

Student thesis series INES nr 338

Testing the robustness of the Plant Phenology Index to changes in temperature

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2015
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Iain Lednor (2015). *Testing the robustness of the Plant Phenology Index to changes in temperature*

Master degree thesis, 30 credits in *Physical Geography and Ecosystem Analysis*
Department of Physical Geography and Ecosystems Science, Lund University

Level: Master of Science (MSc)

Course duration: *June 2014 until January 2015*

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Testing the robustness of the Plant Phenology Index to changes in temperature

Iain Lednor

Master thesis, 30 credits, in *Physical Geography and Ecosystem Analysis*

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Abstract

Traditional vegetation indices have long encountered a problem of saturating at high biomass levels. A newly formulated vegetation index, the Plant Phenology Index (PPI), which has a near linear relationship with canopy green leaf area index (LAI) is tested in this study against temperature at 12 sites across Sweden. For comparison, the performance of the Normal Difference Vegetation Index (NDVI) and Enhanced Vegetation Index 2 (EVI2) are also tested. This study aim was robustness of PPI, and to see how well PPI correlates to temperature. PPI was shown to correlate very well with temperature for 11 out of the 12 sites, and also demonstrated a much more linear relationship to temperature than NDVI and EVI2. These results were replicated in a test of the vegetation indices against Growing Degree Days, a measure of accumulated heat, with high correlation coefficients for PPI. This indicated that PPI was more sensitive to changes in temperature than NDVI and EVI2 and is thus an efficient tool to show the phenological stages of vegetation.

Key Words: Physical Geography and Ecosystem Analysis, Remote Sensing, Plant Phenology Index, NDVI, EVI2, Vegetation Index, Temperature, Phenology

Table of Contents

1 Introduction	1
2 Background	2
2.1 Remote Sensing of Vegetation	2
2.2 Phenology.....	3
2.3 Phenological Characteristics of Plants	4
2.4 Leaf Area Index.....	5
3 Vegetation Indices	5
3.1 Normalized Difference Vegetation Index	6
3.2 Enhanced Vegetation Index and Enhanced Vegetation Index 2.....	8
3.3 Normalised Difference Water Index.....	9
3.4 Normalized Difference Snow Index	10
4 Relationship between LAI and Vegetation Indices	11
5 Plant Phenology Index (PPI)	11
6 Vegetation Indices and Temperature	13
6.1 NDVI	13
7 Aims and Purpose	14
7.1 Working Hypothesis	15
8 Methodology	15
8.1 Study Area	15
8.2 Data	17
8.3 Analysis	19
Results	21
9.1 PPI and NDVI Correlating with Temperature (Pearson R).....	21
9.2 Regression Analysis	21
9.3 Growing Degree Days	27
9.4 Monthly Growing Degree Days vs PPI and NDVI	27
9.5 Accumulated Growing Degree Days and Vegetation Indices' Quadratic Regression Analysis	28
10 Discussion	33
10.1 Saturation of NDVI	33
10.2 Two Stage Results of NDVI and EVI2.....	34
10.3 Performance of PPI.....	36
10.4 Growing Degree Days and VIs	37
10.5 Anomalous Result	38
10.6 Hypothesis.....	39
11 Conclusions	40
11.1 Further Scope	41
12 References	42
13 Appendix	46
13.1 Growing Degree Days.....	46
13.2 Annual Mean Temperature (°C).....	47
13.3 Regression Analysis of Full Data Set, entire temperature range	48
13.4 Regression Analysis: Entire Data Set Results Table	52

13.5 List of Previous Publications	53
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List of Equations

Equation 1 – NDVI.....	7
Equation 2 - EVI2.....	9
Equation 3 – Beer’s Law.....	11
Equation 4 – PPI.....	12

List of Tables

Table 1 - Study Site Locations	15
Table 2 - Climate Data Acquisition from the Swedish Meteorological and Hydrological Institute (SMHI).....	17
Table 3 - PPI/NDVI and Temperature Correlation Results	21
Table 4 - Regression Analysis Results. All Results are significant at a level of 0.0.....	22
Table 5 - Correlation Analysis between Growing Degree Days (5) and PPI/NDVI.....	28
Table 6 - Quadratic Regression Analysis of Accumulated Growing Degree Days (5) and PPI, NDVI and EVI2.....	28
Table 7 - Appendix: Growing Degree Days – Section 9.3 in Text	46
Table 8 - Appendix: Mean Annual Temperature (°C) – Section 9.4 in Text	47

List of Figures

Figure 2 - Arjeplog PPI, NDVI and EVI2 Regression Model	23
Figure 3 - Dravagen PPI, NDVI and EVI2 Regression Model.....	23
Figure 4 - Glommerträsk PPI, NDVI and EVI2 Regression Model.....	24
Figure 5 - Horn PPI, NDVI and EVI2 Regression Model	24
Figure 6 - Hunge PPI, NDVI and EVI2 Regression Model.....	24
Figure 7 - Kroksjö PPI, NDVI and EVI2 Regression Model.....	25
Figure 8 - Malung PPI, NDVI and EVI2 Regression Model.....	25
Figure 9 - Norrberg-Norrhög PPI, NDVI and EVI2 Regression Model	25
Figure 10 - Saxnäs PPI, NDVI and EVI2 Regression Model.....	26
Figure 11 - Storfinnforsen PPI, NDVI and EVI2 Regression Model	26
Figure 12 - Växjö PPI, NDVI and EVI2 Regression Model.....	26
Figure 13 - Vidsel PPI, NDVI and EVI2 Regression Model.....	27
Figure 14 - Arjeplog; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	29
Figure 15 - Dravagen; GDD5 vs PPI, NDVI and EVI2 Regression Analysis.....	29
Figure 16 - Glommerträsk; GDD5 vs PPI, NDVI and EVI2 Regression Analysis.....	29
Figure 17 - Horn; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	30
Figure 18 - Hunge; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	30
Figure 19 - Kroksjö; GDD5 vs PPI, NDVI and EVI2 Regression Analysis.....	30
Figure 20 - Malung; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	31
Figure 21 - Norrberg-Norrhög; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	31
Figure 22 - Saxnäs; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	31
Figure 23 - Storfinnforsen; GDD5 vs PPI, NDVI and EVI2 Regression Analysis.....	32
Figure 24 - Växjö; GDD5 vs PPI, NDVI and EVI2 Regression Analysis	32
Figure 25 - Vidsel; GDD5 vs PPI, NDVI and EVI2 Regression Analysis.....	32
Figure 26 - Appendix: Regression Analysis Entire Dataset.....	51

Acknowledgments

Firstly, I would like to express my sincere gratitude towards Dr. Veiko Lehsten for his unwavering patience over a long period of time and various stalled project ideas, and his help and guidance on this final topic, particularly in the alien world of Matlab. Secondly to Hongxiao Jin and Professor Lars Eklundh for allowing me to look at the manuscript on the Plant Phenology Index before it was officially published.

Secondly, to all my friends around the world for their words of encouragement when the project was not going as planned.

Last but not least, to my family, particularly my parents, for their support and inspiration over the past 25 years.

1 Introduction

From a general perspective, remote sensing is the science of acquiring and analysing information about an object, area or phenomena from a distance (Lillesand et al., 2004). In the sense of optical remote sensing using satellites, electromagnetic radiation (EMR) is measured as it interacts with an object. When EMR reaches an object it can interact with said object in 3 ways; it can be absorbed by it, reflected off it, or transmitted through it. Whether an object absorbs, reflects or transmits EMR depends on the wavelength of the light, and therefore one object can absorb EMR of one frequency, and reflect light at another (Aggarwal, 2004, Jones et al., 2010). The reflectance of light by a certain object/living thing/feature is why we as humans see them as we do. For example, humans see vegetation as green because wavelengths in the green region of the spectrum are reflected by pigments in the leaf, while the other visible wavelengths are absorbed.

There are two types of remote sensing, active and passive. Active remote sensing, the instrument on which the sensor is mounted uses its own energy source to illuminate the object/scene which it is trying to sense. Passive remote sensing, however, relies on the Sun's energy for illumination. Due to the nature of satellite remote sensing, it is performed almost entirely by this method.

This thesis will look into a common remote sensing tool that can be used, for example, to survey the health of vegetation and determine land use; the vegetation index. Vegetation indices are usually dimensionless measures derived from radiometric data that are primarily used to indicate the amount of green vegetation present in a view (Jones et al., 2010). More specifically, this thesis will look at the influence of temperature has on their results; looking at the more traditional indices such as the Normalized Difference Vegetation Index (NDVI), and the newly formulated Plant Phenology Index.

As discussed in more detail later, there are inherent problems associated with vegetation indices. Of the traditional VI's, the most widely used has been NDVI which has a tendency to saturate at high Leaf Area Index (LAI)/levels of biomass (van Wijk and

Williams, 2005). This makes it unreliable at the height of the growing season when high biomass levels are expected. Because of this, new VI's that are more linear to LAI are being formulated and tested. Of these, this thesis will test the Plant Phenology Index and it's robustness to temperature, in terms of how well it responds to changes in temperature and how this compares to NDVI and EVI2. Temperature can also be used as a proxy for biomass, and as such the problem of VIs saturating at high levels of biomass can be partially addressed.

2 Background

2.1 Remote Sensing of Vegetation

The physical basis for remote sensing of vegetation is based around several characteristics of the vegetation. The photosynthetic activity, pigmentation, leaf structure and plant water content are important on the scale of an individual leaf, whilst the canopy structure and phenological cycles are important on a wider scale.

The interaction of radiation with plant leaves, and hence the magnitudes of spectral reflectance, spectral absorption and spectral transmission, depends not only on the wavelength but also on a range of structural and chemical characteristics such as leaf chemical composition, leaf age, leaf thickness, leaf structure, leaf water content, etc. Structural characteristics all affect the radiative properties of the leaves of individual species; and as such various characteristic combinations gives scope for distinguishing them on the basis of reflected radiation (Jones et al., 2010).

Generally, a leaf is built up of layers of structural fibrous organic matter, within which are pigmented water filled cells and air spaces. Each of these properties reflects a different part of the spectrum of electromagnetic radiation. Absorption of light targeted at a leaf is centred around 0.65um, visible red, by chlorophyll pigment in the chloroplast cells that occur on the outer layers of the leaf; leaves also absorb similarly in the blue part of the spectrum, thus predominantly reflecting in the green part of the visible wavelengths (Gates et al., 1965). Thus, most vegetation has a green leafed colour.

Strong reflectance of the NIR band occurs in the spongy mesophyll cells located in the interior or back of a leaf, within which light reflects mainly at cell wall and air space interfaces. Because the intensity of the reflectance is much higher than from most inorganic materials, vegetation appears bright in the NIR wavelengths. These properties account for the spectral signatures of different vegetation types on multispectral images (Gates et al., 1965, Jones et al., 2010).

2.2 Phenology

Lieth (1974), defined phenology as the study of the timing of recurring biological events, the causes of their timing with regards to biotic and abiotic forces, and the interrelation among phases of the same or different species. So, phenology is not only concerned with certain aspects of plant life in terms of their life biological life cycles, but it also attempts to understand the processes and drivers behind the cycles, and what can influence the timing of certain events.

Environmental drivers like climate, topography and soil properties affect vegetation dynamics at different spatial and temporal scales, ranging from long term and from local and regional scales (Kariyeva and Van Leeuwen, 2011). Global change over the last 15 years especially has led to an increase in the acknowledgment of the importance of the phenology (Richardson et al., 2012) stemming from the fact that plant phenology could be used as an indicator of the long term biological impacts of climate change on terrestrial ecosystems. And so, recent warming trends have been associated with earlier onset of vegetation activity in spring and a lengthening of the overall growing season. With climatic seasonality accepted as one of the main drivers in phenological changes, Menzel (2002) discusses the fact that in temperate and boreal climatic regions the air and ground temperature, and associated measures such as growing degree days have the largest influence on the timing of these changes.

The study of vegetation phenology using remote sensing has experienced considerable progress over the past two decades; both in terms of generating the basic satellite data sets required for documenting phenology over large areas and developing

methodologies for working with the data to derive metrics that describe the seasonality of vegetation.

Satellite systems/sensors, such as Landsat were deemed to have a return period (16-18 days) that was too infrequent to support that the number of observations necessary during rapidly changing phenological cycles, despite their high spatial resolution. Despite a much lower resolution, MODIS is well suited for phenological studies due its return period of 1 day, as well as maintaining spectral bands in the visible and near infrared wavelengths, and additional bands that can be utilised for a variety of different applications. To study the effects of climate on phenological events, the data is required to be of a large spatiotemporal scale.

2.3 Phenological Characteristics of Plants

The capacity of satellite sensors to detect important phenological events is limited due to resolution issues, and influencing factors such as other vegetation and soil characteristics. Despite being limited, satellite sensors are still able to measure some broad-scale changes that are not specific to the individual plant, but are relevant to the ecosystem as a whole (Reed et al., 1994).

The photosynthetic activity of evergreen forests persists year round at a low rate, providing the temperature is above 0°C. Because these patterns of photosynthetic activity are largely dependent on temperature and photoperiod which are relatively stable from year to year, the interannual variability of satellite derived phenological measures is expected to be low (Reed et al., 1994).

In deciduous forests, the photosynthetic period is dependent on photoperiod, moisture and temperature, but with specific adaptations per species. However, like evergreen forests, because photosynthetic activity in deciduous forests is predominantly determined by the photoperiod and temperature, variability in the satellite phenological measures is also expected to be low (Reed et al., 1994).

2.4 Leaf Area Index

Vegetation Indices are often linked to Leaf Area Index (LAI). This measures the amount of leaf material in an ecosystem, which imposes important controls on photosynthesis, respiration, interception and other processes that intrinsically link vegetation to climate. LAI is defined as 'one half of the total leaf area per unit ground surface area' in current literature when assessed by Jonckheere et al. (2004).

The interaction between vegetation surface and the atmosphere, e.g. absorption of radiation, precipitation, interception, energy conversion and gas exchange is substantially influenced by the vegetation surface. Taking deciduous trees in a temperate environment as an example; during the summer months and their periods of vegetation, the total vegetation surface of one particular tree is comprised mainly of leaf area and less of woody parts of that tree. In contrast, during the winter months and the subsequent absence of foliage, the woody parts such as twigs, branches and stem surfaces determine the vegetation surface. Of course, most exchanges occur at the leaf surface and therefore during the growing season, and as such it is during the growing season that LAI becomes a key measure of vegetation health.

The usual temporal trend for LAI and a deciduous tree follows a distinct temporal pattern, as one might expect. LAI will peak at the height of the growing season and trough in the middle of winter when they have shed all or most of their leaves. LAI values for coniferous and other evergreen species vary much less temporally.

3 Vegetation Indices

Vegetation indices are usually dimensionless measures that are derived from radiometric data (Jones et al., 2010). They are primarily used to indicate the amount of green vegetation or biomass present in a region; high reflectance from vegetation occurs around 700 nm, which is called the red-edge, and most vegetation indices are based on this reflectance.

Satellite vegetation indices (VI) are commonly used in a wide variety of terrestrial science applications that aim to monitor and characterize the earth's vegetation cover from space. First used in the 1970s, they have been highly successful in assessing vegetation condition, foliage, cover, phenology, and processes such as evapotranspiration and primary productivity, related to the fraction of photosynthetically active radiation absorbed by a canopy (fPAR) (Pettorelli et al., 2005, Kerr and Ostrovsky, 2003).

Vegetation Indices are robust, computed the same way across all pixels in both time and space, irrespective of surface conditions; they optically measure vegetation canopy 'greenness', a composite property of leaf chlorophyll, leaf area, canopy cover, and canopy architecture. They are obtained through combining the results of measurements of the vegetation in different spectral bands. Different amounts of EMR will be reflected off vegetation in different spectral bands, and the amount of reflection is determined by the state of the vegetation, or its health. It is therefore possible to combine vegetation surface reflectances from two or more spectral bands to obtain an index that will give the state of the vegetation. This is normally computed through a ratio or similar mathematical equation, depending on the index used.

Whilst VIs are not intrinsic physical quantities, they are widely used as proxies in the assessment of many biophysical and biochemical variables. Healthy vegetation strongly absorbs in the blue and red spectral bands, as the energy from these two bands are used during photosynthesis. There is strong reflectance in the NIR part of the spectrum due to the physical cell structure of the plants, particularly representative of the moisture content of the vegetation.

3.1 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is the most commonly used VI, after first being used by Rouse Jr et al. (1974) It is a numerical indicator that uses the visible and near-infrared (NIR) bands of the electromagnetic spectrum. It is based on the surface reflectance in two spectral bands: Red and NIR. These two bands are used

because green vegetation shows strong absorption in the red part of the spectrum, and weak absorption in the NIR part (Gitelson, 2004).

The index value is calculated by obtaining a ration of the reflected radiation in those two spectral bands in the following way (Jones et al., 2010, Rouse Jr et al., 1974):

$$\text{NDVI} = (P_{\text{NIR}} - P_{\text{red}}) / (P_{\text{NIR}} + P_{\text{red}}) \quad , \quad \text{Equation 1 - NDVI}$$

where P_{NIR} - P_{red} are the NIR and red reflectances. The index ranges from -1 to +1. High levels of green vegetation are indicated by values close to +1 and in general, typical vegetation values range from 0.1 - 0.8, with small positive values being more indicative of bare ground with little to no green vegetation. Negative values indicate that water bodies, in any form, are present. NDVI has a theoretical maximum value of 1, and its relationship to characteristics such as biomass, productivity, percentage cover and LAI is asymptotically nonlinear as it approaches 1 (Raynolds et al., 2008).

Generally, healthy vegetation will absorb most of the visible light that falls on it, and reflects a large proportion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils, however, reflect moderately in both the red and infrared portion of the spectrum. As the behaviour of plants across the electromagnetic spectrum is well documented, NDVI can be derived from the satellite bands that are most sensitive to vegetation information. The bigger the difference between the near infrared and the red reflectance, the more vegetation there has to be. The NDVI algorithm allows users to cope with certain situations where two identical patches of vegetation could result in different values, if for example; one patch was in bright sunshine and the other under a cloudy sky. The bright pixels would have larger values and therefore larger absolute difference between the bands. These potential anomalies are avoided to an extent using NDVI by dividing the sum of the reflectances.

NDVI has been used successfully for land cover classification (Townshend et al., 1994), derivation of biophysical properties (Sellers et al., 1994), estimation of NPP (Prince,

1991), and as a time series NDVI can be used as an indicator for phenological events (Hill and Donald, 2003) and as an indicator of GPP (Wang et al., 2004).

A major advantage of NDVI is that there are long time series readily and easily available from both the National Oceanographic and Atmospheric Administration (NOAA) satellites and the moderate resolution imaging spectroradiometer (MODIS) (Tagesson et al., 2009).

Despite its extensive use, NDVI does have its pitfalls. Its major disadvantage lies in its inherent nonlinear relationship with biophysical characteristics such as LAI. NDVI approaches saturation asymptotically under moderate to high biomass conditions and for certain ranges of the LAI (Gitelson, 2004). With NDVI's nonlinear relationship to characteristics as stated in Reynolds et al. (2008) it becomes less sensitive to ground characteristics at higher levels, and essentially saturates when LAI is greater than 1 (van Wijk and Williams, 2005). The saturation effects have important consequences for detecting change and monitoring the dynamics of vegetated land surfaces including phenology. For this reason, it has been identified that an important feature of improved Vis should be extended linearity to characteristics such as LAI, and a reduction in saturation effects.

3.2 Enhanced Vegetation Index and Enhanced Vegetation Index 2

The nonlinearity and saturation issues can be partly addressed by the Enhanced Vegetation Index (EVI), which is more sensitive to canopy variations in high biomass regions (Huete et al., 2002) and thus less sensitive to saturation at high LAI (Rocha and Shaver, 2009). However, EVI requires noise removal parameters and reduces sensitivity to modest land surface change under low to moderate greenness conditions. Specifically developed for use as a data product produced by MODIS, the EVI is often employed as an alternative to NDVI because of its lesser sensitivity to the above limitations. It was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmospheric influences (Huete et al., 2002).

However, it requires information on reflectance in the blue wavelengths, which is not available on some satellites and is difficult to extract from broadband radiation measurements.

A two band EVI (EVI2) that does not require the blue band reflectance has been developed by taking advantage of the auto correlative properties of surface reflectance spectra between the red and blue wavelengths. EVI2 negates the fact that an older satellite such as the Advanced Very High Resolution Radiometer (AVHRR) does not contain any blue band information which limits the use of EVI and its use with older data.

For older datasets to be utilised, Jiang et al. (2008), developed EVI2 using an equation with just the red and NIR bands:

$$\text{EVI2} = 2.5 (P_{\text{NIR}} - P_{\text{red}}) / (P_{\text{NIR}} + 2.4P_{\text{red}} + 1), \quad \text{Equation 2 - EVI2}$$

where P_{NIR} - P_{red} are the NIR and red reflectances. The EVI2 equation has been optimized to achieve the best similarity with the original, 3 band EVI and is applicable to sensors without a blue band (Jiang et al., 2008). EVI2 produces values ranging from -1 to 1 with negative values representing water bodies and positive values representing green vegetation.

3.3 Normalised Difference Water Index

The Normalised Difference Water Index (NDWI) was developed by Gao (1996), to determine the vegetation water content (VWC) based on physical principles (Jackson et al., 2004). It is derived from NIR and SWIR channels and the amount of water present in the leaf structure mainly affects the spectral reflectance in the SWIR bands; the SWIR is also sensitive to internal leaf structure (Gao, 1996) and is therefore 'a measure of liquid water molecules in vegetation canopies that interacted with the incoming solar radiation' (Gao, 1996). NDWI uses the reflectance of two MODIS bands, one centred around 0.86 μm (NIR - MODIS band 2) and second one centred around 1.24 μm (SWIR -

MODIS band 6. NDWI gives a positive value for green vegetation and a negative one for dry vegetation.

The NIR bands are not reflected by the water content in the leaf, but by the internal structure and leaf dry matter, the combination of the SWIR and NIR bands that are computed to make up the NDWI removes dry matter and internal structure. NDWI is less susceptible to atmospheric scattering than NDVI, but does not completely remove the background soil reflectance effects, similar to NDVI. As the information about vegetation canopies contained in the SWIR channel is very different from the visible channels, NDWI should be considered as an independent VI.

3.4 Normalized Difference Snow Index

Whilst not a VI, the Normalized Difference Snow Index (NDSI) is a spectral index that is used to map snow, normalizing the difference between two bands; one in the NIR or SWIR and one in the visible part of the spectrum (Hall and Riggs, 2014). Snow is highly reflective in the visible part of the electromagnetic spectrum, but highly absorptive in the NIR and SWIR bands. The reflectance of clouds remains high in the NIR and SWIR bands, allowing distinction between clouds and snow. It was for this reason, to distinguish between clouds and snow in remote sensing imagery, that Valovcin first conceived the concept of a ratio index for this purpose in 1976. It was not until 1995 that the term NDSI was coined by Hall, with the original algorithms used and adapted for the launch of the MODIS satellites in the late (Hall and Riggs, 2014). Values of less than 0.4 typically indicate the presence of snow.

In this study, data was collected for NDWI and NDSI and briefly tested, but was subsequently removed from the analysis as it was deemed the results given were not relevant nor could they explain the results used in the analysis.

4 Relationship between LAI and Traditional Vegetation Indices

As previously stated, VIs are often used as proxies or indicators of LAI, despite being most closely related to fractional vegetation cover. The fraction of radiation that is intercepted by a vegetation canopy, and thus the apparent vegetation cover; is therefore dependent on not only LAI but also on the leaf angle and most importantly the angle of incident radiation (Jones et al., 2010)

The non-linearity of LAI to most VI's is caused by the relationship between fractional vegetation cover and light interception; given here as a integrated form of Beer's Law (Jones et al., 2010):

$$f_{veg} \cong (1 - e^{-kL}),$$

Equation 3 - Beers Law

where k is the extinction coefficient and L is the LAI. It becomes apparent that for any given change in LAI, there is less and less impact on radiation interception as canopy density increases, and that this relationship is even less linear than the relationship between NDVI and f_{veg} . Therefore, remote sensing becomes much less effective at distinguishing between canopies with high LAIs than between sparser canopies. This leads to NDVI saturating at high LAI levels, as the relationship is very non-linear.

5 Plant Phenology Index (PPI)

As is widely known, traditional vegetation indices face problems, particularly when used in high northern latitudes when they are faced with low turnover of coniferous forest biomass, frequent clouds and long periods of snow (Jin and Eklundh, 2014). A new index, the Plant Phenology Index (PPI) has been proposed by Jin and Eklundh (2014) which aims to negate the nonlinearity of NDVI to LAI as PPI is approximately linear to LAI, and is in the same unit ($m^2 \cdot m^{-2}$), whilst being derived from radiative transfer equations.

They argue that green LAI is the most dynamic visible canopy variable during the phenological cycle, and as such linearity with green LAI within a phenology vegetation index is a fundamental property. By demonstrating the PPI-LAI relationship through satellite derived PPI with 350 field LAI data from 46 global sites, and through demonstrating its robustness against snow influence, and analysing the similarity of satellite PPI time series to temporal profiles of ground observed manual phenology and GPP, they show the superiority of PPI to NDVI and EVI (Jin and Eklundh, 2014).

PPI was formulated to have a nearly linear relationship to LAI given a fixed soil effect, and whilst having a slightly more complicated expression than NDVI or EVI, it is still based on a straightforward formulation from red and NIR reflectances. This makes it a promising and useful tool for plant phenology studies over a range of vegetation densities, and it aims to highlight subtle changes in the growing season while avoiding the saturation effects with dense vegetation encountered with other indices (Jin and Eklundh, 2014).

Whilst the radiative properties of plants are complex, approximations allow us to see the radiative transfer of plants in a simpler fashion. If assuming an homogenous canopy, all absorbing components are evenly distributed and small in relation to the canopy and radiation is scattered and transferred uniformly. Where the absorbers are black, so radiation is absorbed and not scattered, radiation is attenuated with depth reducing exponentially according to Beer's Law, which determines the rate of attenuation and depth travelled in the medium (in this case the depth of the canopy) (Jones et al., 2010). Hapke (2012) (from Jin and Eklundh, 2014) modified Beer's Law to reflect the relationship between canopy reflectance and LAI. This modified version of Beer's Law founded the basis of PPI (unit: $m^2 \cdot m^{-2}$), linearly related to LAI to indicate canopy growth dynamics (Jin and Eklundh, 2014):

$$PPI = -k \times \ln \left(\frac{M - DVI}{M - DVI_s} \right), \quad \text{Equation 4 - PPI}$$

where DVI (Difference Vegetation Index) is computed from sun-sensor geometry corrected red and NIR reflectances, M is a site specific canopy maximum DVI, which can

be estimated in several different ways. k is a gain factor which is dependent the canopy leaf filling factor, the canopy light extinction efficiency (itself dependent on leaf inclination angle, solar angle and the diffuse fraction of solar radiation). DVI_s is the DVI of the soil. For further and complete details on the formulation of the Plant Phenology Index, see Jin and Eklundh (2014).

6 Vegetation Indices and Temperature

6.1 NDVI

The effect of temperature on plants and vegetation is well known, in the fact that it affects the growth and productivity of plants. The effect obviously varies depending on the season. Dendrochronology studies have often found increased growth during warmer growing seasons, leading to a positive relationship between growing season temperature and growth in northern forests (D'Arrigo et al., 2008). Both precipitation and temperature directly influence water balance, causing changes in soil moisture regime, which in turn, influences plant growth (Wang et al., 2003). Thus, soil moisture is widely recognized as a key parameter that links precipitation, temperature and NDVI, though temperature also affects plant phenology and growth directly through its control on the rate at which a plant can photosynthesize (Öquist, 1983).

Tiziana et al. (2012) investigated the correlation between vegetation and temperature patterns at 250m resolution MODIS NDVI and Temperature profiles. The study was carried out in a Mediterranean environment in Southern Italy, and thus has a wide range of land covers that are analysed in the study. However, the two land classes that showed the highest correlation coefficient between mean NDVI and seasonal temperature profile was 'broad-leafed mixed forests with close to 0.9, and coniferous forests with an r value of 0.7. This shows a high positive correlation between NDVI and temperature for these land classes, which are the most dominant in the study site for this investigation.

Seasonal variations of NDVI are closely related to vegetation phenology, such as green-up (Beck et al., 2006) and spring phenology is one of the vegetation traits that is most sensitive to climate (Shen et al., 2014). Because of this, many of the studies that involve

linking climate, in particular temperature and NDVI are related to climate change and how any potential changes will influence the phenology of vegetation. As mentioned, NDVI can be used as an indicator for the onset of spring with vegetation becoming greener around these times. Studies, such as the one carried out by Hogda et al. (2001) when investigating the changing length of the growing season in Fennoscandia using NDVI, show that the growing season can be delayed in onset or more than 4 weeks earlier depending on climate and the vegetation zone. Furthermore, they found that an increase in mean springtime temperatures (April and May) in central Sweden lead to earlier snowmelt. However, they found no significant change of timing of the onset of spring in passing of 0°C and 5°C, which can be credited to the vegetation being photosynthetically inactive at temperatures below 5°C.

A well know study that looks into the relationship between NDVI and temperature was carried out by (Wang et al., 2003) when they looked at the spatial patterns of NDVI in response to temperature and precipitation in the central Great Plains. They concluded that there was a positive correlation between temperature and NDVI at both the beginning and the end of the growing season, and that temperature was negatively correlated with NDVI during the middle of the growing season.

7 Aims and Purpose

This thesis is based around the problems that current VIs have, especially when it comes to their relationship with biophysical characteristics such as LAI

However, the nature of NDVI to saturate at high LAI/biomass levels (Huete et al., 1997, Mutanga and Skidmore, 2004) and its propensity to be sensitive to snow in conifer dominated boreal biomes (Jin and Eklundh, 2014) meant that problems have been encountered in using NDVI for phenological retrieval. Jin and Eklundh (2014) argue that most VIs are vague in their quantitative biophysical meaning, and most of them were formulated to minimize the effect of non vegetation factors on spectral data. The Plant Phenology Index was created on this basis, as previously discussed.

Therefore the aim of this thesis is to test the robustness of PPI to changes in temperature and changing biomass, using temperature as a proxy for biomass; and to see how well PPI directly correlates to temperature. NDVI and EVI2 will also be tested against temperature, and so the three VIs can be compared.

7.1 Working Hypothesis

It is anticipated that PPI will respond well to temperature, and will demonstrate a more linear relationship than that of NDVI. This is mainly due to the propensity of NDVI to saturate at high levels of biomass.

8 Methodology

8.1 Study Area

Twelve sites were selected for the study as shown in Table 1 below; and selection criteria is later described in section 8.2.

	Latitude (°)	Longitude (°)	Altitude (m)
Arjeplog	66.05	17.91	430
Dravagen	62.09	13.61	566
Glommerträsk	65.28	19.67	395
Horn	57.89	15.87	90
Hunge	62.75	15.09	342
Kroksjö	64.51	17.99	520
Malung	60.70	13.69	310
Norrberg-Norrhög	62.26	15.67	327
Saxnäs	64.97	15.38	542
Storfinnforsen	63.59	16.18	232
Växjö	56.87	14.80	170
Vidsel	65.88	20.12	180

Table 1 - Study Site Locations

The total area of forest land in Sweden is 28 million hectares which are primarily boreal but also in the boreonemoral (hemiboreal), and nemoral zones (Nilsson et al., 2001). The standing volume is approximately 3000m³, of which 41% is spruce/Norwegian spruce (*Picea abies*), 40% pine/Scots pine (*Pinus sylvestris*), 18% birch and 6% consists of other deciduous trees. In the southern, hemi-boreal regions of Sweden, a wide belt of

mixed forests with both coniferous and deciduous species is found. From the northernmost forests in Sweden of latitudes 69°N (Arctic circle at 66.5°) to the southern most extremity at 55.5°N there is a considerable gradient from boreal to nemoral forests. Two thirds of the forests are boreal, composed of almost equal parts Norwegian Spruce and Scots Pine; this area also known as the Swedish Taiga. The remaining third is boreonemoral.

Deciduous species such as birch, aspen, sallow, rowan and grey alder grow throughout the boreal zone. The proportion of these deciduous species increase southwards into the boreonemoral zone, although pine and spruce are still dominant, whilst oak begins to appear. Despite it's northerly location, Sweden has a fairly mild and temperate climate due to the Atlantic Gulf Stream. The monthly mean temperature can for each site can be seen in the appendix (figure 13.2).



Figure 1 - Map of Test Sites. Source: QGIS and www.openlayers.org

Figure 1. on the previous page, shows the physical locations of the test sites throughout Sweden. This was produced using QGIS and the associated Openlayer Plugin.

8.2 Data

Climate data was selected from sites in the study area that had a continuous data set for daily average temperature between 2000 and 2010. This data was obtained from the Swedish Meteorological and Hydrological Institute (SMHI) open data resource (<http://opendata-download-metobs.smhi.se>). Downloaded in a csv. format, this was processed into 8-day averages over the ten year period to reflect the acquisition period of the MODIS satellite, starting on the 26th February 2000 and ending on 18th February 2010. The full daily temperature record from 2000-2010 was used in the calculation of GDD5. The annual mean temperature for all sites is given in the appendix, section 13.2; as Table 8. The following table (Table 2) shows the full extent of data downloaded and the periods of time where no data was recorded.

	Data Missing	Dates Missing
Arjeplog	No	N/A
Dravagen	Yes	11/11/2007 - 22/01/2008
Glommerträsk	No	N/A
Horn	No	N/A
Hunge	No	N/A
Kroksjö	No	N/A
Malung	No	N/A
Norrberg-Norrhög	Yes	02/08/2010 - 3/11/2010
Saxnäs	Yes	11/07/2001 - 01/08/2001, 02/08/2003 - 29/08/2003, 18/06/2005 - 08/09/2005, 02/08/2010 - 03/11/2010
Storfinnforsen	Yes	19/10/2005 - 01/11/2005, 03/08/2008 - 08/08/2005
Växjö	No	N/A
Vidsele	Yes	02/06/2005 - 01/07/2005, 02/06/2006 - 01/07/2006, 02/06/2007 - 01/07/2007

Table 2 - Climate Data Acquisition from the Swedish Meteorological and Hydrological Institute (SMHI)

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor is on-board of NASA's Terra and Aqua platform satellites, launched on December 18th 1999, and May

4th 2002, respectively (NASA. 2011). These are sun-synchronous satellites, resulting from a combination of orbital period and inclination such that the satellite keeps pace with the sun's westward progress as the earth rotates (Lillesand et al., 2004). Terra and Aqua have north to south polar orbits with a 98° inclination and travel across the equator at the same time locally in the morning for Terra and in the afternoon for Aqua. MODIS provides 36 spectral bands between 0.405µm and 14.385µm for the entire planet, every one or two day with a viewing swath width of 2,330km (NASA, 2011). Data is available at 250, 500, 1000 and 5600 meter spatial resolutions in HDF-EOS (Hierarchical Data Format-Earth Observing System) format.

In this study, MODIS product MCD43A4 was used, this being a Nadir BDRF adjusted reflectance 8-Day 500m product. This provides 500m reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the values as they were taken from nadir view. Both Aqua and Terra data are used in the generation of MCD43A4 (LPDAAC, 2014). Due to the calculation of PPI however, and nature of MCD43A4 being nadir-standardized at solar noon, a solar zenith angle correction term was included in the MATLAB script to account for volumetric influence, but the shadow-induced geometrical solar angle influence on PPI is not considered here (Jin and Eklundh, 2014).

The MODIS data was downloaded using a Matlab R2014a script with the MODIS client, and thus enabling data from a specific date range for a particular latitude and longitude, which for each site were taken as the coordinates from the climate station. The script instructed the MODIS client to download data with a range of 5 pixels around the coordinates given. All bands (red, blue, green, near infrared, short wave infrared, and the snow albedo quality) were downloaded by the MODIS client, in a text format suitable for further processing and analysis. The MODIS derived spectral data from the MODIS client was then fed into an adapted Matlab R2014a script from Jin and Eklundh (2014) for use in this investigation.

Growing Degree Days (GDD) can be used as an approximate measure of growth of vegetation during the growing season. Due to the temperature dependency on the growth of certain vegetation types, vegetation only grows over a certain temperature.

However, the value of GDD represents an entire year of growth. McMaster and Wilhelm (1997) set 5°C as a threshold value, and GDD is calculated by taking an average temperature of the day $(T_{max} - T_{min}/2)$ and subtracting the base or threshold temperature. In this case, a base temperature of 5°C was chosen as this is seen as the temperature above which vegetation growth begins. To get the GDD5 (5 representing the base temperature) value for a particular day, the GDD of all previous values must be summed together, including the day's value you wish to know (McMaster and Wilhelm, 1997). In this investigation, GDD was calculated daily and accumulated to give monthly and yearly totals, which were both included in the analysis.

Growing Degree Days were accumulated for each year, and reset to 0 on January 1st of each year data was collected for this study. For years that did not have a full data set, such as a month missing, GDD5 was calculated up to and including the last consecutive date. All subsequent data was ignored. Results for yearly accumulated GDD5 can be seen in Table 6, section 9.6.

8.3 Analysis

The Matlab script generated text files of the vegetation index results that were processed so to make them suitable for analysis in SPSS. This was then used to correlate PPI and NDVI with the temperature data using the correlation and regression functions. Temperature data was processed into 8 day averages, and GDD was calculated for each year as per stated in the previous section.

Firstly, Pearson's correlation coefficient was computed for PPI and temperature, and other VI's and temperature. This measures the strength and the direction of a linear relationship between two variables. Positive values represent a positive linear correlation and negative values represent a negative correlation. The closer the +1 or -1, the stronger the respective positive or negative correlation is between the two variables. If there is no correlation between the two variables, or a very weak one, a near 0 value will be computed. R is a dimensionless quantity, and as such does not depend on the units of the variables in question.

Secondly, linear regression tests were carried out for all sites, with the respective VIs (PPI, NDVI and EVI2) being the dependent variable and temperature the independent variable, which is obviously changing throughout the study. Results come in the form of Pearson's R^2 , or coefficient of determination, which gives the proportion of the variance or fluctuation of one variable that is predictable from the other variable. It is a measure that allows the user to determine how certain they can be in making predictions from a certain graph/model.

Temperatures were also lagged weekly and regression analysis was carried out to see the effects of the previous weeks temperature on the respective VI. This lag was computed for 6 weeks prior to any recorded VI. So, one VI value would have a R^2 value for the temperature of the week it was recorded, and one for the previous 6 weeks temperature. However, due to the insignificant results, only the one week lag was included in the results section.

A quadratic regression analysis was carried out on the accumulated yearly GDD5 values for each site. This analytical technique was used because the statistical software package, SPSS, did not offer another function with a uni-modal shape and with more degrees of freedom.

The coefficient of determination represents the percentage of data that is the closest to the line of best fit. For example, an R^2 value of 0.850 means that 85% of the total variation in one variable (in this investigation, this will be PPI) which can be explained by the linear relationship between x and y. The other 15% of variation would be down to other factors.

Analysis of Variance (ANOVA) was also computed, which essentially tells us if the model generated by the results (the regression line) is significantly better at predicting the values of the variable being predicted (in the case the dependent variable: PPI) than if you simply used the mean of the predicted variable. 'F' is the value given, and the 'Sig' value is also important; as if the 'Sig' value is less than 0.05, we can conclude that the F value is large enough to have not occurred by chance and that the regression line is a

significantly better fit to the data than a model based on using the mean of the values for the predicted variable.

Results

9.1 PPI and NDVI Correlating with Temperature (Pearson R)

As can be seen in table 3, both PPI and NDVI show strong correlations with temperature (T) for the majority of sites. This analysis includes temperature data for the entire 10-year period of the study, including both summer and winter temperatures. Arjeplog shows a negligible negative correlation between PPI and T of -0.43, yet shows a good positive correlation between NDVI and T of 0.791. Norrberg-Norrhög shows the strongest correlation between PPI and T, with a correlation coefficient of 0.849. All the correlation tests bar Arjeplog were significant at the 0.01 level (2-tailed test).

	Correlation (Pearson R)	
	PPI/Temp	NDVI/Temp
Arjeplog	-0.43	0.791
Dravagen	0.817	0.863
Glommerträsk	0.805	0.863
Horn	0.820	0.805
Hunge	0.818	0.857
Kroksjö	0.821	0.844
Malung	0.833	0.862
Norrberg-Norrhög	0.849	0.846
Saxnäs	0.808	0.843
Storfinnforsen	0.833	0.869
Växjö	0.813	0.735
Vidsel	0.806	0.837

Table 3 - PPI/NDVI and Temperature Correlation Results

9.2 Regression Analysis

The results in table 4 were computed from a filter of the full data set, and all results below -5C were excluded from the analysis. The results of the whole data set can be seen in the appendix, section 13.3.

	R²		
	PPI	NDVI	EVI2
Arjeplog	0.059	0.626	0.574
Dravagen	0.743	0.72	0.791
Glommerträsk	0.721	0.646	0.735
Horn	0.677	0.567	0.724
Hunge	0.709	0.673	0.761
Kroksjö	0.694	0.571	0.678
Malung	0.735	0.646	0.743
Norrberg-Norrhög	0.776	0.594	0.73
Saxnäs	0.683	0.577	0.691
Storfinnforsen	0.748	0.715	0.793
Växjö	0.663	0.536	0.76
Vidsel	0.717	0.53	0.659

Table 4 - Regression Analysis Results. All Results are significant at a level of 0.0

For all sites but one, R^2 values between PPI and temperature ranged between 0.663 (Växjö) and 0.776 (Norrberg-Norrhög). Arjeplog resulted in a R^2 of 0.059, showing no correlation between PPI and temperature; this result will be explored in further detail later.

As can be seen from the above table, all results bar Arjeplog showed a positive relationship between PPI and temperature. Tests were done to see if a temperature lag would have an effect on the results of the regression analysis. This was done for 6 weeks lag, with results showing in the table for just one week's lag. For all sites, there was a decrease in the R^2 value; Arjeplog again bucked the trend with a minimal increase but nothing that is significant.

The R^2 values were slightly lower for NDVI and temperature than that of PPI for all the test sites. This is not, however, a measure of the performance of the VI's but merely shows the degree of influence that temperature has upon the VI, and a lower R^2 for NDVI and temperature suggests other factors also influence the final NDVI value. Similarly, EVI2 showed higher R^2 numbers than both PPI and NDVI, suggesting temperature has a significant control on the VI.

Below are the charts plotting the regression analysis of PPI, NDVI and EVI2 against temperature for all plots:

Arjeplog

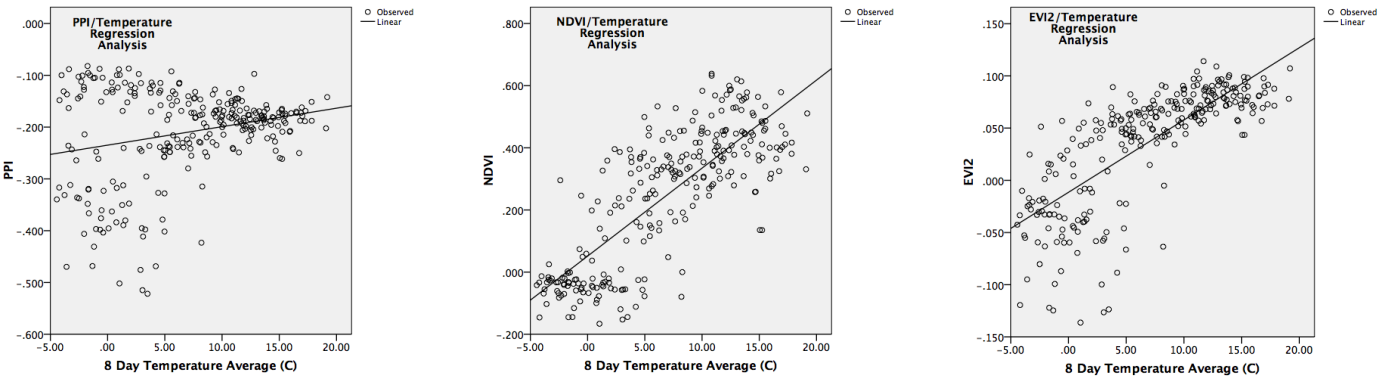


Figure 2 - Arjeplog PPI, NDVI and EVI2 Regression Model

Dravagen

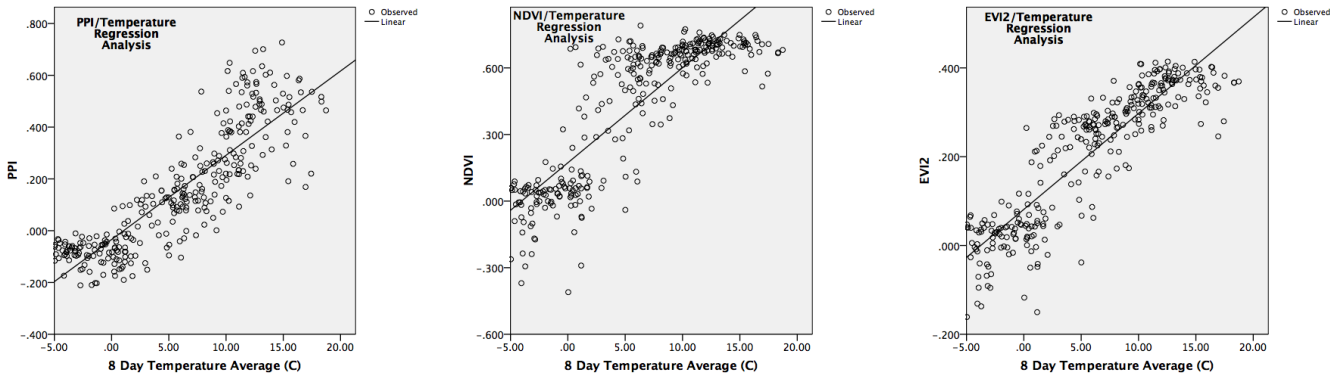


Figure 3 - Dravagen PPI, NDVI and EVI2 Regression Model

Glommerträsk

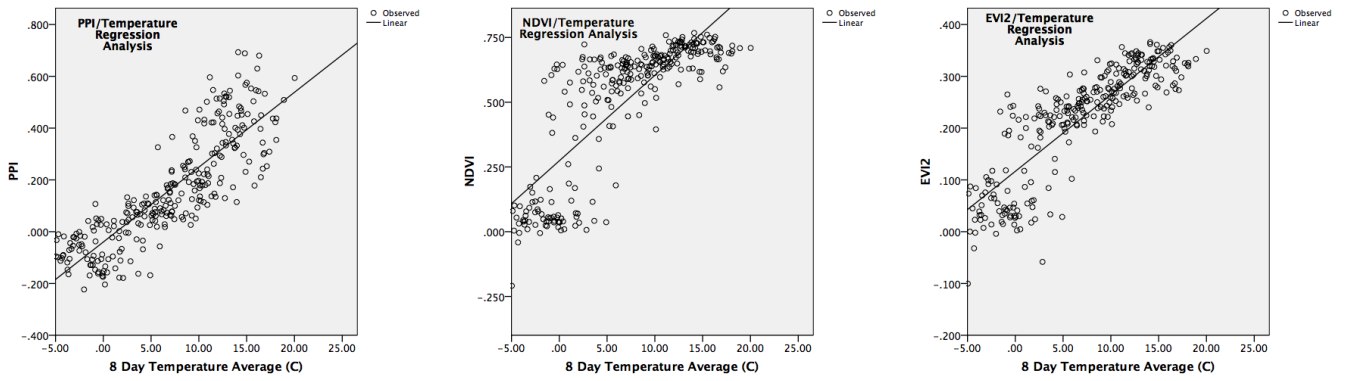


Figure 4 - Glommerträsk PPI, NDVI and EVI2 Regression Model

Horn

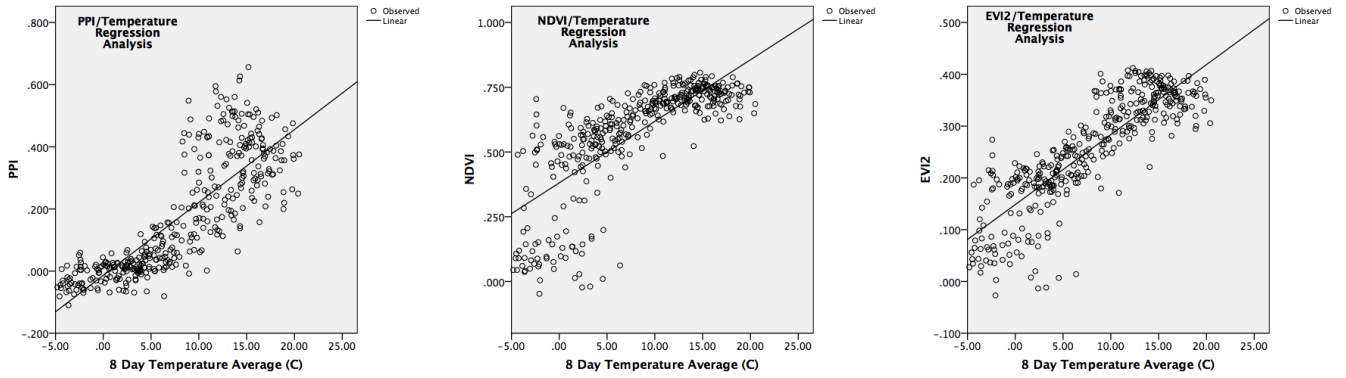


Figure 5 - Horn PPI, NDVI and EVI2 Regression Model

Hunge

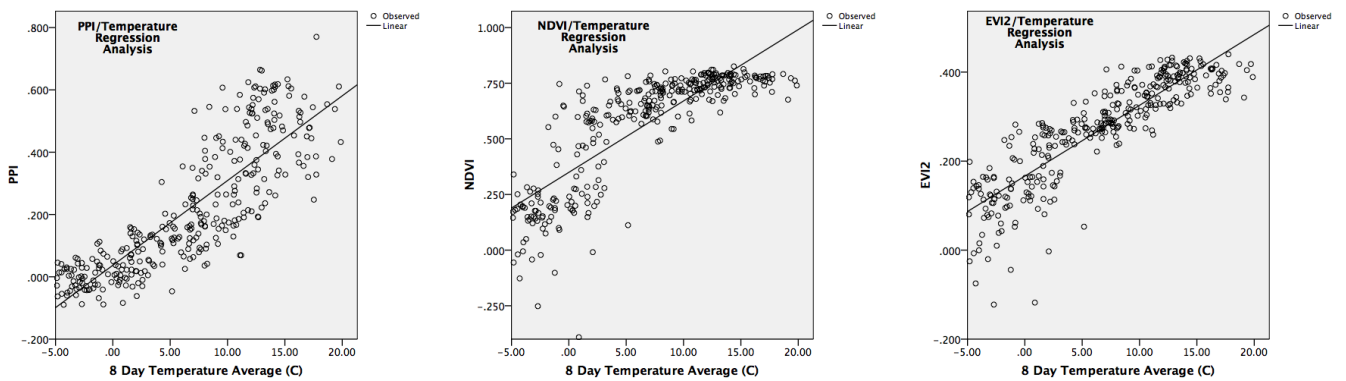


Figure 6 - Hunge PPI, NDVI and EVI2 Regression Model

Kroksjö

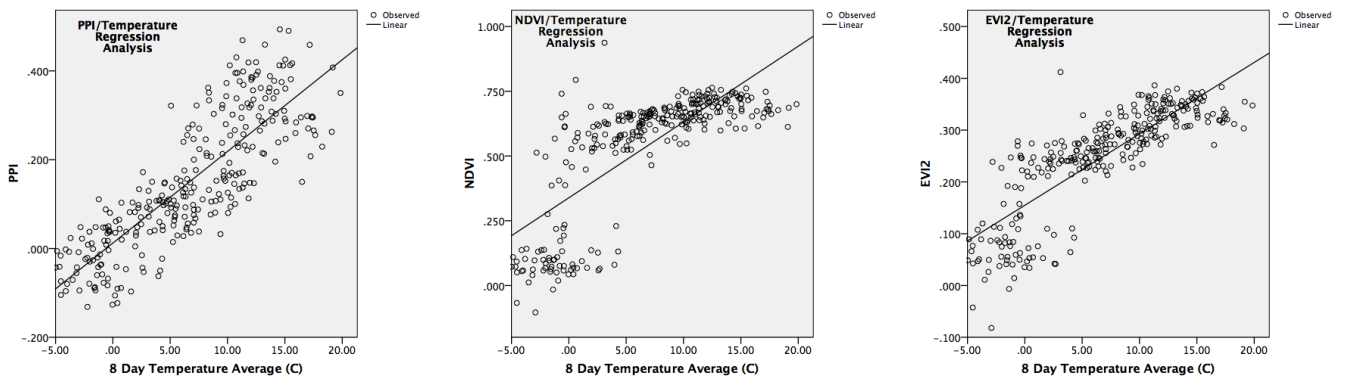


Figure 7 - Kroksjö PPI, NDVI and EVI2 Regression Model

Malung

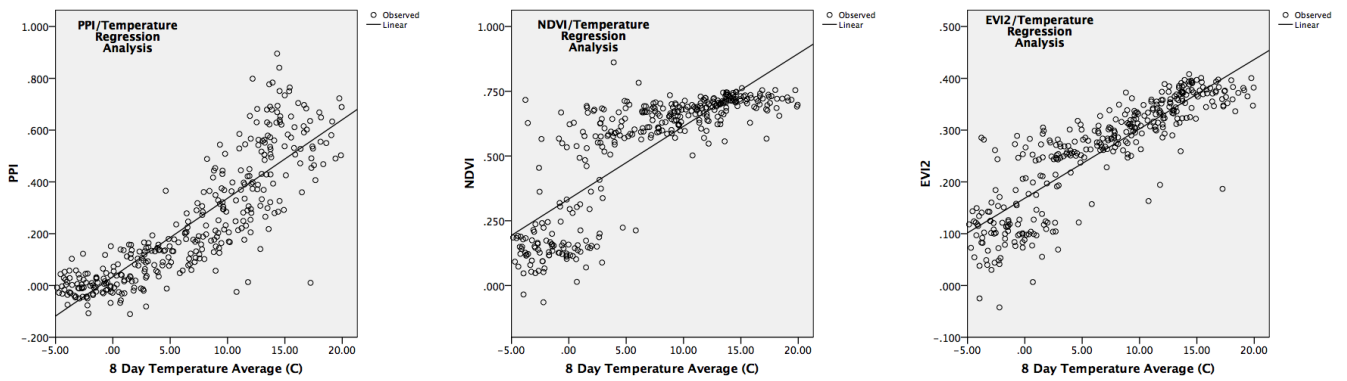


Figure 8 - Malung PPI, NDVI and EVI2 Regression Model

Norrberg-Norrhög

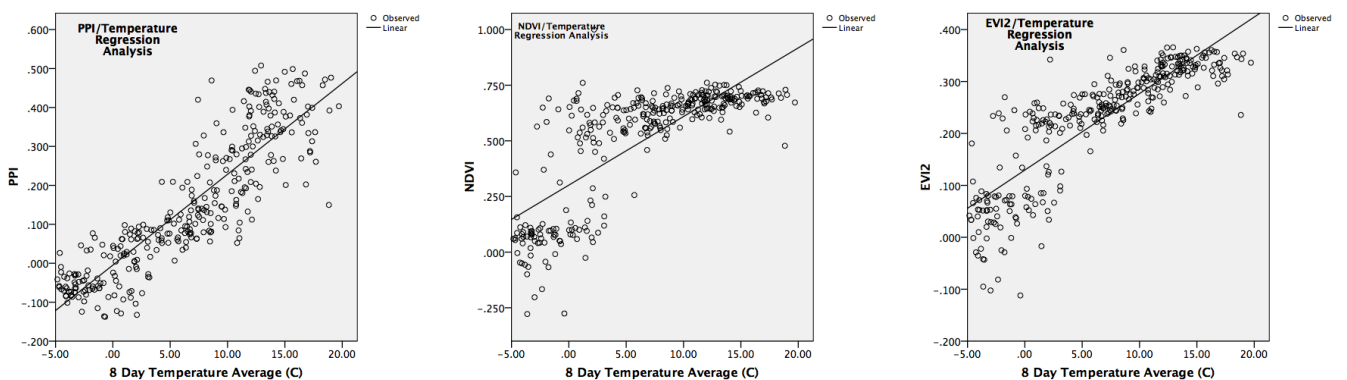


Figure 9 - Norrberg-Norrhög PPI, NDVI and EVI2 Regression Model

Saxnäs

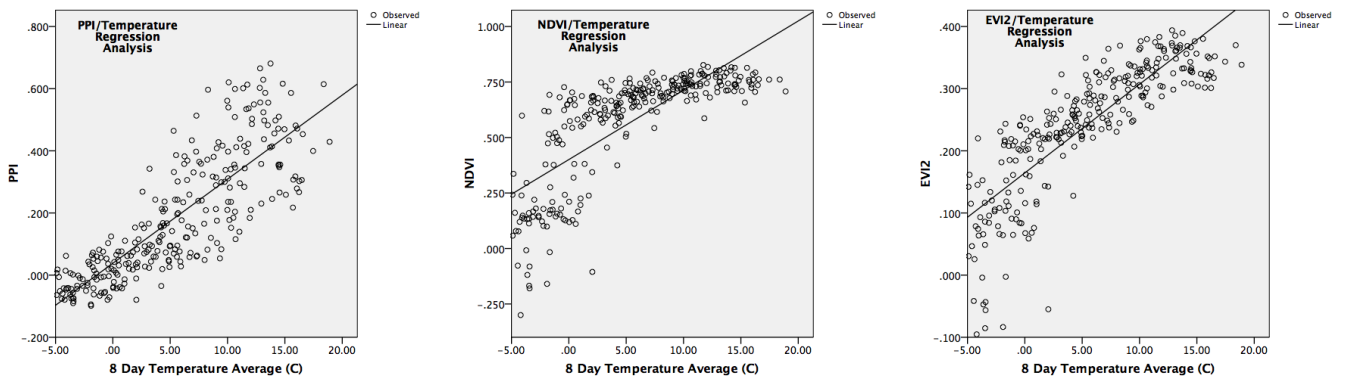


Figure 10 - Saxnäs PPI, NDVI and EVI2 Regression Model

Storfinnforsen

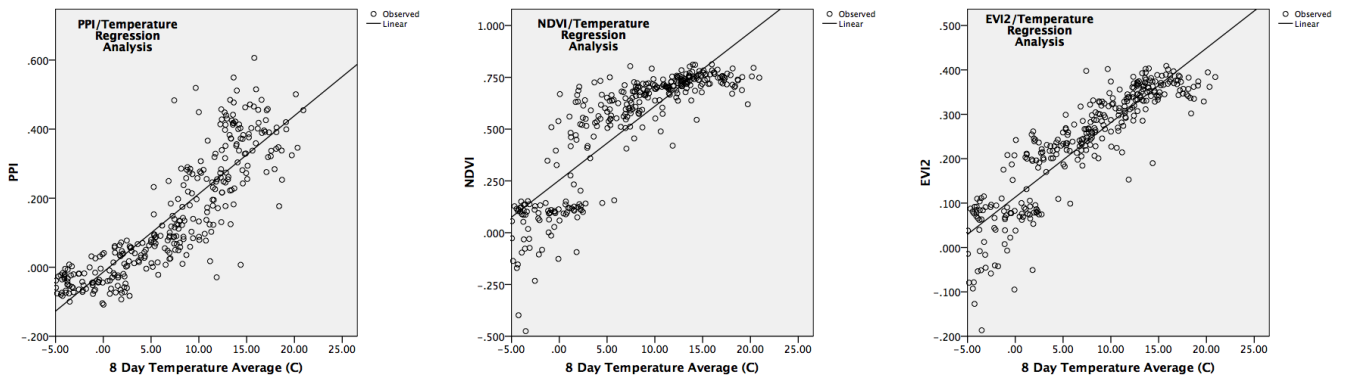


Figure 11 - Storfinnforsen PPI, NDVI and EVI2 Regression Model

Växjö

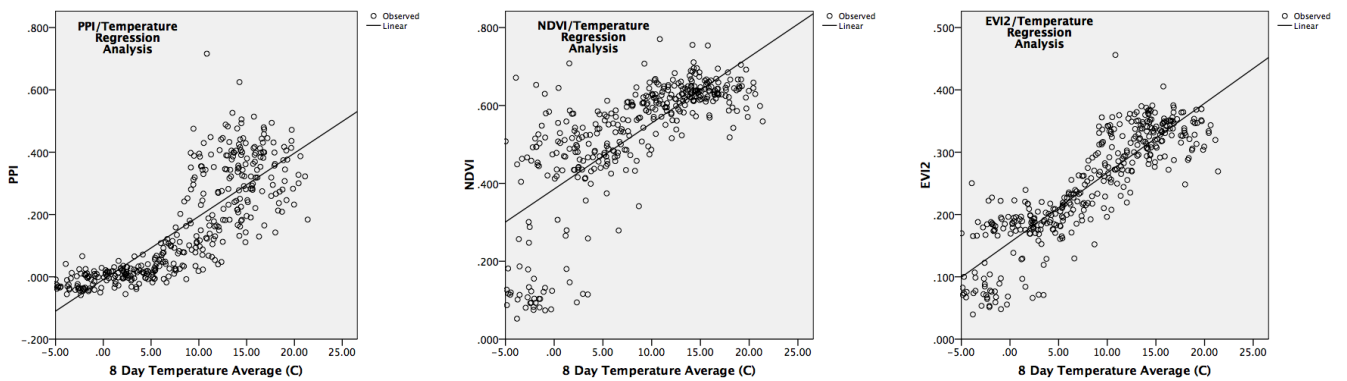


Figure 12 - Växjö PPI, NDVI and EVI2 Regression Model

Vidssel

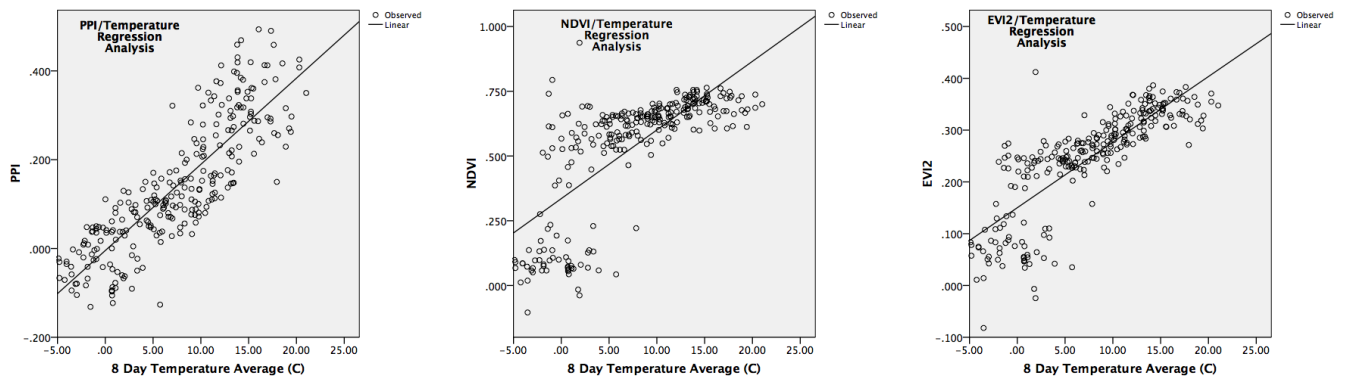


Figure 13 - Vidssel PPI, NDVI and EVI2 Regression Model

9.3 Growing Degree Days

Growing Degree Days were calculated monthly and yearly. Table 7, in the Appendix, section 13.1 show the accumulated GDD5 values for each year of all 12 sites. Values in red indicate times where temperature data was not available and so the values are not a full representation of that year. GDD5 raw values were placed in the appendix due to them not being used in the analysis in this format; only when used in subsequent regression and correlation analysis.

9.4 Monthly Growing Degree Days vs PPI and NDVI

Table 5 shows that the majority of sites indicate very strong correlations between Growing Degree Days and PPI, Malung showing both the highest R^2 and Pearson R value with 0.898 and 0.948. With all sites bar two (Arjeplog and Saxnäs) showing values over 0.75 for both R^2 and Pearson R, it is clear there is a strong correlation and significance between GDD and PPI, and the factors that influence these indices. On the whole, NDVI also shows strong correlations with temperature, but less so than PPI. Interestingly, Arjeplog, with such poor results for PPI, records the highest correlation of 0.839 between NDVI and GDD and the highest R^2 of 0.704.

	PPI		NDVI	
	R ²	Pearson R	R ²	Pearson R
Arjeplog	0.022	-0.148	0.704	0.839
Dravagen	0.888	0.942	0.629	0.793
Glommerträsk	0.873	0.895	0.578	0.76
Horn	0.802	0.895	0.487	0.698
Hunge	0.817	0.904	0.556	0.746
Kroksjö	0.84	0.916	0.507	0.712
Malung	0.898	0.948	0.520	0.721
Norrberg-Norrhög	0.882	0.939	0.478	0.691
Saxnäs	0.624	0.79	0.377	0.614
Storfinnforsen	0.863	0.929	0.583	0.764
Växjö	0.78	0.883	0.398	0.631
Vidsele	0.757	0.87	0.476	0.69

Table 5 - Correlation Analysis between Growing Degree Days (5) and PPI/NDVI

9.5 Accumulated Growing Degree Days and Vegetation Indices' Quadratic Regression Analysis

Growing Degree Days were accumulated for each year, and reset to 0 on January 1st of each year data was collected for this study, as can be seen in Table 6 below. For years that did not have a full data set, such as a month missing, GDD5 was calculated up to and including the last consecutive date. All subsequent data was ignored.

	R ²		
	PPI	NDVI	EVI2
Arjeplog	0.271	0.292	0.326
Dravagen	0.536	0.431	0.454
Glommerträsk	0.6	0.582	0.572
Horn	0.667	0.35	0.527
Hunge	0.589	0.476	0.497
Kroksjö	0.488	0.5	0.475
Malung	0.691	0.445	0.526
Norrberg-Norrhög	0.638	0.505	0.52
Saxnäs	0.425	0.384	0.366
Storfinnforsen	0.68	0.544	0.577
Växjö	0.743	0.347	0.634
Vidsele	0.599	0.538	0.522

Table 6 - Quadratic Regression Analysis of Accumulated Growing Degree Days (5) and PPI, NDVI and EVI2

Below are the charts plotting the quadratic regression analysis of PPI, NDVI and EVI2 against GDD5 for all sites:

Arjeplog

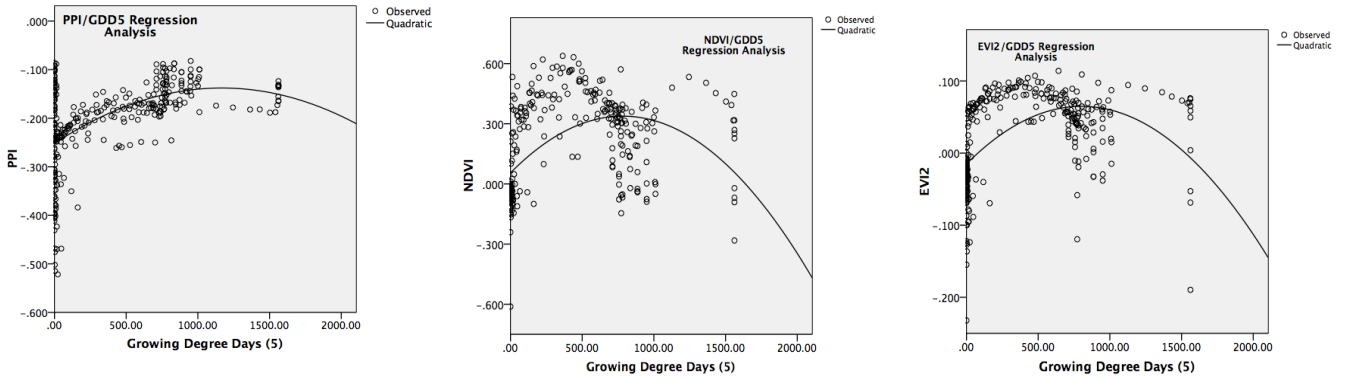


Figure 14 - Arjeplog; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Dravagen

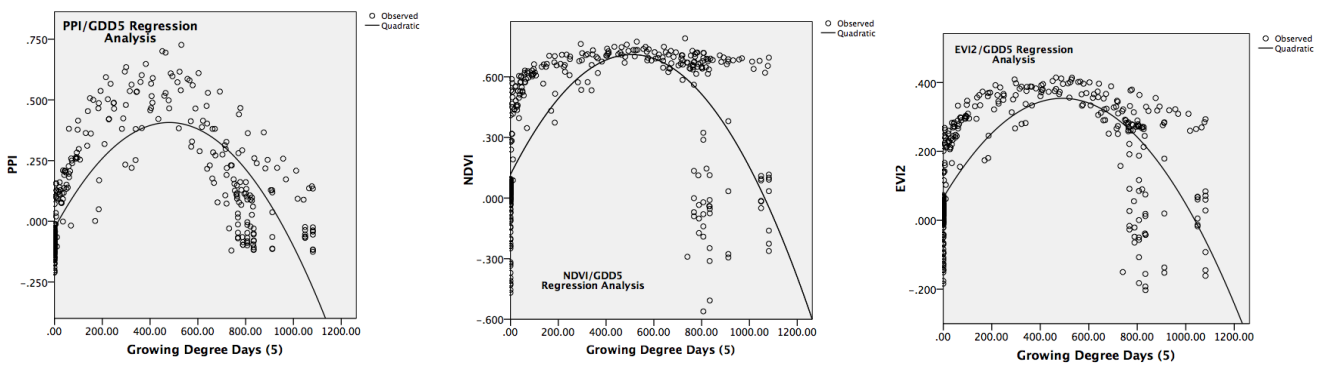


Figure 15 - Dravagen; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Glommerträsk

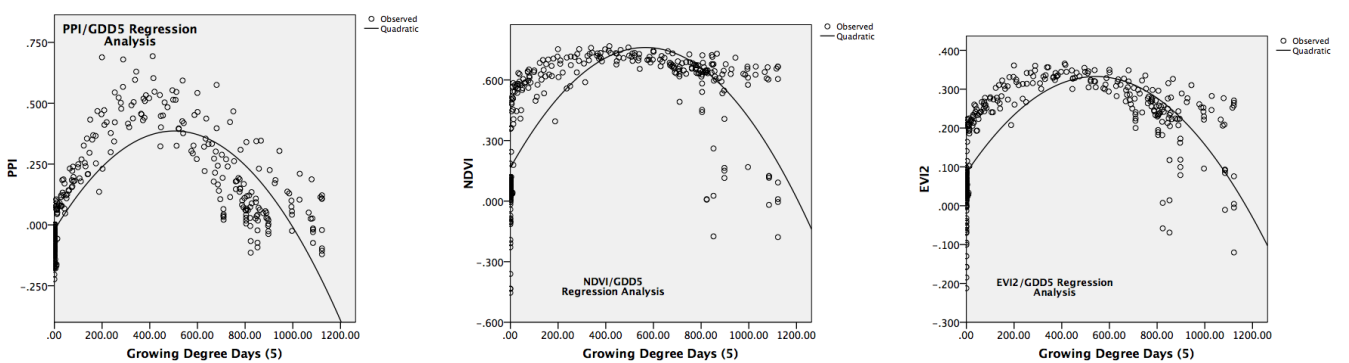


Figure 16 - Glommerträsk; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Horn

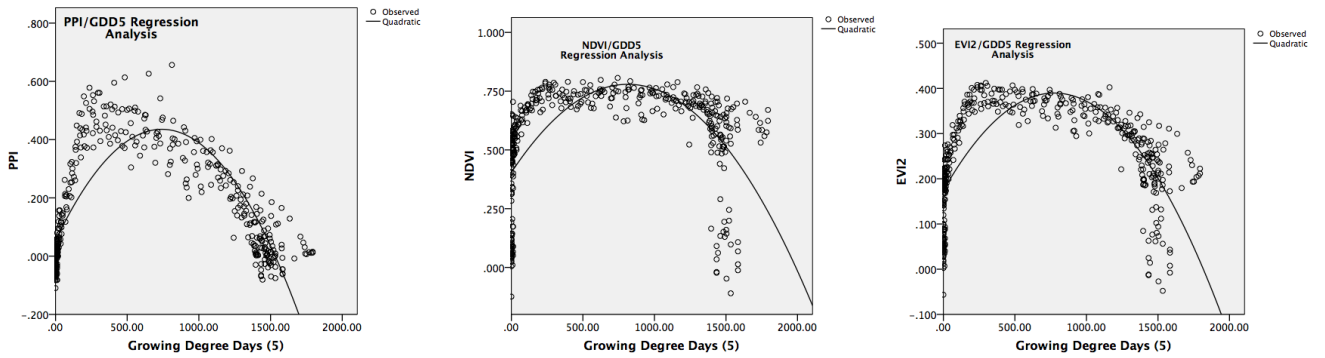


Figure 17 - Horn; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Hunge

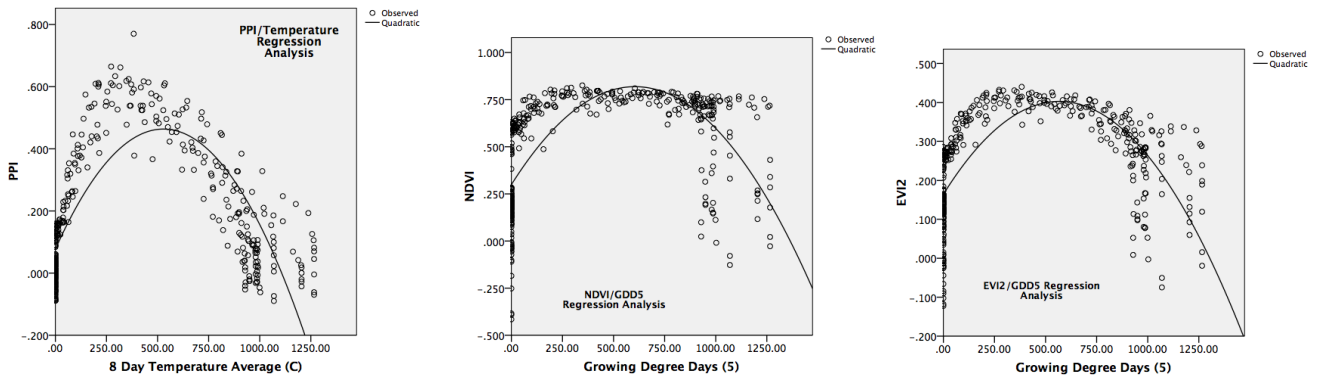


Figure 18 - Hunge; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Kroksjö

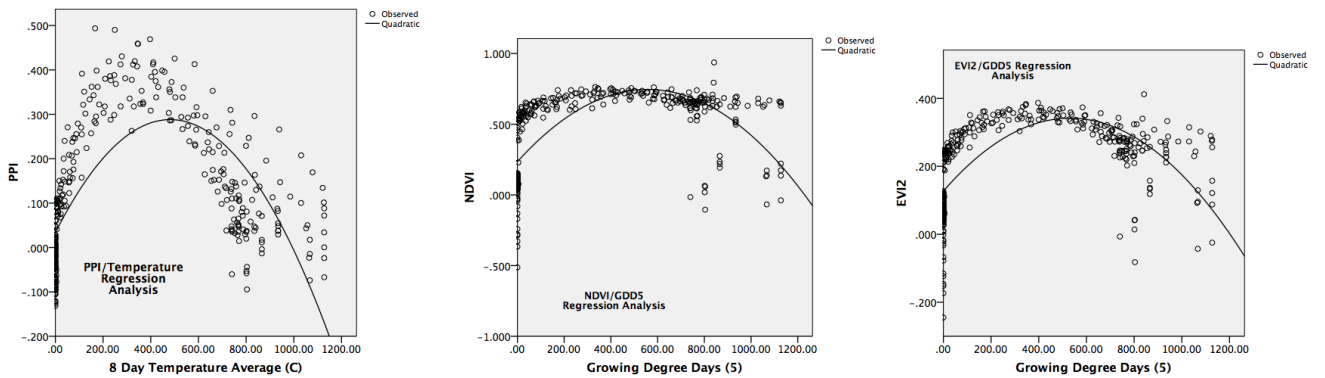


Figure 19 - Kroksjö; GDD5 vs PPI, NDVI and EVI2 Regdion Analysis

Malung

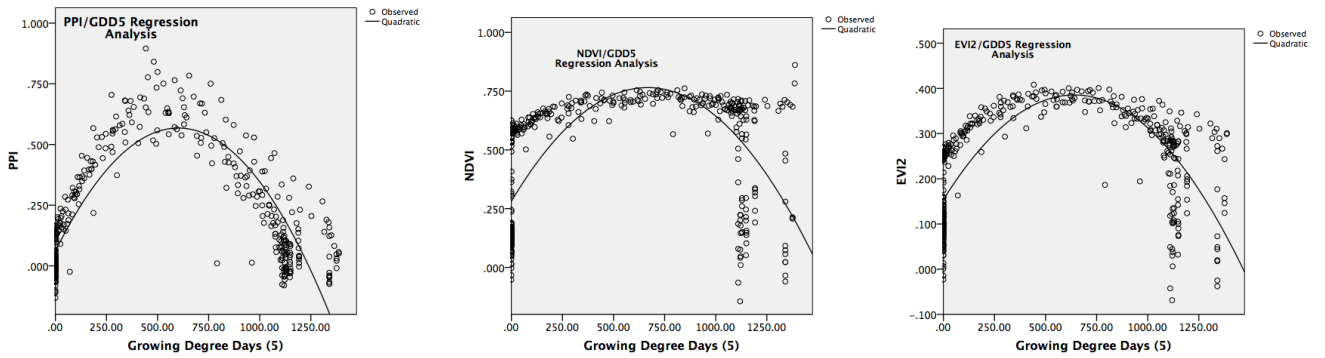


Figure 20 - Malung; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Norrberg-Norrhög

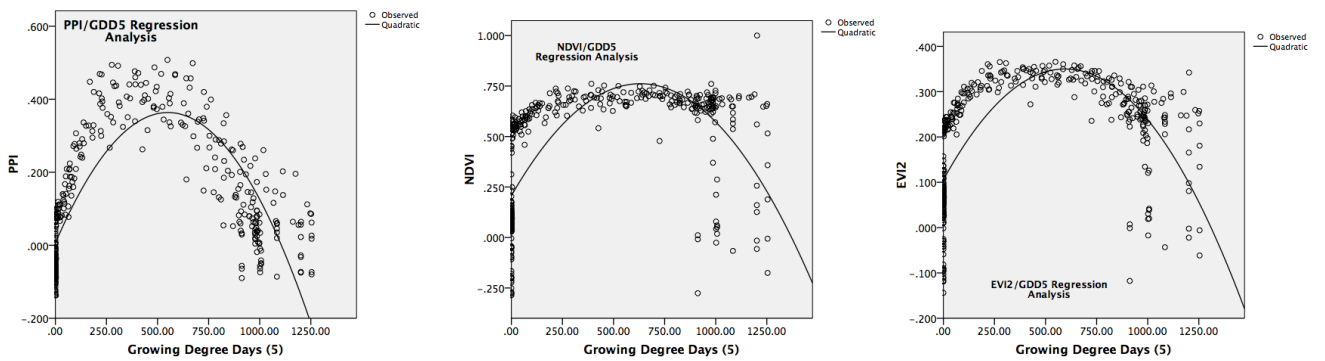


Figure 21 - Norrberg-Norrhög; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Saxnäs

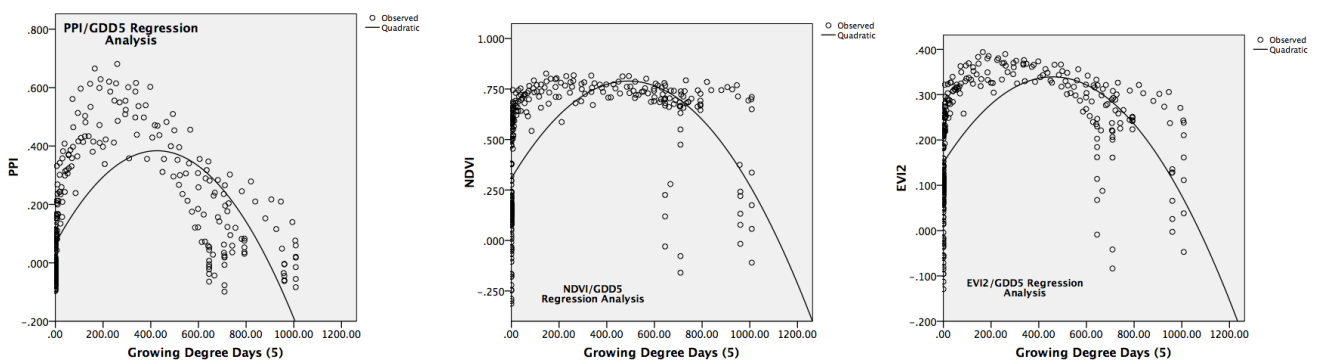


Figure 22 - Saxnäs; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Storfinnforsen

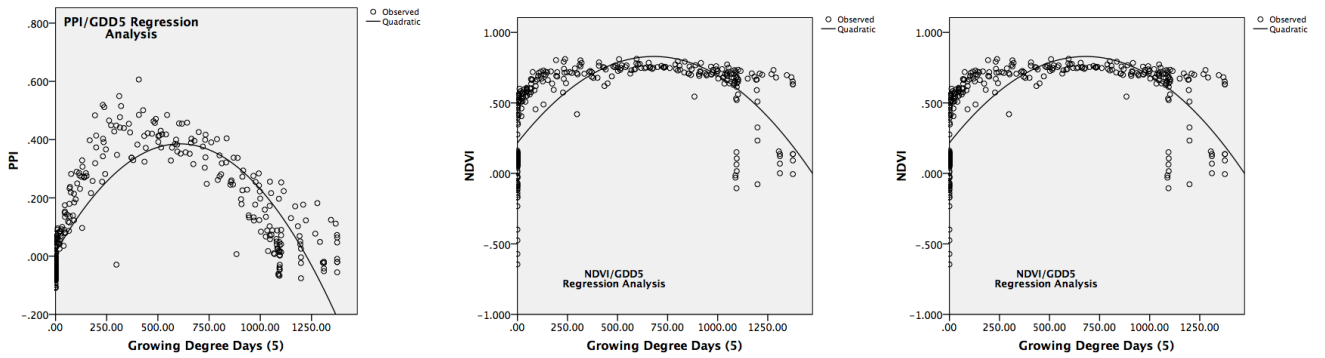


Figure 23 - Storfinnforsen; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Växjö

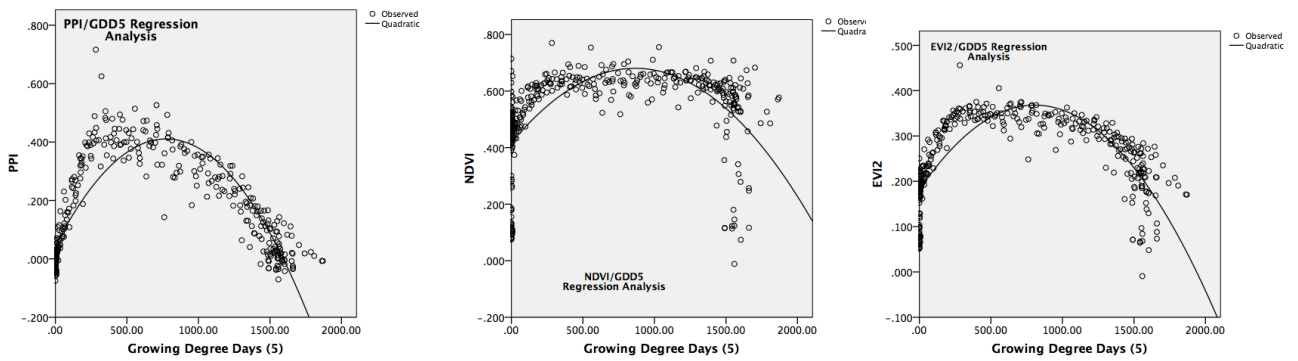


Figure 24 - Växjö; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

Vidsel

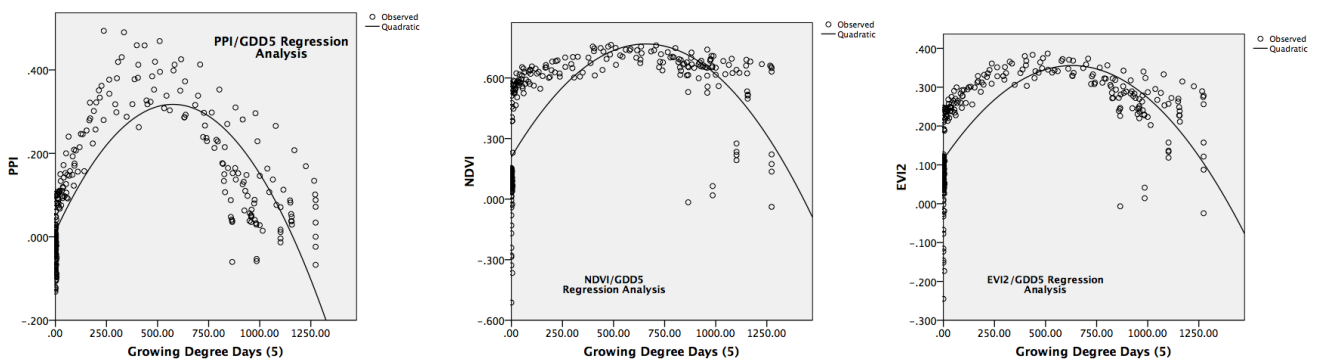


Figure 25 - Vidsel; GDD5 vs PPI, NDVI and EVI2 Regression Analysis

10 Discussion

10.1 Saturation of NDVI

Variations in climatic factors, in particular precipitation and temperature, have a strong influence on vegetation indices, such as NDVI, for a given site (Wang et al., 2003). The major limitation of current Vis, particularly NDVI however, was their propensity to saturate in high biomass areas (Huete et al., 1997)

The same authors deduced that the structure of the NDVI equation (a non-linear transform of the simple ratio NIR/RED) was the main reason behind the non linearity and saturation in high biomass situations, and a substitute of the 'green' for the 'red' channel only had a minimal effect on improving its sensitivity in high biomass regions.

This saturation effect can be seen in the results from most of the sites with the NDVI measurements, when NDVI does no longer increase with temperature. Temperature can be used as a proxy of biomass (Marbach et al., 2008), under the assumption that with increasing temperature, levels of biomass will also increase. This assumption is fairly safe to make, as temperature is a key control on plant productivity (Moles et al., 2014, Went, 1953). At the majority of sites in this investigation, when a regression analysis was carried out investigating the relationship between temperature and NDVI, NDVI becomes saturated once the temperature goes above 10°C.

Plants can photosynthesize across a broad temperature range (0°C-50°C) but are limited across this range by several different factors. At low temperatures (0°C-10°C), the efficiency of enzymes is limited, whilst between 10°C and 35°C, CO₂ diffusion is limited, thus slowing down photosynthesis. Beyond the temperature range in which photosynthesis occurs, which differs per species, biological activity is inhibited, and thus photosynthesis slows down or stops. Evergreen coniferous trees have a net photosynthesis optimum temperature of between 10°C-25°C, under ambient CO₂ and light saturation. For broadleaved evergreens, this is higher at between 25°C-30°C (Dawson, 2014). Temperature affects photosynthesis because sufficient, if not excessive, heat is a prerequisite for biochemical reactions. Within the temperature range, and optimum temperature is reached, beyond which the rate of photosynthesis slows down (Bonan, 2002). Whilst temperature is a limiting factor of the rate of photosynthesis and

therefore potential growth (Berry and Bjorkman, 1980), several other factors play an important role, which are not investigated in this study. However, it can be seen that NDVI values saturate above a certain level for each site, suggesting a high level of biomass has resulted from the increasing temperatures.

10.2 Two Stage Results of NDVI and EVI2

One aspect worth noting is that both NDVI and EVI are generally clustered in two distinct groupings. This would suggest that PPI is more sensitive to subtle changes in the canopy. For example, most of the site's NDVI and EVI results have one distinct group of results at just above a value of 0, indicating bare ground and little to no green vegetation (Holben, 1986). Whilst there is no temporal analysis in this investigation, an assumption can be made that these clusters relate to the winter months of the study, as the temperatures for these low NDVI and EVI values rarely exceed 5°C. The next cluster of results begin at values around 0.5 for NDVI and 0.2 for EVI, both representing green vegetation and the greening up process at the start of spring (Holben, 1986, Jiang et al., 2008) as temperatures rise and photosynthesis becomes more efficient.

As noted, photosynthesis only occurs above 0°C (Dawson, 2014, Moles et al., 2014, Went, 1953) due to the chemical reactions involved not having sufficient energy to act as a catalyst. At all sites, temperatures were recorded well below 0°C but as such had no effect on the NDVI. In the analysis, all temperatures below -5°C were filtered out and excluded from the results; as due to the linear regression model used they were skewing the results even though they had no influence on the NDVI value. It was decided that although photosynthesis only occurs above 0°C, temperatures down to -5°C would be shown to illustrate the lack of photosynthetic activity that is reflected in the associated vegetation indices. In the site-specific plots of the regression analysis, the first grouping of NDVI and EVI2 represent this dormant behaviour from the plants in the cold winter months. Whilst some sites show positive values for all VI's at low temperatures, below zero there is little to increase in value, again reflecting probable dormant activity.

Hao et al. (2012) investigated NDVI and its links to temperature and precipitation in the upper catchments of the Yellow River. They found that the monthly highest

temperature strongly correlated with NDVI, so that higher temperature lead to higher NDVI values. For all the three monthly climatic variables they used (monthly lowest temperature, monthly highest temperature and monthly precipitation), they found that the results of the regression analysis, like this study, where 'scattered into two zones' (Hao et al., 2012). They split this into the 'left zone and right zone' where in the left zone NDVI fluctuates a little, but increases rapidly in the right zone with temperature. They say the conjuncture between the two points is a threshold value of the temperature, beyond which vegetation begins to grow. It can be said that the results of this investigation are the same; but due to the use of an 8-day temperature average so to match the satellite data, and the 10-year sample period being shown simultaneously, the results manifest themselves in a slightly different fashion. However, the two distinct zones can be seen in the NDVI and EVI2 analysis, which shows that there is a threshold value of temperature for inducing the growth of vegetation.

Precipitation, and other climatic derived variables, whilst not included in this investigation, may still have a large degree of influence on the results. Wang et al. (2003) conclude from previous literature that there is a strong linear relationship between precipitation and NDVI, but only when precipitation is within a certain range. This range obviously varies spatially, but above a particular threshold level, moisture is no longer a limiting factor and the rate of NDVI increase decreases substantially with any further increase in precipitation (Davenport and Nicholson, 1993).

Wang et al. (2003) studied which climatic variables best explain variations in NDVI over time and over what time period. In terms of temperature, they found that temperature was only a contributing factor at specific times in the growing season. Within season analysis, taking one growing season at a time showed strong correlations between NDVI and temperature. However, cross-season analysis showed that NDVI is only strongly positively related to temperature only at the beginning and the end of the growing season (Wang et al., 2003).

The 'two stage' results shown by NDVI and EVI2 in this study could also be a result of the behaviour demonstrated by Wang et al. (2003). As the results are gathered from 10 years of data, and represent such a time period, a singular growing season cannot be

seen nor can any cross-seasonal analysis be carried out. However, it can be seen that none of the values for any of the sites exceed 5°C, with a considerable increase in NDVI above this point. It is possible to identify this point as the threshold value that Hao et al. (2012) discussed, with it also holding true that temperature has a significant impact on NDVI at the start of the growing season, as shown by Wang et al. (2003).

One final possible explanation for the 'two stage' results of NDVI and EVI2 lie in the formulation of PPI. Jin and Eklundh (2014) demonstrated PPI to be relatively insensitive to the influence of snow at high northern latitudes, and to noise during the phenology transition period due to the higher response to LAI variations of reflectance, meaning the reflectance noise is relatively less dominant in PPI than the other VIs. The noise reduction effect in the transition phase is further enhanced by the relatively smaller K factor, due the relatively larger sun zenith angle and consequently larger extinction efficiency (Jin and Eklundh, 2014). Relating this to this investigation, the difference in performance between PPI and NDVI/EVI2 occurs in the transition period, and thus this could be explained by the difference in formulation of the VI's as described above. A time series in Jin and Eklundh, (2014) showing the VIs sensitivity to the variation of snow cover show NDVI to have large fluctuations before the start of the growing season; reflected in the results shown here.

10.3 Performance of PPI

Whilst PPI's results do not form 2 distinct groups like NDVI and EVI, they do show a similar pattern in the fact that there are plenty of results around 0.0 where temperatures would not be conducive to photosynthesis and therefore there would be a lack of green vegetation. Where PPI differs from NDVI and EVI, however, is how the increasing temperature is mirrored in a proportionate increase in PPI value. This suggests that PPI as a VI is much more sensitive to temperature changes than NDVI, and can more accurately determine at what temperature the green up process begins.

As well as this, PPI shows its robustness against temperature changes as values increase even in the higher temperature ranges of each site. Whereas NDVI saturates and levels off in value in the higher temperatures due to a high biomass/LAI level, PPI increases.

This would give users a more accurate depiction of the health of the canopy in comparison to NDVI, which can only tell you so much, and EVI2, whilst being more sensitive to temperature changes than NDVI, doesn't show the same sensitivity as PPI. The fact that PPI highlights subtle changes during the growing season and avoids the saturation effects with dense vegetation (Jin and Eklundh, 2014) is a very important merit for phenology monitoring and vegetation change detection (Huete et al., 2002).

10.4 Growing Degree Days and VIs

Growing Degree Days are a measure of accumulated heat and can be used as an approximate measure of vegetation growth. This investigation used a base temperature of 5°C as this is seen as the temperature above which all vegetation grows. GDD was calculated daily to match the acquisition of VI data, and monthly. The daily values were accumulated over each calendar year to give the AGDD5 for that year, and this was tested against the VIs in a quadratic regression model. A quadratic regression analysis was used as even though it didn't result in the best fit the software used (SPSS) did not contain another unimodal function with more degrees of freedom. However, they did show that above a certain point, temperature and/or AGDD5 could have a negative effect on plant growth, reflected in the downward slope of the curves. Wang et al. (2003) showed a negative correlation between NDVI and maximum temperatures.

The monthly GDD5 values were used in the correlation with PPI. High positive correlations resulted for all sites, which is due to the fact that GDD serves as an indirect measure of the available energy for plant growth, and above a certain base temperature, a plant's rate of growth is often found to be proportional to temperature (Li et al., 2002). This high correlation also dovetails nicely with the regression analysis between temperature and PPI, which as discussed above shows how PPI doesn't succumb to the same problems long associated with more traditional VIs such as NDVI, that at high temperatures and an assumed high biomass level it becomes saturated and loses sensitivity to further increases in biomass.

GDD becomes relevant in this case because of its measure of accumulated heat, and used as a proxy for vegetation growth. A high correlation between PPI and GDD shows that PPI is sensitive to changes in temperature and continues to be under dense canopy

conditions. It must be noted however, that when calculated from climate station data, GDD provides precise point estimates (Hassan et al., 2007) and for this investigation might not entirely represent the grid cells used to calculate the respective Vegetation Indices.

10.5 Anomalous Result

Eleven out of the twelve sites tested all produced results that show little variance in terms of the analysis used. One site, Arjeplog (Fig.1), did produce results that were markedly different to the rest. Whilst the results for NDVI and EVI2 at Arjeplog seem quite fitting in terms of the other sites, the PPI results are all negative. Being situated at 66°N, this was the most northerly test site in the investigation, and as such had the lowest mean annual temperatures of the test sites used. Under the Köppen climate classification, Arjeplog falls into the Dfc category. This means it is classified as a Continental Subarctic or boreal climate, the 'f' meaning significant rainfall in all seasons, and the 'c' meaning three or fewer months with mean temperatures above 10°C. However, Dravagen is also situated in this climatic zone and the results for this site are in keeping with the rest of the site and as such this suggests that the relative climatic extreme of Arjeplog is not the reason for the anomalous results.

A possible cause of the results produced at Arjeplog can be seen when looking at the NIR and Red reflectances through time. Vegetation has a unique spectral signature, which enables it to be distinguished readily from other land cover types in an optical/near-infrared image. The reflectance is low in both the blue and red regions of the spectrum, due to absorption by chlorophyll for photosynthesis. It has a peak in the green region that gives rise to the green colour of vegetation. In the NIR region, the reflectance is much higher than in the visible red band due to the structure of the cells within the leaves. Hence, vegetation can be identified with a high NIR but generally low visible reflectances. At Arjeplog, this is not the case; the NIR reflectance at Arjeplog appears to be much higher during the winter months, and much lower during the summer months than the rest of the sites. The mean value of NIR reflectance did not vary too much from the other sites, but the standard deviation (variance around the mean) was 0.253, compared to the average of 0.081 across the rest of the test sites.

The Red reflectance values are much higher in winter also, and lower in summer. Contrary to the other eleven test sites, where during the growing season NIR reflectance is much higher than Red reflectance, reflecting the greening of vegetation, the values for NIR and Red stay much the same at Arjeplog. Due to PPI being formulated in part using the Difference Vegetation Index (DVI), which is simply $NIR - RED$, the fact that the reflectances of the respective bands show little difference will impact on the PPI results heavily.

However, due to the fact that the results for Arjeplog correlated well with temperature for NDVI and EVI2, the anomalous results for PPI are more likely to be found somewhere in the PPI formulation. Jin and Eklundh (2014) state that PPI is very sensitive to noise during the peak of the growing season, and due to Arjeplog's high latitude, this period is likely to be very short leading to a possible exacerbation of the noise within the results. As all the results for Arjeplog are negative, this suggests leafless or snow covered canopies (Jin and Eklundh, 2014). One possible reason could lie in the influence of soil reflectance, something not really considered in this paper. In the formulation of PPI, DVI_s (the DVI of the soil and so the difference between the NIR and red of the soil) was given a value of 0.09. The same value was used in this investigation and kept constant throughout, regardless of the site. The creators, Jin and Eklundh (2014), state that choosing any constant DVI_s may result in negative PPI when the measured canopy DVI is smaller than the DVI_s , such as for leafless or snow covered canopies. With Arjeplog having such a short growing season and long snow covered winters, as reflected by the NDSI results, this is a reasonable explanation for the poor results seen here.

10.6 Hypothesis

A working hypothesis as follows was stated:

'It is anticipated that PPI will respond well to temperature, and will demonstrate a more linear increase than that of NDVI and EVI2. This is mainly due to the propensity of NDVI to saturate at high levels of biomass.'

This hypothesis was proven to be correct, on the basis of the regression and correlation analysis carried on the VIs. On the whole, PPI responded better than NDVI when analysed against temperature, whilst EVI2 and PPI showed similar R^2 results. Whilst the hypothesis was proven, it is clear that there are many factors that influence the performance of vegetation indices. Whilst it can be said that temperature is a firm controlling factor and the VI's respond well to changes temperature, factors not included in this study influence plant growth and thus the result of the a vegetation index. A study incorporating these influences, such as precipitation, soil moisture and soil temperature, for example would offer a more in-depth comparison and evaluation of the vegetation indices in this study.

11 Conclusions

This study investigated the robustness of the Plant Phenology Index against temperature. The index (PPI) performed well at 11 of the 12 sites across Sweden that it was tested, with high Pearson R values for the 11 sites. When comparing its relationship with temperature to other VI's such as NDVI, PPI held up well in terms of absolute correlation between the respective VI's and temperature. Whilst the correlation coefficients were all around the 0.8 mark, it was site specific as to whether these were higher for PPI or NDVI.

Growing Degree Days and PPI were also correlated, again yielding high positive correlations. As GDD can be seen as an accumulated heat source, this helps to confirm that PPI has a good level of robustness against temperature, which as a proxy for biomass can show that PPI as a VI can perform well at high levels of biomass.

The majority of the variations in the results are likely to be explained as a function of the geographical region that the tests were performed. This investigation solely used remotely sensed data, and would have potentially been enhanced by ground data validation. Temperature was the only variable used to test PPI, and whilst the results produced were positive, other climatic variables such as precipitation and non climatic such as soil moisture could have also been tested.

The aim of this study was to test the robustness of PPI to temperature, which acts as a proxy for biomass in that higher temperatures result in higher levels of biomass, and as such this study can conclude that PPI responds well to changes in temperature and is sensitive to change across a wide range. This, by proxy, means that it can perform linearly to LAI at high levels and not succumb to the same pitfalls of saturation at high biomass levels as commonly seen with NDVI.

11.1 Further Scope

Whilst the paper's aim of testing the robustness of PPI to temperature has been tested and PPI has shown to perform well, the study could be enhanced with further investigation including ground study to include a detailed analysis on the vegetation type and other variables such as water availability, soil type, winter snow cover etc. Temperature is not the only factor affecting plant growth and therefore it's reflectance and the subsequent results of VI's and as such to get an overall indication of the performance of any particular vegetation index it is important to take all environmental factors that control vegetation growth into account, as they will vary both seasonally and regionally.

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13 Appendix

13.1 Growing Degree Days

Year	Arjeplog	Dravagen	GT	Horn	Hunge	Kroksjö	Malung	NN	Saxnäs	SFF	Växjö	Vidsele
2000	583.6	740.4	861.9	1482.3	931.3	770.5	1119.4	901.7	667	1081.6	1592.3	1014.3
2001	781.2	788.7	851.9	1533.6	949.7	801.6	1147.9	1001.5	543.9	1093.9	1558.9	984.9
2002	1562.2	1081.4	1122.2	1583.8	1265.9	1127.5	1340.5	1253.8	1008.2	1375.4	1660.4	1273.4
2003	950	911.7	996.5	1491.4	1069.2	934.8	1192.3	1084	627	1198.6	1588.2	1157.2
2004	757.2	807.1	804.1	1400.4	980.1	767.6	1128.4	977.8	644.7	1095.1	1491.6	959.8
2005	835.5	834	896.4	1503.6	1002.6	843.2	1121.9	1002	133	1063.2	1603.8	883.6
2006	1011.2	1048.8	1084.6	1793.8	1205.6	1067.2	1388.4	1202	960.4	1310.7	1870.6	980.6
2007	772.4	833.5	823.4	1526.3	986.7	803.5	1149.9	1006.5	743	1088.7	1581.9	741
2008	711.5	767.8	709.7	1460.5	928.5	740.4	1109.8	912.1	709.2	973.5	1552.6	865.3
2009	885.8	735.9	897.6	1434.4	989.6	865.9	1120.1	986.8	792.9	1101.8	1542.6	1101.7
2010	756.7	769.5	846	1453.6	930.2	802.2	1096.5	349.2	397.6	1042.3	1471.2	1018.7

Table 7 - Appendix: Growing Degree Days - Section 9.3 in Text

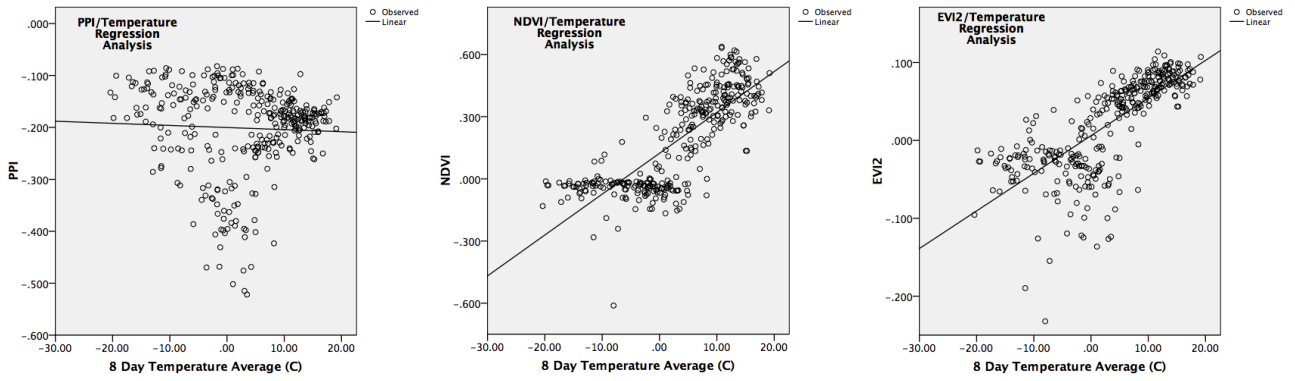
13.2 Annual Mean Temperature (°C)

Year	Arjeplog	Dravagen	GT	Horn	Hunge	Kroksjö	Malung	NN	Saxnäs	SFF	Växjö	Vidsele
2000	0.13	2.75	2.33	7.42	3.58	2.38	4.96	3.55	1.62	4.25	8.69	2.44
2001	0.15	1.25	0.79	6.35	2.21	1.02	3.13	2.36	-0.35	2.95	6.71	0.76
2002	0.88	2.11	1.68	7.00	3.16	2.19	3.75	2.92	2.98	3.87	7.40	1.46
2003	0.99	2.62	1.93	6.17	3.13	2.16	4.13	3.06	0.56	3.54	6.99	1.83
2004	0.50	2.25	1.43	6.19	3.23	1.83	4.11	2.89	1.02	3.59	6.78	1.11
2005	1.23	2.65	2.05	6.54	3.40	2.36	4.48	3.29	-1.41	3.72	7.14	1.29
2006	1.56	3.08	2.30	6.74	3.96	2.70	4.65	3.78	2.06	4.22	7.70	1.15
2007	1.06	3.66	1.87	7.35	3.29	2.20	4.22	3.49	1.72	3.65	7.81	0.80
2008	1.11	2.75	1.62	7.42	3.16	2.10	4.62	4.11	1.66	3.67	7.78	1.81
2009	0.50	1.06	1.20	6.44	2.38	1.54	3.54	2.33	0.91	3.34	7.00	1.51
2010	-1.39	-0.48	-0.36	4.61	0.30	-0.08	1.27	-3.84	-3.70	0.34	5.35	-0.37

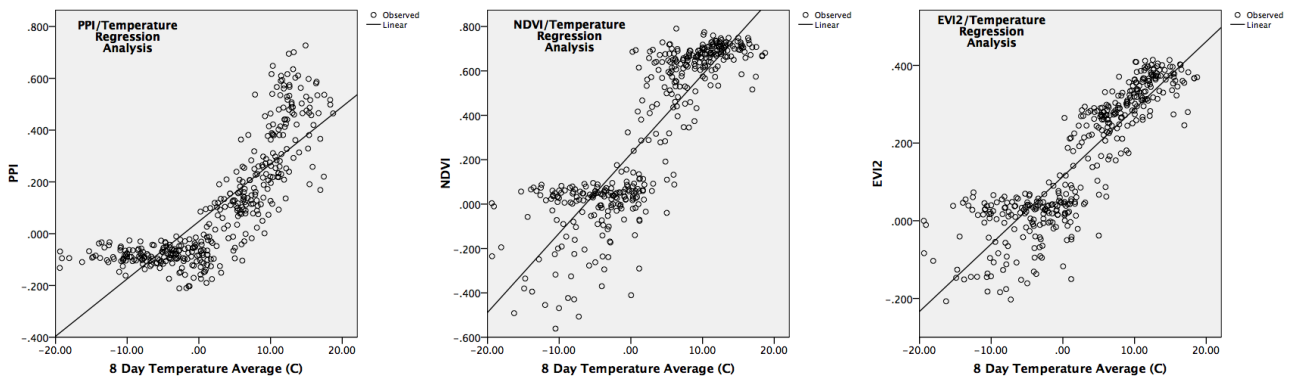
Table 8 - Appendix: Mean Annual Temperature (°C) – Section 9.4 in Text

13.3 Regression Analysis of Full Data Set, entire temperature range

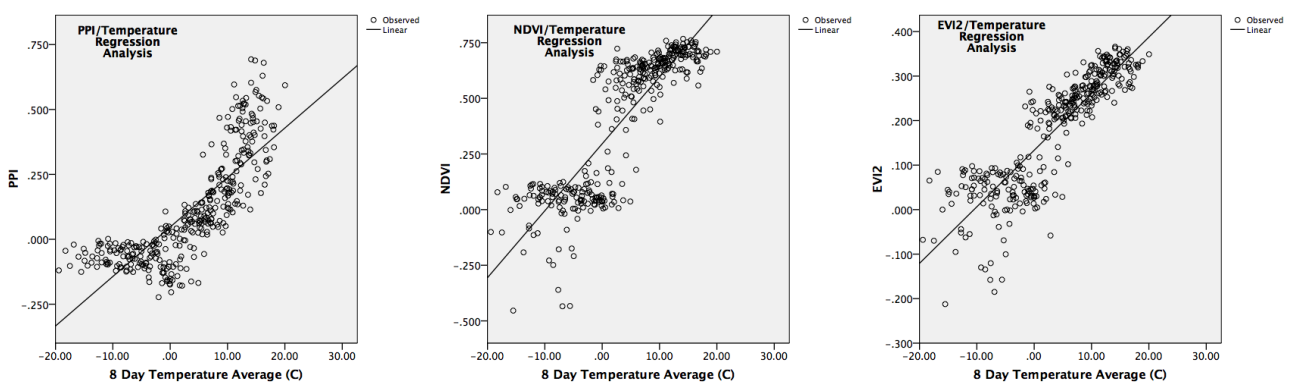
Arjeplog



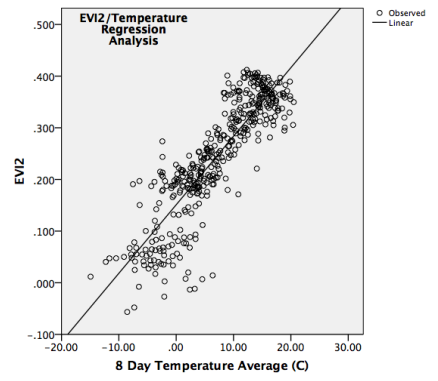
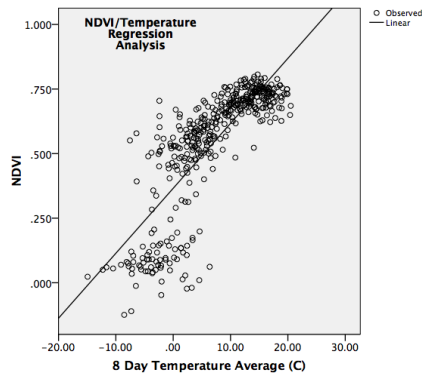
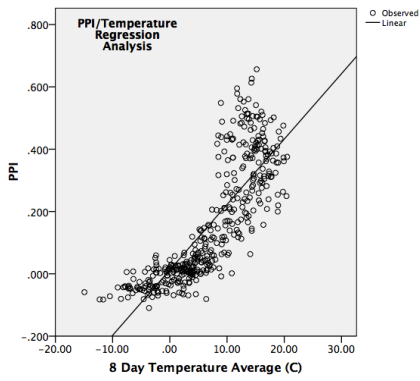
Dravagen



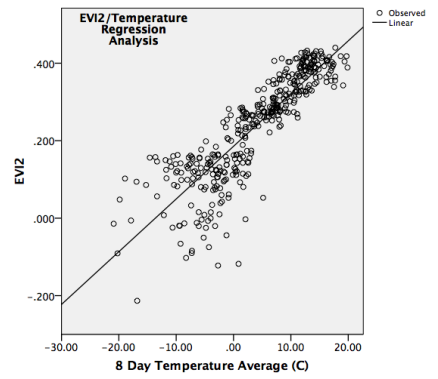
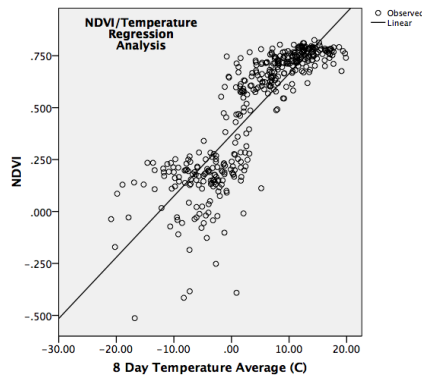
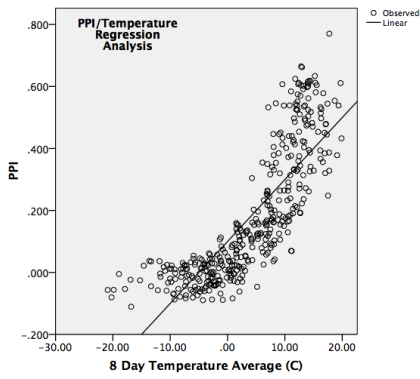
Glommertask



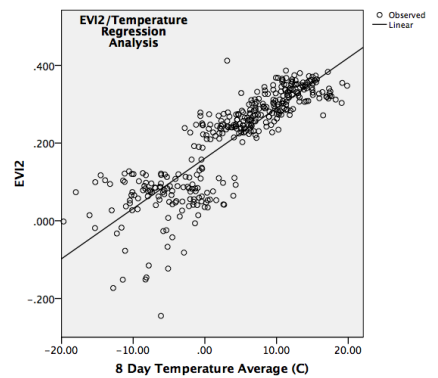
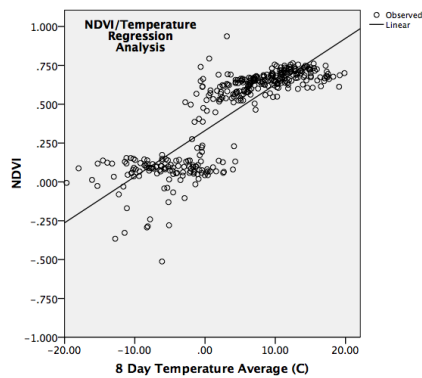
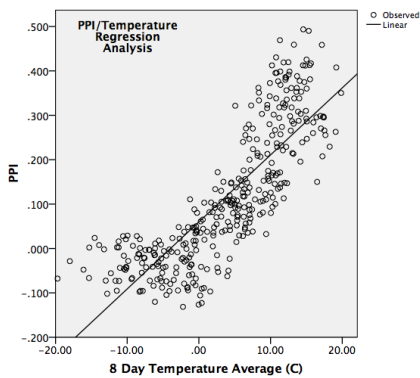
Horn



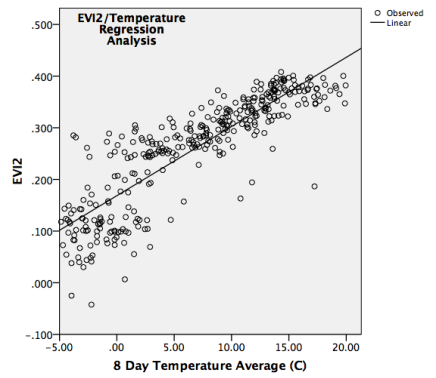
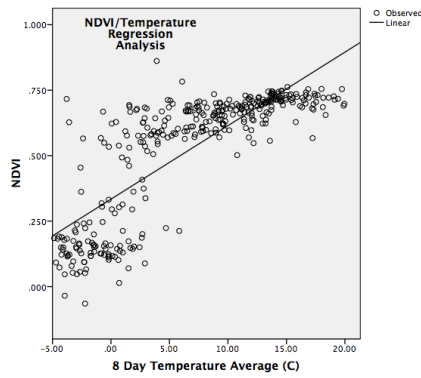
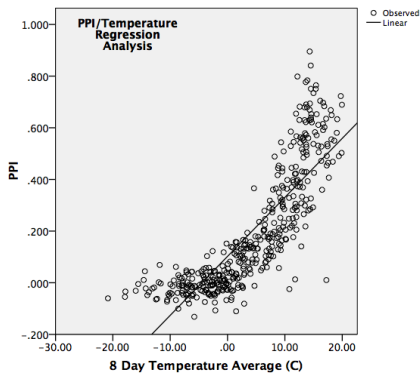
Hunge



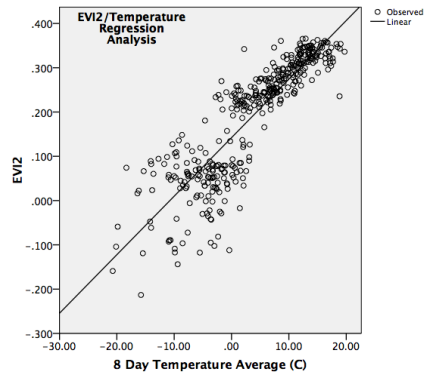
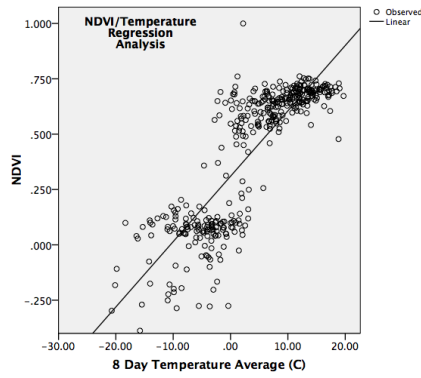
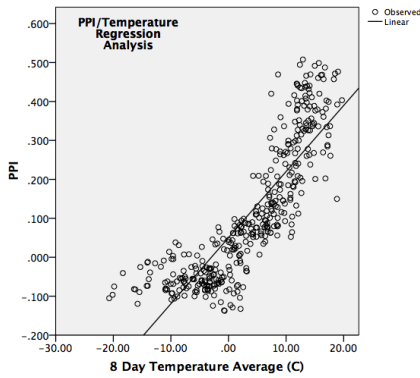
Kroksjö



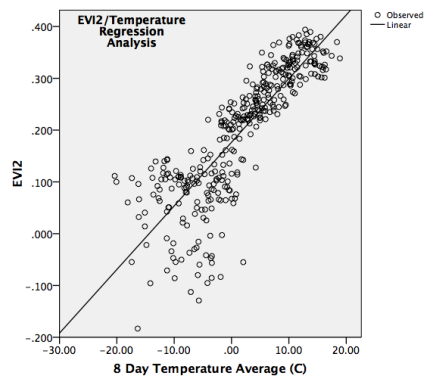
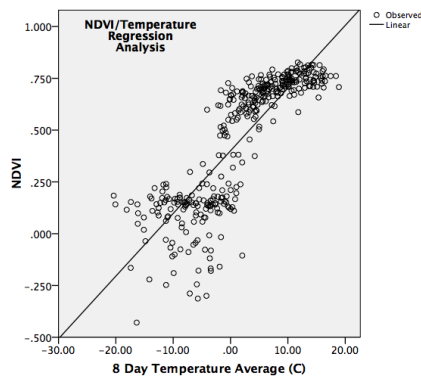
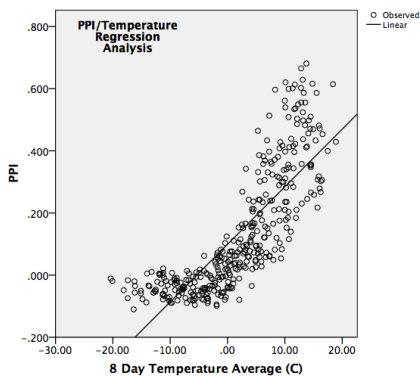
Malung



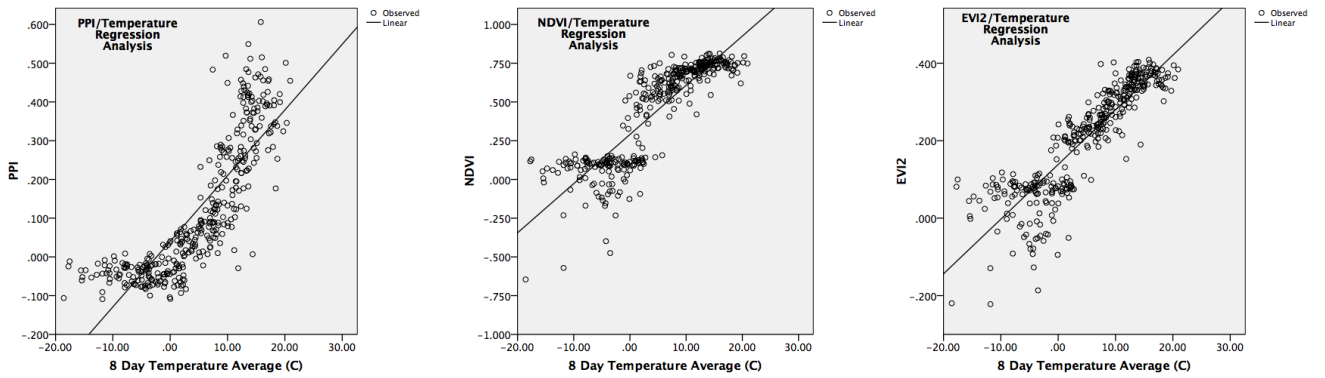
Norrberg-Norrhög



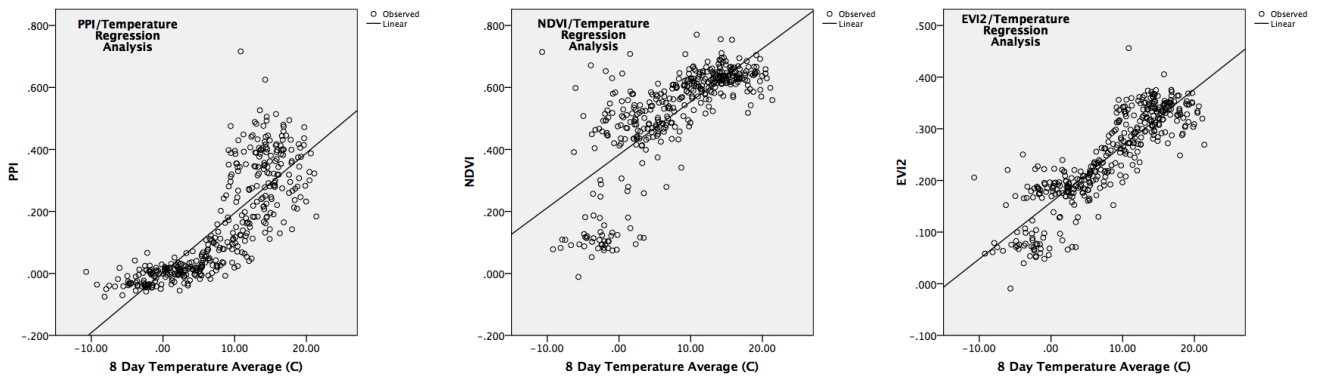
Saxnäs



Storfinnforsen



Växjö



Vidsele

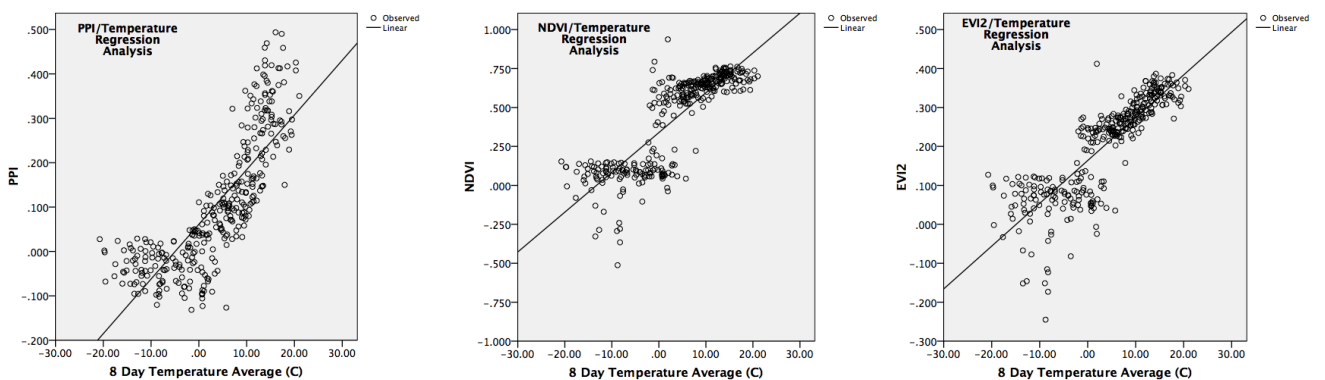


Figure 26 - Appendix: Regression Analysis Entire Dataset

13.4 Regression Analysis: Entire Data Set Results Table

	PPI/8 Day Average (NDVI/8 Day Average) EVI2/8 Day Average					PPI/1 Week Lag (NDVI/1 Week Lag) EVI2 1 Week Lag				
	R2	F	df1	df2	Sig.	R2	F	df1	df2	Sig.
Arjeplog	0.002	0.64	1	338	0.4	0.004	1.388	1	338	0.239
	0.626	566.444	1	338	0	0.646	617.619	1	338	0
	0.545	404.681	1	338	0	0.577	461.029	1	338	0
Dravagen	0.668	788.573	1	392	0	0.637	687.899	1	392	0
	0.745	1147.832	1	392	0	0.721	1011.716	1	392	0
	0.779	1379.355	1	392	0	0.742	1129.798	1	392	0
Glommerträsk	0.648	656.46	1	357	0	0.617	575.403	1	357	0
	0.744	1037.971	1	357	0	0.732	977.389	1	357	0
	0.76	1133.174	1	357	0	0.725	939.983	1	357	0
Horn	0.673	858.654	1	418	0	0.602	631.702	1	418	0
	0.648	768.332	1	418	0	0.579	573.976	1	418	0
	0.76	1325.25	1	418	0	0.677	874.589	1	418	0
Hunge	0.67	798.764	1	394	0	0.599	588.73	1	394	0
	0.735	1092.058	1	394	0	0.715	986.38	1	394	0
	0.756	1,222,283	1	394	0	0.712	973.737	1	293	0
Kroksjö	0.674	742.477	1	359	0	0.622	589.865	1	359	0
	0.713	890.495	1	359	0	0.685	781.772	1	359	0
	0.73	972.01	1	359	0	0.679	758.41	1	359	0
Malung	0.693	949.641	1	420	0	0.654	794.511	1	420	0
	0.744	1218.757	1	420	0	0.718	1071.996	1	420	0
	0.787	1556.154	1	420	0	0.755	1292.138	1	420	0
NorrbergNorrhog	0.721	1021.264	1	396	0	0.684	855.347	1	396	0
	0.716	999.708	1	396	0	0.707	956.088	1	396	0
	0.769	1320.424	1	396	0	0.745	1159.97	1	396	0
Saxnäs	0.653	687.317	1	366	0	0.575	495.546	1	366	0
	0.711	900.264	1	366	0	0.681	780.615	1	366	0
	0.718	931.643	1	366	0	0.661	715.097	1	366	0
Storfinnfor sen	0.694	854.39	1	376	0	0.647	688.92	1	376	0
	0.756	1168.158	1	377	0	0.748	1116.862	1	376	0
	0.78	1332.962	1	377	0	0.753	1144,165	1	376	0
Växjö	0.661	759.766	1	390	0	0.58	539.645	1	390	0
	0.54	458.328	1	390	0	0.497	385.08	1	390	0
	0.761	1243.11	1	390	0	0.683	840.174	1	390	0
Vidsele	0.65	628.599	1	339	0	0.612	534.987	1	339	0
	0.7	792.391	1	339	0	0.696	777.103	1	339	0
	0.713	841.25	1	339	0	0.686	740.077	1	339	0

13.5 List of Previous Publications

Institutionen för naturgeografi och ekosystemvetenskap, Lunds Universitet.

Student examensarbete (Seminarieuppsatser). Uppsatserna finns tillgängliga på institutionens geobibliotek, Sölvegatan 12, 223 62 LUND. Serien startade 1985. Hela listan och själva uppsatserna är även tillgängliga på LUP student papers (www.nateko.lu.se/masterthesis) och via Geobiblioteket (www.geobib.lu.se)

The student thesis reports are available at the Geo-Library, Department of Physical Geography and Ecosystem Science, University of Lund, Sölvegatan 12, S-223 62 Lund, Sweden. Report series started 1985. The complete list and electronic versions are also electronic available at the LUP student papers (www.nateko.lu.se/masterthesis) and through the Geo-library (www.geobib.lu.se)

- 300 Johan Westin (2014) Remote sensing of deforestation along the trans-Amazonian highway
- 301 Sean Demet (2014) Modeling the evolution of wildfire: an analysis of short term wildfire events and their relationship to meteorological variables
- 302 Madelene Holmblad (2014). How does urban discharge affect a lake in a recreational area in central Sweden? – A comparison of metals in the sediments of three similar lakes
- 303 Sohidul Islam (2014) The effect of the freshwater-sea transition on short-term dissolved organic carbon bio-reactivity: the case of Baltic Sea river mouths
- 304 Mozafar Veysipanah (2014) Polynomial trends of vegetation phenology in Sahelian to equatorial Africa using remotely sensed time series from 1983 to 2005
- 305 Natalia Kelbus (2014) Is there new particle formation in the marine boundary layer of the North Sea?
- 306 Zhanzhang Cai (2014) Modelling methane emissions from Arctic tundra wetlands: effects of fractional wetland maps
- 307 Erica Perming (2014) Paddy and banana cultivation in Sri Lanka - A study analysing the farmers' constraints in agriculture with focus on Sooriyawewa D.S. division
- 308 Nazar Jameel Khalid (2014) Urban Heat Island in Erbil City.
- 309 Jessica Ahlgren & Sophie Rudbäck (2014) The development of GIS-usage in developed and undeveloped countries during 2005-2014: Tendencies, problems and limitations
- 310 Jenny Ahlstrand (2014) En jämförelse av två riskkarteringar av fosforförlust från jordbruksmark – Utförda med Ekologgruppens enkla verktyg och erosionsmodellen USPED
- 311 William Walker (2014) Planning Green Infrastructure Using Habitat Modelling. A Case Study of the Common Toad in Lomma Municipality
- 312 Christiana Marie Walcher (2014) Effects of methane and coastal erosion on subsea-permafrost and emissions
- 313 Anette Fast (2014) Konsekvenser av stigande havsnivå för ett kustsamhälle- en fallstudie av VA systemet i Beddingestrand

- 314 Maja Jensen (2014) Stubbrytningens klimatpåverkan. En studie av
stubbrytningens kortsiktiga effekter på koldioxidbalansen i boreal barrskog
- 315 Emelie Norhagen (2014) Växternas fenologiska svar på ett förändrat klimat -
modellering av knoppsprickning för hägg, björk och asp i Skåne
- 316 Liisi Nõgu (2014) The effects of site preparation on carbon fluxes at two
clear-cuts in southern Sweden
- 317 Julian Will (2014) Development of an automated matching algorithm to
assess the quality of the OpenStreetMap road network - A case study in
Göteborg, Sweden
- 318 Niklas Olén (2011) Water drainage from a Swedish waste treatment
facility and the expected effect of climate change
- 319 Wösel Thoresen (2014) Burn the forest - Let it live. Identifying potential
areas for controlled forest fires on Gotland using Geographic Information
System
- 320 Jurgen van Tiggelen (2014) Assimilation of satellite data and in-situ data
for the improvement of global radiation maps in the Netherlands.
- 321 Sam Khallaghi (2014) Posidonia Oceanica habitat mapping in shallow
coastal waters along Losinj Island, Croatia using Geoeye-1 multispectral
imagery.
- 322 Patrizia Vollmar (2014) The influence of climate and land cover on
wildfire patterns in the conterminous United States
- 323 Marco Giljum (2014) Object-Based Classification of Vegetation at
Stordalen Mire near Abisko by using High-Resolution Aerial Imagery
- 324 Marit Aalrust Ripel (2014) Natural hazards and farmers experience of
climate change on highly populated Mount Elgon, Uganda
- 325 Benjamin Kayatz (2014) Modelling of nitrous oxide emissions from clover
grass ley - wheat crop rotations in central eastern Germany - An
application of DNDC
- 326 Maxime Rwaka (2014) An attempt to investigate the impact of 1994 Tutsi
Genocide in Rwanda on Landscape using Remote Sensing and GIS analysis
- 327 Ruibin Xu (2014) Spatial analysis for the distribution of cells in tissue
sections
- 328 Annabelle Finck (2014) Bird biodiversity in relation to forest composition
in Sweden
- 329 Tetiana Svystun (2015) Modeling the potential impact of climate change
on the distribution of Western Corn Rootworm in Europe”
- 330 Joel Forsmoo (2014) The European Corn Borer in Sweden: A Future
Perspective Based on a Phenological Model Approach
- 331 Andrew Ekoka Mwambo (2015) Estimation of Cropland Ecological
Footprint within Danish Climate Commissions 2050 Scenarios for Land
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on soil erosion in the Mara region, Tanzania: Using satellite remote
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degradation between 1986 and 2013

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