

Computer Aided Analysis And Collection Of Phenological Image Series

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Abstract

Monitoring has recently taken center stage in the discussion of anthropogenic climate change. Indeed, ecological monitoring is a means of providing the data sets necessary to model the slow moving characteristics of the relation between climate and ecosystems. In this context, phenology is key as it is one of the most responsive and easily observable impact of climate on nature. Technological advances such as remote sensing satellites have allowed for phenological measurements on a global scale that elucidate universal behavior of large ecosystems. However, it is still a challenge to relate these measurements that cover extended areas to organism level data characterized by its fine granularity. The scaling up of ground based measurements has been embraced as a way to complement remote sensing data. But the unprecedented growth of data that results needs to be addressed.

With this in mind we present three prototypes that focus on scaling up ground based measurements by producing data in the form of image series. Our prototypes take care of the explosion of data by providing computer aided methodologies that streamline the analysis of data. Our first prototype is a python (www.python.org) library called EcoIS that is capable of producing aligned image series from high resolution images taken from the field. The second prototype is an R (www.r-project.org) toolkit designed to automate the analysis of vast quantities of data in the form of image series by means of Naive Bayesian statistical models. Finally we describe EcoAN, which is a Matlab (www.mathworks.com) graphical user interface used to create metadata of image series in the form of labeled annotations.

Our three prototypes are all open source and are part of a pipeline that begins in the field and ends with the consolidation of ground based data into a representation that can be easily understood and is conducive to the design, implementation and evaluation of environmental policy. In this dissertation we present EcoIS as a producer of data that adds to the scale up effort by producing spatiotemporal ecological data in the form of image series. In the same way we introduce EcoIP and EcoAN by presenting them as applications that transform data in the form of image series into ecological indicators fit to describe ecosystems on the ground.

To Sophie. Thank you for your patience.

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Chapter 1

Introduction

1.1 Context

1.1.1 Monitoring

Ecosystems are changing rapidly and dramatically along with observed variations in climate (Post et al., 2009). This is visible in most regions with early spring onset dates, lengthening of growing seasons (Badeck et al., 2004) together with changes in range boundary shifts and phenology (Parmesan and Yohe, 2003). This is specially visible in arctic regions (Post et al., 2009) where effects of climate fluctuations are larger than in other latitudes (Stendel et al., 2008). Changes like earlier snow melt (Post et al., 2009) will affect arctic vertebrates in different and sometimes unpredictable ways (Gilg et al., 2012) like increase in population numbers (Tyler et al., 2008).

Quantifying the effects of climate on a given ecosystem is a complex task. It requires extended data from multiple places (Meltofte et al., 2008b). These quantifications are laborious because there exists a long term lag between cause and effect in ecological responses (Magnuson, 1990). This is likely the reason why some have described our understanding of the climate ecosystems relation as inferior (Meltofte et al., 2008b).

Monitoring is important and relevant because it leads to an improved understanding and management of complex ecological systems (Lindenmayer and Likens, 2009). Monitoring programs have the ability to provide information that can be used for the implementation and evaluation of environmental policy (Lovett et al., 2007). Indeed, our ability to understand and predict the effects of climate change on ecosystems depends on coordinated long-term monitoring programs (Schmidt et al., 2012b) that establish the difference between effects inherent to ecosystems and those caused by environmental perturbations like climate change (Meltofte et al., 2008b). It is with long term monitoring efforts that we are able to measure anthropogenic climate change and ascertain its effects on the ecosystem (Rosenzweig et al., 2008).

Ecological monitoring dates as far back as 1736 with the Marsham phe-

nological records (Sparks and Carey, 1995) which was an effort spanning for many decades focused mainly on plant behavior description. In contrast, and to address the need for larger and denser datasets, we are beginning to see a tendency towards the use of computer aided methodologies as the field moves forward (Arzberger, 2004). More specifically, there are all sorts of efforts directed towards the use of digital photography (Graham et al., 2010; Richardson et al., 2007; Nagai et al., 2011; Ide and Oguma, 2010) to gather and analyze data of phenological phenomena.

1.1.2 Phenology

Plant phenology is the study of plant life cycle events and how these are influenced by seasonal and interannual variations in climate (Betancourt et al., 2007). It is one of the most responsive and easily observable traits in nature that are impacted by changing climate (Badeck et al., 2004). Phenological studies have been used in the past to assess human intervention like for fertilizer application, in forest provenance studies and to predicting crop productivity as well crop sustainability (Badeck et al., 2004). It relates strongly to primary productivity and is sensitive to microclimatic variations, thus its study is vital to understanding species responses, ecosystem functions, and the effects of climate (Wright et al., 1999).

The interest in plant phenology and global climate change has increased significantly in recent years, especially with estimates of the advancing initiation of spring activity by both ground-based (Walther et al., 2002; Root et al., 2003) and satellite observations (Slayback et al., 2003; Stöckli and Vidale, 2004). This tendency has led to the creation of national phenological initiatives like the United States National Phenology Network (Betancourt et al., 2007; Schwartz et al., 2012, USA-NPN, www.usanpn.org) devoted to observing continental-scale trends in plant systems. As well as international initiatives like the European Phenological Network (Vliet et al., 2003) which tackled the challenge of measuring continental phenology by promoting international collaboration (Vliet et al., 2003).

Methods to measure and analyze phenology are of great interest as they provide the data that feed further studies. Images as a measuring data unit are gaining traction because they capture both spatial and spectral information in one shot. They have been used to measure different ecological indicators (Richardson et al., 2007; Sonnentag et al., 2012; Ide and Oguma, 2010) and are becoming a plausible alternative for fast and reliable ground measurements. Indeed image ecological data is becoming a feasible choice in phenological contexts given the ubiquitousness of digital photography and low cost of photographic systems; it is posed to make phenological monitoring easier and more cost effective.

1.1.3 Image Series

Digital photography and technology in general have had a great influence on how ecological and agricultural monitoring is done (Arzberger, 2004). Sensors have helped to characterize lake behavior during typhoons (Jones et al., 2008; Arzberger, 2004), they are part of platforms capable of telemetry from the sea bed that elucidate anthropogenic effects on underwater ecosystems (Barr, 2003; Arzberger, 2004) and are crucial for precision agriculture applications where they are posed to provide a steady stream of data to feed crop management policies (Payne et al., 2013; Wallen and Philpotts, 1971; Granitto et al., 2000; Camargo and Smith, 2009).

Digital photography is a part of the ample technological spectrum available for ecological and agricultural monitoring (Sonnentag et al., 2012; Graham et al., 2009). It is widely used in the form of image series (Richardson et al., 2007; Graham et al., 2006; Crimmins and Crimmins, 2008) that add a temporal dimension to the before mentioned spatial and spectral one which is an advantage over individual images. They have the potential to improve spatial and temporal resolution of phenological data measurements while reducing the labor required to gather data (Ide and Oguma, 2010).

Image series are sequence of images taken from the same view point at a predefined frequency for a period of time and are visualized by chronologically stacking individual images into series. Sampling frequencies range from seconds (Graham et al., 2006) to days (Granados et al., 2013) and deployments vary from short periods of less than a year (Richardson et al., 2007; Sonnentag et al., 2012) to more extended ones that span multiple years (Ide and Oguma, 2010; Granados et al., 2013). By configuring these types of systems to match a specific phenomena it is possible to capture changes that occur at very slow speeds, like the blossoming of a flower or leaf out in summer. By taking data acquired of an extended time period and replaying it at a faster pace, it is possible to visualize slow changes in short amounts of time. Besides visualization, image series can be related to phenological indicators like bud burst and spring greenup (Bauer and Cipra, 1973; Richardson et al., 2007; Ide and Oguma, 2010; Crimmins and Crimmins, 2008) through the information contained in pixels. These reflect not only spatial characteristics but also contain spectral information of the light being reflected off the elements in the image.

One way of classifying the camera systems responsible for creating image series is to separate them into three groups: satellite, areal and ground based (Mulla, 2013). Image series created from satellite photography are very useful because they give a general overview of the behavior of a large piece of land (Bauer and Cipra, 1973; Mulla, 2013). Aircraft images also give a wider overview, but suffer less from atmospheric interference and can be used to characterize large crops (Duhaime et al., 1997). Ground based platforms refer to hand held or tractor mounted cameras (Mulla, 2013) and are the ones that contain more detail due to their closeness to subjects. These types of systems reflect the trade off inherent in images taken from far with very little detail but cover vast tracts of land and images taken from the ground which offer a lot

more detail but cannot easily give a general overview of a site.

1.2 Problem

Satellite measurements have been very useful in the past for the broad analysis of great extents of land (Mulla, 2013). The advent of precision hardware has managed to narrow down the resolution of remote images to sub-meters accuracy (Mulla, 2013) and are able to measure variables such as crop yield and biomass, crop nutrient and water stress, weed and insect infestation as well as soil properties (Mulla, 2013). Work is currently being done to increase resolution and time frequency of remote satellite sensing in order to produce more reliable measurements (Mulla, 2013).

While remote sensing has been used successfully to extract information for various applications (Mulla, 2013; Moran et al., 1997), it needs to deal with a series of problems associated with acquiring images from orbit like calibration of raw digital numbers to true reflectance values. Other issues include correcting for atmospheric interference, correcting off-nadir views and rectifying pixel positions by using GPS-based ground values. Not to mention that there are situations where the visible spectrum process fails completely as with cloudy skies (Mulla, 2013). Of special interest is the problem related to satellite images not being able to measure detail in phenological data contexts.

The best way to observe large-scale phenological changes is by linking remote sensing (e.g. satellite imagery) with ground-based measurements (Badeck et al., 2004). On the one hand remote sensing is captured over wide areas but at low spatial resolution providing data in the form of image pixels that represent average reflectance values of pieces of land. On the other hand it is often too coarse to detect species and community level responses which makes it ill suited to decompose pixels into the individual components that make up the average reflectance value (Badeck et al., 2004). For example, remote NDVI¹ measurements done on homogeneous environments can accurately identify periods of growth and senescence but the same measurements done on heterogeneous environments might mistake the variation of one species (e.g. understory vegetation) for the response of the target (e.g. deciduous forests) species (Badeck et al., 2004).

Though the ground-based collection of phenological data provides information at the organism level, it is not scalable nor does it give a general overview of the mixture of species (Badeck et al., 2004) contained in heterogeneous environments. The use of new technology is being investigated to scale up (Allen et al., 2007) and standardize ground-based measurements by using a subset of species (Betancourt et al., 2007; Schwartz et al., 2012), and modeling local climatic conditions (Jolly et al., 2005). This indeed is the current challenge regarding ground and remote measurements: to exploit their great potential by scaling up the first one while increasing resolution of the second (Badeck et al., 2004).

¹See Ellebjerg et al. (2008) for information on NDVI

This challenge frames the problems that we address in this thesis, and that we describe in the rest of this Section.

1.2.1 Alignment in Image Series

Alignment is a spatial property of image series and is present when all the images of a series have or seem to come from the same view point. When aligned, inanimate objects stay in the same image coordinates throughout all the series which facilitates their identification and analysis. This attribute does not necessarily need to exist in order to analyze consecutive unaligned images of the same place. In some cases, where there is considerable human involvement, "true" image alignment can be replaced by image associations based on patterns and additional metadata like GPS coordinates (Blumenthal et al., 2007). However, when image series are analyzed automatically, it is crucial that there be some sort of alignment.

Correcting for nonalignment, camera specific inaccuracies and atmospheric responses is common with satellite data (Mulla, 2013; Moran et al., 1997) where problems like off-nadir² viewing is common (Moran et al., 1997). Alignment is also relevant in systems that acquire images closer to the ground where image view point standardization is achieved by fixing the camera to a specific place with the help of a structure that is permanent or needs to be carried around (Ratliff and Westfall, 1972; Booth et al., 2004; Bennett et al., 2000). Other approaches implement a more automated solution where a camera is left on a fixed platform (Brown et al., 2012; Lusier et al., 2006) and produces aligned images by default as it is left static for the duration of the deployment. However, cameras do not need to be completely static: rotational (Granados et al., 2013) as well as translational (Graham et al., 2009) movement can be handled by software in order to produce completely aligned images.

Despite general use, image series alignment is still a relevant research topic for cases where it is not possible to use fixed camera platforms in the field. Their inherently invasive nature prevents deployments in protected areas where anthropogenic influence is purposefully kept to a minimum (Meltote et al., 2008c). In these cases more subtle solutions need to replace camera platforms that require constant maintenance and affect ecosystem surroundings. Here, we might be able to use old techniques that require small mobile platform (Ratliff and Westfall, 1972) or explore new methodologies that further reduce required platform hardware.

Policy is not the only problem that prevents deployment of camera housings needed for image alignment. As research moves away from well known infrastructure (electricity grids and communication networks) camera platforms become difficult or otherwise prohibitively expensive to maintain. Deploying a simple static tower camera in a remote area might be feasible with reduced capabilities such as low resolution and lossy compression algorithms (Hinkler et al., 2002), but doing the same with energy hungry platforms such as systems

²Nadir is a vertical vector pointing in the direction of the force of gravity

capable of rotational and translational movement that output large amounts of data becomes unmanageable or otherwise infeasible. This is another reason to explore other solutions to getting aligned images without an overwhelming camera infrastructure.

Finally, as we move towards the eventual replacement of human observers by unmanned autonomous vehicles (Grémillet, 2012) capable of terrestrial and areal mobility that also serve as camera platforms (Grémillet, 2012; Lucieer et al., 2012), we need to consider ways of analyzing the stream of unaligned images that they produce. It is clear that these free ranging unmanned platforms will successfully use digital photography, if we are able to normalize images and transform them into aligned series that can be mined for temporal and spatial patterns. With this in mind, automatic alignment of images should be one of the main concerns going forward.

1.2.2 Unmanageable Data

There is a general increase in amount of data (Hey and Trefethen, 2003; Emmott, 2006) that is exacerbated by novel data acquisition technologies like robotics (Grémillet, 2012) and sensors (Arzberger, 2004). It affects how data is analyzed as processing is delegated to automated mining procedures or specialized database constructs (Emmott, 2006). It also impacts storage as increasing amounts of metadata need to be created in parallel and everything has to be made compatible with presentation tools like digital libraries (Hey and Trefethen, 2003). There are also concerns regarding preservation and curation of large amounts of data for extended periods of time (Hey and Trefethen, 2003).

The increase is especially critical in image based ecology as it requires large amounts of storage for an increasing number of images that can no longer be processed manually (Granados et al., 2013). This concern is especially relevant for projects with requirements of up to one gigabyte per image (Brown et al., 2012) which, depending on the frequency of sampling, can quickly get out of hand. Capturing images once or twice per day can be hand-processed (Graham et al., 2010; Blumenthal et al., 2007), but for more complex systems where there is rotational and translational movement (Graham et al., 2009; Granados et al., 2013; Brown et al., 2012) and frequency is in the order of several images per day there needs to be a fundamental change in the way raw image data is handled to produce ecological knowledge.

With the increase of data, there needs to be an equal and parallel move towards analysis automation to keep up. Tools must take advantage of spatial information in order to characterize elements with variables like size and position (Hinkler et al., 2002); use spectral information contained in pixels for analysis based on light reflections (Bauer and Cipra, 1973; Richardson et al., 2007); and employ time variations contained in series of images to make temporal analysis (Parrott et al., 2008). These three types of data could be used individually and in conjunction to create spatiotemporal analysis that sample morphological traits while following elements through time.

Unfortunately extracting valuable information from images is not trivial.

Research has explored the use of automatic image processing to extract ecological information from images with various degrees of success. Projects have tried to use the spectral responses recorded by camera sensors and correlate them to ecological indicators like leaf area index (Ryu et al., 2012) or gross primary production (Saitoh et al., 2012) with one of the main concerns being how to control the fluctuation of the digital values from lighting changes (Richardson et al., 2007). Others have concentrated in trying to detect specific states of produce through color analysis (Payne et al., 2013) with one of the main concerns being lack of color consistency in the produce. In general, research has shown that there is great promise for computer aided image analysis of ecological data with few counter examples (Ksiksi and El-Keblawy, 2013). Trying to address the increasing amount of image data through computer aided approaches will continue to be an active research topic within ecology and precision agriculture.

1.2.3 Annotation Lacking

Annotations refer to added metadata in the form of a comments or a label (Hey and Trefethen, 2003) and is part of an active discussion in the field regarding ecological data management (Metzger et al., 2011; Leinfelder et al., 2010). It is important as it pertains to making sense of heterogeneous data sources for the advancement of scientific knowledge (Leinfelder et al., 2010) and is relevant in automated, semi-automated and manual curating processes that cleanse large amounts of data (Hey and Trefethen, 2003; Metzger et al., 2011). Data annotation is a fundamental property of long term monitoring efforts because it provides a way to validate and keep collected data (Hey and Trefethen, 2003; Karasti and Baker, 2008) as well as facilitate its dissemination (Karasti and Baker, 2008) and understanding (Madin et al., 2007).

Annotations can be applied to any type of data where it usually represents semantic metadata attached to a measured point (Pennington et al., 2007). They are especially relevant with image series because they can be overlain on top of an image and related to relevant labels to enhance presented information as well as to make the image searchable by automatic means (Torres and Qiu, 2013). Specifically, annotations allow the creation of time stamped metadata that can express categories or relate an image position to an informative note (Brown et al., 2012). And, as data moves towards multidimensional representations (image, image series and video), annotations become of great relevance as tools that facilitate data management (Karasti and Baker, 2008) and as instruments that help mine existing data for new information that could answers new questions.

Automatic annotating applications are of great interest as they aid ecologists in the current challenge of sifting through a growing mountain of data (Torres and Qiu, 2013). Yet manual and semi-automatic processes are still relevant: for the creation of representation models (Sorokin et al., 2008), certain levels of data curation (Hey and Trefethen, 2003) and for detailed classification that is not yet automatic (Brown et al., 2012). Indeed applications designed for manual annotation of image data range from the very general (National Institutes

of Health, 2008) that take any type of image and have an assortment of predefined functionalities focused on creating image metadata. To the very specific (Roshier et al., 1996) that are used for certain types of images and are context specific.

Applications designed for manual annotation of images series focus on elucidating spatial and temporal aspects (Brown et al., 2012) while at the same time giving importance to the way images are collected (Brown et al., 2012; Roshier et al., 1996). These applications are concerned with how the information is displayed to trained technicians and their features are designed to streamline the process of creating image metadata. With this in mind there are still elements that might be improved; more specifically, toolkits still need to explore diverse ways of creating annotations in search of features that will increase accuracy and allow metadata to be created in a timely manner.

1.2.4 Looking Ahead

The disparity between remote sensing and ground based data, the alignment issues from images taken from different view points, the overwhelming amount of ecological data being produced and the importance of annotations for data analysis is our motivation for putting forth this dissertation. We use computer aided processes to analyze and collect ecological data hoping to streamline repetitive tasks that might lead to reduction of effort and an increase in data accuracy. We used close-range photography because, in our opinion, it generates rich data sets that can be dissected in various ways and lead to spatial, spectral and temporal aspects that are suitable for describing ecological phenomena.

In this research we address unaligned image series not only because of their relevance to current issues like satellite imagery, but also because they will become relevant as new technologies are used to collect ecological data. We also see the importance of the relationship between the increasing amount of available data and the processes used to analyze it. We understand the importance of close-range ecological indicators in answering new scientific questions as well as implementing public policy. We view monitoring as a process that can generate historical image data which is critical to answering questions related to phenomena that exist in a prolonged time line. Each of our contributions is focused at optimizing the output of ground-based measurements in order to more easily relate them to remote sensing data which will ultimately increase our understanding of local as well as global ecosystems.

1.3 Approach

Our interest is on how established ecological procedures are affected by computer aided methodologies of phenological data analysis and collection. Our general approach consists in building software prototypes around the manipulation of data in the form of image series with the objective of producing relevant phenological estimators using automatic and semi-automatic procedures. To

evaluate our prototypes we deploy them in two monitoring programs located in different ecosystems and assess their behavior. Given that our efforts are located between research in ecology and computer science we rely on collaboration with research groups that harbor experts in the fields of biology, ecology and computer science.

Our first prototype (EcoIS) addresses the acquisition of ground based images and how they can be collected with a minimum amount of hardware. It is concerned with normalizing images into a common view point as well as with the effects it has on established ground based procedures. In our approach we go as far as to propose and evaluate changes in known work-flows in order to characterize their effectiveness. Understanding the difficulty of changing customary procedures and knowing the adversity related with automatically handling images we also describe possible downsides related to the use of our prototype.

Our second prototype (EcoIP) will address the automatic and semi-automatic analysis of image series expanding on the need for these types of applications and their scope within phenological data acquisition. We touch on image specific complications that affect our approach such as light variability and other sources of noise to elucidate how they impact the accuracy of ecological estimator calculations. Our approach includes the analysis of different species in order to show its versatility and is compared to other methodologies to describe its relevant value.

Seeing that there are still some limitations on what can be fully automated, we explore the use of computer aided methods that collect and analyze phenological data. Our third prototype (EcoAN) explores human computer interaction when identifying individual species in an image series and delves into the effects of using such a prototype within established procedures. We see EcoAN as an instrumental tool for supporting fully automated processes as well as providing the means to do data curation and annotations that are not yet automatic.

Pushed by a conviction that images are the best possible dataset representation for phenology, we look at using them in the form of image series which contain temporal, spatial and spectral dimensions fit for sampling phenological phenomena. Given that we are replacing established work-flow patterns, we feel the need to compare our prototypes and their related changes with established practices in order to assess their integrity and quantify the impact that they have in the field. We are equally concerned in how the resulting measurements compare with those from established practices and seek to generate analogous results.

We are in between two fields (computer science and ecology) that have their own idiosyncrasies, and approach research from different perspectives. With this in mind we understand the need to create a team with diverse research backgrounds that understands ecological variables as well as computational constraints. This collaboration between fields has been crucial to create, deploy and evaluate our prototypes and continues to be a source of important discussion regarding the convergence of ecology and computer science. Our approach depends fully on multiple feedback processes simultaneously originating from

opposite but complementing fields that come together in order to push ecology technology forward.

We have collaborated with a part of the Department of Bioscience at the Aarhus University in Denmark in order to understand the specific needs of Arctic ecology exploration. With them we traveled to Zackenberg (www.zackenberg.dk) a high Arctic monitoring station and had a first hand experience of what shapes a monitoring program. This collaboration was key in the design of our prototypes and, more specifically, gave us important insight on the special requirements that our system needed to consider in order to be successful. It was through interviews and shared experiences with researchers and technicians that these requirements were embodied into the prototypes. Collaboration was further strengthened where technicians from the institute have actively participated by testing new data acquisition methodologies related to our prototypes and given us invaluable feedback.

We further sought opportunities with research projects that emphasized on the application of computer science to ecological processes. This is how we met with the Center for Embedded Networked Sensing (CENS) in the University of California Los Angeles (UCLA) where their research was focused on the application of computers as terrestrial ecology observation systems. The collaboration was productive with a publication and release of our first prototype (EcoIP) which we used to analyze data collected by CENS throughout various years in the James Reserve located in the San Jacinto Mountains of southern California. The insight created by discussion regarding design and methodology set the foundation for our EcoIP prototype and knowledge generated within that collaboration permeated our research done in the Arctic.

1.4 Contribution

Our main contribution is divided between the three toolkits that we developed: EcoIS, EcoIP and EcoAN. They relate to the issues described in section 1.2 in different ways and have at their core the use of image series as a data unit. In this chapter we explore the specific contributions from each toolkit and how they relate to current problematics of ecological data. We present these toolkits in order to create a community of applications that come together to form a pipeline that culminates in the creation of ecological indicators. At the end of the section we describe how the three toolkits address the link between ground and remote based phenological measurements.

1.4.1 EcoIS

EcoIS is a versatile open-source python (www.python.org) library that has the ability of aligning images of plots containing special ground markers. Transformed images will all seem to have the same view point and can make up image series. We characterize EcoIS by listing its key features, discussing its limitations and behavior in a deployment conducted in a monitoring station in

the high arctic. In this way our contribution not only includes the toolkit itself, but a description of the lessons learned and what to expect when using it in a deployment.

We redefine the relationship that exists between cameras and infrastructure needed to produce aligned images. Where traditional methods used cameras hardwired into housings designed to force same view images, we allow the camera to move freely effectively dissociating it from housing constructs. As we avoid the infrastructure holding the camera in place, we give way to new possibilities of acquiring data through images. Our approach, which is tested with hand held cameras, can be extended to other more automatic scenarios where the technician is completely taken out of the picture and replaced by an autonomous agent like an Unmanned Aerial Vehicle (UAV).

We minimize the infrastructure needed to create image series from field images. Though we could have created a system where the technicians carry a tripod-like structure around the field in order to give the images the same view point, we choose to create one that does away with known camera platforms (Booth et al., 2004) and replaces them with an approach that depends on small artificial markers placed in the field. These markers which are deployed and collected only once, serve as reference points to create same view point images.

1.4.2 EcoIP

EcoIP is an open-source toolkit that leverages current computer vision and machine learning techniques to automate the creation of phenological indicators. The toolkit creates a statistical model that it then uses on image series to detect elements of interest. Human interaction is needed to create the model and to adjust the automatically generated results. The toolkit is built using the R statistical environment (R Core Team, 2013) and provides a command line user interface as well as a library.

We minimize human involvement in image data analysis by providing a library that reduces image series into manageable data representations (e.g. sigmoid function) and allows easy and fast assessments of multiple species in vast tracts of land covered by digital photography systems. We tackle questions related to specific dates of flowering and senescence in different species and with different camera systems by extracting temporal as well as spatial information from vast collections of image series and presenting it in ways that are easy to handle manually. We believe that EcoIP stream lines processing and makes it easier for scientists to process more data in the same or less amount of time.

We calculated ecological estimators based on automatic analysis done of species in image series. These estimators were validated by visually inspecting image series for ground truth measurements and then comparing them to the automatically generated ones. In the cases where there was considerable deviation between the two, we gave possible causes and described how to deal with unwanted outcomes. One of the things to point out is that the estimators were calculated without the need to directly handle the images series, which made this particular process quick and painless.

We relate our approach to current developments in image processing for ecology and agriculture by describing their commonalities and differences. Additionally we comment on the difficulties present in our image processing algorithms and how these difficulties affect the level of automation, the accuracy of the analysis and what we can do to mitigate them. Indeed the application of computer vision to ecological and agricultural data acquisition is growing as analysis methods become more robust and we expect to see more of these solutions as the field moves forward.

1.4.3 EcoAN

EcoAN is an open-source toolkit that uses a Graphical User Interface (GUI) to aid the creation of annotations on image series. It was developed using Matlab (MathWorks, 2009) and allows the visualization and manipulation of labeled annotations on top of image series. Spatial and temporal aspects can be extracted from the annotation representations and serve as starting points for further calculations. As part of an assortment of applications EcoAN is related to EcoIS and EcoIP by requiring aligned image series and providing the means to create statistical models.

By leveraging latent spatial, spectral and temporal information contained in image series together with annotation features provided by EcoAN, we are able to formulate new questions and answer them with historical data. Though this property was implied by the nature of the interaction between image series and EcoAN, we were able to exemplify it by creating measurements in image annotations that answered new questions. Our contribution in this respect also included an accuracy analysis that compared how well EcoAN behaves against other methodologies.

We contribute an effort characterization that gives insight on how new technologies, such as our prototypes, might impact the way of doing ecological monitoring. More specifically we measure the time it takes to create a particular phenological estimators with established processes and compare it with workflows that use our prototypes. We also measure cost and describe how savings are achieved while using EcoAN in an Arctic field deployment with considerations that go from salary to station fees. In detailing these monitoring times and costs we increase the understanding of how these two relate and extend it to the effects of using digital photography in ecological monitoring environments. This characterization is valuable when creating new monitoring policies and we expect our findings to further push the adoption of digital photography as an alternative for phenological monitoring.

We use EcoAN's annotations to create ecological indicators able to describe ecosystems. We show how to create these indicators in real deployments and compares their accuracy with indicators created with established work-flows. We explore places where errors might creep into EcoAN generated estimators and give solutions involving review processes. Finally, we suggest a procedure centered in EcoAN that can be used to curate ecological data based on image series; we give a short description and measure its impact on data collected in

the high arctic.

1.4.4 Satellite measurements limitations

There is special interest in scaling up ground level measurements to acquire detailed information that can then be linked to remote sensing data in order to get a better knowledge of individual species. Our three prototypes contribute by implementing different approaches to either increase the production of data or support its timely analysis. They do so by applying software implementations to known phenological monitoring efforts.

We contribute to the ground based scale up by providing additional means of creating images of phenological phenomena in situations where the usual methods are not enough. EcoIS and its related work-flows promote the creation image series taken of plots and facilitate the collection process in order to increase data output. We contribute to the analysis of the growing amount of data produced from ground based measurements by implementing a toolkit (EcoIP) that automates the analysis of vast amounts of images. With EcoIP the focus is taken away from individual images and placed in functions that describe phenological phenomena. We further contribute to the analysis of vast amounts of images by implementing an application that aides in the identification of individual species within image series. EcoAN is meant to be used when current computer vision approaches cannot handle specific data analysis tasks. It aids in the description of ground based image data and also servers as support for our other prototypes indirectly relating to the scaling up of ground based data.

1.5 Document Outline

Three papers conform this dissertation: EcoIS, EcoIP and EcoAN. Each touches on a part of the underlying problematic related to scaling up ecological ground based measurements in order to link them to remote sensing data. Each stands alone and is included in this document as it was sent for peer reviewed publication³. In order to tie them together in a logical thread of thought we have added a preamble and a concluding remarks section to each one that places them in context. The preamble will relate each major section with the general problematic as well as with the other publications. The concluding remarks, on the other hand, will explain how the different conclusions and contributions fit within the general context and relate to the other sections.

The rest of this document is organized as follows:

1. **EcoIS:** In this chapter we delve into the importance of image series as a data unit for ecological data acquisition. We see how it relates to scaling ground based measurements and look at alternative ways of generating image series through computer aided processes. We analyze the behavior

³EcoAN will be sent shortly after this dissertation is delivered

of a prototype that generates aligned series from unaligned images in an arctic monitoring context.

2. **EcoIP**: In this chapter we see the relevance that automatic and semi-automatic analysis of image data has on the increasing amount of ecological output. We further describe how we can use automation to address raising amounts of data in order to scale ground based measurements. We introduce our second prototype that is designed to analyze large amounts of image series and translate them into ecological indicators.
3. **EcoAN**: In this chapter we see the importance of data annotations to answer new questions from historical image series and we see how this relates to the scaling of ground based measurements. Here, we introduce our third prototype and describe its behavior with data collected from a monitoring station in the high arctic. We additionally make a cost benefit analysis and show the relevance of the common assumption that semi-automatic processes reduce effort.
4. **Conclusions & Future Work**: We finalize our dissertation by giving general conclusions where we list the contributions of each of our prototypes and relate them to each other and to the underlying theme of scaling up ground based measurements. The future work will point towards where the field is headed and how we want to advance in our research.

Chapter 2

Related Work

2.1 Image Based Plot Phenology

The practice of acquiring plot phenological data by using photographic equipment dates back to 1924 when a tripod specifically designed for ecology was presented to the British Ecological Society (Cooper, 1924). It questioned the relation between measurements and individual judgments made by technicians, and how it could be addressed by keeping a photographic record that allowed a more objective assessment. The paper pointed to difficulties inherent in field measurements and how photography could reduce time spent collecting data as well as shift much of the field work out of the field.

The author in Cooper (1924) identified the need for pictures to be taken from above while using a stable and reliable stand so as to get correct relative measurements from the image. The height of vegetation, its uniformity, shadows on the plot and the levelness of the ground were listed as limitations to the newly presented system (Cooper, 1924). In other words the system was optimal for plants with uniform and relatively short height set upon a plot that was relatively level. These limitations are as relevant today as they were in 1924.

There have been lots of camera systems since Cooper (1924) that have been designed for various situations. There has been special interest in stereophotographic techniques because of the slightly different view points of the same plot (Pierce and Eddleman, 1973; Wells, 1970; Ratliff and Westfall, 1972). Distance from the plot in order to cover more ground has also been a concern where research has been conducted towards structures that hoist the camera to a height of 7m while still being able to be carried easily (Owens et al., 1985).

Marking plots to give a sense of scale has also been an important subject of discussion; in Pierce and Eddleman (1969) the authors discuss a setup that includes a frame on the ground to facilitate spatial analysis. In fact most of the projects related to plot photography have some sort of artificial marker that serves as physical reference (Pierce and Eddleman, 1973; Ratliff and Westfall, 1972; Wells, 1970). One can see the importance of having a reference in the

pictures even in Cooper's original paper (Cooper, 1924) where the plot image is fitted with relevant information like plot ID and date.

These projects addressed stable and repeatable images, easy data acquisition and an increase in objectivity but were not able to predict how data collected as images could quickly become unmanageable. No automatic analysis of images was attempted because images were not digital and there was little or no access to computational artifacts. However, as digital photography became wide spread and computers were readily available, computer aided image analysis techniques began to be explored as an alternative to handle collected images.

Work followed that brought together the advantages of camera stands with the qualities of computer aided image analysis. In Roshier et al. (1996) they implemented a plot measuring platform mounted on a car operated by two technicians. It did not need a stable camera stand as it depended on permanent markers to use as reference and was able to track individuals throughout a season by using computer aided techniques. All classification and metadata addition was done by the technicians and the system aided them in automatically identifying previous element's location.

Camera stands are relevant as they are still needed (Luscier et al., 2006; Laliberte et al., 2007) with recent work centered in reducing its size, adding supplementary structures to adjust for shadows on sunny days (Booth et al., 2004) or redesigning in order to reduce effects on the flora (Luscier et al., 2006). However, focus has mostly shifted towards describing image processing techniques (Laliberte et al., 2007) and continues to progress into situations where camera stands are designed to hold cameras in the field for longer periods of time (Graham et al., 2006).

2.2 Image Based Landscape Phenology

An alternative to close ground-based images is landscape photography which involves placing cameras where they encompass more than just a couple of square meters. Cameras placed above 30m focused parallel to the ground with a "birds eye view" allow for the inclusion of more elements. But with them come new challenges that include large perspective distortions where sizes of elements in the foreground and the background are different, and size to pixel ratios where pixels cover different areas depending on distance from the camera. This contrasts with images taken of small plots (e.g. 1 m x 1 m) from a nadir perspective that have a constant scale and constant size to pixel ratio.

The camera can be placed on a natural occurring landmass (e.g. a mountain) in order to gain a vantage point from where to sample phenomena. A camera was located 500m above sea level in Hinkler et al. (2002) and directed towards a valley in order to detect snow cover. The researchers addressed the issue of perspective differences by applying an in-house differential rectification algorithm. They also created an automated mechanism that produced a time lapse of the valley by taking daily images. The mechanism was solar powered and kept the images in a memory card.

Countless projects have man made towers to house a camera and take pictures of various types of landscapes. In Richardson et al. (2007) the authors used a 26.5m tower and placed a camera with a field of view of 20° below the horizon. They were able to capture images of a deciduous forest to try to monitor the trajectory of spring green-up. In this case they did not have to cope with issues related to perspective differences as they did not care for spatial data. They used part of gathered images in the form of rectangular Regions Of Interest (ROI) where they focused on spectral rather than spatial responses. Other projects use specialized lenses to be able to increase their field of view to increase the amount of information while still using ROIs to point to interesting phenomena (Nagai et al., 2011).

The Region Of Interest approach is well known and is used in lots of projects (Richardson et al., 2007; Nagai et al., 2011; Sonnentag et al., 2012; Zhao et al., 2012) because it avoids the need to analyze the totality of collected images. It implies the intervention of technicians which decide exactly where to put the ROI. It is interesting to note that one of the recurring themes is illumination variability and techniques devised to reduce it: a color square is placed in the line of sight of the image in order to aid posterior automatic color and lighting adjustments (Sonnentag et al., 2012; Richardson et al., 2009). Towers are used when there are no available infrastructure elements but in the case where images are being acquired close to man made environments (e.g. close to towns or cities), the cameras can be placed on readily available infrastructure (Ide and Oguma, 2010).

While images of plots are easily sampled by individual field visits, this is not the case for tower based digital image systems where there is little reasoning behind repeatedly climbing a 30m tower or a 500m mountain to take an image. A better approach involves autonomous systems taking images at a predefined frequency based on certain environmental characteristics. This approach is used by all tower projects with varying levels of sophistication where some have simple repeat photography setups (Richardson et al., 2007; Ide and Oguma, 2010) while others have complex systems with various degrees of movement that enrich the collected data (Brown et al., 2012; Graham et al., 2009; Granados et al., 2013)

Indeed, camera stands are moving away from being static to structures that implement rotational and translational movement. Pan-tilt-zoom cameras have been used to extend sampling range by including three degrees of freedom: pan, tilt and zoom (Granados et al., 2013; Morisette et al., 2009). This allows the camera to include more information and creates the possibility to actively search for interesting elements in the range of view. Pan, tilt and zoom Rotation and translational movement bring new challenges to the phenological data acquisition process: it is now necessary to stitch images Kopf et al. (2007), align them (Song et al., 2006) and cope with various types of movement (Graham et al., 2009).

Indeed these innovative systems are meant to increase potential view points of cameras in order to get better samples. For now the movement has been constraint to a few dimensions: two dimensional (Graham et al., 2009) or three degrees of freedom on pan-tilt-zoom cameras (Granados et al., 2013; Kopf et al.,

2007). Research continues in this respect and is set to include projects that give full rotational and translational movement through the use of Unmanned Aerial Vehicles (UAV) able to give very detail account of a particular section of land (Grémillet, 2012; Lucieer et al., 2012). UAVs can not only capture vast traces of land, but can also get close to species while reducing the effect it has on them (Grémillet, 2012).

2.3 Automatic Collection and Analysis

As computers became cheaper and more available, research moved towards automating image analysis. In Wallen and Philpotts (1971) an IBM drum scanner was used to digitize areal images taken of bean crops to calculate diseased percentages. In Gerten and Wiese (1987) video of wheat fields was analyzed in search of diseased patches. While in Adamsen et al. (1999) the senescence of a wheat field was estimated with areal photographs of the field. These efforts seek to increase the speed and effectiveness of data processing by covering extensive tracts of land from the air and digitizing it into computer memory

Research began to use gray scale images to automate segmentation of interesting elements within images (Gerten and Wiese, 1987; Eyal and Brown, 1975). As color cameras became more available, three color dimensions (red, green, blue) were used for image segmentation. Agriculture related research headed the move towards color segmentation of close-range plot photography with studies like Woebbecke et al. (1995) which tried to detect specific weed species by thresholding a color image in order to improve a pesticide spreading mechanism.

Color has been used to automatically measure greenness levels during spring, summer and fall seasons (Richardson et al., 2009), and is used to follow general changes of forest canopy (Richardson et al., 2007; Zhao et al., 2012; Graham et al., 2010). Image data has been correlated with measurements of gross primary productivity (Richardson et al., 2009), green-up and senescence (Ide and Oguma, 2010; Zhao et al., 2012; Graham et al., 2010) and CO_2 exchange (Richardson et al., 2007, 2009). Color indexes and color spaces have been identified as useful to generate automated phenological data (Richardson et al., 2007; Sonnentag et al., 2012). Additionally, lighting, hardware problems and weather conditions are identified as detrimental to the correctness of the generated data (Sonnentag et al., 2012; Richardson et al., 2007; Ide and Oguma, 2010). Finally there have been projects that have worked with publicly available cameras containing images of natural areas in order to extract phenological data (Graham et al., 2010).

There has been work that relates color to Leaf Area Index (LAI) (Nagai et al., 2011) through normalized image values where cameras frame the canopy from the bottom (Montes et al., 2007; Macfarlane et al., 2007). It is important to consider leaf position with respect to the camera and how non leaf elements interact in the processing of raw data (Montes et al., 2007). Additionally interest in the relation between Plant Area Index (PAI) and LAI has also used camera

systems pointing towards the zenith (Ryu et al., 2012). Finally, tower mounted cameras have also been used to calculate LAI (Nagai et al., 2011).

Indeed automatic analysis of image data is widespread with the use of specialized platforms that target specific visual traits like diseased kernels (Serranti et al., 2013), detect the presence of microorganisms (Wu et al., 2012; Kumar and Mittal, 2008), calculate total crop yields (Payne et al., 2013; Zheng and Lu, 2012) or classify individual species in plots (Chen et al., 2010). While automatic analysis of the images gathered by plot digital photography has been successful (Laliberte et al., 2007; Adamsen et al., 1999, 2000), it still remains to be seen how well it specifies ecological data (Ksiksi and El-Keblawy, 2013). The exploration of the different aspects of ecological automation in data analysis and gathering should continue to be one of the main focuses in the field.

Chapter 3

EcoIS

Preamble

We begin by mentioning the importance of monitoring and phenology, and how these relate to technology and image series. The methodology described here is meant to target very real needs in monitoring and we show how we address them by applying our methodology to a plot-based plant flower phenology monitoring deployment in the high Arctic.

The main objective of EcoIS is to produce image series that can be used by other tools to generate ecological estimators. The raw data that it produces can be annotated by EcoAN (or applications like EcoAN) to further continue the analysis in the data pipe line; it can also be used by EcoIP (or other automated tools) to generate intermediate or final results. Indeed, in order for EcoIS to produce data that is usable, it needs to create data that is spatially and temporally consistent. Annotations on aligned image series produced by EcoIS maintain their spatial characteristics (position in the image) throughout the image series and give a very unique structure to ecological data that can be taken advantage by automatic tools like EcoIP or Parrott's (Parrott et al., 2008) spatiotemporal metrics. It further relates to

EcoIS creates image series from pictures of plots in the field and in doing so adds to the methodologies that are incrementing the amount of ecological data. It plays an active part in increasing images of ecosystems and forming them in such a way that they can be analyzed to produce very detailed models. Indeed, the high resolution image series from EcoIS help to bring together remote sensing and ground based measurement by helping to generate detailed image representations of what has already been photographed remotely.

Our EcoIS paper was submitted to Ecological Informatics¹ -an International Journal on ecoinformatics and computational ecology- on July first 2013 and accepted for publication on the 25th of September of the same year. The defendant is first author and is responsible for developing the toolkit and testing its

¹www.journals.elsevier.com/ecological-informatics

performance. Images used in the toolkit evaluation were provided by technicians of the Department of Bioscience at Aarhus university who collected data from a monitoring station in the high Arctic. The defendant was responsible for the initial drafts, integrating and gathering co-author feedback as well addressing the entire review process.

EcoIS: An Image Serialization Library For Plot-Based Plant Flowering Phenology

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Abstract

Image series are increasingly being used to output ecological indicators because they provide the ability to reanalyze data that has already been collected and they improve temporal as well as spatial resolution. We address both the increased utilization and the need to diversify the way they are produced by introducing an open source Python (www.python.org) library called EcoIS that creates image series from unaligned pictures of specially equipped plots. We use EcoIS to sample flowering phenology plots in a high arctic environment and create image series that later generate phenophase counts and automatically estimate phenological dates of interest. Our results exhibit one day difference between EcoIS estimations of local indicators and the ones calculated with the established field-based process. We show that EcoIS' error is similar to the one of image series generated with fixed camera setups. We see that EcoIS processes an image in 3.8 seconds and show how it is equipped to handle data intensive scenarios. We additionally identify in-camera automatic image formatting and image acquiring oversight as contributing factors for increasing the overall error. Our main conclusion is that EcoIS creates usable image series that maintain the spatiotemporal qualities of the original images and can successfully be utilized to generate ecological indicators. EcoIS is relevant as a replacement for traditional image series infrastructure where the cost of deploying EcoIS is smaller or less intrusive to the ecosystem.

Keywords: Image Series; Ecological Monitoring; Phenology; Arctic; Computer Vision; Photo-plot

3.1 Introduction

Arctic ecosystems are changing rapidly and dramatically along with observed changes in climate (Gilg et al., 2012; Post et al., 2009). Quantifying the interaction between climate and ecosystems is complex and requires extended concurrent data collection from multiple compartments of an ecosystem (Meltotte et al., 2008b). Our ability to understand and predict the effects of climate change on ecosystems depends on coordinated long-term monitoring programs (Schmidt et al., 2012b) that establish the difference between effects inherent to ecosystems and those caused by environmental perturbations like climate change (Meltotte et al., 2008b), as well as provide context for interpreting experiments conducive to designing, implementing and evaluating environmental policy (Lovett et al., 2007).

Technology has long aided long-term monitoring by providing solutions like tape recorders that facilitate documentation, personal desktop assistants (PDA) that automate data transmission and loggers that collect data for long periods of time (Michener et al., 2011). Recent developments in digital photography have broadened this scope by facilitating projects that range from phenological event detection (Richardson et al., 2007) to demographics (Bolger et al., 2012).

Image series (ISeries) are of special interest because they provide the ability to reanalyze data that has already been collected and can improve spatial and temporal resolution of long-term monitoring variables while at the same time reduce labor (Ide and Oguma, 2010). Plant phenology which is an observable trait impacted by climatic variations (Badeck et al., 2004; Høye et al., 2007) vital for understanding species responses, ecosystem function and the effects of climate (Wright et al., 1999) has been detailed by ISeries (Graham et al., 2009; Richardson et al., 2007) and has been related to measurements such as carbon dioxide uptake (Mizunuma et al., 2013) and gross primary production (Saitoh et al., 2012).

In general, ISeries are generated from cameras placed in housing platforms designed to provide stability, power and protection. Housing platforms have been used to fix cameras close to the ground in order to measure leaf area index (Ryu et al., 2012), have enclosed cameras that generated simple field estimations of photosyntheses (Graham et al., 2006) and have positioned cameras near and above forest canopies (Sonntag et al., 2012; Zhao et al., 2012). They provide translational (Graham et al., 2009) as well as rotational (Granados et al., 2013) movement increasing the amount of possible arrangements. A housing platform is what aligns all images by providing the same view point.

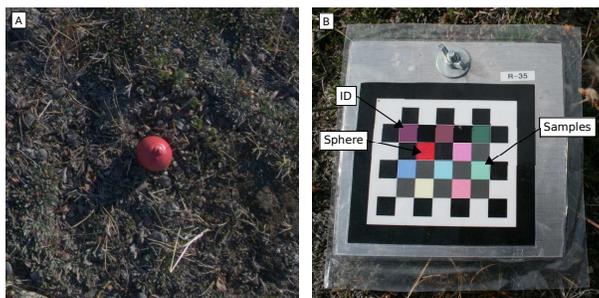


Figure 3.1: Closeup of markers in the field. A) Sphere marker painted with water proof paint. B) Chessboard marker is printed on paper, placed on an aluminum base and laminated to make it waterproof. This is a marker for plot 35 containing red spheres. Samples section used to model squares containing encoding colors. Sphere section holds sphere color. ID section has encoding squares detected by models from Samples section.

But what if a housing platform cannot be deployed? As we move monitoring efforts away from well known infrastructure (electricity grids and communication networks) into remote areas where powering and maintaining equipment

is expensive and resource intensive, we encounter situations where the cost of a camera housing platform is prohibitively expensive. Moreover, the inherent invasive nature of housing platforms might prevent their deployment in research stations where invasive structures are prohibited inside denominated undisturbed areas (Meltote et al., 2008c). It is in these situations where we need an alternative way to create ISeries.

In these cases we replace the invasive housing platform with a more versatile approach that uses autonomous mobile entities, like humans or unmanned autonomous vehicles (UAV) as vessels that transport and actuate a camera. Because of their mobile nature, they would generate unaligned images which would not be suitable for generating ISeries. Projects have addressed this by manually aligning the images (Liang et al., 2012), but this becomes unmanageable as the amount of images increase.

Inspired by the need to generate ISeries from unaligned images we have created EcoIS (Granados, 2010b), a Python (<http://www.python.org>) library that automates the alignment process and suggests an alternative way of gathering data based on ISeries. We give a detailed description of its inner workings and outline how it was used in an existing long-term phenological monitoring program located in a high arctic research station. We characterize changes in the arctic monitoring work-flows by describing their established processes and comparing them to new ones brought on by the use of EcoIS. We see how ecological indicators (from established work-flows) can be created and demonstrate how to generate other spatiotemporal measurements that can only proceed from ISeries. Finally, we see how errors intrinsic to camera systems and image transformations affect ISeries and the indicators that they generate.

3.2 Materials and Methods

3.2.1 EcoIS

EcoIS (Granados, 2010b) is an open source Python library that creates ISeries from images taken of regions of interest delineated by special markers. It aligns images giving them a unique virtual view point which is similar to creating orthophotos (Duhaime et al., 1997). It creates ISeries which are the foundation for spatiotemporal analysis used in ecological indicator calculations.

3.2.1.1 Photo-Plot Layout

Photo-plot layout (Figure 3.2.B) is square and enclosed by three spherical (Figure 3.1.A) and one chessboard (Figure 3.1.B) marker. Spheres mark three of the plot corners (center of chessboards mark the fourth) while Chessboards contain information used for plot identification (Samples and ID sections, Figure 3.1.B) as well as sphere detection (Sphere section, Figure 3.1.B). All markers are fastened to the ground for the duration of deployments.

The Samples section contains squares depicting six possible colors that appear in the ID section (Figure 3.1.B) two of which were not used in our im-

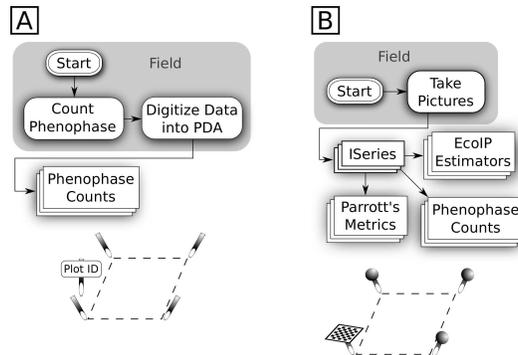


Figure 3.2: Established and Photo-plot work-flows. A) Established work-flow. Counting and digitizing of phenophases manually done in the field at a predefined frequency. Plot layout is rectangular of varying size marked by stakes driven into the ground at each corner. Next to each plot there is a sign containing plot ID. B) Photo-plot work-flow. Digital images are taken from several view points at a predefined frequency. ISeries are automatically created by EcoIS from field images which in turn are used for phenophase counts, EcoIP estimators and Parrott’s metrics. Plot layout is rectangular enclosed by three spherical and one chessboard marker which are all driven into the ground. Chessboard marker contains plot ID.

plementation but were left in the chessboard for future use. Each square from the ID section encodes two bits and contains part of the plot ID representation (Figure 3.3). The amount of squares in the ID section depends on the number of plots being identified (greater number \rightarrow more ID squares). For example, figure 3.1.B shows three squares in the ID section which encode to 35 (see Figure 3.3 for encoding calculation) and have the potential to identify 64 plots.

3.2.1.2 Serialization Algorithm

EcoIS begins searching for a chessboard (Figure 3.3) by using OpenCV’s *findChessboardCorners* function (Bradski and Daebler, 2008a) which operates in five steps (Ruffi et al., 2008): 1) Images are converted to grayscale. 2) They are then segmented by applying adaptive thresholding which binarizes the images (Bradski and Daebler, 2008b). 3) The binary image is then eroded (Bernd Jähne and Horst Haußecker, 2000a) with a 3×3 rectangular kernel which is gradually increased when quadrangles (squares) are difficult to detect. 4) Closed contours (Bradski and Daebler, 2008c) are then calculated which the algorithm uses to fit into quadrangles. 5) Finally, every successfully fitted quadrangle is linked to adjacent ones (Ruffi et al., 2008). If a chessboard is not found after these steps, the image is discarded and EcoIS continues with the next image.

After the chessboard is found, the plot number contained in the ID section (Figure 3.3) is calculated. First, the HSV color space (Smith, 1978) is segmented

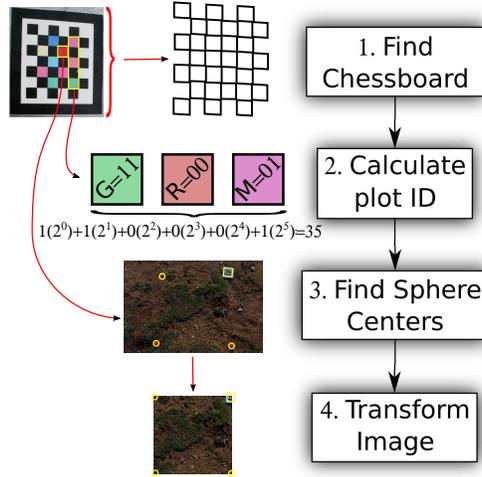


Figure 3.3: Serialization algorithm. First step: find a chessboard in each image. Second step: Calculate ID from ID section. Each color encodes two bits: green encodes 11, red 00 and magenta 01. They each represent a power of 2 and sum to 32. Third step: With color sample from Sphere section, find sphere centers. Fourth step: Transform image so all centers are placed in the image corners.

into six consecutive compartments based on mean hue values of the Samples squares (Figure 3.4.A). We then use this segmentation to count the hue values of the ID squares and choose the color based on the segment where the count is greater (Figure 3.4.B). Sampling of colors prior to detecting is done for every image in order to adjust for pixel value variability in the ID section caused by lighting differences and automatic camera adjustments.

To find the sphere centers (Figure 3.3) we first sample the Sphere square (Figure 3.1) and calculate mean (\bar{c}) and standard deviation (σ_c) for color components in CIE L*a*b (CIE (Commission Internationale de l'Eclairage), 1986) color space. We then create a range containing the sphere color ($\bar{c} \pm \sigma_c$) and use it to binarize the image. We continue by applying consecutive *open* and *close* operations (Bernd Jähne and Horst Haußecker, 2000a) with a circle shaped kernel of varying size that reduces noise and makes the spheres more prominent. Finally, we use OpenCV's *HoughCircles* function which uses Hough circle transform (Bradski and Daebler, 2008d) to approximate the circle centers. If EcoIS does not find exactly three spheres, the image is discarded.

The final step in our algorithm consists in moving all the pixels in the image in such a way that the corners of the plots (spheres and chessboard) are in the image corners (Figure 3.3). This involves multiplying all coordinates by a transformation matrix and then performing pixel value interpolation on the result. The matrix is calculated by solving $X'_i = M \cdot X_i; i = 0, 1, 2, 3$ where M is the transformation matrix, X_i is the i^{th} plot coordinate and X'_i is the

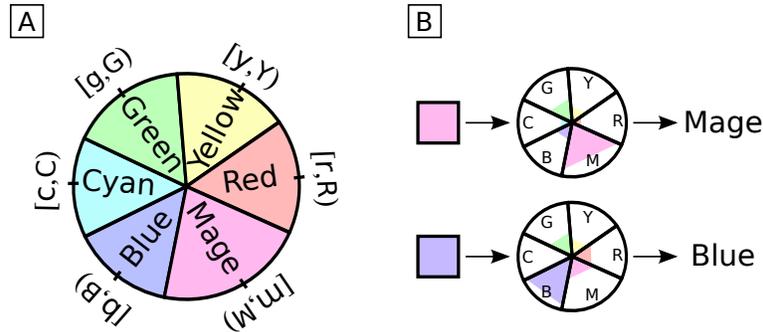


Figure 3.4: Chessboard color detection. A) For each of the Samples squares we calculated min value (lower case), mean (midrange cue) and max value (upper case) effectively segmenting the Hue dimension of the HSV color space (Smith, 1978). The "Mage" abbreviation means magenta. B) Each ID square is binned into ranges and the one with greater value is selected. The first is detected as magenta and the second as blue.

i^{th} destination coordinate. For our particular case the plot coordinates are the image coordinates where the spheres and chessboard are located; the destination coordinates are the re-projected image corners (coordinates for a 5000×5000 pixel image are $\{(5000,0); (5000,5000); (0,5000); (0,0)\}$). Once the matrix is calculated we use OpenCV's *warpPerspective* function (Bradski and Daebler, 2008d) to actually move the pixels and perform the interpolation.

These four steps (Figure 3.3) take the view point of the original image and re-project it into a virtual one which is shared by all re-projections of the plot (Figure 3.5). The new image is scaled to a resolution of 5000×5000 pixels and indexed into a directory using its plot ID. Additional sanity checks are executed to avoid images where corner detection errors occurred.

3.2.1.3 Photo-Plot Work-Flow

Plots are created by arranging three spherical markers and a chessboard in a square containing elements of interest (Figure 3.2.B). Spheres are painted with the same color as the Sphere section (Figure 3.1.B) which should contrast with the elements in the plots to avoid interference. Images are taken of only four markers, if a fifth (sphere or chessboard) is visible in the frame, it might interfere with correct detection and could contribute to inaccuracies. Moreover, plots should occupy as much of the frame as possible in order to maximize the amount of pixel information available for markers and for elements of interest.

Plots are photo sampled (photographed) at a predetermined frequency taking care of acquiring several photographs from different view points per photo sample in order to increase the possibility of at least one image getting serialized (Figure 3.2.B). When we have finished collecting images, EcoIS is executed in order to create an ISeries for each plot which can subsequently be used to

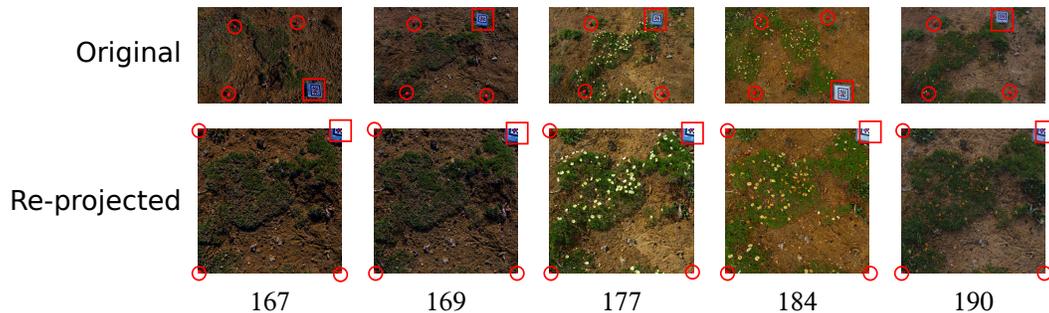


Figure 3.5: Plot image originals and their transformations. The first row contains original images taken for each DOY of plot four. The second are the transformed images using EcoIS algorithm (Figure 3.3). Notice that there are no shadows on the markers in the original images. DOY 167 and 169 contain *Dryas* buds (too small to see), DOY 177 shows the plot flowering and DOY 184 and 190 show the senescent stage of this species.

explore the behavior of the elements of interest. This work-flow is denominated photo-plot work-flow (Figure 3.2.B).

EcoIS requires an image based storage system which has its own challenges, yet having the data in an ISeries representation creates new potential in terms of data usability. ISeries not only provide the possibility for re-measuring plots (for corroboration), it also allows scientists to ask and answer new questions given sufficient image quality. We demonstrate this in an arctic deployment by using ISeries to create three types of ecological indicators (Figure 3.2.B).

3.2.2 Field Deployment at Zackenberg

We deployed in 2012 at Zackenberg station in northeast Greenland ($74^{\circ}30'N$, $20^{\circ}30'W$), a high arctic research station run by the Department of Bioscience at Aarhus University in Denmark. There, we focused on the established plant flowering phenology work-flow which has kept track of phenological phases of interest (phenophases) by doing seasonal counts (Figure 3.2.A). The process is mostly done in the field where technicians count individuals in a plot and then digitize the information into a PDA (Figure 3.2.A), they do this once every week for the duration of the season. This process is carried out for 28 permanent monitoring plots located in the valley lowland and produces files containing yearly plot phenophase counts (Figure 3.2.A).

3.2.2.1 Photo-Plot Layout

We implemented the EcoIS photo-plot layout (section 3.2.1.1) with spheres of 40 mm in diameter (Figure 3.1.A) and chessboards that measured 110 x 90 mm (Figure 3.1.B) We used water resistant paint on the spheres and laminated the

Table 3.1: Cameras in Zackenberg. Characteristics of cameras used in our Zackenberg deployment. Resolution is given in pixels, focal length is given in millimeters and is normalized to 35 mm equivalence, exposure is given in seconds and "Imgs" gives the number of images taken with each camera. Formats refers to how the images were formatted in camera; only the Sony camera kept each image in raw and JPEG (ITU, 1992) format.

	Sony Nex-3	Nikon D700	Nikon D300
Lens	Sony E 18 – 55mm <i>f</i> /3.5 – 5.6	AF-S Nikkor 14 – 24mm <i>f</i> /2.8G ED	AF-S Nikkor 14 – 24mm <i>f</i> /2.8G ED
Resolution	4608 x 3072	4288 x 2844	4352 x 2868
Aperture	<i>f</i> /9.0 – 22.0	<i>f</i> /10.0 – 11.0	<i>f</i> /8.0 – 11.0
ISO	200	200 – 500	200 – 640
Exposure	1/320 – 1/8	1/500 – 1/125	1/500 – 1/160
Focal Length	27	24	25 – 27
Imgs	108	56	101
Flash	No	No	No
Formats	JPEG/Raw	Raw	Raw

chessboard marker with transparent plastic (Figure 3.1.B) to prevent weather damage. We used a seven by six chessboard that allowed us to track 64 plots (we deployed nine) and placed it on top of an aluminum plate to prevent it from deforming. Stakes were screwed on all markers and driven into the ground to hold them in place. Plots had dimensions of 80 x 80 cm and were captured from an approximate height of 125 cm with an average focal length of 26.0 mm (35 mm equiv).

3.2.2.2 Photo-plot Work-flow

We applied EcoIS' photo-plot work-flow (Figure 3.2.B) by visiting (weekly) nine plots containing Mountain Avens (*Dryas octopetala* / *integrifolia*; hereafter referred to as *Dryas*) from Day Of Year (DOY) 167 to 219 which generated a total of 60 photo samples with an average of four images per sample. Here it is important to distinguish between photo samples and individual images: the first is a series of consecutive images taken of a plot from different view points on one specific date, the second is just one picture. Notice that there are redundant images per photo sample to compensate for EcoIS' raw error.

A total of 265 images were taken with three cameras (Table 3.1) which produced raw files that were formatted into Joint Photographic Experts Group (JPEG; ITU, 1992) with a Raw Image Processing Application (RIPA) called Rawtherapee (www.rawtherapee.com). The Sony camera generated raw and JPEGs versions which allowed us to add 108 Sony generated JPEGs bringing the total to 375². Plots were visited between ten in the morning and seven in the afternoon. Images were taken by avoiding shadows on markers, avoiding

²216 Sony images: 108 formatted by Rawtherapee and 108 formatted by the camera

positions where chessboards reflected the sun and including only four markers.

EcoIS automatically created all the ISeries on a Lenovo W500 (Model W500, Lenovo, Morrisville, North Carolina) laptop with eight gigabytes of memory and an Intel Core Duo (2.66GHz) processor. After analyzing all the JPEGs, EcoIS had effectively put all images into their respective ISeries and put all discarded images into an error directory. The photo-plot work-flow ended by counting the phenophases of interest on the created ISeries in an office back in Denmark.

3.2.2.3 Calculating Error

We calculated two types of error related to discarded images: raw error and ISeries error. The first refers to the total number of discarded images which points to how often EcoIS fails but does not reflect the proportion of missing photo samples. The second refers the total amount of missing photo samples and increases when EcoIS fails to serialize all the images of a photo sample. The ISeries error expresses missing data that cannot be reclaimed by the photo sample redundancy and gives us an idea of the impact of taking multiple images. Additionally we looked at image quality by measuring the virtual movement related to OpenCV’s *warpPerspective* function (Bradski and Daebler, 2008d) by following specific elements throughout an ISeries and calculating their euclidean distance from image to image.

We calculated missing and movement values from ISeries created with a pan-tilt-zoom (PTZ) camera (Model VB-C50iR, Canon U.S.A., Lake Success, New York) placed 30m above ground and compared them to the ones from EcoIS ISeries. Given that the camera configurations were different we normalized the focal length, distance to objects and crop factor using a simple pinhole camera model (Bradski and Daebler, 2008a) in order to compare the EcoIS images with the PTZ ones (model not shown). For the movement comparisons we only considered inanimate objects that did not grow such as rocks, markers or pebbles. Finally we characterized the impact of using camera formatted JPEGs in the photo-plot work-flow by comparing the success rate of images formatted using a RIPA with images formatted using the Sony camera. We report the number of rejected images in both of these cases.

3.2.2.4 Using Image Series

Parrott’s three dimensional metrics (Parrott et al., 2008) are based on a stack of successive spatial images sampled at uniform intervals called *space-time cubes*. The smallest constitutional units are voxels which are regular pixels with an added temporal dimension that, when put together, make up three dimensional blobs (Figure 1b in Parrott et al., 2008). The two ways of making blobs are: with 26-voxel (Moore’s system) and with 6-voxel (Von Neumann’s system) neighborhoods. These constructs are used to characterize three-dimensional data sets by calculating metrics designed to represent a property. Among the ones described in Parrott et al. (2008) there is shape complexity defined as the ratio of blob volume to bounding box volume which ranges from zero (complex shapes) to one

Table 3.2: Missing samples. *EcoIS* refer to Zackenberg ISeries. *PTZ* refer to ISeries gathered in the James Reserve by a pan-tilt-zoom camera. *ID* is the plot ID for *EcoIS* and the position ID for *PTZ*. *Sample* is the number of intended samples. *Missing* is the number of samples that went missing. The last row is the error calculated as the number of discarded images proportional to the number of intended ones.

EcoIS			PTZ		
ID	Sample	Missing	ID	Sample	Missing
4	8	0	0	365	88
35	8	0	6	365	82
59	4	0	1	365	35
0	8	1	2	365	25
16	4	1	3	365	44
20	4	1	4	365	34
24	8	1	5	365	76
47	8	2	7	365	89
63	8	2	8	365	82
Error: 13.33%			Error: 16.86%		

(simple rectangular shapes). There is also contagion measuring the dispersion of blob types and ranges from zero (random mix of voxel types) to one (contiguous landscape with little change). Finally, there is spatiotemporal complexity which measures how one type of blob occupies the *cube* and also ranges from zero (uniform blob shapes) to one (complex and random shapes).

To demonstrate EcoIS' usability we applied Parrott's metrics to see how well they describe the resulting ISeries. We created an intermediate representation of our ISeries data (*space-time cube*) by stacking binary versions of individual images into a three dimensional *cube*(we used Moore's system). We then took this *space-time cube* and used it to run Parrott's code which ultimately gave us values for each of the metrics.

EcoIP (Granados et al., 2013) is a toolkit used for characterizing phenophases of different species which bear distinct colors, like the tones of leaves in the fall. It involves creating a statistical model with a set of training images and applying it to an ISeries to produce a representative signal which is then analyzed by a semiautomatic process that ends with the estimation of beginning and ending dates. It is based on a Naive Bayesian model of color values applied to ISeries images that produces temporal estimators by finding the inflection points of fitted sigmoid signals. Among its outstanding features is the ability to use a variety of color transformations to adjust the accuracy of the estimations.

To further demonstrate the quality of the generated ISeries, we estimated flowering periods with EcoIP (Granados et al., 2013). Of all the deployed photo-plots we chose plot four because it had a high *sample* number and a *missing* value of zero (Table 3.2). We trained a model with the characteristic yellow of the flowering *Dryas* and used that to generate the representative signal. The

semiautomatic procedure described in Granados et al. (2013) then estimated beginning and ending dates of flowering periods.

Finally, to demonstrate that no functionality was lost with the photo-plot work-flow (Figure 3.2.B), we generated season counts by identifying phenophases of interest (buds, flowers and senescent) in ISeries with an annotation tool (Granados, 2010c). These phenophase counts (new work-flow, Figure 3.2.B) were validated by two trained field ecologists and were compared with field counts by looking at the actual counts (Table 3.3) as well as 50% flowering and senescence onset estimators (Table 3.4; Høye et al., 2007, 2013; Iler et al., 2013).

Table 3.3: *Dryas* flowering phenology Counts. Values are from plot four. *DOY* is Day Of Year. *F* are the field counts. *I* are counts done on ISeries minus field counts where a plus (+) is for larger ISeries, a minus (-) is for smaller and (0) when there is no change. *Buds* are flowers that are not yet open, *Flowers* are open *Dryas* giving access to their reproductive organs and *Senescence* is when all the petals turn brown or are missing (Schmidt et al., 2012a). *Total* is the sum of all the elements and *AF* is the average absolute difference between the *F* and *I* that varied.

DOY	Buds		Flowers		Senescence		Total	
	F	I	F	I	F	I	F	I
167	75	+24	0	0	0	0	75	+24
169	93	+31	2	-2	0	0	95	+29
177	3	+22	108	-12	1	-1	112	+22
184	0	0	22	+14	91	+5	113	+19
190	0	0	1	0	70	+57	71	+57
197	0	0	0	0	105	+10	105	+10
204	0	0	0	0	101	+14	101	+14
211	0	0	0	0	105	-7	105	-7
AF	25.6		7		15.6		22.75	

Table 3.4: 50% phenophase onset counts. Timing of phenological events in *Dryas* using field counts and images series counts, respectively. Values represent DOY. *Field* numbers come from counts done in the field. *ISeries* numbers come from counts done on the ISeries. *Flowering Onset* is the DOY when 50% of the plot flowered. *Senescence Onset* is the DOY when 50% of the plot became senescent. *Duration* is (*Senescence Onset*) - (*Flowering Onset*).

	Field	ISeries
Flowering Onset	173	174
Senescence Onset	181	182
Duration	8	8

3.3 Results

3.3.1 General

EcoIS spent a total of 962 minutes analyzing a subset of 248 images. On average, it spent 3.8 minutes per image which meant that we had to leave it overnight to process all the 373 images. It spent more time on error images as the algorithm was designed to try different detection configurations before discarding an image. Given the approximate view point height of 125 *cm*, we calculated an average distance to the markers of 150 *cm* which produced images containing spheres of 100 pixels in diameter and chessboard markers with dimensions of 170 *x* 200 pixels.

3.3.2 EcoIS Error

Raw error was the number of discarded images (180) proportional to the total number of images (373) and was calculated to be 48.25% (Table 3.5). The error for the Sony images formatted by the Sony camera was 67.59% (Table 3.5). Image taken with the Sony camera formatted by the raw image processing application (RIPA) had error of 42.59% while the ones taken with the Nikon cameras had an error of 38.85% (Table 3.5). The error of the images formatted only with the RIPA was 40.37% (Table 3.5).

Of the 60 photo samples that should have produced 60 images for the ISeries, EcoIS produced 52 (eight missing) which represented an ISeries error of 13.33% (Table 3.2). The other 86.66% were correctly identified, re-projected and placed in a directory as an ISeries image. Virtual movement for the EcoIS generated ISeries was, on average, 1.85% of the image size which represented a distance of 130.85 pixels. PTZ objects, on the other hand, moved an average distance of 0.31% of the image size.

3.3.3 Image Series

We calculated number of blobs, shape complexity, contagion and spatiotemporal complexity (Table 3.6) with Parrott's metrics (Parrott et al., 2008). We also applied EcoIP's semiautomatic process to the data of plot four which resulted in estimations of the beginning and ending dates of the *Dryas* flowering period (Figure 3.6). We further used the field and ISeries counts to calculate and compare 50% flowering and 50% senescence onsets where the duration of the *Dryas* flowering period was the same (8 days) with both count types (Table 3.4). Finally, we compared field counts and ISeries counts from plot four and calculated the average differences in numbers to be 25.6, 7 and 15.6 for the bud, flowers and senescence counts respectively which averaged to 22.75 for the whole plot (Table 3.3).

Table 3.5: Raw error. *Img* is total number of images, *Discarded* is the amount of discarded images and *Err* is $Discarded/Img$. The row labeled *Sony by Sony* contains the JPEG files that were taken and formatted by the Sony camera. The *Sony by RIPA* and *Nikon by RIPA* are image taken by the Sony and Nikon cameras and formatted by the raw image processing application (RIPA) Rawtherapee (www.rawtherapee.com). The fourth row contains all RIPA formatted JPEGs and the last row consolidates the first three rows to display the total number of analyzed JPEGs.

	Img	Discarded	Err
Sony by Sony	108	73	67.59%
Sony by RIPA	108	46	42.59%
Nikon by RIPA	157	61	38.85%
Sony & Nikon by RIPA	256	107	40.37%
Total Raw Error	373	180	48.25%

3.4 Discussion

3.4.1 Applicability of Image Series

3.4.1.1 Phenophase Counts

There was a tendency to undercount buds in the field (Table 3.3) due to the difficulty of seeing them at an early stage (buds are small). On the other hand, detection was facilitated on ISeries because technicians could identify the position and state of a bud by referring to images in the past and in the future. In other words, technicians had information in images from different dates which hinted at the location of very small elements; if one image in an ISeries contained an element in one location, the other images probably had the same element in the same location.

The average difference between the field and ISeries counts dropped from 25.6 for the buds to 7 for the flowers. This was because the white flowers were easier to detect on a dark green background in both the field and the ISeries scenarios. This difference went back up to 15.6 for the senescent counts which were more difficult to spot in the field as the *Dryas* turned brown and blended with the background.

Despite the differences in the counts for all *Dryas* phenophases, 50% flowering onset and 50% senescence onset for both the field and the ISeries counts coincided well with a difference of just one day (Table 3.4) and the duration of the flowering period (from flowering onset to senescence onset) was identical in both cases (Table 3.4). This gives credibility to results generated with EcoIS ISeries and suggests that the ecological indicators are contained in the ISeries themselves.

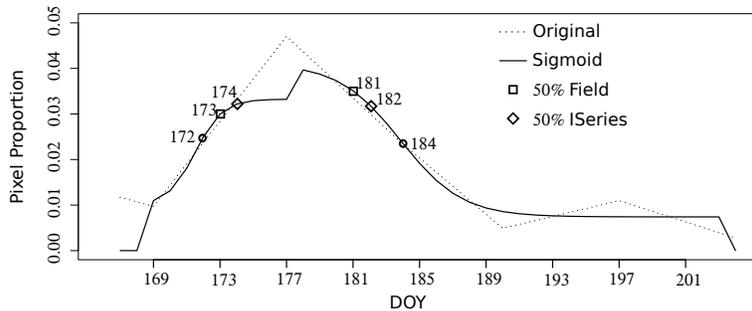


Figure 3.6: Phenophase estimations. Sigmoid fit (solid line) to the original signal (dotted line) calculated by EcoIP (Granados et al., 2013) of plot four containing *Dryas*. Training was done with images from other plots of the 2012 season. Circles are estimated from the inflection points of the sigmoid and represent beginning and ending days of year (DOY). Squares show 50% onset flowering and senescence calculated from field counts. Diamonds show 50% onset flowering and senescence calculated from ISeries counts.

3.4.1.2 Parrott’s Algorithm

Parrott’s algorithm (Parrott et al., 2008) generated metrics that accurately described the spatiotemporal form of the Zackenberg plots. The shape complexity mean value (Table 3.6) was greater than 0.6 and points to simple blob complexities where the blob shape tends to fill its bounding box. This agrees with elements in the Zackenberg plots moving little throughout their three stages (bud, flower and senescent) effectively creating a cylinder in the *space-time cube*. A contagion value of over 0.6 was expected as values that tend to one are considered to originate from continuous blobs which should be formed when we stack our images one on top of the other. Though we would expect a value closer to one due to the cylindrical nature of the *Dryas* elements in the *space-time cube*, the result tended towards 0.5 due to the virtual movement caused by the *warpPerspective* function (Bradski and Daebler, 2008d) which separates blobs that should otherwise be together. This inadvertent separation also caused the number of blobs (261) to be greater than the maximum amount of elements present in the plot (134, Table 3.3); these two values should be closer as each three dimensional blob is supposed to represent a *Dryas* element in the plot. Finally we have the spatiotemporal value of 0.28 which agrees with the uniform shape characteristic seen in the *Dryas* plots. In other words, instead of having complex patterns in the *space-time cube* we see long rectangle shapes which are the longest in the time axis.

3.4.1.3 EcoIP

EcoIS was able to provide EcoIP (Granados et al., 2013) with ISeries that produced an estimation of the beginning and ending flowering dates for plot four

(Figure 3.6). This shows that EcoIS generated ISeries maintain pixel positional coherency and pixel color values even after going through OpenCV’s *warpPerspective* transform (Bradski and Daebler, 2008d). The estimated onset date fell between the day where most of the *Dryas* were still buds (DOY 169) and the day where most of them had bloomed (DOY 177) which was the same date for the field and the ISeries counts (Table 3.3). The estimated ending date fell between the day where most of the *Dryas* were flowering (DOY 177) and the date where they were almost no flowers because they were mostly senescent (DOY 190) which again was equal for the field and ISeries counts (Table 3.3). Finally there was at most four days of difference between the 50% onset field and ISeries values and the ones calculated by EcoIP (Figure 3.6) which supports the notion of EcoIS producing usable ISeries that contain spatiotemporal information fit for estimations.

3.4.2 Accuracy

3.4.2.1 Serialization Error

On average, close to half (48.25%) of the JPEGs analyzed by EcoIS were discarded because of lack of information (Table 3.5) and that value only dropped to 40.37% when we ignored the Sony created files which had a negative effect on the process (Table 3.5). If the same proportion of dates were missing from an ISeries, it would have been useless; which is the reason we had multiple images per photo sample. Though we managed to go from the raw error of 48.25% (Table 3.5) to the ISeries error of 13.33% (Table 3.2), we also increased the amount of images being analyzed which, in turn, increased the amount of analysis time. This suggests that the raw error is important because its reduction directly translates into the reduction of the execution time and is relevant for the user experience of EcoIS.

An ISeries error of 13.33% (Table 3.2) meant that 86.66% of the dates were correctly serialized which was enough to characterize the season using EcoIP (Figure 3.6), Parrott’s three-dimensional metrics (Table 3.6) and the 50% onset values (Table 3.4). This error (13.33%) was lower than the PTZ deployment error (Table 3.2) of 16.86% and though they did not have the same cause, they could be compared as they both represented missing images. This comparison was relevant because it showed that an ISeries is still useful despite a 13.33% ISeries error and showed that EcoIS generated ISeries could be used for ecological analysis in the same way as ISeries generated with PTZ cameras in Granados et al. (2013).

We experienced additional serialization error related to automatic camera formatting of variables like white balance, saturation and contrast (Table 3.5). We could clearly visualize the effect that the Sony camera had on the error by comparing the first two rows of Table 3.5 where both represent JPEGs generated from the same raw files yet have very different behavior. This points towards the use of raw formats for automating phenology as the better choice over camera generated JPEGs which have great variability because of diversity in manufac-

Table 3.6: Parrott’s three dimensional metrics (Parrott et al., 2008). All values except *Number of Blobs* range from 0 to 1. *Number of Blobs* is the amount of blobs in the *space-time cube*. *Shape Complexity* ranges from 0 (complex ratio) to 1 (simple ratio). *Contagion* ranges from 0 (random blobs) to 1 (continuous blobs). *Spatiotemporal Complexity (STC)* ranges from 0 (uniform shapes) to 1 (complex shapes).

	Value
Number Of Blobs	261
Shape Complexity Mean	0.664
Contagion	0.656
STC	0.282

turers, formatting variables and user customizations. The use of Rawtherapee (www.rawtherapee.com) allowed the standardization of raw image formatting variables reducing the error in EcoIS but also restricted the type of cameras that we could use to those that could produce raw files.

Finally, EcoIS’ ability to analyze images depends on the lighting on the chessboard being similar to the one on the spheres and although we tried to avoid it, 24 images were excluded due to the photographer casting shadow on at least one marker. None of these were correctly serialized and represented 13.33% of the total error. This implies that we can potentially reduce the error by 13.33% if we are more careful when acquiring the images.

3.4.2.2 Virtual Movement

As expected from the outset, the amount of movement in ISeries generated with the PTZ camera was less than the ones generated by EcoIS. Though it has three degrees of freedom, the PTZ camera was able to return to a predefined position which resulted in a virtual movement of 0.31%. EcoIS, on the other hand, was less accurate (Figure 3.7) with a virtual movement value (1.85%) that was six times larger. This greater variability (Figure 3.7) did not overly affect the phenophase counts as individual elements could still be identified based on their locations in prior and posterior images. Moreover an average difference of 130 pixels (1.85%) is not significant when compared to the resolution of the original images (Table 3.1) or the generated re-projections (5000 \times 5000 pixels).

The analysis done with EcoIP (Granados et al., 2013) was also mostly unaffected by virtual movement (130 pixels) as its temporal estimations are based on complete images instead of regions of interest. In contrast, Parrott’s (Parrott et al., 2008) numbers were affected where estimators like contagion were expected to be closer to one but ended up being 0.656 (Table 3.6) due to blob separation caused by virtual movement. This was addressed by using Moore’s neighborhood (Parrott et al., 2008) which reduced the chance of blobs getting separated due increased number of adjacent voxels.

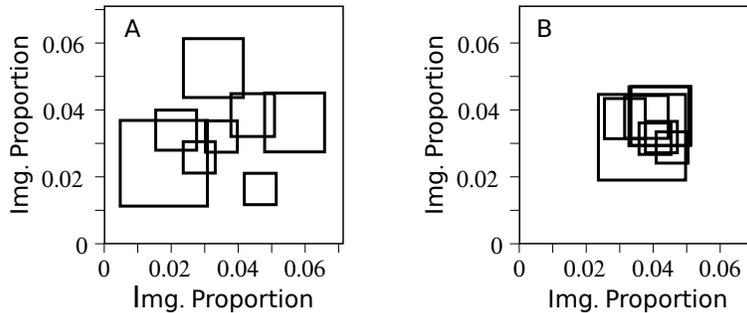


Figure 3.7: Virtual movement. A) Squares represent the position of the same flower throughout an EcoIS generated ISeries. B) It is the movement in A calculated with the movement values of the PTZ cameras. Both plots are a subset of a complete image and the axis are given proportional to the total size of the original image. This figure shows the difference in type of movement between EcoIS and PTZ cameras.

3.4.3 Deploying EcoIS

3.4.3.1 In The Field

We looked at the workload already in place (Figure 3.2.A) and revised it in order to increase automation while at the same time reduced the number of steps at the field (Figure 3.2.B). We replaced the two steps needed to service a plot (counting and digitizing, Figure 3.2.A) with just one (imaging, Figure 3.2.B) and in the same way replaced the hardware needed for the old work-flow (PDA and mechanical counters) with one camera. And though this reduction is relevant, it still remains to be seen if EcoIS' overhead is optimal (in terms of time and cost).

3.4.3.2 Time Of Analysis

Our experiments show that the algorithm spent 3.8 minutes (on average) analyzing images taken in eight weeks from nine plots (one photo sample per week per plot). But how would EcoIS behave with more data? How long would it take EcoIS to serialize a hypothetical year-round deployment that measured once every day on nine plots? Having four pictures per photo sample of nine plots we would have 36 pictures taken per day. This would give us a total of 13140 images per year which would need 49932 minutes to be serialized (34.67 days). We can reduce this hypothetical month if we segment the totality of the images and analyze each in a separate process. If we had 16 processors, we would reduce the 34.67 days to just 2.16 and as machines get faster this time will be reduced even more. Additionally these are not man-hours and is time where researchers can do other tasks.

3.4.3.3 EcoIS Scope

Dryas are a few centimeters across when fully bloomed and flower stems usually grow to a height of five to seven centimeters. This is a pattern that repeats itself across the species at Zackenberg and is a very convenient characteristic for EcoIS because virtual movement is minimized for elements that are close to the ground. If we measured taller species (e.g. shrubs in the low Arctic) the virtual movement caused by OpenCV's *warpPerspective* function (Bradski and Daebler, 2008d) would be too much to follow the plant through the ISeries. Depending on the height it could even block the markers, rendering serialization impossible. Our approach fits comfortably with species found at Zackenberg as well as cases where the studied elements have manageable height as in Graham et al. (2006).

3.5 Conclusions

We have introduced EcoIS, a toolkit that creates image series by re-projecting and identifying images taken of specially marked plots. We have successfully fit EcoIS into an established work-flow in a high arctic monitoring station and reduced the amount of steps that were needed to sample field plots. We have shown that the phenophase count differences between our photo-plot work-flow and the established Zackenberg procedure do not affect the 50% onset event interpolation values (flowering onset and senescence onset) used as an ecological indicator. We have demonstrated that in addition to procuring phenological counts, ISeries produced by EcoIS can be used to calculate spatiotemporal metrics (Parrott et al., 2008) and estimate beginning and ending phenophase dates (Granados et al., 2013).

We found that the number of EcoIS discarded images is similar to more traditional PTZ camera setups and documented how camera formatted images can increase this number. We showed that despite the presence of missing images, temporal and spatial information was maintained in ISeries. We demonstrated that the virtual movement of ISeries created with EcoIS, which was greater than the ones created with PTZ setups, does not impede analysis based on visual inspection nor analysis based on automatic processes. Finally we show how EcoIS can be used in a data intensive scenario by spreading the load among several processors to adjust for the extended time of execution.

3.6 Acknowledgments

The authors thank Palle Smedegaard Nielsen and Jannik Hansen for assistance in the field as well as Aarhus University for providing access to Zackenberg. We are also thankful for receiving funding from the European Union's Seventh Framework Program [FP7/2007-2013] under grant agreement number 262693 [INTERACT].

Concluding Remarks

We described EcoIS deployed in an arctic monitoring context and showed how it modified established processes in order to output relative phenological indicators. We outline changes to both plot layout and procedure that exemplify the use of aligned image series for ecological data acquisition. With our photo-plot work-flow we demonstrate the possibility of reducing overall effort in the field by allocating most of the labor out of it while still being able to successfully create phenological indicators.

We show the richness of image series created by EcoIS by using them to create spatiotemporal metrics, descriptive sigmoid signals and 50% ecological indicators where annotations played an instrumental roll in creating the statistical model needed for automatic calculation and where the basis for phenophase counts. The ecological estimators produced with EcoIS image series contribute to the detailed characterization of ecosystems that can be linked to remote sensing measurements to advance in our understanding of natural phenomena. Indeed the generation of high resolution aligned image series is an important contribution from EcoIS towards the linkage between remote sensing and ground based measurements.

EcoIS has an interesting effect on the growing volume of ecological data as it both produces large quantities while at the same time provides a way to automatically align data in preparation for further use. As a data producer it is concerned with generating the richest possible representation and it does this through high resolution images series that have spatial, spectral and temporal dimensions facilitating ecosystem characterizations. As it produces high quantities of data, it expects other tools to use computer aided methodologies for further analysis.

Chapter 4

EcoIP

Preamble

EcoIP is directly related to ecological monitoring through phenology as it is a tool that automates phenological measurements of data collected through multiple years. EcoIP can work with image series generated from multiple places and we exemplify it by using images gathered with a pan-tilt-zoom camera. EcoIP is equally capable of using images generated by EcoIS and we show this in our EcoIS paper where we generated signals of collected data from plants in the high Arctic. In this way EcoIP is the consumer of the data produced by EcoIS.

In our EcoIP paper we describe a process that is able to automate most of the calculations leading to phenological estimations of multiple years and of multiple species. In this way, EcoIP, addresses the automatic analysis of the growing volume of data and allows information to be extracted from image series. EcoIP has the ability of taking a vast amount of images gathered at ground level and translating them into ecological estimators that answer questions about specific species in a vast tracts of land; it is in this way that it contributes to the scaling up of ground measurements that will eventually close the gap between remote sensing and ground based data.

EcoIP, like EcoAN, produces ecological indicators by taking advantage of the spectral, spatial and temporal information encoded in image series. They are both consumers of image series and producers of ecological information and though EcoIP does not have the capacity to annotate, it shares the goal of trying to make sense of an increasing volume of data. They (EcoIP and EcoAN) also have in common the capacity of taking historical image series taken in the past and answering new questions by taking advantage of the richness of data contained in images.

The EcoIP paper was submitted to Ecological Informatics¹ -an International Journal onecoinformatics and computational ecology- on December 11th 2012

¹www.journals.elsevier.com/ecological-informatics

and accepted for publication on the 15th of March 2013. As with EcoIS, the defendant is first author and is responsible for developing the toolkit and testing its performance. The data used in the evaluation of EcoIP was provided by the Center for Embedded Networked Sensing of the University of California (Los Angeles) which collected images from a natural reserve in southern California. The defendant was responsible for most of the initial drafts, integrating and gathering co-author feedback as well addressing the entire review process.

EcoIP: An Open Source Image Analysis Toolkit To Identify Different Stages Of Plant Phenology For Multiple Species With Pan-Tilt-Zoom Cameras

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Abstract

Because of the increased number of cameras employed in environmental sensing and the tremendous image output they produce, we have created a flexible, open-source software solution called EcoIP to help automatically determine different phenophases for different species from digital image sequences. Onset and ending dates are calculated through an iterative process: (1) training images are chosen and areas of interest identified, (2) separation of foreground and background is accomplished based on a naive Bayesian method, (3) a signal is created based on the separation model and (4) it is then fit to a sigmoid that contains the dates of interest. Results using different phenological events of different species indicate that estimated dates fall within a few days of the observed dates for most cases. Our experiments indicate that color separability and scene illumination are contributing factors to this error. EcoIP is implemented as an open platform that encourages anyone to execute, copy, distribute, study, change, and/or improve the application.

Keywords: Phenology; Digital Photography; Camera; Onset Ending Date; Color Transformation; Bayesian Analysis

4.1 Introduction

Plant phenology is one of the most responsive and easily observable traits in nature that are impacted by changing climate (Badeck et al., 2004). Indeed, plant phenology relates strongly to primary productivity and is sensitive to microclimatic variations, thus its study is vital to understanding species responses, ecosystem function, and the effects of climate Wright et al. (1999). The interest in plant phenology and global climate change has increased significantly in recent years, especially with estimates of the advancing initiation of spring activity by both ground-based (Walther et al., 2002; Root et al., 2003) and satellite observations (Slayback et al., 2003; Stöckli and Vidale, 2004). The new U.S. National Phenology Network (Betancourt et al., 2007; Schwartz et al., 2012, USA-NPN, www.usanpn.org) is devoted to observing continental-scale trends in plant systems and growth dynamics.

Ideally, the best way to observe large-scale changes in phenological patterns with climate change is with remote sensing applications that are linked to

ground-based measurements. Indeed, the manual collection of phenological data provides important information at the organism level while satellite imagery is captured over wide areas but at low spatial resolution, often too coarse to detect species and community level responses (Badeck et al., 2004). The use of new technology is being investigated to scale up (Allen et al., 2007) and standardize ground-based measurements by using a subset of species (Betancourt et al., 2007; Schwartz et al., 2012, USA-NPN, www.usanpn.org), and by modeling local climatic conditions (Jolly et al., 2005). Though methods are still lacking, the use of visible light digital cameras holds promise (Richardson et al., 2007).

Color in digital photography, computer vision and plant physiology have been used in studies that range from the extraction of individual concealed leaves in an image (Neto et al., 2006) to assessing the forest under story (Liang et al., 2012). Simple image processing techniques are making standard the use of digital cameras for phenological event detection (Graham et al., 2009; Morissette et al., 2009; Richardson et al., 2007).

Agriculture is at the forefront of the use of image processing (Slaughter et al., 2008). Automation through digital photography was seen as early as 1995 in a weed detection application (Woebbecke et al., 1995). The automatic identification and control of unwanted species also occurs in precision agriculture (Swain et al., 2011; Granitto et al., 2000) with concurrent work on the relation between leaf color and nutrient deficiencies (Wiwart et al., 2009) and automatic identification of the visual symptoms of plant disease (Camargo and Smith, 2009).

Many ad-hoc methods have been developed for using color to examine targeted aspects of plant health and phenology (e.g., (e.g Camargo and Smith, 2009; Ide and Oguma, 2010)). Color is attractive because calculating values in an image is straightforward and many open-source software packages have functions that facilitate this analysis, such as the Python Imaging Library (Secret Labs AB; Linkping, Sweden; www.pythonware.com), and the R environment (R Core Team, 2013). However, using images captured in natural environments has some disadvantages such as color shifts caused by illumination changes which disrupt color-based analysis (Richardson et al., 2007), and displacements in Regions of Interest (ROI) caused by plant growth or movement by wind which requires repeated manual segmentation (Ide and Oguma, 2010). Solutions to these problems include the projection into other color indexes like *gcc* Sonnentag et al. (2012) and transformations to other color spaces like CIE $L^*a^*b^*$ CIE (Commission Internationale de l'Eclairage) (1986), which have been used to increase stability when dealing with illumination issues Sonnentag et al. (2012) and have been shown to greatly contribute toward an optimal segmentation process (Panneton and Brouillard, 2009). There are also many ways to automate image segmentation (Cheng et al., 2001; Litwin et al., 2001) that address plant displacement. However, no single color transformation or segmentation method may be able to capture all the phenological events of a single species (e.g., green-up, flowering, senescence), much less that of multiple species that may be captured within one or several images.

The recent expansion of imaging hardware, such as portable and Internet-

connected visible light digital cameras, coupled with methods such as repeat photography and digital image processing, provide the means for detecting a wide range of scales of plant phenology, from mosses (Graham et al., 2006) to forests Richardson et al. (2007). Indeed, visible-light digital cameras are becoming common-place in research for quantitatively describing vegetation (Crimmins and Crimmins, 2008).

A few fixed digital cameras capturing plant images once or twice a day creates a data stream that can be readily hand-processed with excellent results Graham et al. (2010). The proliferation of fixed-perspective Internet-connected cameras that are placed in either ecological areas or human-dominated systems is creating a situation where the data stream is approaching a limit after which it is no longer manually controllable. A new generation of inexpensive robotic pan-tilt-zoom (PTZ) cameras can now be employed to maintain high-resolution panoramic displays of natural environments (Song et al., 2006), creating a data stream that is orders of magnitude greater than a fixed view camera. For example, a downward-facing camera on a tower that can pan 350° , tilt 90° , and has a $10 - x$ zoom, may have a 10° view angle and thus can collect many hundred unique-location images from a single vantage point. Thus, many more species and phenological events may be captured with a PTZ camera at the cost of much larger and potentially unwieldy image data sets being created.

Inspired by the need of investigators working in plant phenology in their efforts to use ground-based images for scaling up to regional phenomena coupled with the increased number of cameras used in environmental sensing and the tremendous image output of PTZ cameras, we have created a flexible, open-source software solution called EcoIP to use images to determine multiple phenophases for different species. It has been created specifically to address the lack of an open-source automated system for plant phenology and its objectives directly relate to ongoing research on segmentation and color transformations in this field. The paper is organized in the following way: Section two provides details on the process we followed and how we used the naive Bayesian model in EcoIP. In section three we describe our results and in section four we outline their relevance within the current state of the art. There is a short description of the future work in section five and we finish with conclusions.

4.2 Materials and Methods

4.2.1 Processing Images With EcoIP

The input for the Ecological Image Processing (EcoIP) software toolkit (Grana-dos, 2010a) is a series of images taken of the same location, with the same camera and at the same time of day. Through an iterative process (Figure 4.1) EcoIP creates a representation of the image series which is then used to estimate onset and ending dates of phenophases.

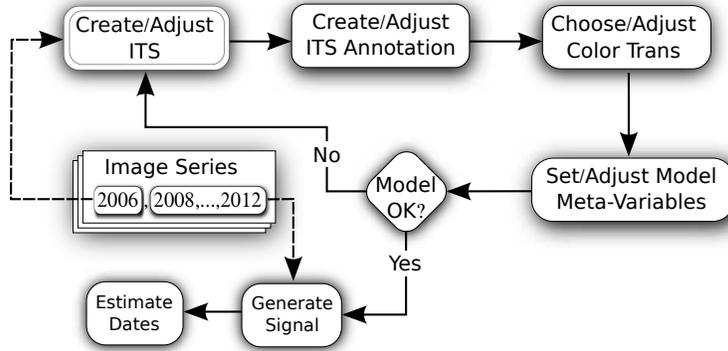


Figure 4.1: EcoIP data processing work-flow begins with creating the ITS. Models and signals are created with input from image series. Model creation is iterative. Data used for model creation is ignored in signal generation.

4.2.1.1 Image Training Set Generation

The creation of Image Training Sets (ITS) is the first step in the iterative process to find an optimal model that describes a phenophase. We generate it by selecting a subset of images that contain different types scenarios of one year in an image series (winter, summer, sunny, cloudy, rainy, foggy...). We then manually identify a subgroup of pixels from individual images within the ITS as representative of a phenophase with the aid of an annotation tool (Annotation tool for Matlab Granados, 2010c) that allows for the selection of pixels by enclosing them with annotated polygons or annotations. Pixels that represent the phenophase of interest are labeled as foreground (FG; e.g., leaves and flowers) and pixels that represent everything else are labeled as background (BG; e.g., sky, soil, and surrounding plants). Care is taken when creating the training set to include enough images to capture a representative sample of the changing phenology (e.g., beginning, middle, and end of the phenophase of interest) and though filtering noisy (foggy and rainy) images is common, we include them in the training set.

4.2.1.2 Choosing the Color Transformation

We determine frequency distributions of BG and FG pixels for each color transformation (calculated from original RGB coordinates) supported by EcoIP. These are used to manually select the appropriate transformation (Table 4.1) which is rated based on its ability to maximally separate BG and FG pixels for each phenology and species of interest (Figure 4.2). After choosing a color transformation we adjust model variables such as Bayesian class prior probabilities, smooth filter characteristics, number of bins for frequency analysis and model accuracy calculation characteristics. These adjustments directly affect the accuracy of the resulting model.

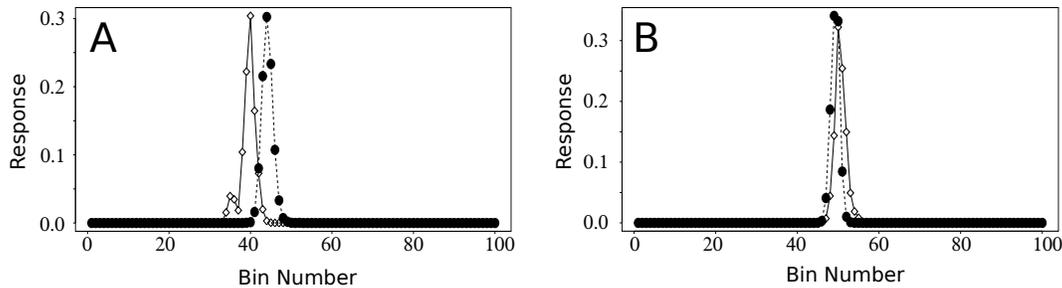


Figure 4.2: Examples of EcoIP’s histogram comparison between background (open symbol) and foreground (closed circle) of two color transformations. The color transformation values are binned to 100 values and the response represents the proportion of pixels per bin, normalized by the total number of pixels in the image. (A) Displays the second (*a) channel in the CIE L*a*b* color space and is an example of good separability between FG and BG. (B) Displays the excess green color index and is an example of a bad separability.

4.2.1.3 Naive Bayesian Model generation

The creation of a Naive Bayesian Model (NBM) is done automatically by EcoIP and results in an R (R Core Team, 2013) data file. By default an S-fold cross-validation (Bishop, 2007, p. 33) is used to calculate the false positives (incorrectly classified FG pixels) and the false negatives (incorrect BG pixels) of the training data and is used to rate and compare models. Their values are indicated relative to the total number of pixels examined and can be used to predict how the model will behave with new data for the same phenophase. Re-annotating or modifying the images in the ITS, selecting a different color transformation, and further adjustments to EcoIP variables is part of the iterative process (Figure 4.1) to determine an optimal NBM that is chosen among the results of the manual iterations and that minimizes the false positives and false negatives for specific phenophase.

4.2.1.4 Phenology Signal generation

Each NBM is then applied to a series of new images to classify each pixel as either FG or BG resulting in a new series of binary (black and white) images. Counts of binary pixels are used to create proportion values for each image by dividing the number of identified FG pixels by the total image pixels. Blob count values, which require a morphological transformation (Bernd Jähne and Horst Haußecker, 2000b, p. 483) of the original binary image, are also created by counting the number of contiguous areas of white (FG) pixels in the resulting binary image. The signal is then a sequence of these values related to an image and a date. It is important to note that data used to create the models are set aside (Figure 4.1) when calculating the values (Bishop, 2007, p. 32) to avoid a preexisting bias towards the data used for model creation.

Table 4.1: Summary for model values. Sample size is the range of years used for each phenophase. We display the color transformation that resulted in the best model for each phenophase. The Average error (in days) is the average absolute value of the difference between estimated dates and observed dates for each phenophase.

Phenophase	Sample Size	Transformation	Average Error
Summer 'Oak Canopy'	2009 – 2010	CIE L*a*b*	2.00
Autumn 'Oak Canopy'	2009 – 2010	CIE L*a*b*	1.25
Summer 'Oak Close-up'	2007 – 2010	Excess Green	1.39
Autumn 'Oak Close-up'	2007 – 2011	CIE L*u*v*	3.64
Bracken Fern	2008 – 2011	Excess Green	2.79
Wallflower	2007 – 2011	YCbCr	2.84
Average Total			2.78

Our data contained species captured by several signals. In these cases it was of interest to consider the phenological behavior of a set of signals effectively increasing the scale given by just one image frame. We created a consolidated signal by averaging the values of a date of individual signals. The resulting signal, like the individual signals, is a sequence of values.

4.2.1.5 Estimating Phenology Dates

Phenological dates are estimated by a semiautomatic process of fitting the data with a sigmoid function (Eq. 4.1) and then identifying the inflection points in these functions (Ide and Oguma, 2010; Richardson et al., 2007). The first inflection point in the phenological signal (onset date) is located where the second derivative changes sign in the first sigmoid (positive Eq. 4.1) and the second point (end date) is where the second derivative changes sign in the second sigmoid (negative Eq. 4.1). This places the inflection point midway between the maximum and minimum of the sigmoid. The 'a' and 'b' values in Eq. 4.1 define the vertical range, 'c' controls horizontal translation of inflection points, 'd' controls steepness and 'x' is time.

$$f(X) = a \pm \frac{b}{1 + e^{(c-d*X)}} \quad (4.1)$$

For the consolidated signals we implemented two approaches for estimating the phenological dates: the first is the process that was just described applied to a consolidated signal. The second estimates the onset date and ending date of a phenophase with the minimum onset date and maximum ending date of the component signals.

4.2.2 Applying EcoIP

4.2.2.1 Gathering Images

We used two PTZ networked video cameras (Model VB-C50iR, Canon U.S.A., Lake Success, New York) placed on 30m fiberglass towers in the University of California James Reserve located in the San Jacinto Mountains of southern California ($33^{\circ}48'30'' N, 116^{\circ}46'40'' W$) at 1658m elevation in a mixed conifer and hardwood forest. The cameras were installed at different times starting in 2005. The reserve acts as a testbed for technology developed by the Center for Embedded Networked Sensing (CENS), an NSF funded Science and Technology Center located at the University of California, Los Angeles (<http://research.cens.ucla.edu>).

Acquired images were sent to a repository at CENS where each one contained meta-data describing the time of day, the PTZ coordinate, and location of the camera inside the reserve. The files which had a resolution of 480x640 pixels were kept in Joint Photographic Experts Group (ITU, 1992) format with a minimum amount of compression. In general we collected images ranging from 2006 to 2012. From the repository we created multiple series of images (PTZ-series) for pan-tilt-zoom coordinates which make up our raw input and contain species of interest. As in other digital repeat photography projects (Ide and Oguma, 2010; Sonnentag et al., 2012) there were missing data due to adverse weather conditions, failures in hardware and software, and changing on-site data collection policies. Table 4.1 summarizes the ranges of each PTZ-series for each selected species and phenology.

4.2.2.2 Selected Species and Phenologies

To demonstrate the flexibility of analysis we selected three species that presented noticeable (in the visual spectrum) phenological changes, had a minimum of photography issues and continued for more than one year: oak (*Quercus* sp.), bracken ferns (*Pteridium aquilinum*), and wallflowers (*Erysimum capitatum*) (Figure 4.3). The perennial oak and bracken fern were different because we could predict where the leaves would emerge for the oak whereas for the underground rhizome of the bracken fern, such predictions were difficult and so a more zoomed out approach was necessary. For the annual wallflower, the uncertainty of location was taken to an even greater extreme requiring a larger canvassing of the area with images.

Phenophases for the three species included the green-up and senescence for the oak, the green-up and senescence for the bracken ferns, and the blooming period for the wallflowers (mid-summer). We collected two types of PTZ-series for the oak: a full canopy view ('oak canopy') and a close-up of the canopy ('oak close-up') where individual leaves could be isolated; we estimated summer and autumn colors in each.

The 'oak canopy' images (Figure 4.3.A) had an oak tree in the foreground and a view of the surroundings that included pines, other oaks, some bushes, remote mountains, and the sky in the background. The 'oak close-up' images (Figure 4.3.B) were zoomed such that oak leaves filled all of the image in summer

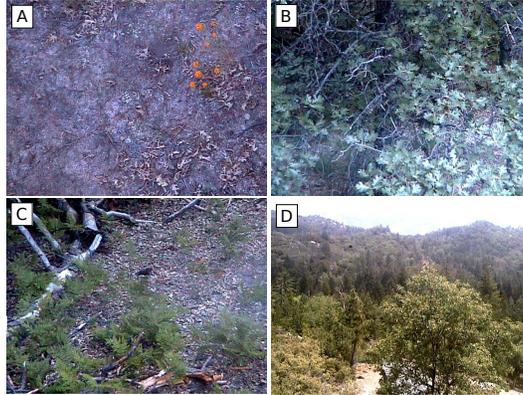


Figure 4.3: Representative images captured from three PTZ cameras at the James Reserve. (A) Yellow meadow wallflowers (*Erysimum capitatum*). (B) Close-up of deciduous oak (*Quercus* sp.). (C) Bracken ferns (*Pteridium aquilinum*). (D) Canopy of deciduous oak (*Quercus* sp.).

while fallen leaves, debris, and snow were visible through the leafless canopy in winter. For both the 'oak canopy' and 'oak close-up' we trained a summer and autumn model, where the summer one used green leaves for their input and the autumn one used red ('oak canopy') and yellow ('oak close-up') leaves for theirs. We used different autumn colors for 'oak canopy' and 'oak close-up' because of different microclimates experienced between the two types of photographed individuals. This is further exacerbated by the camera's automatic adjustments controlled by drastically different lighting environments where everything in the 'oak canopy' image is modified by the excessive brightness of the sky as opposed to a more homogeneous frame for the 'oak close-up'.

The bracken ferns (Figure 4.3.C) were located in a meadow where they shared space with the wallflowers (Figure 4.3.D). Leaf litter from nearby trees (fallen branches, pine needles, and autumn leaves) constituted the background. We identified the green color of the ferns and the yellow of the wallflowers as the specific colors related to the growth phenology of the ferns and the flowering time for the wallflowers. For the wallflowers signals were generated from the resulting blob counts whereas for the rest of the species used the initial proportions were used.

From 2006 to 2012 over 700000 images were collected of which 79000 contained images of chosen phenologies. We further sifted the set into one series of 'oak canopy', four series of 'oak close-up', eight series of ferns and ten series of wallflowers. The 'oak canopy' was trained with a subset of the series while the 'oak close-up', fern and wallflower were trained with one, one and four of their respective series. Given the proximity of the locations of the images of the fern and the wallflowers, we created consolidated PTZ-series for each.

4.2.3 Estimated vs. Observed Data

To generate our observed dates for the wallflowers we marked an onset date when we identified the first visible flower and an ending date when the last flower disappeared. For the ferns we marked an onset date when we saw the first green fern frond emerge from the soil and an ending date when we visually assessed that 90% of the green fronds had turned dark yellow or light brown.

For the summer 'oak canopy' we marked an onset date at the first signs of new leaves and an ending date when 90% of the canopy had lost its green and turned red. For the autumn 'oak canopy' we marked an onset date when 90% of the canopy had changed to red and an ending date when most of the leaves of the canopy had fallen. For the summer 'oak close-up' we marked an onset date when most of the emerging leaves turned green and an ending date when 90% of the leaves had turned yellow. For the autumn 'oak close-up' we marked an onset date when 90% of the leaves had lost their dark green color and turned either light green or yellow and an ending date when 90% of the leaves had fallen from the tree.

Table 4.2: Cross validation error. Percentage of false negatives (pixels that were misclassified as BG) and false positives (pixels that were misclassified as FG) calculated for each species phenophase. False Negatives were calculated using an s-fold method (Bishop, 2007). Wallflower values are prior to blob analysis calculations.

Phenophase	False Negatives	False Positives
Summer 'Oak Canopy'	8.91	4.51
Autumn 'Oak Canopy'	25.32	0.31
Summer 'Oak Close-up'	2.11	1.38
Autumn 'Oak Close-up'	17.61	0.025
Bracken Fern	5.13	1.20
Wallflower	63.86	5.50

After determining the observed dates we calculated model accuracy by comparing them with the estimated dates calculated by the algorithm. For the consolidated case (ferns and wallflowers) we first calculated observed consolidated dates by considering an onset date as the minimum of all observed onset dates (per phenophase) and, in a similar way, considering an ending date as the maximum of all observed ending dates (per phenophase). We then compared the observed dates with the two approaches (section 4.2.1.5) used to calculate the estimated dates.

4.3 Results

4.3.1 Size of ITS

To train the 'oak canopy' models we used the totality of one of the two years (Table 4.1) in the image series (294 images). Since images did not change on a daily basis we reduced this number to 124 (roughly ten images per month) for 'oak close-up' in the hope of producing models with similar error values. By creating a model with a smaller error (summer 'oak close-up') than the one created with the larger ITS (summer 'oak canopy'), We show that we can get workable models with a reduced image sets (Table 4.1).

4.3.2 Selected Color Transformations

We selected the color transformation based on the model error values (Table 4.2) and on EcoIP's histogram comparison (Figure 4.2). As in other projects (Ide and Oguma, 2010; Panneton and Brouillard, 2009; Richardson et al., 2007) the excess green color index and the CIEL*a*b* (CIE (Commission Internationale de l'Eclairage), 1986) color space optimized vegetation color analysis. These two color transforms were selected for all the green phenophases in our study (Table 4.1). Only in autumn 'oak close-up' and wallflower did we use different color transformations (Table 4.1).

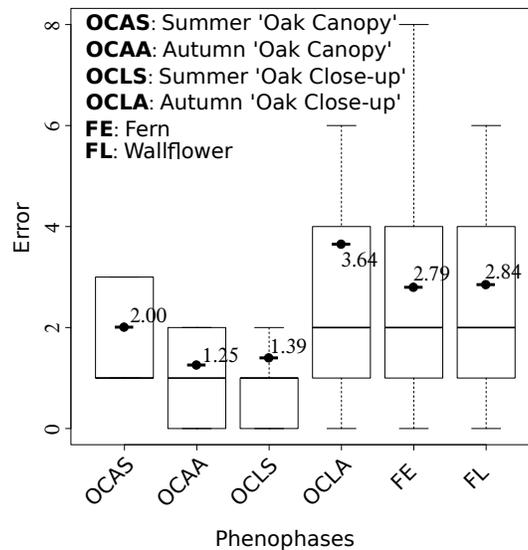


Figure 4.4: Distribution of error values (in days) for each phenophase. Mean value is marked and displayed for each phenophase. Though outliers are not included in the figure, we include them in the mean value calculation.

4.3.3 Model Error

The cross validation error (Table 4.2), used to compare models, provides hints at the behavior of the model with real data. We used the false negatives and false positives as accuracy measures based on the assumption that the distribution of the training and real data are the same, since the camera, the time of day and the location were the same for training and real data. Although the wallflower model appeared to have a poor cross validation error (Table 4.2), applying the blob count method suppressed the greater-than and smaller-than blobs to contribute to a well behaved average error of 2.84 (Table 4.1). The remainder of our experiments fell within 90% accuracy (Table 4.2) except for the autumn 'oak close-up' (25.32% false negatives) and autumn 'oak canopy' (17.61% false negatives) of which the autumn 'oak canopy', despite the 17.61%, led to a good average error of 1.25 (Table 4.1).

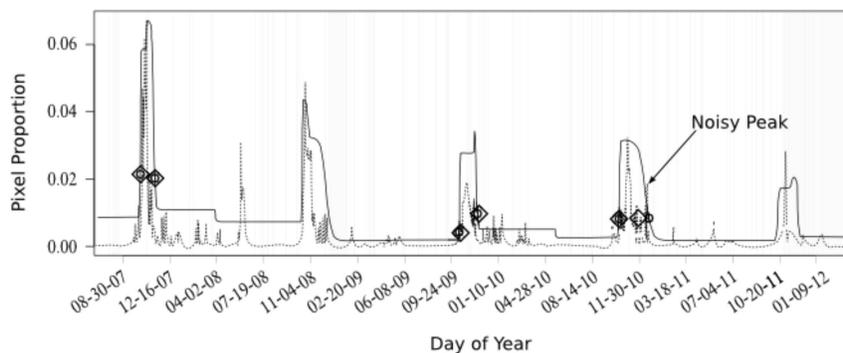


Figure 4.5: Sigmoid fit (solid line) to the phenological signal (dotted line) of an autumn 'oak close-up'. Shaded areas represent missing data. Training was done with images from 2009. Circles are estimated dates and diamonds are observed dates for both the onset and ending of autumn in the 'oak close-up' image series. 2008 and 2011 not included due to missing data. Fit is particularly noisy in 2010 where there is a large difference between the estimated and observed ending date.

4.3.4 Dates of Phenophases

The average error for the combined experiments was 2.78 (Table 4.1), indicating that, on average, the estimated onset and ending dates fell within a range of ± 2.78 d of the observed dates. The best results occurred for the autumn 'oak canopy' that had an error of 1.25 days and the worst value was for the autumn 'oak close-up' with 3.64 error value. This relatively poor performance is a result of an error of 24 days in the 2010 end of Autumn date (Figure 4.5) due to a

noisy peak that is near and similar in size to the main signal. In Figure 4.4 we compare the error distribution of all the studied phenophases.

4.3.5 Consolidated PTZ-series

The comparison of the consolidated observed dates with the ones estimated by the first approach (section 4.2.1.5) resulted in an average error of 3.87 days and 3.5 days for the wallflowers and ferns respectively (Table 4.3). When we compared the consolidated observed dates with the ones estimated by the second approach (section 4.2.1.5), we saw an average error of 2.9 days and 2.75 days for the wallflowers and ferns respectively (Table 4.3). These values coincide with the ones in Table 4.1 and represent the accuracy of our method for multiple PTZ-series of the same species.

4.4 Discussion

4.4.1 Phenology and the EcoIP Toolkit

With the advent of new technology it is becoming easier to generate great amounts of digital image data. Pan-Tilt-Zoom cameras increasing resolution coupled with portable field data collection devices and large databases are creating situations where the amount of digital image data collected can exceed the capacity for prompt analysis. The method described in this paper, together with the EcoIP toolkit, contribute to the automation of phenological data analysis based on digital images by completely controlling the signal creation. The use of a naive Bayesian model to generate a probabilistic representation of a color transformation to determine the dates for phenophases allows rapid and robust model creation that directly translate into semi-automatic date estimations.

Table 4.3: Average of the absolute value of the difference between the consolidated estimated dates and the observed dates. The consolidated sigmoid error is estimated from the consolidated signal inflection points (first approach, section 4.2.1.5). The individual sigmoid error is estimated from minimum and maximum estimates (second approach, section 4.2.1.5).

Type	Consolidated Sigmoid Error	Individual Sigmoid Error
Fern Consolidate	3.50	2.75
Wallflower Consolidate	3.87	2.90

EcoIP is implemented as an open platform that encourages anyone to execute, copy, distribute, study, change, and/or improve the application (Granados, 2010a). The code is made available for download and examples are provided for every function to aid the user. EcoIP is designed as an R (R Core Team, 2013) package and it can easily be installed in any platform where R is available. Help

within EcoIP is provided with sample data and executable examples. Two data sets are included: One of an Oak and another of wallflowers.

EcoIP has a lot of room for improvement. One of its major weaknesses is that it focuses exclusively on color. It ignores other, potentially useful, aspects of the image like the temporal information (contained in the image series) that could be used to make decisions based on preceding and posterior images. The texture and shape of the FG and BG could be added as an additional dimension to the NBM. EcoIP is also constrained by the statistical model it uses. For the moment it only works with a naive Bayesian approach but there could be an increase in accuracy if we could experiment with approaches like support vector machines, FFT analysis, wavelet transform or neural networks.

4.4.2 Color Transformations

In our experiments, there was no optimal color transformation that allowed separation of phenological events among species or even within species. For example, for the summer 'oak canopy' we used a version of the excess green color index (Richardson et al., 2007; Woebbecke et al., 1995) to detect green leaves, but in autumn we used CIEL*a*b* (CIE (Commission Internationale de l'Eclairage), 1986) to detect the color change from green to red leaves. Indeed, color transformations influence image segmentation and posterior classification, and should be incorporated as yet another variable when doing these analysis as opposed to fixing it on one value.

EcoIP has not only tackled image series that are characteristically green (summer 'oak canopy', summer 'oak close-up' and ferns), it has also extended previous ecological work (Ide and Oguma, 2010; Richardson et al., 2007; Sonntag et al., 2012) by estimating onset and ending dates of non-green phenophases (autumn 'oak canopy', autumn 'oak close-up' and wallflowers). Our results show that there are other color transformations (YCbCr, CIE L*u*v*) that are better equipped for segmenting these non-green phenophases and therefore a broader set of transformations should be considered when doing analysis of phenophases like the blooming period of flowers (wallflowers) and the autumn period in oaks (autumn 'oak close-up' or autumn 'oak canopy').

The choice of color transformation to analyze the phenophases of the 'oak canopy' and 'oak close-up' were different in order to maximize the signal and detect the timing of events with the greatest resolution. However, the ability to compare the two data streams analyzed with different methods may thus be compromised. The flexibility of EcoIP allows analysis with any choice of color transformation and so it is left up to the investigators using EcoIP to use the system as a tool for data exploration.

4.4.3 Noise

While the color signals contain the underlying structure of the phenophases, they also contain noise (Figure 4.6) which represent a high concentration of false positives and negatives. Noise in images is produced by natural changes

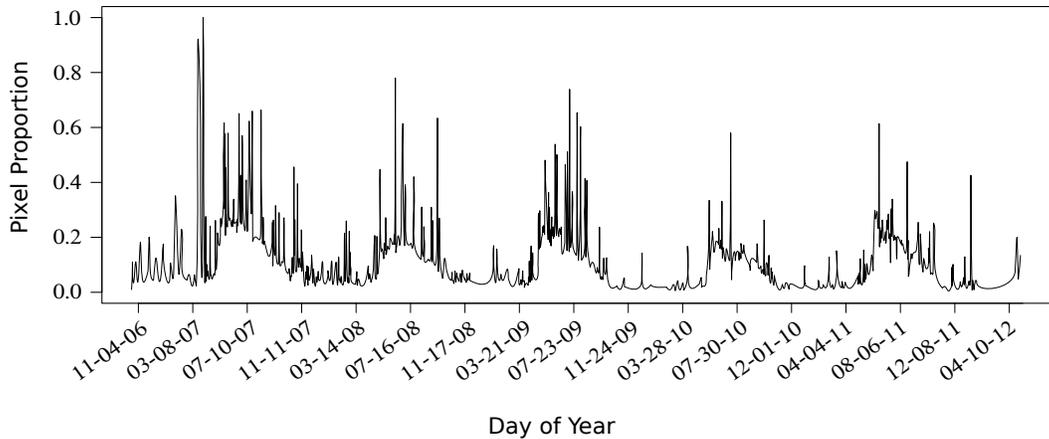


Figure 4.6: Bracken fern raw signal. 2008 is ignored due to noisy values.

in illumination, undesired automatic camera adjustments, and hardware failure. The choice of a color transformation that minimizes the effect of illumination (e.g., L^*a^*b , where luminance is separate from the color channels) can reduce naturally-occurring noise while color transformations with less separation of FG and BG (Figure 4.2) resulted in a nearly random signal (data not shown). Mitigation of camera-created noise requires full control of the camera settings (aperture, exposure time, and white balance), which may not be possible in many situations where cameras are controlled by third parties (e.g., land owners or reserve managers). We also experienced hardware and software malfunctions: In Figure 4.6, before the beginning of the 2007 season, there are uncommonly large signal responses caused by erroneous exposure times, erroneous aperture values or bad focus resulting in completely black or blurry images. Given the amount of ignored data due to lack of camera resilience and camera control, we argue that more emphasis should be placed on these two aspects to mitigate these types of errors.

An additional problem with images in natural areas is the impossibility to separate regions of interest based on color alone. For example, Figure 4.7 has two peaks per season, which is caused by direct sunlight striking fallen leaves in the meadow that reflect a color that is nearly identical to the yellow of the wallflower. We reduced this effect by manually identifying and ignoring the erroneous signals. Something similar occurred with the colors in summer 'oak close-up' where autumn yellow and summer green were being classified as FG pushing the estimated ending summer date approximately one month after the observed one. Figure 4.8 is used to compare the position of each element in the excess green color index. We see a large separation between greens of summer and the browns of bark and fallen leaves. But unfortunately, autumn yellow and summer green are in close proximity, which led to the misclassification. We see the same behavior in the summer 'oak canopy' where the green of the oak

is classified as FG together with the greens of the distant pines. This however did not incur in any date miscalculation because the pine colors were constant throughout the summer.

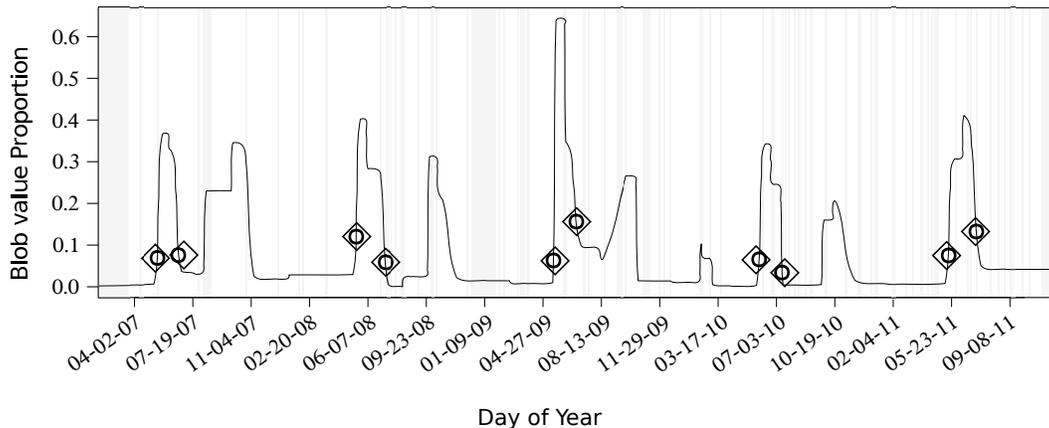


Figure 4.7: Consolidated sigmoid fit of the wallflower signal from six independent PTZ image series. Circles on sigmoid are estimated dates and diamonds are observed dates for both the beginning and ending of the blooming period of the wallflower image series. Here we show a specific type of noise where there are two peaks per season instead of one.

4.4.4 Consolidating Signals

The process of adding different local elements into a global response is a way to visualize the behavior of individuals with respect to their containing ecosystem. Our consolidated signal was aimed at giving global onset and ending dates for ferns and wallflowers. Results showed that the way the consolidation was done had an effect on the accuracy. While we expected the first approach (section 4.2.1.5) to suppress erroneous responses (given the added data), we found that it increased the final error (Table 4.3). The averaging of noisy signals, together with the recalculation of inflection points resulted in a final error that surpassed the consolidation done with the second approach (section 4.2.1.5). We therefore preferred it to determine the onset and ending dates of ferns and wallflowers. We see that we need to consider additional noise and error factors of procedures used to consolidate local measurements.

4.5 Future Work

An increase in the accuracy of phenological date estimates can occur on several fronts. Computer vision features such as texture (Bernd Jähne, 2005, p. 435), shape (Bernd Jähne, 2005, p. 515), and even motion (Bernd Jähne, 2005,

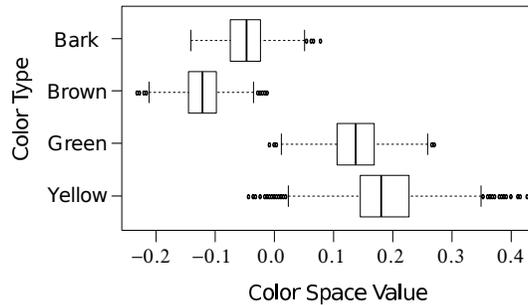


Figure 4.8: Distribution of color values in the excess green color index for summer 'oak close-up'.

p. 397) can mitigate or even completely remove some sources of noise in image series used for phenology. Motion and an understanding of the temporal characteristics of the phenomenon of interest is of particular interest given the characteristics of time series data. Motion features can separate ROIs (a moving branch compared to an immobile soil surface) and short-term situations, like the sun reflecting off a patch of fallen leaves, can be removed by incorporating temporal filtering (a flower persists in one location through many images whereas a sun fleck may move within a day or within a season). One exciting possibility, after the automatic detection of colors within an image have been established with EcoIP, is to create a more independent ROI detector. In this way, images from PTZ cameras may be captured at a high frequency and in locations not pre-programmed and then subsequently analyzed for ROIs. If nothing is found, then the image is discarded, reducing the transmission load from remote ecological reserves and reducing image storage needs. If an ROI is detected, then the image may be sent to a human operator for evaluation and feedback refinement of the NBM.

4.6 Conclusions

We have introduced EcoIP, a toolkit that calculates onset and ending dates of phenologies of interest based on pan-tilt-zoom image series. In our experiments the toolkit estimated with an overall error of 2.78 days from the observed date and was able to analyze phenophases with characteristic colors different than green. We consolidated individual image series to describe ecosystems that could not be captured in one scene. We found that color separability and scene illumination are contributing factors to the overall error. And we were able to effectively use initial false negative and false positive values to pinpoint usable models.

4.7 Acknowledgments

The research leading to these results has received funding from INTERACT (grant agreement No 262693, under the European Union's Seventh Framework Program. A portion of this research was also supported by National Science Foundation award 0120778 to the Center for Embedded Networked Sensing at the University of California, Los Angeles. References

Concluding Remarks

We have described EcoIP as a toolkit that fits into ecological monitoring by providing the means to automatically analyze phenological data in the form of image series. In this chapter we took images taken from a tower camera that produced aligned images by default, but we could have used image series produced by EcoIS just as easily. EcoIP takes advantage of spectral and temporal dimensions contained in image series and assumes spatial alignment to produce its estimations.

Annotations are a constitutional part of how EcoIP outputs its estimations; they allow the creation of the statistical model needed to automate image series analysis leading to ecological estimations. In this respect EcoIP depends on applications like EcoAN to provide image series annotations that reveal what parts of the image are of interest and what parts are not. In the same way EcoIP depends on applications like EcoIS or processes that produce aligned image series.

EcoIP directly addresses the increase of data by providing a way to make deductions from vast quantities of information with minimum human intervention. By creating summaries in the form of signals or ecological indicators, EcoIP exemplifies a way to make use of massive amounts of data. It describes a methodology that can easily scale up to handle images gathered with EcoIS, tower cameras or even unmanned areal vehicles and gradually provide enough information to close the gap between ground based and remote measurements.

EcoIP is not only designed to handle big quantities of data but is also able to elucidate behavioral patterns from different species throughout the year. This ability is of great importance to the effort of scaling ground based measurements as it describes individual behavior of collocated species and can further associate what is seen in remote sensing methodologies with ground based ones. EcoIP also describes a method that consolidates signals of different locations from the same species effectively allowing scientists to cover vast tracts of land with high resolution imagery and analyze them with minimum interaction.

Chapter 5

EcoAN

Preamble

Monitoring is again the starting point for our discussion as we relate EcoAN to extracting information from image series of a monitoring deployment in the high Arctic where we center our attention in plot based flowering phenology. EcoAN emphasizes the importance of creating metadata for collected measurements and it does so by implementing and evaluating annotations on image series. EcoAN is concerned with the creation of metadata that can lead to the curation and generation of content from ecological data in the form of image series.

EcoAN, as EcoIP, is able to use image series to produce ecological indicators that answer relevant questions about ecosystems. In our paper we exemplify its use by using image series produced by EcoIS; but as with EcoIP, it can use image series produced from various sources as long as they are aligned. It differentiates itself from EcoIP in the sense that it is not a fully automatic image series analysis tool but rather an annotation interface that depends and takes advantage of interaction with knowledgeable technicians. It is also capable of generating very accurate measurements that lead to estimators that are not yet possible with techniques used in EcoIP.

EcoAN contributes to the scale up of ground based measurements as an instrumental part in the training of statistical models like the ones used in EcoIP. Indeed annotation is an important part of supervised machine learning and EcoAN is part of the first steps to create a fully automatic statistical model. Data curation and the evaluation of automatic processes is also important when analyzing any type of data and EcoAN facilitates these processes for image series originating from ecological monitoring efforts. Finally, EcoAN contributes to the ground based knowledge by adding content in the form of annotations to existing image series data.

Our paper has not yet been submitted, but we plan to so right after we hand in this dissertation. We hope to submit to one of the following venues:

Ecological Informatics¹, Methods in Ecology And Evolution² or the new ACM International Workshop on Multimedia Analysis for Ecological Data³. As with the previous papers, the defendant is first author and is responsible for developing the toolkit and testing its performance. Images used in the toolkit evaluation were provided by technicians of the Department of Bioscience at Aarhus university who collected data from a monitoring station in the high Arctic.

¹www.journals.elsevier.com/ecological-informatics

²www.methodsinecologyandevolution.org

³maed2013.dieei.unict.it/

EcoAN: An Annotation Toolkit For Image Series Of Plot-Based Plant Flowering Phenology

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Abstract

In light of the growing attention on ground based ecological measurements and inspired by the need to address a generalized increase in data with methodologies like metadata generation, data annotation, data curation and data management in general; we introduce EcoAN an image series annotation toolkit specifically designed to assess phenological measurement. In evaluating our toolkit we look at how we can generate answers to new questions with old image series datasets with the help of image annotations created with EcoAN. We investigate how different ways of annotating an image series relate to content generating tasks and describe a trade off between accuracy and speed in using different types of annotations. We evaluate the correctness of our toolkit by comparing measurements generated with established processes to those generated with EcoAN and see that the latter have sufficient quality to serve as ecological indicators and can potentially describe ecosystems. We further evaluate our toolkit by comparing the cost of producing plot phenophase counts using an established procedure with a modified one based on EcoAN. We conclude that EcoAN is capable of producing annotations as an intrinsic part of ecological data analysis. We see that it answers new questions and produces ecological indicators such as phenophase counts and 50% onset estimators. We detect small costs savings related to EcoAN and see how it can be used to produce curated ecological image series.

Keywords: Annotation; Image; Label; Phenology; Arctic; Work-Flow;

5.1 Introduction

Measuring climate and ecosystems interactions requires concurrent data collection from multiple subsections of the ecosystem for extended periods of time (Melfoite et al., 2008a). It is a complex and difficult task but one that is posed to differentiate between phenomena that occur naturally and those that are caused by climate change (Melfoite et al., 2008b). Monitoring of ecological trends has had impact by allowing scientists to make discoveries that have given direction to research and influencing local and international policy (Lovett et al., 2007). Its importance stems from producing high quality data, generating contexts for interpreting experiments and providing information that leads to the design, implementation and evaluation of environmental policy (Lovett et al., 2007).

Yet, in practice, monitoring is sometimes riddled with flaws that make it inefficient or, in some cases, lead to failure. In general, issues come when monitoring efforts are based on political and funding opportunities rather than carefully crafted scientific questions (Lindenmayer and Likens, 2009). Poor planning and lack of focus lead to overlooking basic criteria, like the inclusion of a statistician in the planning phase, that inevitably affect results (Lindenmayer and Likens, 2009). Equally as important is the difficulty in deciding what to monitor; with limited budgets, it is not possible to gather all possible available variables (Lindenmayer and Likens, 2009).

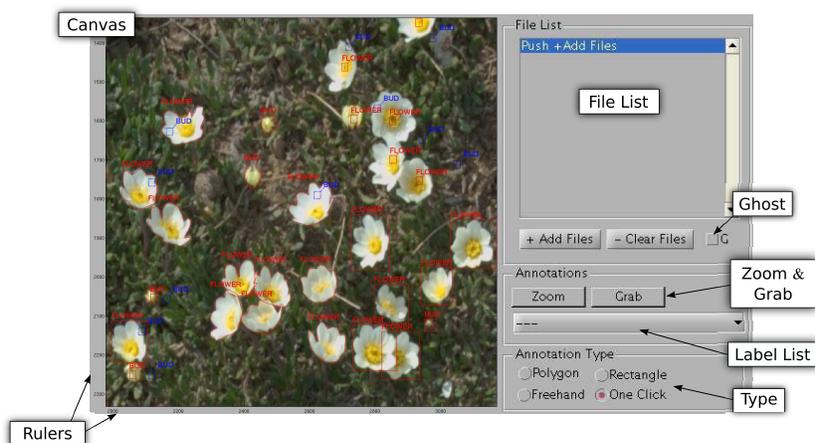


Figure 5.1: GUI Described. *Canvas* is where the image and annotation are drawn. *File List* is where the series files are shown and selected. *Ghost* is a checkbox used to activate ghost annotations. *Zoom & Grab* buttons used to toggle in and out of zoom and grab modes. *Label List* a list of phenophases. *Type* is where we select the type of annotation. *Rulers* displays the pixel offsets of what is currently on the *Canvas*.

Specifically, the general proliferation of scientific data (Hey and Trefethen, 2003; Emmott, 2006) exacerbated by novel data acquisition technologies like robotics (Grémillet, 2012) and sensors (Arzberger, 2004) is an important challenge in long-term monitoring. It affects management as things like standards, annotations and data mining strategies become a requirement (Hey and Trefethen, 2003). Automation of data processing and specialized database constructs (Emmott, 2006) replace old storage practices as increasing amounts of metadata need to be created in parallel and everything has to be made compatible with tools like digital libraries (Hey and Trefethen, 2003).

Repeat digital photography is posed to be a contributor in closing the gap that currently exists between remote sensing (satellites) and close range measurements. Yet, it multiplies challenges as it requires large amounts of storage for an increasing number of images that can no longer be processed manually (Granados et al., 2013). There has been research related to digital photography

that have used cameras mounted on towers (Richardson et al., 2007; Grana-dos et al., 2013; Ide and Oguma, 2010), pan-tilt-zoom systems that sweep large amounts of land from a vantage point (Kopf et al., 2007) and cameras installed on the ground pointed skywards that measure Leaf Area Index (Ryu et al., 2012; Montes et al., 2007; Macfarlane et al., 2007); all generating up to a gigabyte per image (Brown et al., 2012).

Creating metadata is part of a group of methodologies that is posed to ad-dress the increase in scientific data where the main focus is information creation and knowledge management (Hey and Trefethen, 2003). Metadata should go hand in hand with ontologies and standards (Hey and Trefethen, 2003; Madin et al., 2007; Leinfelder et al., 2010) while providing the building blocks for data mining techniques, provenance creation and content generation; all focused to-wards making sense of overflowing data. For data in the form of images we consider metadata as manual and automatic annotations on an image. We see image annotations as part of a process where most are created automatically allowing for timely analysis of vast quantities of data. And a reduced number related to data curation (Hey and Trefethen, 2003), model training (Sorokin et al., 2008) and tasks that cannot yet be automated are done manually (Hey and Trefethen, 2003). We consider that annotations are an intrinsic part of making sense of the vast amounts of data generated by long-term monitoring efforts.

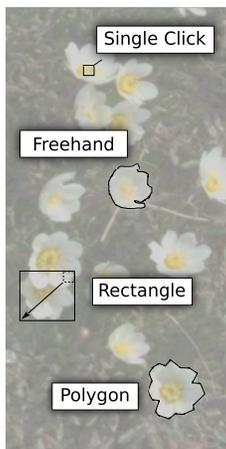


Figure 5.2: Annotation types. *Rectangle* are created by clicking (and hold-ing) and releasing when the rectangle is complete. *Polygons* are generated by consecutively creating polygon corners. *Freehand* annotations are created by clicking (and holding) while delineating the element. *Single click* annotations are created by clicking once.

By taking advantage of images and their annotations there is potential to formulate and answer new questions which depend on features that were pre-viously unused. Specifically, we are concerned about how tomorrow’s questions

can be answered with today’s monitoring (Lovett et al., 2007). It is difficult to know exactly what questions are going to be relevant in the far future; centuries ago we could not have known about the importance and impact that atmospheric CO_2 would have on environmental and social policy. However, by including predictions of what may come in the future together with a good understanding of what is being monitored it is possible to produce durable records (Lovett et al., 2007). Image annotations play an important role in rediscovering data as it can point to new attributes by rediscovering old (previously ignored) image features.



Figure 5.3: *Dryas* phenophases. A) Picture taken at the beginning of the season containing several buds; the red annotation points to one bud; the blue annotation is a ghosted annotation from the middle image. B) Picture taken at the middle of the season containing flowers; we have annotated one flower to exemplify. C) Picture taken at the end of the season containing senescent flowers; red annotation marks a senescent individual while the blue annotation is ghosted from the image in the middle.

Additionally, clever use of images might minimize the more expensive parts of deployments and drive the overall cost (and effort) down. Certainly there is a great cost involved with providing data for monitoring endeavors (Crimmins and Crimmins, 2008; Lovett et al., 2007) and as we move away from known infrastructure (energy grids and communication networks) into more remote and inhospitable areas, the cost increases accordingly. Consequently, it is fitting to optimize processes to reduce overall effort (in time and cost) in deployments; especially considering that, in some cases, expenses double for technicians carrying out the monitoring measurements (ZERO-Zackenber, 2013). We find that this as well as answering new questions are additional gains made possible by the use of image annotations. Yet these possibilities don’t occur automatically when images are used; there needs to be an intermediate layer designed to harbor the qualities of images and channel them into useful applications.

With this in mind we introduce EcoAN, a Matlab (MathWorks, 2009) open source tool kit designed to visualize and annotate data collected as images.

We describe its features in detail and outline how it might fit into established monitoring efforts while at the same time depicting its connection with addressing increase of data, answering tomorrow’s research questions and overall monitoring cost. Predecessors to EcoAN include Time System (Brown and Zimmermann, 2006) a commercial application that has a variety of features able to handle annotations of image series and ImageJ (National Institutes of Health, 2008) an open source Java application develop to create metadata for images. EcoAN differentiates itself from existing approaches by being an open source experimental platform where the effects of different annotation strategies can be tested on image series of natural subjects.

5.2 Materials and Methods

5.2.1 EcoAN

EcoAN (Granados, 2010c) is a Graphical User Interface (GUI) that is able to manipulate special cues called annotations lain on top of images that identify elements of interest. It is optimized to handle sequences of images representing temporal change (image series) by extending annotations through image series. EcoAN manages various types of annotation each of which is a trade off between accuracy and effort. It keeps track of who creates and modifies components and keeps everything in text files that contain annotation coordinates, labels, modification dates and other relevant data.

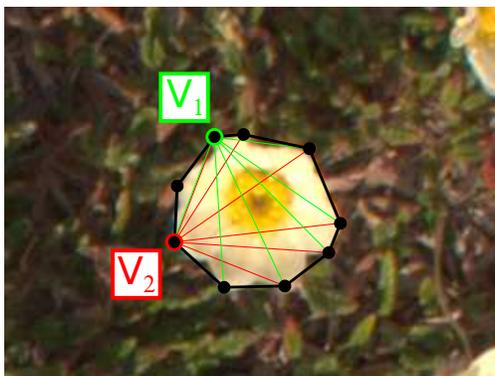


Figure 5.4: Diameter calculation. We calculate the diameter for each vertex of the annotation. Here we show diameter calculation for V_1 and V_2 . The diameter which is greater of all the vertices is the one chosen as flower size.

EcoAN displays images in the canvas (Figure 5.1) which also contains the annotations and their labels. It shows the current pixel ranges on two rulers placed on the sidelines (Figure 5.1). The file list contains all files from an image series and is managed by the two buttons located on the bottom of the pane (“Add Files” and “Clear Files”, Figure 5.1). Several types of polygons used to

make an annotation can be selected in the pane named Annotation Type (Figure 5.1). Labels for annotations are selected from the Label List (Figure 5.1) located below the Zoom and Grab buttons which are used to control the navigation through the canvas. Finally there is the Ghost checkbox which activates ghost annotations (section 5.2.1.3).

EcoAN is developed in Matlab (MathWorks, 2009) which was a natural choice because of the ease with which it handles image matrices. Indeed, by using images as multidimensional matrices of pixels we get already implemented features like pan and zoom that are heavily used. EcoAN is capable of dealing with large image matrices than contain great detail which requires quick image transformation (zooming and panning) when searching for elements within images. EcoAN is also capable of handling a variety of image formats (JPEG, PNG and TIFF) effectively fitting different deployment situations. This is especially useful when considering that different work-flows might create different image formats. However, it is not particularly suited for implementing GUI applications which lengthened the initial development and is only available through license acquisition which in most cases involves fees. Despite these circumstances we managed to develop EcoAN as an open source GUI.

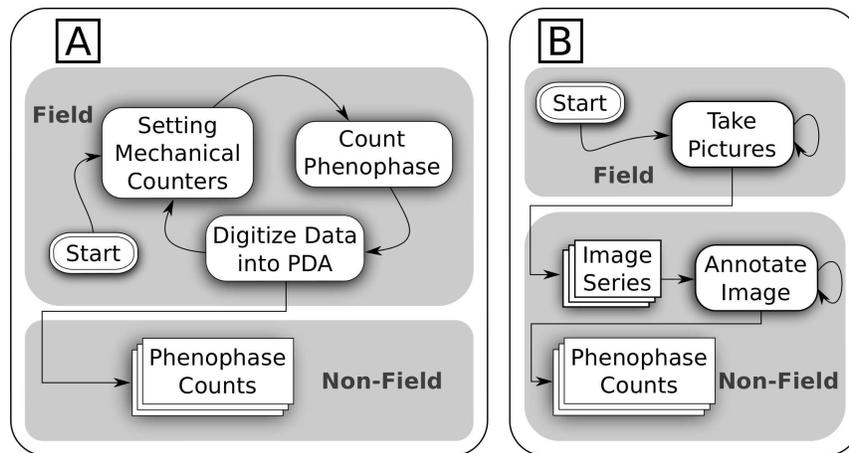


Figure 5.5: Work-flows. Depicts activity both in the field and out. A) Established work-flow where mechanical counters are used to count phenophases which are then digitized with a Personal Digital Assistant (PDA). It occurs all in the field and the phenophase counts are published afterwards. B) EcoAN work-flow where image series are created with images taken in the field and produce phenophase counts through image annotation. Most of it occurs out of the field.

5.2.1.1 Image Annotations

Annotations are the basic building block in EcoAN and are made up of two elements: polygons that enclose elements of interest and their labels. A text file is linked to every image and holds a record for every annotation in the form of polygon coordinates, label name, date of creation and other relative data that effectively mirror the image series. In our case each annotation represents individual plant phenology phases (phenophases) that are identified in images and tracked throughout image series. Ideally, it is possible to follow the appearance, development and demise of each individual phenophase.

There are four types of annotations: rectangle, polygon⁴, freehand and single click which can be selected in the Type panel (Figure 5.1). Rectangles are created by clicking (and holding) the initial position, dragging the cursor and releasing it when the rectangle has enclosed the element of interest (Figure 5.2). Polygons are generated by consecutively creating polygon corners (Figure 5.2). Freehand annotations are created by clicking (and holding) while delineating the element of interest which requires a steady hand (Figure 5.2). Finally, single click annotations are created by clicking once in the middle of elements of interest in order to generate a small square (Figure 5.2).



Figure 5.6: Mechanical counters. Example of the mechanical counters used in Zackenberg. Each one represents a phenophase.

Each annotation is related to labels which are selected in the drop down Label List (Figure 5.1). Labels are meant to describe state of elements of interest at a certain point in time (e.g. Bud, Flower or Senescence; Figure 5.3) and appear in red on the canvas so they can be clearly distinguished from the rest of the image. Anticipating that it would become time consuming to constantly switch from Label List to Canvas (Figure 5.1), we allow the first five numbers to control which labels are selected. In this way pressing "4" selects the fourth label.

⁴Polygon refers to a type of annotation and to the fact that all annotations are polygonal

5.2.1.2 Zoom & Grab

To take advantage of high resolution images for searching elements of interest, EcoAN implements two key functionalities: "zoom" and "grab" (Figure 5.1). The "zoom" mode is toggled by pressing on the "z" key or when the "zoom" button is pushed. The mouse scroll wheel is used to zoom in and out of the image where the mouse pointer serves as a reference for the zoom center. The "grab" mode is toggled by pressing the "t" or the "p" keys or by pushing the "grab" button. This feature is useful to move around "zoomed in" images and works by pressing (and holding) the pointer in order for the image to follow the movements of the mouse. It is not possible to be in "zoom" and "grab" mode at the same time and the key presses ("z", "t" and "p") were implemented to avoid having to go back and forth between then canvas and the Zoom & Grab pane (Figure 5.1).

Table 5.1: Cameras in Zackenbergl. Characteristics of cameras used in our Zackenbergl deployment. Resolution is given in pixels, focal length is given in millimeters and is normalized to 35 mm equivalence, exposure is given in seconds and "Imgs" gives the number of images taken with each camera. Formats refers to how the images were formatted in camera.

	Sony Nex-3	Nikon D700	Nikon D300
Lens	Sony E 18 – 55mm <i>f</i> /3.5 – 5.6	AF-S Nikkor 14 – 24mm <i>f</i> /2.8G ED	AF-S Nikkor 14 – 24mm <i>f</i> /2.8G ED
Resolution	4608 x 3072	4288 x 2844	4352 x 2868
Aperture	<i>f</i> /7.1 – 22.0	<i>f</i> /10.0 – 11.0	<i>f</i> /8.0 – 11.0
ISO	200	200 – 500	200 – 640
Exposure	1/320 – 1/8	1/500 – 1/125	1/500 – 1/160
Focal Length	27 – 28	24	25 – 27
Imgs	162	56	101
Flash	No	No	No
Formats	Raw	Raw	Raw

5.2.1.3 Ghost Annotations

The ghost feature is located next to the zoom and grab buttons (Figure 5.1) and is activated on an image that already contains annotations. After activation all annotations of the current image are "ghosted" and the next image placed on the canvas will contain them drawn in blue instead of red (Figure 5.1 and 5.3). These ghost markers aid in finding small, almost hidden (not occluded) elements with the position of a previous or following images, and allows referencing other images without actually having to go back and fourth through the image series. They also serve as a reminder of the presence of elements and might contribute to preventing situations where annotations are missed.

5.2.2 Zackenberg Deployment

We deployed at Zackenberg station in northeast Greenland ($74^{\circ}30'N, 20^{\circ}30'W$), a high arctic research station run by the Department of Bioscience at Aarhus University in Denmark where we ran our experiments in the summer season (June and July) of 2012 and 2013 on plots containing Mountain Avens (*Dryas octopetala* / *integrifolia*; hereafter referred to as *Dryas*). We gathered data related to the three main *Dryas* phenophases (bud, flower and senescence) on a total of nine plots (six in 2012 and three in 2013). Plots were sampled every week in 2012 and three times in 2013, on every visit we created manual phenophase counts and took several pictures from different view points which were used to create image series that later led to phenophase counts. Days for 2013 were chosen carefully to coincide with season initialization, peak and end where manual counts were filmed and flower sizes were measured during season peak.

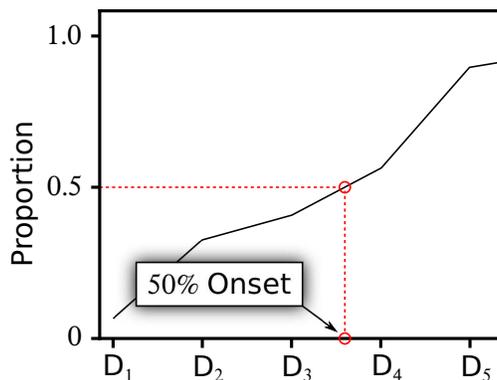


Figure 5.7: 50% Onset. The process to calculate the 50% onset values. *Proportion* are values from equation 5.5 or 5.6. D_i is a sampling day. The 50% onset is chosen where the proportion surpasses 0.5.

5.2.3 Measuring Size

The size of the *Dryas* flower is interesting as it reflects the potential to attract pollinators and may impact plant fitness (Johnson et al., 1995). We used a vernier caliper to measure the diametrical size at the height of the 2013 season when most individuals were fully bloomed. Diametrical size in this case refers to the largest diameter of a fully bloomed individual. A total of 32 measurements were performed which covered two of the three plots from 2013; all of the flowers in the first were considered while only one quadrant of the second was included.

After looking at the diametrical size in the field, we turned to the image series. We first identified which of the image flowers corresponded to field measurements and proceeded to annotate them with EcoAN. We used the polygon annotation (Figure 5.2) type which allowed us to accurately portray the size of

the flowers without spending too much time in the process. To calculate the size of each annotation we found all possible diagonals and chose the largest (Figure 5.4). This was done automatically by analyzing the annotation files.

Our measurements in the image series resulted in sizes expressed in pixels which had to be adjusted to millimeters in order to be compared to the caliper sizes. For this purpose we assumed a linear relation between the two where multiplying each pixel size with a constant C would result in a caliper size (in millimeters). We used five of the 32 measurements to find C by using equation 5.1 where SC_j is the j^{th} caliper size, SP_j is the j^{th} pixel size, C is the transformation constant and we sum through the first five elements. We select the constant value that minimizes the sum of the absolute difference between the caliper value and the adjusted (with C) pixel value (Equation 5.1).

Table 5.2: Values in table are in number of corrections. *Added* refers to new annotation being added. *Label* refers to annotation labels being changed. *Removed* refers to annotations being removed. *R1* is the first review and *R2* is the second. We evaluated the changes on three plots from 2013. *Total* is the sum of the corrections for all the considered plots. *Removed* is a special case in that it does not actually remove annotations but rather changes their labels to "removed".

	Added		Label		Removed	
	R1	R2	R1	R2	R1	R2
Plot0	0	0	2	0	2	1
Plot4	3	0	5	0	14	0
Plot63	3	1	8	0	2	0
Total	6	1	15	0	18	1

$$\min \left(\sum_{j=1}^5 \sqrt{[SC_j - (SP_j * C)]^2} \right) \quad (5.1)$$

After calculating C , we used it to estimate the size of the rest (27 flowers) of pixel measurements that were not used in the calculation. The estimation was a straightforward multiplication of pixel values with the constant which created estimated millimeter values. These were then compared with the caliper values by using the average absolute difference between the two ($\overline{S_e}$). We used equation 5.2 where SC_j is the j^{th} caliper value, EM_j is the j^{th} estimated value and we use all the size values except the five that were used to calculate C .

$$\overline{S_e} = \frac{\sum_{j=1}^{(N-5)} \sqrt{(SC_j - EM_j)^2}}{N - 5} \quad (5.2)$$

To further add to our analysis we defined the range for $\overline{S_e}$ by calculating the error of the mean ($\sigma_{\hat{\theta}}$; Wackerly et al., 2008) with equation 5.3 where σ is the standard deviation of the average absolute difference and N is the total number (32) of measured sizes. The final range extends 1.96 standard deviations

from the calculated error ($\overline{S}_e \pm [1.96 * \sigma_{\hat{\theta}}]$) and signifies that the real absolute difference between caliper and estimated measures has a 5% change of falling outside this range.

$$\sigma_{\hat{\theta}} = \frac{\sigma}{\sqrt{N-5}} \quad (5.3)$$

5.2.4 Plot Counts

Plot counts refer to the enumeration of phenophases within a plot of land which, for us, meant measuring *Dryas* buds, flowers, senescence and eaten. Buds are flowers that are not yet open, flowers are open *Dryas* giving access to their reproductive organs, senescence is when all the petals turn brown or are missing (Schmidt et al., 2012a) and eaten is when it has been eaten by a herbivore. We compare two work-flows for creating plot counts: established and EcoAN⁵. The first refers to processes currently used in Zackenberg to procure plot counts (Figure 5.5.A) while the second is the procedure that produces plot counts with image series and our annotation toolkit EcoAN (Figure 5.5.B).

Table 5.3: Man hour costs. All values are costs of a man hour in Danish kroner (kr). *Field* are field only costs. *Non-Filed* are out of field costs. *Salary* represents what a technician earns per hour. *Ticket* is the travel cost to Zackenberg spread out on a hypothetical three month deployment. *Station Fee* is what is payed per hour to the station administration. *Field Allowance* is the hourly allowance given to technicians traveling to Zackenberg. *Total* represents a sum of all hourly costs. For these calculations we assume a monthly salary of 37800 kr, a monthly field allowance of 22000 kr, a daily station fee of 1100 kr and a plane ticket of 25000 kr. We further assume that there the month has a total of 26 working days and each day is 7.4 hours long. One time prices (like the ticket) where spread out on a hypothetical deployment of three months.

	Field	Non-Field
Salary	196.47	196.47
Ticket	43.31	-
Station Fee	148.65	-
Field Allowance	114.35	-
Total	502.77	196.47

5.2.4.1 Established Work-Flow

The established work-flow has both field and non-field procedures (Figure 5.5) where the first is repeated for every plot on each day of sampling and the second only involves publishing the data. It depends on a technician doing the actual counting and begins with the setting of mechanical counters (Figure 5.6 & 5.5.A) which are used to keep count of individual phenophases (each

⁵EcoAN is the toolkit and also refers to a work-flow

representing a variable: Bud, Flower, Senescent or Eaten). Counters are set to zero, technicians kneel beside a plot and click the respective counter every time they spot a specific phenophase (Figure 5.5.A). This is done until the totality of the plot is covered at which point the individual phenophase numbers can be digitized from the counters.

Table 5.4: Annotation types times. Values are in seconds. *Freehand*, *Polygon*, *Rectangle* and *SingleClick* refers to the freehand, polygon, rectangle and single click annotation types described in section 5.2.1.1.

Polygon Type	Time (seconds)
Freehand	267
Polygon	207
Rectangle	108
SingleClick	57

In Zackenberg it is standard to carry a Personal Digital Assistant (PDA) designed for extreme applications which, in this case, is used to digitize the plot counts (Figure 5.5.A). Each counter value is typed into the PDA which keeps everything internally and also synchronizes to a centralized server located in Zackenberg station. The digitizing and synchronizing mark the end of the field cycle (Figure 5.5.A) after which the counts are taken back to Aarhus university facilities located in Roskilde (Denmark). The data at this point is verified for consistency and then published as a database containing phenophase counts (Figure 5.5.A).

5.2.4.2 EcoAN Work-Flow

The EcoAN work-flow also has both field and non-field procedures (Figure 5.5.B) where the first is repeated for every plot on each day of sampling and the second involves data analysis and publication. Activity in the field for EcoAN work-flow is reduced to one step involving the acquisition of several pictures from different view points (Figure 5.5.B) which concludes when all images are transported to the Aarhus University facilities in Roskilde (Denmark). All pictures were taken from a standing position close to the plot, three cameras were used (Table 5.1) and a total of 319 pictures were taken (265 in 2012 and 54 in 2013). All the images were taken in raw format and then transformed into Joint Photographic Experts Group (ITU, 1992) by a raw image processing application (RIPA) called Rawtherapee (www.rawtherapee.com).

With the collected pictures we generated image series with EcoIS (Granados, 2010b) which we then annotated with EcoAN (Figure 5.5.B). We used both rectangular and one click types (Figure 5.2) and began annotating image series at the point where most flowers had bloomed (Figure 5.3.B) which allowed us to detect elements with ease as the white and yellow colors of the bloomed flowers stood out from the background. We then used the ghost feature (section 5.2.1.3) to project annotations into previous (for buds; Figure 5.3.A) and following (for

senescence; Figure 5.3.C) images which helped to pinpoint the whereabouts of phenophases in other images.

The annotation step (Figure 5.5.B) is done for all the image series and the resulting annotation files are used to automatically generate phenophase counts. A script took all the metadata generated in the annotation phase and translated it to a format that was similar to the one produced by the established work-flow. After the creation of the EcoAN counts, the two work-flows (Figure 5.5) could be compared in terms of plot counts.

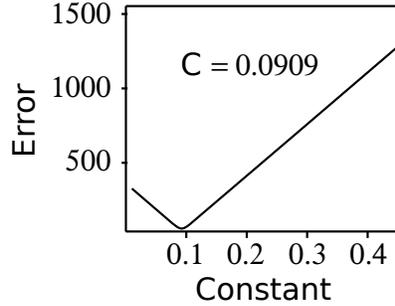


Figure 5.8: Constant (C) value. This is a plot of equation 5.1 where we have varied the constant C value from 0 to 0.5 and found that the minimum value in that range is when $C = 0.0909$. Error represents the sum of the absolute difference between caliper and EcoAN flower sizes.

5.2.4.3 Comparison

The comparison was done by calculating the average absolute difference between counts produced with the established work-flow and EcoAN. Equation 5.4 calculates this difference where k is the phenophases of interest ($k=\{\text{BUDS, FLOWERS, SENESCENCE}\}$), N_k is the number of dates where phenophase k was not zero for both types of counts (established and EcoAN), $E_{j,k}$ is the count done with the established work-flow count for the j^{th} date of phenophase k and $A_{j,k}$ is the count done with EcoAN for the j^{th} date of phenophase k .

$$\overline{Ce_k} = \frac{\sum_{j=1}^{N_k} \sqrt{(E_{j,k} - A_{j,k})^2}}{N_k} \quad (5.4)$$

Besides working with actual counts, we calculated 50% estimations for each plot and used them to make comparisons between the two work-flows. Equations 5.5 and 5.6 were used for this purpose where the subscript (p, d) refers to plot p and date d , $FO_{(p,d)}$ is the flower onset relation (for date d of plot p), $SO_{(p,d)}$ is the senescence onset relation, $B_{(p,d)}$ is the number of buds, $F_{(p,d)}$ is the number of flowers and $S_{(p,d)}$ is the number of senescence. We calculate onset relations for every date and select the one in which the relation crosses the 50% threshold (50% dates; Figure 5.7). We calculated 50% dates for counts done

with the established and EcoAN work-flow on all plots in the 2012 and 2013 deployments.

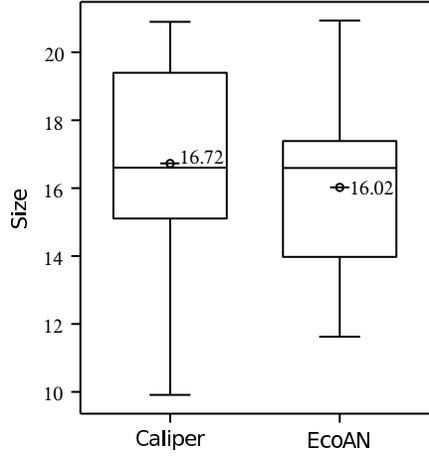


Figure 5.9: Distribution of *Dryas* size comparison. *Caliper* are the sizes measured in the field with a caliper. *EcoAN* are the sizes measured out of the field with EcoAN. In both cases we calculate the mean value.

$$FO_{(p,d)} = \frac{F_{(p,d)}}{B_{(p,d)} + F_{(p,d)}}; \quad (5.5)$$

$$SO_{(p,d)} = \frac{S_{(p,d)}}{F_{(p,d)} + S_{(p,d)}} \quad (5.6)$$

We compared the 50% values by calculating the average absolute difference between the values from the established work-flow and ones from EcoAN. Equation 5.7 shows the calculation where $\overline{H_e}$ is the difference (error), N_p is the number of deployed plots, E_j is the 50% value calculated with counts done with the established work-flow from plot j , A_j is the 50% value calculated with EcoAN counts from plot j . H_e represents how the 50% estimator calculated with the established work-flow differs from the one calculated with EcoAN.

$$\overline{H_e} = \frac{\sum_{j=1}^{N_p} \sqrt{(E_j - A_j)^2}}{N_p} \quad (5.7)$$

5.2.4.4 Incremental Accuracy

In order to see how the count accuracy evolved over a series of reviews, we took the original counts from the three 2013 plots (Table 5.2) and applied consecutive review sessions. Reviews amended annotations with three types of corrections: added, label and removed (Table 5.2). The first refers to phenophases that were added after the review, the second refers to mislabeled phenophases that

were relabeled and the third refers to phenophases that were removed. The removed action was special in the sense that the annotation was not actually removed but re-annotated with a label describing a state of deletion; this was done in order to show future reviewers that whatever was contained under the "removed" annotation should not be seen as a phenophase of interest. A second review was conducted on the results of the first with the same conditions and using the same correction types.

Table 5.5: Each value is the average of the absolute difference between counts done with the established work-flow and counts done EcoAN. Note that there is a difference for each plot. Values in parenthesis are the standard deviation of the absolute different values. *Bud* are the values related to the *Dryas* bud phenophase. *Flower* are the values related to the *Dryas* flower phenophase. *Senescent* are the values related to the *Dryas* senescence phenophase. 2012 are value from plots deployed in 2012. 2013 are values from plots deployed in 2013. *Total* represents both the sum of values for all phenophases in a specific year and the sum of values for all years of a specific phenophase.

	Bud	Flower	Senescent	Total
2012	19.06(10.64)	07.43(09.74)	11.41(14.52)	12.17(12.93)
2013	3.83(2.40)	2.33(1.86)	4.67(1.15)	3.40(2.10)
Total	15.25(11.41)	06.29(08.85)	10.83(14.00)	10.64(12.23)

5.2.5 Effort

In order to answer the question of how much effort EcoAN saves, we timed each of the work-flows (established and EcoAN) both for field and non-field situations (Figure 5.5). Given the elevated costs related to activities in the field, we focus on the differences in field times between the established and EcoAN work-flows, and explore how the reallocation (with EcoAN) of most components out of the field affected the overall (field + non-field) times and costs. For this we only used data from 2013 and ignored situations that were common between work-flows like time spent walking to plots, travel periods to and from Zackenberg and phenophase count publication.

The established work-flow was timed only in the field as it has no other components⁶ (Figure 5.5.A). We filmed technicians while conducting the three activities depicted in figure 5.5.A which was enough to calculate cycle times. Times for individual steps in the field were not calculated as they were too short and did not add any value to the analysis. Since time of completion was so short, calculation were done in man-seconds which is the amount of seconds it takes a person to do a task.

For the EcoAN work-flow (Figure 5.5.B) we calculated field and non-field times. We subtracted the time stamp of the first picture taken of a plot (on a specific date) from the time stamp of the last picture of that batch. Having

⁶phenophase counts (Figure 5.5) is ignored as it is equal for both work-flows

addressed the field, we proceeded to measure non-field times by looking at how long it took technicians to annotate images with EcoAN. For this purpose we used a regular chronometer that started when the process began and stopped when technicians were satisfied with the annotations. We used the single click annotations as we were concerned with acquiring a phenophase count in a minimum amount of time.

Costs are related to time spent in each work-flow and the different (in cost) between expenses in the field and out of it. Costs for people wanting to go to Zackenberg include tickets, station fees, field allowance and regular salary while the price for non-field only includes salary (Table 5.3). We took this difference and analyzed its impact on overall effort by calculating the cost of producing phenophase counts with the established work-flow and comparing it with the cost related to producing the same phenophase counts with the EcoAN work-flow. The values on table 5.3 assume that there are 7.4 working hours in a day, 26 days in a working month and the duration of a trip to Zackenberg is three months.

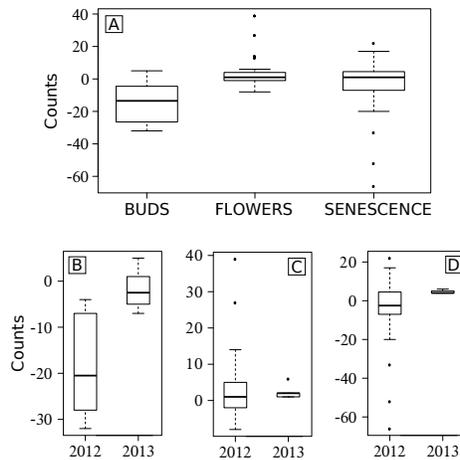


Figure 5.10: Phenophase count error. Values are differences between counts done with the established work-flow and those done with the EcoAN work-flow. *BUDS* are the bud counts. *FLOWERS* are the flower counts. *SENESCENCE* are the senescence counts. 2012 are counts created with data from our 2012 deployment. 2013 are counts created with data from our 2013 deployment. Positive numbers occur when counts from the established work-flow are greater. Negative numbers occur when counts from the EcoAN work-flow are greater. A) Values for both the 2012 and 2013 deployments separated by phenophase. B) Bud values separated by deployment year. C) Flower values separated by deployments year. D) Senescence values separated by deployment year.

Given that our deployment in 2013 was small (3 days of sampling 3 plots) we explored more involved (hypothetical) deployments by extending sampling frequency. The first hypothetical deployment considers sampling 28 plots once

a week for a period of four months. The second hypothetical situation samples 28 plots once a day for four months. Finally, we consider an atypical case where we sample 28 plots once a day for 365 days of the year,

5.3 Results

5.3.1 EcoAN

The fastest annotation types are the rectangle and single click (Table 5.4) which give the technician the ability of creating an annotation with at most three clicks. Rectangle annotations require three clicks to the canvas and still maintain certain sense of proportion and size. However, they are not very precise as four corners do not describe complex shapes very well (Figure 5.2). The single click is by far the fastest of the four types of annotations (Table 5.4) but it is also the most inaccurate. It annotates position and relates it to a label, but does not describe morphology.

Table 5.6: 50% estimator error. Each value is the average of the absolute difference between estimations done with the established work-flow and EcoAN. *Flower* are all values related to the 50% flowering onset estimations. *Senescent* are all values related to 50% senescence onset estimations. 2012 refers to values calculated for the 2012 season. 2013 refers to values calculated for the 2013 season. *Total* refers both to the sum of the errors for both *flower* and *senescent* onset estimations and the sum of errors for both seasons (2012 and 2013).

	Flower	Senescent	Total
2012	1.50	0.17	0.83
2013	0.33	0.67	0.50
Total	1.11	0.33	0.72

5.3.2 Measuring Size

The minimization in equation 5.1 is described graphically in figure 5.8 where we varied the value of C from 0 to 0.5 and found that the minimum value in this range was when $C = 0.0909$. The range $([0, 0.5])$ came from making estimations by observing the relation of pixels and millimeters for one element. We compared caliper sizes with the ones estimated with EcoAN and found that their means were 16.72 and 16.02 respectively (Figure 5.9). To describe the difference between the values we calculated the mean of the difference (Equation 5.2) and its standard error (Equation 5.3); we found that their values were 1.14 mm and 0.18 respectively which puts the mean of the differences in the range described by $1.14 \text{ mm} \pm 0.35$. Finally, and to further describe the relation between the caliper and estimated size measurements we calculated the correlation coefficient to be 0.87.

5.3.3 Plot Counts

We created counts using both work-flows and calculated the mean of the absolute difference between the two to be (in number of elements) 12.17 and 3.40 for deployments in 2012 and 2013 respectively (Table 5.5). The phenophase with the most errors during the two years was the "buds" with 15.25 and the one with the least errors was the "flowers" with 6.29. Finally the total difference between the established and EcoAN work-flows for all the phenophases in the two years of deployment was 10.64 elements of difference (Table 5.5).

Table 5.7: Times and Costs of our 2013 deployment. *Est* is the values of the estimated work-flow, *EcoAN* is the values for the EcoAN work-flow, *Saved* is the saved time or cost. All values under *Seconds Per Plot* represent the average time it took to sample a plot, values in parenthesis represent average times per element. *F* is field. *NF* is non-field. *T* is total. All cost values are in Danish kroner. Values are related to phenophase counts only.

	Seconds Per Plot			Cost 2013 (Kr)		
	Est	EcoAN	Saved	Est	EcoAN	Saved
F	108.78(4.22)	40.33(1.69)	68.44(2.53)	136.73	50.70	86.03
NF	0.00(0.00)	104.78(3.37)	-	0	51.46	-
T	108.78(4.22)	145.11(5.06)	-36.33(-0.84)	136.73	102.16	34.57

We used box plots to further characterize the count difference (Figure 5.10). We see that EcoAN counted more buds (Figure 5.10.A) with measurements in 2012 being a major contributor for the over counting (Figure 5.10.B). The over counts and under counts for flowers and for senescence phenophases are more evenly distributed around zero with a few minor outliers (Figure 5.10.A, 5.10.C and 5.10.D). We further see a larger variability in all the phenophases for the 2012 season compared to 2013 (Figure 5.10.B, 5.10.C and 5.10.D).

Related to the counts are the 50% onset estimations (Equation 5.5 and 5.6) originating from both work-flows which we plugged into equation 5.7 in order to find the average absolute difference. For the 50% flowering estimation we see that the difference between the two work-flows averaged to 1.11 *days* and the one for senescent estimations averaged to 0.33 *days* (Table 5.6). The difference for the totality of counts was calculated to be 0.72 *days* and most of the average differences were under one day (Table 5.6).

Finally, the review process for counts done on the three plots of the 2013 deployment resulted in a decrease in number of amendments. In the first review we say six new labels, 15 changes of label and 18 removals (Table 5.2). All those values were lowered on the second review where we got one added label, one removed label and no label changes.

5.3.4 Effort

When calculating the time spent in the field for both the established and EcoAN work-flows we saw that the first was 68.44 seconds faster per plot (2.53 per

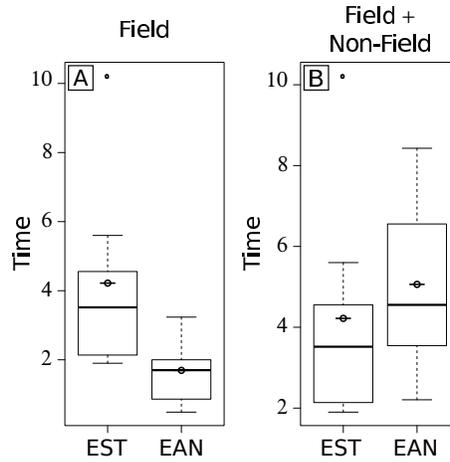


Figure 5.11: Distribution of times for work-flows. *EST* refers to the established work-flow. *EAN* refers to the EcoAN work-flow. A) Field only times for the established and EcoAN work-flows. B) Field plus Non-Field times for the established and EcoAN work-flows. Time is in seconds.

element) than the second (Table 5.7). Once we added the non-field time, EcoAN was 36.33 seconds slower (0.84 per element) than the established work-flow (Table 5.7). If we only consider field times there is a noticeable difference between both work-flows where EcoAN is clearly faster (Figure 5.11). But once we include non-field times in the calculation we see an opposite result where EcoAN spends more time (on average) than the estimated work-flow (Figure 5.11).

We calculated the total cost⁷ of creating phenophase counts to be 136.73 *kr* and 102.16 *kr* for the established and EcoAN work-flow respectively (Table 5.7). The money saved if we had deployed only using the EcoAN work-flow was 34.57 *kr* (Table 5.7). For our three hypothetical situations we calculated savings of 1720.65 *kr*, 12904.93 *kr* and 39252.50 *kr* (Table 5.8).

5.4 Discussion

5.4.1 Measuring Size

We explored methods to estimate the diametrical size of fully bloomed *Dryas* flowers in image series and show its accuracy by comparing our estimations with field measurements. We calculated the average absolute difference between our estimations and the field measurements to be 1.14 *mm* which points to a close approximation fit to be used to estimate diameters from other seasons. Scale in this case is of paramount importance: we were able to calculate our estimations

⁷Currency in Danish crowns

Table 5.8: Cost analysis. Values are in Danish kroner. *E* are costs related to the established work-flow. *A* are costs related to the EcoAN work-flow. *S* represent costs savings. *Field* refers to field specific costs. *Non-Field* refers to work-flow costs out of the field. *Field + Non-Field* is the sum of the *Field* and *Non-Field* values. *Case* refers to one of three hypothetical situations: the first (*Case 1*) is a deployment of 28 plots sampled once a week for four months; the second (*Case 2*) is a deployment of 28 plots sampled once a day for four months; the third and last (*Case 3*) is a deployment of 28 plots sample every day for one year.

	Case	E	A	S
Field	1	6805.919	2523.543	4282.376
	2	51044.39	18926.57	32117.82
	3	155260	57568.33	97691.7
Non-Field	1	0	2523.543	4282.376
	2	0	18926.57	32117.82
	3	0	57568.33	97691.7
Field + Non-Field	1	6805.919	5085.262	1720.657
	2	51044.39	38139.46	12904.93
	3	155260	116007.5	39252.5

assuming that all the images containing flowers were taken from the same point of view, which in our case was managed by EcoIS (Granados, 2010b). This means that, for the cases were this assumption does not hold, a rescaling of the images must be done prior to estimation.

Our error value ($1.14 \text{ mm} \pm 0.35$) represents how close EcoAN size measurements are from the ones done with the caliper but it does not include the variability inherent in field measurements done by technicians (Sykes et al., 1983; Bennett et al., 2000). With this in mind the 1.14 mm error value should be understood as the difference between two approximations to the ground truth which, in this case, is elusive. This does not mean that the two size measurements are useless, indeed the error value points to EcoAN and caliper size measurements potentially being used to calculate estimators about species population fitness which is one of the objectives of measuring flower size.

In our deployment we identified several points where there was a possibility of introducing errors in the measurements with both the caliper and EcoAN methodologies. The difficulty of accurately acquiring the maximum diagonal of a flower (which is malleable) by using a caliper is challenging especially when done in the field and might introduce unwanted variability to the results. For EcoAN's case we identified occlusion as a contributor to error: when a flower was covered by another element, it was difficult to exactly annotate its size. Furthermore there were lens distortions where pixels in the periphery of the image did not represent the same size as in the center which might have contributed in a lesser extent to the overall EcoAN error.

The polygon annotation type (Figure 5.2) played an important role in the

size measurements where it was able to accurately describe morphological traits while reducing time interacting with EcoAN. Additionally, the zoom feature (section 5.2.1.2) was crucial to get close to the flowers and annotate them accurately. Finally, having the annotations as lists of vertices facilitated the automation of size calculation by exploring different diagonal possibilities (Figure 5.4).

By measuring the size of *Dryas* flowers we have demonstrated that EcoAN is able to answer new questions that were not previously conceived. We see how EcoAN uses manual data annotation to achieve a task that is still challenging to fully automate and, in the process, uses data annotation to generate new content. We believe that with this we make the case for both image series and manual annotation as tools that help make use of an increasing amount of ecological data. Additionally we have shown how to increase the longevity of data as image series by describing a process that has the potential to extract new info from old data sets.

5.4.2 Polygon Types

The trade off between speed and accuracy inherent in the four types of annotations (Figure 5.2) is important for annotating images in ecological contexts as it gives a flexibility to the process. The polygon and freehand types (Figure 5.2) give an increasing degree of accuracy to the annotation with the freehand being the most accurate of the two. Though these two types are the most accurate of the four, they are also the most time consuming to create (Table 5.4) because they require more attention and precision from the technician. Accuracy was of great importance while annotating images that led to the size estimations where we used the polygon annotation because of its accuracy and speed.

On the other hand the rectangle and single click annotations (Figure 5.2) are the least accurate but are the fastest (Table 5.4) which made them very useful for phenophase counting. Only by using the single click annotation type (Figure 5.2) were we able to compete with the process in Zackenberg which is efficient to begin with. Single click annotations allowed us to focus on a temporal change only while ignoring spatial and spectral dimensions that were not relevant for the plot count comparisons.

5.4.3 Ghost Annotations

Ghost annotation (Figure 5.3) were crucial in locating hard to find phenophases within image series. It was very useful when searching for buds in the initial images of the series as they are small (Figure 5.3) and generally camouflaged or occluded by larger leaves. In our case we used this feature by ghost annotating from an image containing phenophases with high contrast (e.g. flowers; Figure 5.3.B) into images containing the more challenging ones (e.g buds; Figure 5.3.A). Having the ghost annotations in place, it was just a matter of finding the blue ghosts and making a detailed search around them.

We can see that ghost annotations are not always over their respective phenophase (Figure 5.3) and this is due to differences between consecutive images which came from EcoIS (Granados, 2010b) transformations. Its effects were felt when using ghost annotations to find phenophases where instead of locating the phenophase inside the ghost annotation, we had to search the vicinity. For other deployments using fixed cameras or a serialization process other than EcoIS, the movement will be different.

The senescent state of *Dryas* is not as challenging as the buds because flowers wither with a distinct dark yellow color. It is however very challenging to find the flowers that have been grazed by herbivores as there is no mark of their existence other than a small green stem that is very similar in color to the green leaf background. It is in these cases where the ghost annotations were used again and in the same way as with the buds. They were crucial to accurately pinpoint the whereabouts of the eaten *Dryas* flowers.

5.4.4 Plot Counts

To compare counts between work-flows we show their differences in figure 5.10 where positive values mean more counts for the established work-flow and negative values mean more EcoAN. We see a general tendency to over count buds in the EcoAN work-flow (Figure 5.10.A). We attribute this to the difficulty in spotting small buds out in the field where they might have been missed by technicians. Contrasted with EcoAN which facilitated the search for small elements by providing additional positional information in the form of ghost annotations.

The difference between 2012 and 2013 is exceedingly noticeable for the bud phenophase where 2012 season saw EcoAN over counts of up to 30 individuals (Figure 5.10.B). This difference might be explained by the greater number of plots together with a greater density per plot (data not shown) for the 2012 deployments. More plots mean increased fatigue related to walking distances that have to be covered within one day and greater densities mean increased possibility of missing phenophases. In contrast the counts done with EcoAN can be spread out and do not have to occur the same day, image acquisition requires less effort than doing the counts in the field (Table 5.7) and the chance of missing a phenophase is reduced by using ghost annotations.

For the flower count comparison we see that the error was spread out evenly between over counts and under counts and the median was located close to zero (Figure 5.10.A). This is not surprising as the flowers are easier to detect than the buds given their outstanding color which contrasts with that of the background. There are still errors due to technicians double counting (with the established work-flow) or missing elements (both work-flows). Finally, for the senescence phenophase there was a slight increase in variability compared to the flower (Figure 5.10.A) that is explained by erroneously counting senescent individuals from past seasons or erroneously ignoring individuals thinking it from a past season.

We see that even though there were average error values of up to 19.06 (Table 5.5) we saw little effect transferred to the 50% estimator calculations. Of all the

prediction errors, only in 2012 did we see an average absolute difference that exceeded one day (Table 5.6). The rest of the error values stayed below one and contributed to estimations that, on average, did not differ more than 0.72 days from the original estimations done with the established work-flow. This shows the robustness of the 50% estimation calculations and the possibility of using EcoAN for creating these types of phenological indicators.

Table 5.9: Time analysis. Values are in hours and calculations were based on information contained in table 5.7. *E* are times related to the established work-flow. *A* are times related to the EcoAN work-flow. *S* represent time savings, negative values occur when time for EcoAN is greater than the one for the established work-flow. *Field* refers to field specific times. *Non-Field* refers to work-flow times out of the field. *Field + Non-Field* is the sum of the *Field* and *Non-Field* values. *Case* refer to one of three hypothetical situations: the first (*Case 1*) is a deployment of 28 plots sampled once a week for four months; the second (*Case 2*) is a deployment of 28 plots sampled once a day for four months; the third and last (*Case 3*) is a deployment of 28 plots sample every day for one year.

	Case	E	A	S
Field	1	13.53679	5.019259	8.517531
	2	101.5259	37.64444	63.88148
	3	308.808	114.5019	194.3062
Non-Field	1	0	13.03901	-13.03901
	2	0	97.79259	-97.79259
	3	0	297.4525	-297.4525
Field + Non-Field	1	13.53679	18.05827	-4.521481
	2	101.5259	135.437	-33.91111
	3	308.808	411.9543	-103.1463

5.4.5 Work-Flow Times

Our results show that the total time saved in the field for 2013 was 616 seconds (10.27 minutes); we calculated the mean time saved per plot to be 68.44 (Table 5.7) which we then used to create hypothetical deployments that described the saving potential of EcoAN. The first case is inspired by Zackenberg where we see a savings of 8.52 hours in the field (Table 5.9). In this case, just judging by time savings, it would not be worth changing to EcoAN work-flow as the difference can be covered by leaving a technician one more day in the field (hardly an effort).

At this point we wanted to see the savings related to deployments with increased sampling frequency: for the second case (Table 5.9) we calculated a saving of 63.89 hours (approximately 9 days assuming a day of 7.4 hours) which is approximately 7% of a four month deployment and is compelling as a lot can be done in one week. The last case (Table 5.9) is an extreme one and it resulted

in a time saving of 194.32 hours (26 days) representing approximately 7% of the hypothetical time of deployment (one year). One month is very persuasive if we are trying to push for EcoAN implementation. In general there will be substantial time savings with EcoAN in the field with deployments that sample with high frequency.

Timing for individual elements is also relevant: doing annotations with image series is not very different from using the mechanical counters in the field. The two procedures are very fast with the speed being 3.37 seconds per element with EcoAN and 4.22 seconds for the ones done with the established procedure (Table 5.7). With these times, even if we have hundreds of elements in plots the differences will be of minutes per plot. Which again emphasizes our observation that EcoAN would save considerable amount of time in the field with high frequency or large amount of plots.

But what happens when we add the non-field times? There is no time saved when we consider the whole process: counts with EcoAN exceeds the established work-flow by 36.33 seconds (Table 5.7) when we consider non-field times. Therefore, no matter how much time we save in the field, it is lost when EcoAN goes through the non-field part of the process (Figure 5.5.B). If we were deploying with the current Zackenberg setup (Case 1; Table 5.9), we would spend four and a half hours more on our EcoAN work-flow than the established one and while this is additional time (half a day of work),. It is a small overhead, especially considering the benefits put forward by EcoAN, image series and annotations in general.

5.4.6 Work-Flow Costs

Cost is linked to time through the price of a man hour which is considerably higher in the field (Table 5.3). The cost differences between field and non-field stem from additional expenses related to plan tickets, station fees and additional allowances (Table 5.3). Cost and time are linked as costs can be expressed in terms money spent on one man hour. There is a great difference between field and non-field costs which stems from additional expenses incurred when someone is sent to the field (plane ticket, station fee and field allowance; table 5.3). In Zackenberg's case, the cost of an hour in the field more than doubles the non-field (Table 5.3) which introduces an additional dimension to the effort comparison between the established and the EcoAN work-flow.

Even though the EcoAN work-flow still takes more time than the established work-flow (Table 5.7), we should be able to save money by reducing field times (given their cost; Table 5.3). For our 2013 deployment we calculated a total savings of 86.03 *kr* in the field which was reduced to 34.57 *kr* when we included non-field activity (Table 5.7). 86.03 *kr* is not very significant because our test deployment was small, but it increased when we calculate the savings for deployments at a larger scale. In Zackenberg's case (case 1 in Table 5.8) the savings were of 1720.65 *kr* which is approximately what would be payed as a fee for being in Zackenberg one day but does not really stand out in monitoring budgets considerations of the magnitude of Zackenberg. Only in extreme

cases (case 3 in Table 5.8) do we get savings in the tens of thousands of crowns (39252.50 *kr*).

With EcoAN we save time in the field, but it is not consequential. When we consider non-field, we lose time with EcoAN, but it is not consequential. With EcoAN we save money, but again, it is not consequential. In other words time or cost in using EcoAN should not be reasons to prefer or reject it since they are not consequential when compared to the costs and efforts undertaken in a monitoring effort of the size of Zackenberg. In the worst case scenario (infrequent sampling) EcoAN saves an inconsequential amount of money while adding great potential with the possibility of answering new questions and an alternative to address plot sampling variability.

5.4.7 Incremental Accuracy

As expected from the outset we experienced variability in our review processes. There is great discrepancy in the first review where we see 39 total amendments (Table 5.2). But once most of the errors are addressed, the total drops to just two for the second review. By using EcoAN annotations as a conversation tool between consecutive "visits", technicians were able to make a more accurate assessment of what they were seeing. Consider this as a process where annotations are curated with consecutive review processes that add amendments to previous work. Here there is no possibility of missing and individual that was previously seen as they are all annotated; even the removed elements are annotations.

Curation is easier in an image series than on a phenophase count where the only information provided is the number of a phenophase at a particular date. This is how image series are relevant with in curation processes, they are the richest type of data set to represent phenology which provides spatial, spectral and temporal dimensions simultaneously. This review procedure can be used when curating data and is also useful in a long term monitoring effort when accuracy is important: a process could be designed where EcoAN is used to create phenophase counts with a one step review. This would increase the number of people looking at the results and give would give them a higher level of trustworthiness.

5.5 Conclusions

We have introduced EcoAN, a toolkit designed to annotate image series by overlaying them with labeled polygons. We have presented our toolkit in the light of an increasing amount of ecological image data brought on by the push to scale up ground based measurements. We have related our toolkit with the importance of annotations and the generation of provenance and content from data. We have shown how EcoAN is able to produce accurate measurements of flower size from image data effectively answering questions that were previously ignored with data collected in current and past deployments.

EcoAN was instrumental in creating image series annotations that led to accurate 50% onset estimations and size measurements that had an average error of 1.14 *mm* which shows how new content can be produced with data annotations. We showed how EcoAN can increase the longevity of image data by using acquired sets to extract new information with image annotations. We have described different EcoAN features and how they relate to the image annotation process. Specifically we identified ghost annotations as crucial in detecting hidden elements that were either too small or camouflaged in their surroundings. Additionally we identified the need to have different types of annotations that fit different situations and describe how a trade off between speed and accuracy can affect various tasks.

We have made a parallel between using EcoAN and an established work-flow to produce phenophase counts, and compared them in terms of time and overall cost. We see that EcoAN is not the fastest of the two but does save money in the long run which increases as sampling frequencies raise. Our argument for EcoAN is that it brings considerable added value in the form of data processing, content generation, data curation and general data analysis while having moderate cost savings.

Finally, we suggest a EcoAN and data annotations as tools in a curation process based on image series reviews. We found that the amount of corrections of phenophase counts was reduced with progressive reviews and saw that this reduction depended on having explicit image metadata in the form of labeled annotations. We see how this process can be likened to data curation where a dataset increases in accuracy with increasing curation cycles.

5.6 Acknowledgments

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Concluding Remarks

We see how EcoAN was used to produce annotations that identified phenological phases within image series. It used polygonal structures and labels overlain on top of images to described elements of interest of ecological data generated from a monitoring effort in the high Arctic. It manages various annotation types that fit different situations and can be used to generate content as well as a support tool for curation purposes. Indeed, the concept of generating image series metadata through labeled annotations is at the center of EcoAN's implementation.

EcoAN not only used the spatial dimension in images but also took advantage of temporal changes inherent in image series. The process of ghost

annotating is only possible with image series and lacks meaning if applied to only one image. Furthermore, EcoAN assumes aligned image series and in this sense can work with data provided by EcoIS or any other process that produces series with the same point of view (like a tower camera).

In relation with the growing volume of data, EcoAN is instrumental in creating statistical models -like the one used in EcoIP- that automate data analysis of large datasets. It can also be used to tackle operations on image series that are difficult to automate like accurate (within a millimeter) flower size estimations and in the process contribute to diagnose an every increasing data corpus. As ecological data begins to grow, it is important to create datasets of reference that are properly administer and curated; EcoAN addresses this need by providing a curation procedure that might be used for these purposes.

In creating phenophase counts, accurate size and 50% estimations, EcoAN is adding to the diversity of ways to produce ecological data that inevitably lead to greater amounts of ground based measurements. By indirectly increasing ground based data, EcoAN contributes to scaling it up and strengthening the link with remote sensing measurements. Finally, with annotations comes the ability to differentiate species within the same image series which allows detailed characterizations of ground based data that can more easily be correlated its remote sensing counterpart.

Chapter 6

Conclusions

We presented three toolkits as sections of an overall data pipeline that culminates in the creation of ecological indicators. We see EcoIS as a producer of data in that it successfully creates image series from unaligned image. Both EcoIP and EcoAN are intermediate points where each further modifies image series into an intermediate (e.g. annotations for model training) or final (e.g. ecological estimators) state. A recurring theme throughout our dissertation is the use of image series as our main data unit which we have found to be the richest representation for phenological phenomena. We have also associated our work with the link between ground and remote based measurements by linking the three toolkits to the scaling up of ecological ground measurements.

6.1 EcoIS

With EcoIS we have successfully created aligned image series starting from images of plots taken from different view points. We have not limited our presentation of EcoIS to just software, but also included a description of the complications of including EcoIS as a constitutional element within an Arctic monitoring deployment. We see how our implementation of EcoIS was able to reduce the number of steps needed in the field effectively making the collection of data easier for the technicians. This directly relates to our conclusions from EcoAN where we looked at the bigger picture and measured effort in the field as well as out.

The image alignment implemented in EcoIS depends on special markers that can be easily detected by computer vision methodologies. We found that not all images taken from the field were able to be aligned by EcoIS and compensated for this by taking an average of four pictures per plot. We identified illumination, human error and camera specific behavior as main contributors to the discarded images. We specifically see how transformations done in camera from raw image formats to standard ones affect the effectiveness of EcoIS.

We successfully demonstrated the capacity of EcoIS to produce datasets in

the form of aligned image series for multiple destinations by describing three scenarios that depended on spatially aligned images for their calculations. Though we do see intra-image movement in the resulting image series (virtual movement), we describe how this movement does not hinder any of the three situations in which we tested EcoIS. By listing three different ecological results in the form of metrics, estimations and phenological phase counts, we have demonstrated the capacity of EcoIS to produce usable image series.

With EcoIS and its related work-flow we have reduced the amount of infrastructure needed to produce aligned image series from measurements done in the field. We move away from configurations that put cameras in fixed positions and allow them to move freely effectively dissociating it from housing constructs. This is especially relevant as we look towards using UAVs that acquire images from a continuously moving point.

6.2 EcoIP

With EcoIP we have successfully put together known computer vision and machine learning methodologies into a toolkit designed to automate the analysis of vast amounts of ecological data in the form of image series. It uses statistics based on Naive Bayesian concepts to model the occurrence of different phenological phases in image series. We effectively use color to segment phenophases of interest within images and create sigmoid signals that describe their behavior.

We created a process that is mostly automatic where minimum human interaction is required at the beginning to train the statistical model by using annotations from EcoAN. A command line interface is provided that gives access to various EcoIP features like color transformation comparisons, use of morphological operators and automatic calculation of inflection points.

We successfully summarize the behavior of phenological phases throughout various season in one sigmoid signal that encodes beginning and ending dates in its inflections points. EcoIP is able to locate the moment when different phases start and end, and it is able to do this for multiple species. Sigmoid signals can be analyzed automatically or may be viewed to further study their implications. We verified that EcoIP estimations of beginning and ending phenophase dates were consistent with visual observations of images series. EcoIP stream lines processing and makes it easier for scientists to process more data in the form of image series in an optimal amount of time.

We implemented a signal consolidation methodology for images taken of the same general region as a way to put together information from vast tracts of land in order to scale up ground based measurements. Additionally we identified variability in lighting as well as failures in software and hardware as contributors to errors in our signal. Finally, we corroborate that there is no single color transformation that optimizes the segmentation of phenological phases in image series and provide a way to test and select the color space that best fits a particular situation.

6.3 EcoAN

We have successfully described a systems (EcoAN) that creates metadata for image series by overlaying them with annotations and labels. We have presented our systems in the form of a Graphical User Interface (GUI) that is meant to interact with know lad eagle technicians to further produce content. We have differentiated our system by describing key features like ghosting as well as annotation types and demonstrated their effects on the overall process.

We have characterized the changes needed for EcoAN to be used within a monitoring effort in the high Arctic by comparing the established processes with a work-flow created specifically to fit EcoAN. We measured time and cost for both and see that EcoAN is conducive to time savings in the field and cost savings in the overall process. With this we give insight on how new applications like EcoAN might impact established data acquisition processes.

With EcoAN we were able to accurately estimate flower sizes in image series by using a small number of ground truth measurements. In this way we effectively demonstrate how EcoAN is able to contribute to the answer of new questions like the size of bloomed flowers that were previously ignored. We further described how the type of annotation was an important factor in reaching accurate size estimates.

In order to show that there was no loss of functionality when implementing the EcoAN work-flow, we compared 50% estimations calculated using the established process with the ones from EcoAN and found that the difference between the two did not exceed a day. We also detected differences in the phenophase counts that led us to believe that EcoAN is more suited than the established methodology at finding small camouflaged elements in plots. Finally, we explore the use of EcoAN as a curation tool that takes annotation of image series and increases their accuracy through consecutive reviews.

6.4 Scaling Up Ground Measurements

We see how our three prototypes add to the necessary scale up of ground based data by concentrating in different points of the data pipeline. EcoIS is a producer of data and contributes to the scale up by creating high resolution aligned image series that help to characterize vast tracts of land. EcoIP is a consumer of data and helps the scale up by allowing scientists to summarize big volumes of data in the form of aligned image series into representation that consolidated important changes. EcoAN is a consumer of data and is directly related to the scaling of ground based measurements through the generation of content and facilitation of data curation. It is also indirectly related by being part of the training phase of automated tools like EcoIP.

Chapter 7

Future Work

As we move towards fully automatic ecological data acquisition we see that one of the most interesting developments in the field is the use of Unmanned Aerial Vehicles (UAV) as camera platforms. Its potential stems from its capacity to automate virtually all translation in the field which is a time consuming task, especially in remote areas. We envision a camera being carried into the field by a UAV and visiting scattered plots containing interesting species without any human intervention. Optimally, the only time there would be interaction is for maintenance and in case of malfunction. We see great potential in this approach as it has the capability of increasing ecological data output by increasing sampling frequency. We also understand that there are still great challenges if we are to use UAVs for ecological data acquisition such as limited range and dependability in difficult weather.

Accuracy is always a concern and it should be a top priority as the field moves forward. Increasing the accuracy of our EcoIS transformation algorithm to reduce virtual movement and adjust for camera system distortions will make resulting image series easier to work with. The ISeries error is also of concern as reducing it will diminish the amount of images needed per plot which will reduce the amount of data needed to create the final image series. We are also concerned with increasing accuracy of the estimations done with EcoIP; we feel that by doing so, we increase the incentive for scientists within the community to use our methodologies. With EcoIP it is important to root out false positives caused by colors similar to the elements of interest.

With EcoIP we are especially interested in continuing our research towards new ways of automatically identifying elements of interest within an image. Specifically, we look towards computer vision methodologies that are currently being used in the field like detection based on texture, shape and movement. In general we would like to take advantage of the whole range of characteristics (spectral, spatial and temporal) offered by image series to advance in automatic segmentation of images that lead to better classification.

In EcoIP we explore way of consolidating separate signals calculated from different image series into one ecological estimator. We believe that this practice

requires more attention due to its importance in helping to scale up ground based measurement of large zones. Specifically, we would like to continue our research into ways of taking images captured by different cameras with varying characteristics in terms of response to light and normalizing them into a common image representation. This would aid consolidation and the scale up effort in general because it increases the sources of data.

The use of markers for automatic alignment in EcoIS is also something that we want to avoid as we move closer to ecological data acquisition automation. It is of great interest to remove all infrastructure from the field in order to reduce logistical matters and to minimize anthropogenic effects. This does not come without a challenge as trustworthy points of reference are hard to come by in natural environments prone to constant change. We should bring together a series of points of reference like GPS coordinates and near by inanimate objects in order to return to predefined places of study with accuracy

The interaction with technicians through EcoAN is important to capture expert knowledge and save it for posterity. With this in mind we would like to explore ways of making phenophase annotation easier within EcoAN. Specifically, we would see how image recognition techniques might help in detecting hard to find elements (e.g. *Dryas* buds) and how these can be incorporated into the EcoAN work-flow. Additionally, we would also explore new interactions possibilities by advancing in annotating methodologies like ghosting or annotation types.

Bibliography

- Adamsen, F. J., Coffelt, T. A., Nelson, J. M., Barnes, E. M., Rice, R. C., 2000. Method for Using Images from a Color Digital Camera to Estimate Flower Number. *Crop Science* 40, 704–709.
- Adamsen, F. J., Pinter, P. J., Barns, E., LaMonte, R. L., Wall, G. W., Leavitt, S. W., Kimball, B. A., 1999. Measuring Wheat Senescence with a Digital Camera. *Crop Ecology, Production & Management* 39, 719–724.
- Allen, M. F., Vargas, R., Graham, E. A., Swenson, W., Hamilton, M., Taggart, M., Harmon, T. C., Rat’Ko, A., Rundel, P., Fulkerson, B., Estrin, D., 2007. Soil Sensor Technology: Life within a Pixel. *BioScience* 57 (10), 859.
URL <http://www.jstor.org/stable/4539731>
- Arzberger, P., 2004. Sensors for Environmental Observatories. Tech. Rep. December, NSF, Baltimore.
- Badeck, F.-W., Bondeau, A., Bottcher, K., Doktor, D., Lucht, W., Schaber, J., Sitch, S., May 2004. Responses of spring phenology to climate change. *New Phytologist* 162 (2), 295–309.
URL <http://doi.wiley.com/10.1111/j.1469-8137.2004.01059.x>
- Barr, N., 2003. Monterey Bay aquarium Research Institute, 2003 Annual Report. Tech. rep., Monterey Bay Aquarium Research Institute, Monterey.
- Bauer, M. E., Cipra, J. E., 1973. Identification of Agricultural Crops by Computer Processing of ERTS MSS Data. Tech. rep., Purdue, West Lafayette.
- Bennett, L. T., Judd, T. S., Adams, M. A., 2000. Close-range vertical photography for measuring cover changes in perennial grasslands. *Journal of Range Management* 53 (6), 634–641.
- Bernd Jähne, 2005. *Digital Image Processing*, 6th Edition. Springer.
- Bernd Jähne and Horst Haußecker, 2000a. *Computer Vision and Applications, A Guide for Students and Practitioners*. Ch. Morphological Operators, pp. 483–515.
- Bernd Jähne and Horst Haußecker, 2000b. *Computer Vision and Applications, A Guide for Students and Practitioners*, 1st Edition. Academic Press.

- Betancourt, J. L., Schwartz, M. D., Breshears, D. D., Brewer, C. A., Frazer, G., Gross, J. E., Mazer, S. J., Reed, B. C., Wilson, B. E., 2007. Evolving Plans for the USA National Phenology Network. *Transactions American Geophysical Union* 88 (19), 211.
- Bishop, C. M., 2007. *Pattern Recognition and Machine Learning*, 6th Edition. Springer.
- Blumenthal, D., Booth, D. T., Cox, S. E., Ferrier, C. E., 2007. Large-Scale Aerial Images Capture Details of Invasive Plant Populations. *Rangeland Ecology & Management* 60 (September), 523–528.
- Bolger, D. T., Morrison, T. a., Vance, B., Lee, D., Farid, H., Oct. 2012. A computer-assisted system for photographic mark-recapture analysis. *Methods in Ecology and Evolution* 3 (5), 813–822.
URL <http://doi.wiley.com/10.1111/j.2041-210X.2012.00212.x>
- Booth, D. T., Cox, S. E., Louhaichi, M., Johnson, D. E., 2004. Technical Note: Lightweight Camera Stand for Close-to-Earth Remote Sensing. *Journal of Range Management* 57 (December 2003), 675–678.
- Bradski, G., Daebler, A., 2008a. Learning OpenCV. *Computer Vision with OpenCV Library*. Ch. Camera Models and Calibration, pp. 370 – 404.
- Bradski, G., Daebler, A., 2008b. Learning OpenCV. *Computer Vision with OpenCV Library*. Ch. Image Processing, pp. 109 – 143.
- Bradski, G., Daebler, A., 2008c. Learning OpenCV. *Computer Vision with OpenCV Library*. Ch. Contours, pp. 222 – 264.
- Bradski, G., Daebler, A., 2008d. Learning OpenCV. *Computer Vision with OpenCV Library*. Ch. Image Transforms, pp. 144 – 192.
- Brown, T., Zimmermann, C., 2006. TimeSystem: Time-lapse Recording and Analysis software package. (Version 1.08.02) [Software]. <http://www.time-science.com/>, [Online; accessed 15-Sep-2013].
- Brown, T., Zimmermann, C., Panneton, W., Noah, N., Borevitz, J., Jan. 2012. High-resolution, time-lapse imaging for ecosystem-scale phenotyping in the field. In: Normanly, J. (Ed.), *High Throughput Phenotyping in Plants. Methods in molecular biology*. Vol. 918. Springer, New York, USA, pp. 71–96.
URL <http://www.ncbi.nlm.nih.gov/pubmed/22893287>
- Camargo, a., Smith, J., Jan. 2009. An image-processing based algorithm to automatically identify plant disease visual symptoms. *Biosystems Engineering* 102 (1), 9–21.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511008002870>
- Chen, Z., Chen, W., Leblanc, S. G., Henry, G. H. R., 2010. Digital Photograph Analysis for Measuring Percent Plant Cover in the Arctic. *Arctic* 63 (3), 315–326.

- Cheng, H. D., Jiang, X. H., Sun, Y., Wang, J., 2001. Color image segmentation : advances and prospects. *Pattern Recognition* 34 (September 2000), 2259–2281.
- CIE (Commission Internationale de l'Eclairage), 1986. *Colorimetry*. CIE Publication 15.22 ed. Tech. rep., Central Bureau of the Commission Internationale de l'Eclairage, Vienna.
- Cooper, W. S., 1924. An Apparatus for Photographic Recording of Quadrats. *Journal of Ecology* 12 (2), 317–321.
- Crimmins, M. a., Crimmins, T. M., Jun. 2008. Monitoring plant phenology using digital repeat photography. *Environmental Management* 41 (6), 949–58.
URL <http://www.ncbi.nlm.nih.gov/pubmed/18288519>
- Duhaime, R. J., August, P. V., Wright, W. R., 1997. Automated Vegetation Mapping Using Digital Orthophotography. *Photogrammetric Engineering & Remote Sensing* 63 (11), 1295–1302.
- Ellebjaerg, S. M., Tamstorf, M. P., Illeris, L., Michelsen, A., Hansen, B. U., 2008. High-Arctic Ecosystem Dynamics in a Changing Climate. Elsevier, London, Ch. Inter-Annual Variability and Controls of Plan Phenology and Productivity at Zackenberg, pp. 249–273.
- Emmott, S., 2006. Towards 2020 science. Tech. rep., Microsoft Research, Cambridge.
- Eyal, Z., Brown, M. B., 1975. A Quantitative Method for Estimating Density of *Septora Tritici* Pycnidia on Wheat Leaves. *phytopathology* 66, 11–14.
- Gerten, D. M., Wiese, M. V., 1987. Microcomputer-Assisted Video Image Analysis of Lodging in Winter Wheat. *Photogrammetric Engineering & Remote Sensing* 53 (1), 83–88.
- Gilg, O., Kovacs, K. M., Aars, J., Fort, J., Gauthier, G., Grémillet, D., Ims, R. a., Meltofte, H., Moreau, J., Post, E., Schmidt, N. M., Yannic, G., Bollache, L., Feb. 2012. Climate change and the ecology and evolution of Arctic vertebrates. *Annals of the New York Academy of Sciences* 1249, 166–90.
URL <http://www.ncbi.nlm.nih.gov/pubmed/22329928>
- Graham, E. A., Hamilton, M. P., Mishler, B. D., Rundel, P. W., Hansen, M. H., Jul. 2006. Use of a Networked Digital Camera to Estimate Net CO₂ Uptake of a DesiccationTolerant Moss. *International Journal of Plant Sciences* 167 (4), 751–758.
URL <http://www.jstor.org/stable/10.1086/503786>
- Graham, E. a., Riordan, E. C., Yuen, E. M., Estrin, D., Rundel, P. W., Jan. 2010. Public Internet-connected cameras used as a cross-continental ground-based plant phenology monitoring system. *Global Change Biology* 16, 3014–3023.
URL <http://doi.wiley.com/10.1111/j.1365-2486.2010.02164.x>

- Graham, E. A., Yuen, E. M., Robertson, G. F., Kaiser, W. J., Hamilton, M. P., Rundel, P. W., Mar. 2009. Budburst and leaf area expansion measured with a novel mobile camera system and simple color thresholding. *Environmental and Experimental Botany* 65 (2-3), 238–244.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0098847208001214>
- Granados, J. A., 2010a. Ecological Image Processor (EcoIP). <https://github.com/Joelgranados/EcoIP>, [Online; accessed 10-Jul-2013].
- Granados, J. A., 2010b. Ecological Image Serilizer (EcoIS). <https://github.com/Joelgranados/EcoIS>, [Online; accessed 09-Apr-2013].
- Granados, J. A., 2010c. Image Annotation tool. <https://github.com/Joelgranados/EcoAN>, [Online; accessed 11-Apr-2013].
- Granados, J. A., Graham, E. A., Bonnet, P., Yuen, E. M., Hamilton, M., 2013. EcoIP : An open source image analysis toolkit to identify different stages of plant phenology for multiple species with pan tilt zoom cameras. *Ecological Informatics* 15, 58–65.
- Granitto, P. M., Navone, H. D., Verdes, P. F., Ceccatto, H. A., 2000. Weed Seeds Identification by Machine Vision. Tech. rep., Universidad Nacional de Rosario, Rosario.
- Grémillet, D., 2012. Robots in Ecology: Welcome to the machine. *Open Journal of Ecology* 02 (02), 49–57.
- Hey, T., Trefethen, A., 2003. The Data Deluge: An e-Science Perspective. In: Berman, F., Fox, G., Hey, A. J. (Eds.), *Grid Computing - Making the Global Infrastructure a Reality*, 1st Edition. No. January 2003. Wiley, Ch. 37, pp. 1–17.
- Hinkler, J., Pedersen, S. B., Rasch, M., Hansen, B. U., Jan. 2002. Automatic snow cover monitoring at high temporal and spatial resolution, using images taken by a standard digital camera. *International Journal of Remote Sensing* 23 (21), 4669–4682.
URL <http://www.tandfonline.com/doi/abs/10.1080/01431160110113881>
- Høye, T. T., Post, E., Meltofte, H., Schmidt, N. M., Forchhammer, M. C., Jun. 2007. Rapid advancement of spring in the High Arctic. *Current biology* 17 (12), R449–51.
URL <http://www.ncbi.nlm.nih.gov/pubmed/17580070>
- Høye, T. T., Post, E., Schmidt, N. M., Trøjelsgaard, K., Forchhammer, M. C., Jun. 2013. Shorter flowering seasons and declining abundance of flower visitors in a warmer Arctic. *Nature Climate Change* 3 (6), 1–5.
URL <http://www.nature.com/doi/abs/10.1038/nclimate1909>

- Ide, R., Oguma, H., Sep. 2010. Use of digital cameras for phenological observations. *Ecological Informatics* 5 (5), 339–347.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1574954110000762>
- Iler, A. M., Hye, T. T., Inouye, D. W., Schmidt, N. M., 2013. Long-term trends mask variation in the direction and magnitude of short-term phenological shifts. *American Journal of Botany*.
URL <http://www.amjbot.org/content/early/2013/05/08/ajb.1200490.abstract>
- ITU, 1992. Information technology - digital compression and coding of continuous-tone still images - requirements and guidelines. Tech. rep., International Telecommunication Union (ITU), Geneva, Switzerland.
- Johnson, S. G., Delph, L. F., Elderkin, C. L. D. A. M., 1995. The Effect Of Petal-Size Manipulation On Pollen Removal, Seed Set, And Insect-Visitor Behavior In *Campanula-Americana*. *Oecologia* 102 (2), 174–179.
URL <http://agris.fao.org/agris-search/search/display.do?f=1996/DE/DE96076.xml;DE95K0437>
- Jolly, W. M., Nemani, R., Running, S. W., Apr. 2005. A generalized, bioclimatic index to predict foliar phenology in response to climate. *Global Change Biology* 11 (4), 619–632.
URL <http://doi.wiley.com/10.1111/j.1365-2486.2005.00930.x>
- Jones, S. E., Chiu, C.-Y., Kratz, T. K., Wu, J.-T., Shade, A., McMahon, K. D., 2008. Typhoons initiate predictable change in aquatic bacterial communities. *Limnology and Oceanography* 53 (4), 1319–1326.
URL http://www.aslo.org/lo/toc/vol_53/issue_4/1319.html
- Karasti, H., Baker, K. S., 2008. Digital Data Practices and the Long Term Ecological Research Program Growing Global. *The international Journal of Digital Curation* 3 (2), 42–58.
- Kopf, J., Uyttendaele, M., Deussen, O., Cohen, M. F., 2007. Capturing and viewing gigapixel images. Tech. rep., GigaPixel, New York, New York, USA.
URL <http://portal.acm.org/citation.cfm?doid=1275808.1276494>
- Ksikisi, T. S., El-Keblawy, A. a., Jan. 2013. Floral diversity in desert ecosystems: Comparing field sampling to image analyses in assessing species cover. *BMC ecology* 13 (1), 22.
- Kumar, S., Mittal, G., Jan. 2008. Geometric and optical characteristics of five microorganisms for rapid detection using image processing. *Biosystems Engineering* 99 (1), 1–8.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511007002772>
- Laliberte, a. S., Rango, A., Herrick, J. E., Fredrickson, L., Burkett, L., 2007. An Object-based image analysis approach for determining fractional cover of senescent and green vegetation with digital plot photography. *Journal of Arid Environments* 69, 1–14.

- Leinfelder, B., Bowers, S., Brien, M. O., Jones, M. B., Schildhauer, M., 2010. Using Semantic Metadata for Discovery and Integration of Heterogeneous Ecological Data. Tech. rep., University of California Santa Barbara, Santa Barbara.
- Liang, L., Schwartz, M. D., Fei, S., Mar. 2012. Photographic assessment of temperate forest understory phenology in relation to springtime meteorological drivers. *International journal of biometeorology* 56 (2), 343–55.
URL <http://www.ncbi.nlm.nih.gov/pubmed/21557038>
- Lindenmayer, D. B., Likens, G. E., Sep. 2009. Adaptive monitoring: a new paradigm for long-term research and monitoring. *Trends in ecology & evolution* 24 (9), 482–6.
URL <http://www.ncbi.nlm.nih.gov/pubmed/19409648>
- Litwin, D., Tjahjadi, T., Yang, Y.-H., Aug. 2001. Color image segmentation using optical models. In: Pluta, M. (Ed.), *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*. Vol. 4535 of *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*. pp. 137–144.
- Lovett, G. M., Burns, D. a., Driscoll, C. T., Jenkins, J. C., Mitchell, M. J., Rustad, L., Shanley, J. B., Likens, G. E., Haeuber, R., Jun. 2007. Who needs environmental monitoring? *Frontiers in Ecology and the Environment* 5 (5), 253–260.
- Lucieer, A., Robinson, S., Turner, D., Harwin, S., 2012. Using a micro-UAV for ultra-high resolution multi- sensor observations of Antarctic moss beds. In: *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. 1. *International Society of Photogrammetry and Remote Sensing (ISPRS)*, Tasmania, pp. 429–433.
- Luscier, J. D., Thompson, W. L., Wilson, J. M., Gorham, B. E., Dragut, D., Dragut, L. D., 2006. Using digital photographs and object-based image analysis to estimate percent ground cover in vegetation plots. *Frontiers in Ecology and the Environment* 4 (8), 408–413.
- Macfarlane, C., Grigg, A., Evangelista, C., Sep. 2007. Estimating forest leaf area using cover and fullframe fisheye photography: Thinking inside the circle. *Agricultural and Forest Meteorology* 146 (1-2), 1–12.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168192307001177>
- Madin, J., Bowers, S., Schildhauer, M., Krivov, S., Pennington, D. D., Villa, F., 2007. An ontology for describing and synthesizing ecological observation data. *Ecological Informatics* 2 (3), 279–296.
- Magnuson, J. J., 1990. Long-Term Ecological Research and the Invisible Present. *BioScience* 40 (August), 495–501.
- MathWorks, 2009. Matlab. <http://www.mathworks.se/index.html>, version 7.9.0.529 (R2009b) - [Online; accessed 15-Sep-2013].

- Meltofte, H., Christensen, T. R., Elberling, B., Forchhammer, M. C., Rasch, M. (Eds.), 2008a. *Advances in Ecological Research. High-Arctic Ecosystem Dynamics in a Changing Climate*. Elsevier, London.
- Meltofte, H., Christensen, T. R., Elberling, B., Forchhammer, M. C., Rasch, M., 2008b. *High-Arctic Ecosystem Dynamics in a Changing Climate*. Elsevier, London, Ch. Introduction, pp. 1–12.
- Meltofte, H., Christensen, T. R., Elberling, B., Forchhammer, M. C., Rasch, M., 2008c. *High-Arctic Ecosystem Dynamics in a Changing Climate*. Elsevier, London, Ch. The study area at Zackenberg, pp. 101–110.
- Metzger, K. J., Klaper, R., Thomas, M. a., Jan. 2011. Implications of informatics approaches in ecological research. *Ecological Informatics* 6 (1), 4–12.
URL <http://linkinghub.elsevier.com/retrieve/pii/S157495411000110X>
- Michener, W. K., Porter, J., Servilla, M., Vanderbilt, K., Jan. 2011. Long term ecological research and information management. *Ecological Informatics* 6 (1), 13–24.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1574954110001159>
- Mizunuma, T., Wilkinson, M., L. Eaton, E., Mencuccini, M., I. L. Morison, J., Grace, J., Feb. 2013. The relationship between carbon dioxide uptake and canopy colour from two camera systems in a deciduous forest in southern England. *Functional Ecology* 27 (1), 196–207.
URL <http://doi.wiley.com/10.1111/1365-2435.12026>
- Montes, F., Pita, P., Rubio, A., Cañellas, I., Aug. 2007. Leaf area index estimation in mountain even-aged *Pinus silvestris* L. stands from hemispherical photographs. *Agricultural and Forest Meteorology* 145 (3-4), 215–228.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168192307001165>
- Moran, M. S., Inoue, Y., Barnes, E. M., 1997. Opportunities and Limitations for Image-Based Remote Sensing in Precision Crop Management. *Remote Sensing of Environment* 61, 319–3461.
- Morisette, J. T., Richardson, A. D., Knapp, A. K., Fisher, J. I., Graham, E. a., Abatzoglou, J., Wilson, B. E., Breshears, D. D., Henebry, G. M., Hanes, J. M., Liang, L., Jun. 2009. Tracking the rhythm of the seasons in the face of global change: phenological research in the 21st century. *Frontiers in Ecology and the Environment* 7 (5), 253–260.
URL <http://www.esajournals.org/doi/abs/10.1890/070217>
- Mulla, D. J., Apr. 2013. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering* 114 (4), 358–371.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511012001419>

- Nagai, S., Maeda, T., Gamo, M., Muraoka, H., Suzuki, R., Nasahara, K. N., Mar. 2011. Using digital camera images to detect canopy condition of deciduous broad-leaved trees. *Plant Ecology & Diversity* 4 (1), 79–89.
URL <http://www.tandfonline.com/doi/abs/10.1080/17550874.2011.579188>
- National Institutes of Health, 2008. ImageJ, Image Processing And Analysis in Java. <http://rsbweb.nih.gov/ij/>, [Online; accessed 09-Apr-2013].
- Neto, J. a. C., Meyer, G. E., Jones, D. D., Apr. 2006. Individual leaf extractions from young canopy images using GustafsonKessel clustering and a genetic algorithm. *Computers and Electronics in Agriculture* 51 (1-2), 66–85.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168169905001912>
- Owens, M. K., Gardiner, H. G., Norton, B. E., 1985. A Photographic Technique for Repeated Mapping of Rangeland Plant Populations in Permanent Plots. *Journal of Range Management* 38 (May), 231–232.
- Panneton, B., Brouillard, M., Apr. 2009. Colour representation methods for segmentation of vegetation in photographs. *Biosystems Engineering* 102 (4), 365–378.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511009000191>
- Parmesan, C., Yohe, G., 2003. A globally coherent fingerprint of climate change impacts across natural systems. *Nature* 421, 37–42.
URL <http://dx.doi.org/10.1038/nature01286>
- Parrott, L., Proulx, R., Thibert-Plante, X., Dec. 2008. Three-dimensional metrics for the analysis of spatiotemporal data in ecology. *Ecological Informatics* 3 (6), 343–353.
URL <http://linkinghub.elsevier.com/retrieve/pii/S157495410800037X>
- Payne, A., Walsh, K., Subedi, P., Jarvis, D., Feb. 2013. Estimation of mango crop yield using image analysis Segmentation method. *Computers and Electronics in Agriculture* 91, 57–64.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168169912002669>
- Pennington, D. D., Madin, J., Villa, F., Athanasiadis, I., 2007. Computer-Supported Collaborative Knowledge Modeling in Ecology. Tech. rep., University of New Mexico, Albuquerque.
- Pierce, W. R., Eddleman, L. E., 1969. A Field Stereophotographic Technique for Range Vegetation Analysis.
- Pierce, W. R., Eddleman, L. E., 1973. A Test of Stereophotographic Sampling in Grasslands. *Journal of Range Management* 26 (2).
- Post, E., Forchhammer, M. C., Bret-Harte, M. S., Callaghan, T. V., Christensen, T. R., Elberling, B., Fox, A. D., Gilg, O., Hik, D. S., Høye, T. T., Ims, R. a., Jeppesen, E., Klein, D. R., Madsen, J., McGuire, a. D., Rysgaard, S., Schindler, D. E., Stirling, I., Tamstorf, M. P., Tyler, N. J. C., van der

- Wal, R., Welker, J., Wookey, P. a., Schmidt, N. M., Aastrup, P., Sep. 2009. Ecological dynamics across the Arctic associated with recent climate change. *Science (New York, N.Y.)* 325 (5946), 1355–8.
URL <http://www.ncbi.nlm.nih.gov/pubmed/19745143>
- R Core Team, 2013. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
URL <http://www.R-project.org/>
- Ratliff, R. D., Westfall, S. E., 1972. A Simple Stereophotographic Technique for Analyzing Small Plots. *Journal of Range Management* 26 (2), 147–148.
- Richardson, A. D., Braswell, B. H., Hollinger, D. Y., Jenkins, J. P., Ollinger, S. V., Sep. 2009. Near-surface remote sensing of spatial and temporal variation in canopy phenology. *Ecological applications : a publication of the Ecological Society of America* 19 (6), 1417–28.
URL <http://www.ncbi.nlm.nih.gov/pubmed/19769091>
- Richardson, A. D., Jenkins, J. P., Braswell, B. H., Hollinger, D. Y., Ollinger, S. V., Smith, M.-L., May 2007. Use of digital webcam images to track spring green-up in a deciduous broadleaf forest. *Oecologia* 152 (2), 323–34.
URL <http://www.ncbi.nlm.nih.gov/pubmed/17342508>
- Root, T. L., Price, J. T., Hall, K. R., Schneider, S. H., 2003. Fingerprints of global warming on wild animals and plants. *Nature* 421, 57–60.
- Rosenzweig, C., Karoly, D., Vicarelli, M., Neofotis, P., Wu, Q., Casassa, G., Menzel, A., Root, T. L., Estrella, N., Seguin, B., Tryjanowski, P., Liu, C., Rawlins, S., Ineson, A., May 2008. Attributing physical and biological impacts to anthropogenic climate change. *Nature* 453 (7193), 353–7.
URL <http://www.ncbi.nlm.nih.gov/pubmed/18480817>
- Roshier, D., Lee, S., Boreland, F., 1996. A digital technique for recording of plant population data in permanent plots. *Journal of Range Management* 50 (January), 106–109.
- Ruffi, M., Scaramuzza, D., Siegart, R., Sep. 2008. Automatic detection of checkerboards on blurred and distorted images. *International Conference on Intelligent Robots and Systems*, 3121–3126.
URL <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4650703>
- Ryu, Y., Verfaillie, J., Macfarlane, C., Kobayashi, H., Sonnentag, O., Vargas, R., Ma, S., Baldocchi, D. D., Nov. 2012. Continuous observation of tree leaf area index at ecosystem scale using upward-pointing digital cameras. *Remote Sensing of Environment* 126, 116–125.
URL <http://linkinghub.elsevier.com/retrieve/pii/S003442571200346X>
- Saitoh, T. M., Nagai, S., Saigusa, N., Kobayashi, H., Suzuki, R., Nasahara, K. N., Muraoka, H., Sep. 2012. Assessing the use of camera-based indices

- for characterizing canopy phenology in relation to gross primary production in a deciduous broad-leaved and an evergreen coniferous forest in Japan. *Ecological Informatics* 11, 45–54.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1574954112000416>
- Schmidt, N. M., Hansen, L. H., Meltofte, H., Hansen, J., Berg, T. B., 2012a. BioBasis Manual. Tech. rep., Aarhus University, Roskilde.
- Schmidt, N. M., Ims, R. a., Høye, T. T., Gilg, O., Hansen, L. H., Hansen, J., Lund, M., Fuglei, E., Forchhammer, M. C., Sittler, B., Nov. 2012b. Response of an arctic predator guild to collapsing lemming cycles. *Proceedings. Biological sciences / The Royal Society* 279 (1746), 4417–22.
URL <http://www.ncbi.nlm.nih.gov/pubmed/22977153>
- Schwartz, M. D., Betancourt, J. L., Weltzin, J. F., Aug. 2012. From Caprio's lilacs to the USA National Phenology Network. *Frontiers in Ecology and the Environment* 10 (6), 324–327.
URL <http://www.esajournals.org/doi/abs/10.1890/110281>
- Serranti, S., Cesare, D., Bonifazi, G., May 2013. The development of a hyperspectral imaging method for the detection of Fusarium-damaged, yellow berry and vitreous Italian durum wheat kernels. *Biosystems Engineering* 115 (1), 20–30.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511013000196>
- Slaughter, D. C., Giles, D. K., Downey, D., Apr. 2008. Autonomous robotic weed control systems: A review. *Comput. Electron. Agric.* 61 (1), 63–78.
URL <http://dx.doi.org/10.1016/j.compag.2007.05.008>
- Slayback, D. A., Pinzon, J. E., Los, S. O., Tucker, C. J., 2003. Northern hemisphere photosynthetic trends 1982 - 99. *Global Change Biology* 9, 1–15.
- Smith, A. R., 1978. Color Gamut Transformation Pairs. In: Beatty, J., Kellogg, S. (Eds.), *Computer Graphics*. IEEE Comput Society Press, pp. 12–19.
- Song, D., Qin, N., Goldberg, K., 2006. A minimum variance calibration algorithm for pan-tilt robotic cameras in natural environments. In: *Proceedings 2006 IEEE International Conference on Robotics and Automation*. Ieee, pp. 3449–3456.
- Sonntag, O., Hufkens, K., Teshera-Sterne, C., Young, A. M., Friedl, M., Braswell, B. H., Milliman, T., OKeefe, J., Richardson, A. D., Jan. 2012. Digital repeat photography for phenological research in forest ecosystems. *Agricultural and Forest Meteorology* 152, 159–177.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168192311002851>
- Sorokin, A., Forsyth, D., Goodwin, N., 2008. Utility data annotation with Amazon Mechanical Turk. In: *Computer Vision and Pattern Recognition Workshops*. No. c. IEEE Computer Society, Anchorage, AK, pp. 1–8.

- Sparks, T., Carey, P., 1995. The responses of species to climate over two centuries : an analysis of the Marsham phenological record , 1736-1947. *Journal of Ecology* 83 (2), 321–329.
- Stendel, M., Christensen, J. H., Petersen, D., 2008. High-Arctic Ecosystem Dynamics in a Changing Climate. Elsevier, London, Ch. Arctic Climate and Climate Change with a Focus on Greenland, pp. 13–43.
- Stöckli, R., Vidale, P. L., Sep. 2004. European plant phenology and climate as seen in a 20-year AVHRR land-surface parameter dataset. *International Journal of Remote Sensing* 25 (17), 3303–3330.
URL <http://www.tandfonline.com/doi/abs/10.1080/01431160310001618149>
- Swain, K. C., Nørremark, M., Jørgensen, R. N., Midtiby, H. S., Green, O., Dec. 2011. Weed identification using an automated active shape matching (AASM) technique. *Biosystems Engineering* 110 (4), 450–457.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511011001656>
- Sykes, J., Horrill, A., Mountford, M., 1983. Use of Visual Cover Assessments as Quantitative Estimators of Some British Woodland Taxa. *Journal of Ecology* 71 (2), 437–450.
- Torres, M., Qiu, G., Sep. 2013. Automatic Habitat Classification using Image Analysis and Random Forest. *Ecological Informatics*.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1574954113000733>
- Tyler, N. J. C., Forchhammer, M. C., Øritsland, N. A., 2008. Nonlinear Effects of Climate and Density in the Dynamics of a Fluctuating Population of Reindeer. *Ecology* 89 (6), 1675–1686.
- Vliet, A. J. H. V., Groot, R. S. D., Bellens, Y., Braun, P., Bruegger, R., Bruns, E., Clevers, J., Estreguil, C., Flechsig, M., Jeanneret, F., Maggi, M., Martens, P., Menne, B., Menzel, A., Sparks, T., 2003. The European Phenology Network. *International journal of biometeorology* 47, 202–212.
- Wackerly, D., Mendenhall, W., Scheaffer, R., 2008. *Mathematical Statistics With Applications*, 7th Edition. Thomson Learning.
- Wallen, V. R., Philpotts, L. E., 1971. Disease Assessment with IR-Color. *Photogrammetric Engineering & Remote Sensing* 1 (679), 443–446.
- Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T. J. C., Fromentin, J.-M., Hoegh-Guldberg, O., Bairlein, F., 2002. Ecological responses to recent climate change. *Nature* 416, 389–395.
URL <http://dx.doi.org/10.1038/416389a>
- Wells, K. F., 1970. Measuring Vegetation Changes On Fixed Quadrants by Vertical Ground Stereophotography. Tech. rep., CSIRO, Deniliquin.

- Wiwart, M., Fordoski, G., uk Goaszewska, K., Suchowilska, E., Jan. 2009. Early diagnostics of macronutrient deficiencies in three legume species by color image analysis. *Computers and Electronics in Agriculture* 65 (1), 125–132.
URL <http://linkinghub.elsevier.com/retrieve/pii/S016816990800197X>
- Woebbecke, D. M., Meyer, G. E., Bargen, K. V., Mortensen, D. A., 1995. Color Indices for Weed Identification Under Various Soil, Residue, and Lighting Conditions. *Transactions of the ASAE* 38 (1), 259–269.
- Wright, S. J., Carrasco, C., Calderón, O., Paton, S., 1999. The el niño southern oscillation, variable fruit production, and famine in a tropical forest. *Ecology* 80 (5), 1632–1647.
- Wu, D., Wang, S., Liu, K., Yu, X., He, Y., Wang, Z., May 2012. Rapid measurement of morphological features of *Spirulina* microalgae filaments using microscopy and image processing algorithms. *Biosystems Engineering* 112 (1), 35–41.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1537511012000293>
- ZERO-Zackenberg, 2013. Zackenberg Ecological Operations: Price List. http://www.zackenberg.dk/price_list/, [Online; accessed 24-Aug-2013].
- Zhao, J., Zhang, Y., Tan, Z., Song, Q., Liang, N., Yu, L., Zhao, J., Jul. 2012. Using digital cameras for comparative phenological monitoring in an evergreen broad-leaved forest and a seasonal rain forest. *Ecological Informatics* 10, 65–72.
URL <http://linkinghub.elsevier.com/retrieve/pii/S1574954112000192>
- Zheng, H., Lu, H., Apr. 2012. A least-squares support vector machine (LS-SVM) based on fractal analysis and CIE Lab parameters for the detection of browning degree on mango (*Mangifera indica* L.). *Computers and Electronics in Agriculture* 83, 47–51.
URL <http://linkinghub.elsevier.com/retrieve/pii/S0168169912000257>