD		p-value
		I-MTCI for normal spring	I-MTCI for anomalous spring	
BLDF	13	185±16	186±13	0.42
NLDF	15	133±7	136±7	0.13
NLEF	11	194±17	185±15	0.10
MF	8	139±4	148±8	0.007

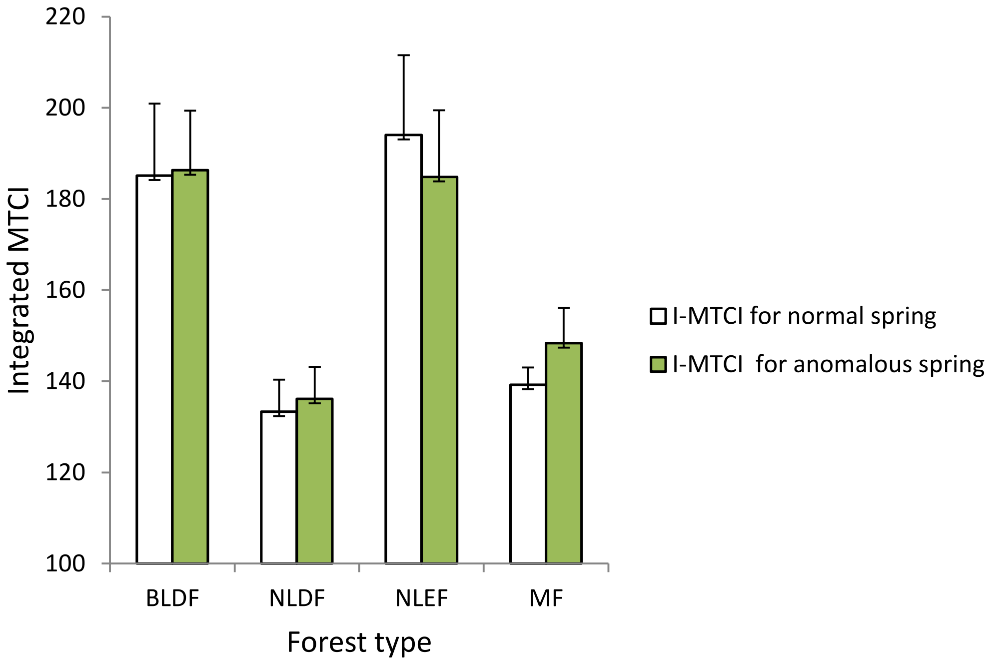

Figure 20. Extreme warm autumn- investigating lagged effect. The forest type and its mean integrated MTCI(the bars- the open bars are the mean I-MTCI when spring was normal and the green shaded bars are mean I-MTCI when spring was anomalous) The error bars show 1 standard deviation of the mean I-MTCI values. The mean I-MTCI for anomalous spring for BLDF, NLDF and MF demonstrates increase in spring productivity whiles NLEF show decrease in spring productivity.

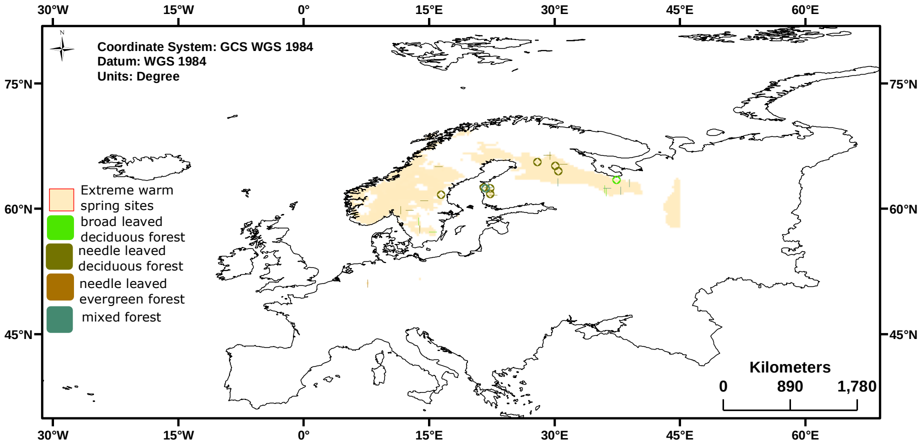

Figure 21. Selected sample areas for extreme warm spring events.

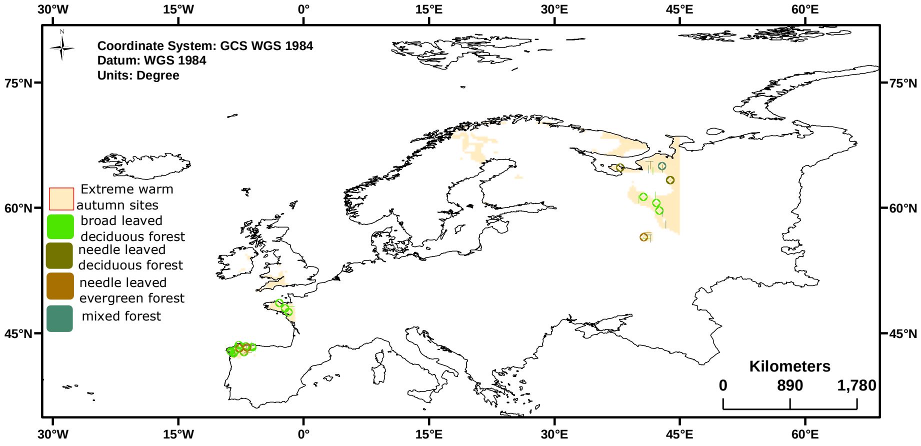

Figure 22. Selected sample areas for extreme warm autumn events.

Chapter 5: DISCUSSION

5.1 Extreme Warm Spring and Autumn Events in Europe

The extreme warm spring events largely occurred in Scandinavia Europe and Russia. A previous work done but with different method of anomaly estimation and a data set, however, shows that Nordic and Arctic part of Europe experienced extreme high warm spring incidents (Tuomenvirta et al., 2000) . In this work, the temperature anomaly was defined by standard anomaly statistic and then subjected to a condition that says the anomaly should be more than 1.5 standard deviation of the long term climatic (1961-1990) mean, but Tuomenvirta et al., (2000) estimated anomalies as absolute deviations from reference climate (1961–1990) only. Additionally, both studies used different sources of data sets. Nevertheless, both results show warm spring events in Northern and Arctic Europe.

Extreme warm autumn events occurred extensively in Russia; but also patches of it occurred in mid-latitude areas of Spain, France and United Kingdom. Previous studies show a pervasive anomalous warm autumn in Europe (Luterbacher et al., 2007; Van Oldenborgh, 2007; Cattiaux et al., 2009); and they confirm the results of this work.

Before the 21st century, Europe experiences cool spring and autumn temperatures; but recently, spring and autumn seasons have been extremely warm, especially, in northeastern Europe (Xoplaki et al., 2005; Overland et al., 2008).

These anomalous warm spring and autumn events have been attributed to anthropogenic greenhouse gas forcing; however, extreme strong positive NAO since 1980s in Northern Europe is partly responsible for the temperature anomalies (Hurrell and VanLoon, 1997). This is because the strong positive phase of NAO brings along extreme anticyclones and warm air advection from subtropical middle latitude which tends to raise the land surface temperatures (Luterbacher et al., 2007).

5.2 Forest Phenology and Productivity

Consequent to global warming, onset of growth variable for spring phenology is noted to be earlier than normal across Europe (Menzel and Fabian, 1999; Ahas et al., 2002; Schwartz et al., 2006). The result of this study is clearly consistent with these previous studies. Among the forest types considered for this study, only broad-leaved deciduous forest fails to portray statistically significance earlier onset of growth. Expectedly, the earlier onset of growth corresponded to direct and immediate increase in forest greenness (productivity). Nevertheless, it is the productivity of needle–leaved deciduous forest that shows statistical significance.

Because of the early onset of growth, all the forest types experienced late end of senescence as reported in other studies done earlier on (Myneni et al., 1997; Menzel and Fabian, 1999; Menzel, 2000; Tucker et al., 2001). Interestingly, all the forest types do not show significance in the end of senescence date; even though, NLDF and MF experienced significant earlier onset of growth. Relatedly, forest productivity in the anomalous spring seasons is lower than that of normal. The interesting point is that all forest types extended their end of senescence; however, BLDF and NLDF show less productivity instead. The reason could be attributed to the fact that total greenness (I-MTCI value) is used to measure productivity. And since the greenness is measured by satellite remote sensor from forest canopy then a traditional challenge, such as false target sensing, in satellite remote sensing could explain for this. To explain, the anomalous spring events extensively happened in boreal Europe where ice cover is common. Therefore, the sensor might have measured greenness which is misleading due to the presence of ice-covered forest canopy. Alternatively, the very species making up the BLDF and NLDF is a case to look into. This is because deciduous species like beech have been noted to be more dependent on photoperiod for growth (Heide, 1993; Fracheboud et al., 2009; Vitasse and Basler, 2013) ; and thus increase in temperature might have less impact on its productivity. Another reason could be attributed to frost damage. Previous studies show that early onset of growth as a result of anomalous warming spring events make forest cover susceptible to decline in productivity by way of leaf loss and late canopy development (Hänninen, 1991; Kellomaki et al., 1995; Inouye, 2008; Hufkens et al., 2012).

In relating direct positive (increase) effect of earlier OG on autumn productivity (Figure 18); it is observed that BLDF experienced negative lagged effect; NLDF showed no lagged effect whiles MF showed positive lagged effect. Nevertheless, these lagged effects experienced in autumn productivity as a result of anomalous warm spring are not statistically significant. And for BLDF, it is consistent with previous studies (Richardson et al., 2009)

For the extreme warm autumn events, BLDF; NLDF; MF and NLEF expectedly show delayed senescence. It is thus not a deviation from already established evidence (Sparks and Menzel, 2002; Jeong et al., 2011). This is to say that the extent of delayed EOS is statistically significant for all forests types. The delayed EOS immediately translated to direct positive autumn productivity for BLDF, NLDF and MF. However, the direct autumn productivity for NLEF remained same as normal, as though it did not experience extreme warm temperatures. Even though, BLDF, NLDF and MF display direct increase in autumn productivity; it is only NLDF and MF that show significant increase.

Indeed, the delayed EOS is followed by early OG for the succeeding spring phenology for NLDF and MF but not BLDF and NLEF. The NLDF and MF therefore recorded increased levels of greenness for lagged effect. However, it is only the MF that experienced significance increase. For BLDF and NLEF, NLEF expectedly show decrease in productivity whiles BLDF strangely show increase in productivity, however, not statistically significant. Clearly, challenges such as snow cover on forest canopy to satellite sensor is potentially responsible for the increase observed in I-MTCI for BLDF. Another reason is that the forest types are sampled from different latitudes of Europe, though grouped per similar latitudes for this study. The variations in phenological profile that emanate from different latitudes of the forest types are potential challenge to I-MTCI estimations (Dash et al., 2010).

Additionally, previous work in Northern Europe found that warming autumns increase photosynthetic activity but it simultaneously fuels up ecosystem respiration which potentially offset photosynthetic gains(Piao et al., 2008). One may argue that this study is looking at productivity from sum of greenness estimation and not carbon gains and losses. However, it is as a result of increased assimilation of carbon by plants that leads to increased leaves making (more greenness); and if this leaves are fallen off as a result of ecosystem respiratory activities then it influences I-MTCI values estimated for this study since Envisat MERIS only estimates greenness of forest canopy (Dash and Curran, 2004; Dash et al., 2010; Jeganathan et al., 2010; Boyd et al., 2011b).

5.3 Role of extreme warm temperatures in the direct and lagged effects

In this study the forest types show either direct positive or lagged effect as a result of extreme warm spring or extreme warm autumn. In the previous section, reasons were attributed to changes in forest productivity in each event type. However, in this section, the study focuses on some possible ways by which warming temperatures promote direct and lagged effects in forest productivity.

So long as extreme warm temperatures do not injure the thylakoid membrane in trees; it ensures increase in the content of photosynthetic pigments (Michelsen et al., 1996; Ormrod et al., 1999). Consequently, forest experiences ontogenetic shift in growth (Higuchi et al., 1999); and positive effect on quantum yields (Methy et al., 1997).

Further, warmer temperatures enhance soil organic carbon decomposition which in turn promotes nitrogen availability for plants use. Nitrogen is a major nutrient plants need to grow and develop; and thus nitrogen availability affects forest productivity than any other minerals (Larcher, 1995). In northern Europe forests, temperature effect on nitrogen is the most important controlling factor on forest primary production (Pastor et al., 1984).

Finally, extreme warm temperature might force premature dormancy break in forest. It is widely known that there is a constant relationship between chilling temperature and rate of dormancy break. However, previous studies found that warming temperature can incite dormancy break prematurely; but the inherent nature in plant system nullifies this effect at a later date(Hanninen et al., 1990; Partanen et al., 1998).

5.4 Importance of Study Findings

The findings of this study provide spatial information to stakeholders such as forest managers, climate change experts and policy makers of Europe. Previous studies (Luterbacher et al., 2007) have clearly demonstrated that there was Europe-wide warming. However, in this study, beyond the traditional anomaly statistic applied to estimating anomalous temperatures, only anomalous areas of more than 1.5 standard deviation of the long term mean (1961-1990) were selected. Therefore, these stakeholders would now know the extremely warm areas of Europe for which scarce resource will be invested to ameliorate further warming. In other words, the spatial information from this study would help in effective management of terrestrial ecosystems.

The phenological and productivity metrics derived in this work can be used as input data for land surface or regional climate models.

5.5 Criticisms on the study

The Envisat MTCI multi-temporal data used in this work is one of Envisat reduced resolution products (~ $1km^2$ spatial resolution). This is a coarse resolution data with temporal resolution, at best 8-days, applied in this study. A relatively finer spatial and temporal resolution data, for example, outdoor webcam stationed around these extremely warm sites could provide improvement in this study.

The study applied E-OBS temperature dataset version 7 and that was the latest release when this study started; but even before this study is rounded up version 8 of the temperature data have been released by ECAD. This means that European countries that did not have stations and thus their surface temperature were estimated based on interpolations would now have direct temperature observation data. Obviously, if this study had worked with this new dataset the quality of result might have improved.

There was a challenge in sampling needle-leaved deciduous forest. In the GlobCover land cover classification map used for this work, needle-leaved deciduous forest was not clearly distinguished since it is mixed with stands of evergreen. This therefore suggests that analysis for NLDF in this study could have been affected by the contribution of stands of evergreen trees. Also, in validating the samples with Google Earth, it is realized that there were misclassification in the GlobCover land cover map. Relatedly, as a result of inadequate time after identifying study sites, previous studies were used to validate results. However, field work would have been useful in validating the naturalness of the forest types sampled.

The code applied to extract the phenological and productivity variables worked pretty well. However, in few instances, for needle-leaved evergreen forest (NLEF) the code could not detect its point of inflection. This is because NLEF lacks seasonality in its profile. The study thus resorted to NLEF that the code extracted the phenological and productivity variables with less than 5 percent errors. This is to say the sample size for NLEF could have been larger.

Chapter 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study applied onset of growth and end of senescence phenological variables to investigate if shifting in onset of growth and end of senescence, as a result of extreme warming temperatures in spring and autumn events, impacts on forest productivity. The study essentially starts on the assumption that extreme warm spring or autumn results in direct positive effect on forest greenness (productivity); and thus designed conceptual models of how the direct positive effect might translate on following spring or autumn forest greenness. The study used a novel method in integrated-MTCI to estimate forest greenness for areas in Europe that experienced extreme warm spring and autumn.

Daily mean temperature data sets for 2003-2011 as study time and 1961-1990 representing reference time were acquired from European Climate Assessment and Dataset (ECAD). Standardized anomaly statistic and certain conditions were applied to the temperature data sets to define temperature anomalous areas in Europe. Out of these areas, those with more than 1.5 standard deviations were selected to represent extreme warm spring and autumn areas of Europe for this study. This work used 8-day and 10-day time series data from Envisat Meris Terrestrial Chlorophyll Index imagery covering Europe for the years 2003-2011. Each of the ~1 km^2 pixel size was analyzed for broad-leaved deciduous forest, needle-leaved deciduous forest, needle-leaved evergreen forest and mixed forest. The forest types were sampled from a reclassified GlobCover land cover 2009 map. A point of inflection based method was applied to derive the phenological metrics. The first four harmonics of Discrete Fourier Transformation were applied to smooth the MTCI-against-time profile whiles preserving original phenological nuance of the forest types. One-tailed t-tests were run to investigate the statistical difference between normal and anomalous phenology and productivity variables.

Under extreme warm spring events, BLDF showed early onset of growth; however, it is not significantly different (p=0.45) from onset of growth under normal spring. Meanwhile, NLDF (p= 0.0007) and MF (p=0.02) showed statistically significant earlier onset of growth.

All forest types extended end of senescence. However, the delay in EOS were not statistically significance-BLDF (p=0.23), NLDF (p=0.1) and MF (p=0.12). For direct positive effect investigations, BLDF (p=0.35) and MF (p=0.36) were not statistically significant but NLDF (p=0.01) experienced statistically significant direct positive effect on spring productivity. For lagged effect investigations, BLDF in autumn, experienced negative lagged effect in its greenness. Similarly, NLDF experienced negative lagged effect. MF experienced positive lagged effect. However, these lagged effects; BLDF (p=0.1), NLDF (p=0.48) and MF (p=0.15) experienced in autumn productivity were not statistically significant.
Under extreme warm autumn events, BLDF (0.02); NLDF (0.001); NLEF (0.0002) and MF (p=0.008) statistically significant delayed EOS. NLDF and MF were statistically significant earlier in onset of green for the following normal spring phenology. However, BLDF and MF showed statistically significant earlier onset of growth. For direct positive effect on spring productivity, apart from NLEF which recorded same total greenness as normal autumn productivity, BLDF; NLDF and MF showed increased total greenness. However, only NLDF (p=0.03) was statistically significant for the direct effect on autumn forest productivity. In investigating lagged effect, BLD; NLDF and MF experienced positive lagged effect but it was only MF (p=0.007) which showed statistical significance. NLEF experienced negative lagged effect but was not statistically significant.

Phenological variables derived for this study can be fed into regional climate models to study climate changes. Further, the onset of growth; end of senescence and I-MTCI variables that constitute the core of this study are important spatial information that may go a long way to help effective forest or ecosystem conservation.

6.2 Recommendations

This study is carried out at coarse resolution (~1km^2). In future, high spatial resolution data can be applied to capture a lot more details in forest dynamism. Second, further studies of this work should carry out field work to see if the forest samples are indeed natural. Third, this study can be improved if it is performed at species level; and other factors such photoperiod; stand age and disturbance history are considered to understand the phenological variability among same vegetation types but in different locations. Fourth, extreme warm summer events can be included in subsequent studies. Time did not permit this study to consider extreme warm summer events in its objectives. Since summer forms part of the vegetation growing period; it will be a complete study if the impact of anomalous warm summer on forest phenology and greenness is investigated. Finally, a breakthrough in remote sensing phenology extraction algorithm for understory vegetation will help estimate the overall greenness of a site for an in-depth landscape characterization.

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