AUTOMATED REPEAT DIGITAL PHOTOGRAPHY FOR CONTINUOUS
PHENOLOGICAL MONITORING: AN ANALYSIS OF FLOWERING IN A
SEMIARID SHRUBLAND

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ABSTRACT

The use of repeat digital photography to track observations of phenology and enhance understanding of climate-ecosystem interactions has become increasingly popular due to the many advantages it has over traditional observer-based methods. Several studies have used digital cameras to document metrics of greenness and senescence in herbaceous and tree species but very few have used digital photography to monitor flowering, especially in shrubs, which is a common plant growth form within many semiarid regions. For this thesis research, digital game cameras were used to monitor flowering phenology of *Larrea tridentata*, a widespread and dominant shrub species throughout North American warm desert ecosystems. Comparing three digital image analysis techniques at three different lens-to-subject distances, flowering metrics of duration, peak flowering, and number of flowers were analyzed and compared. Information contained within this study offers many applications within the research community in addition to citizen science projects focusing on phenology data collection.
1. INTRODUCTION

1.1 The use of automated repeat digital photography as a means to monitor phenology

Climate change involves alterations to temperature as well as precipitation patterns, and effects are predicted to vary across regions (IPCC 2007a). These changes will have significant influences on land surface characteristics such as soil moisture, vegetation patterns, albedo, and microtopography (Houghton 1996) in addition to having a variety of ecological consequences (IPCC 2007b), many of which are still poorly understood. Given the fine-scale of synchrony amongst organisms, if one species responds in a unique way to these expected changes in climate patterns then other species that are dependent upon it could be negatively affected, causing serious consequences to the associations, co-adaptations, and interactions that are essential to ecological functioning (Hegland et al. 2009; Preston et al. 2008). Increasingly more studies are addressing these issues (e.g., Malhi and Phillips 2004; Pertoldi and Bach 2007); however, continued improvement of the methods, tools, and approaches used to understand these ecosystem-climate transitions now and into the future are needed.

In climates with distinct seasonality (i.e., temperate zones), organisms adapt to climate variability across the year through their phenology (Leith 1974). For vegetation, phenology can be easily observed throughout the annual cycles; for instance, the noticeable green-up and flowering in the spring as temperatures warm and days become longer, and ripening of fruits and drop of leaves in the fall months when days shorten and
cooler weather sets in. Phenological observations have been recorded for centuries (Aono and Kazui 2008; Ledneva et al. 2004; Miller-Rushing and Primack 2008), but have gained increasing importance and attention in recent decades as climate change awareness has amplified. Phenology data can provide valuable insights into how climate patterns influence ecological systems at multiple scales of observation (Chuine et al. 2000; IPCC 2007b; Menzel 2002; Penuelas et al. 2004). Triggers to phenological activity include photoperiod, moisture, temperature (Rathcke and Lacey 1985; Loomis and Connor 1992), and light availability (Huete et al. 2006). Plant phenologies are strongly coupled to photoperiod (Corbesier et al. 1996; Hempel et al. 1998), but also largely depend on temperature conditions (Rathcke and Lacey 1985; Penuelas et al. 2002; Moza and Bhatnagar 2005). For example, increasing spring temperatures are needed in order for many plants to break from winter dormancy and grow vegetative or reproductive structures (Moza and Bhatnagar 2005). Resource availability also plays a role in the timing of phenological events, with soil water content acting as the primary factor affecting vegetative growth and flowering of many plant species (Cunningham et al. 1979; Singh and Kushwaha 2005).

If divergence from typical annual climatic patterns occurs, some plants may be less well adapted to the surrounding conditions, especially the longer-lived woody species (i.e., shrubs and trees) that are not able to rapidly evolve and adjust to such environmental transitions (Kramer et al. 2000). As a result, these plants will primarily respond through alterations in timing of phenological events. Such shifts for these woody species could include earlier onset of spring events (Badeck et al. 2004; Fitter and Fitter
2002), shifted habitat ranges (Malcolm et al. 2002), a lengthening of the growing season in many regions (Menzel and Estrella 2001; Menzel and Fabian 1999), and potentially many other phenological responses that are not well understood.

In order to better comprehend these recent and predicted changes and their implications, it is important to properly monitor and evaluate ecosystem responses to climate conditions. Accurate information on plant phenology is vital for understanding flowering and fruit production in agriculturally important plants (Chuine et al. 2004), for validating land surface phenology remote sensing products (Schwartz 1997), and for creating reliable climate models (Lu et al. 2001; Arora and Boer 2004).

Before recent technological advances, the most common and affordable means to monitor specific phenological events in plants was through manually recorded human observations at discrete intervals. The accuracy of this manual technique depends heavily upon the observational skills and effort of the observers and is always susceptible to a certain degree of bias and inconsistent data collection frequency (Menzel 2002; Booth et al. 2005). To resolve these issues, researchers have begun to utilize “pheno-cams” (e.g., Kurc and Benton, in press; Crimmins and Crimmins 2008; Richardson et al. 2007), which are in situ cameras set up to capture digital images across time as a means to monitor phenology. Pheno-cam methods hold many advantages over traditional observation-based recording. They allow for continuous, regular monitoring across time (Richardson et al. 2007; Ahrends et al. 2008; Crimmins and Crimmins 2008), provide a permanent data record of phenological stages (Richardson et al. 2007), reduce labor and costs (Seefeldt and Booth 2006; Przeszowska et al. 2006), and decrease chances for in

Detecting the timing of greenness and senescence in forest ecosystems (Richardson et al. 2007; Ahrends et al. 2008) and herbaceous plots (Adamsen et al. 1999; Crimmins and Crimmins 2008) has been carried out with on-ground digital photography, but few studies have focused on detecting the metric of flowering. In fact, to the knowledge of the author there have been no studies using pheno-cams to monitor flowering in shrubs, an increasingly dominant plant functional group throughout many temperature regions of the globe (West 1992), including the water-limited southwestern United States (Archer 1994).

The long-term and continuous collection of flowering phenology data within shrub-dominated landscapes is essential for understanding the healthy functioning of these ecosystems and climatic influences on the phenology of woody plants (Eamus and Palmer 2007). The timing and abundance of flowering affects critical aspects of plant life cycles, particularly pollination and seed production (Jennersten and Nilsson 1993; Norberg et al. 1993), which set the stage for later germination and seedling recruitment. Timing of flowering is also important for avoiding leaf predation by insects (Pettersson 1991; English-Loeb and Karban 1992; Bishop and Schemske 1998) and avoiding resource limitation (Prieto et al. 2008), which is a crucial plant adaptation within dryland ecosystems (Beatley 1974; Barbour et al. 1977).

For the research presented here, *Larrea tridentata* (creosotebush), the most dominant and widely-distributed perennial plant in the North American warm deserts
(Barbour et al. 1977; Turner et al. 1995), was monitored using pheno-cams to detect flowering patterns. This species was chosen because of the spatially-extensive and crucial role that it plays within these dryland ecosystems. The widespread dominance of *L. tridentata* warrants a thorough understanding of how the plant contributes to ecosystem processes and the cycling of resources.

*L. tridentata* is a repeat-blooming shrub (i.e., usually blooms more than once per calendar year) that has yellow, radial flowers which attract over 120 native species of bees, 22 of which are specialists and depend solely on the pollen of the creosotebush for their food source (Mabry et al. 1977; Minckley et al. 1999). Bees, the most efficient insect pollinators, are able to perceive flowers that reflect yellow-green (Glimn-Lacy and Kaufman 2006), one of the most common flower colors throughout North America and the southwestern United States (Figure 1). *Helianthus annuus* (sunflower), another common yellow-flowered plant, is the only known plant to host more bee species than *L. tridentata* (Hurd et al. 1980). One of the potential effects of climate change is the asynchrony that could arise between plant flowering and pollinator emergence (Biesmeijer, Roberts et al. 2006; Hegland, Nielsen et al. 2009), which would pose a serious threat to the functioning of these dryland ecosystems. Furthermore, *L. tridentata* has expanded its range in recent times (Grover and Musick 1990; Schlesinger, Reynolds et al 1990) and accurate monitoring of the species’ flowering phenology could help elucidate why this has occurred. As climatic variability becomes less predictable and precipitation becomes more sporadic and infrequent in the southwestern U.S. (Seager et
al. 2007), understanding how this dominant shrub contributes and responds to ecosystem feedbacks and functioning is of central importance.

Pheno-cams offer a variety of applications for both research-based initiatives (e.g., PHENOCAM 2009) and less formal “citizen science”-based phenology monitoring projects (Morisette et al. 2009; National Phenology Network 2009; Project BudBurst 2009). For citizen science applications, use of pheno-cams could increase the temporal frequency of observations collected by citizens, which would allow for detection of phenological events on the exact dates when they occur and increase the overall amount of data being collected. The enhanced digital data collected by citizens in turn can offer advantages back to the scientific community by providing more accurate records to be used in climate change research initiatives (see Schwartz and Reiter (2000) for an example of how such data can be used).

At the research level, pheno-cams offer promising advances in phenology monitoring capabilities ranging from carbon flux monitoring and validation (Baldocchi et al. 2005; Wingate et al. 2008) to improving remote sensing products (Fisher et al. 2006) and phenological models (Chuine et al. 2000). Using data collected for this thesis research, Figure 1 demonstrates the value of co-locating pheno-cams and micrometeorological stations. Measurements of soil moisture, precipitation, and temperature are plotted across the year 2008 alongside *L. tridentata* flower counts visually obtained from daily digital pheno-cam images. The continuous records that result from such a set-up show great promise in elucidating environmental mechanisms
influencing reproductive phenology at the plot-scale in this shrub-dominated landscape and beyond.
Figure 1. Number of flowers manually detected from daily images for various lens-to-subject distances (top panel), as analyzed in research presented in Appendix A. Climatic variables of soil moisture, precipitation (middle), and temperature (bottom) are reported.
alongside flowering phenology data to demonstrate the utility of co-locating pheno-cams with micrometeorological stations.

1.2 About the Field Site

Research for the study described here was conducted at the Santa Rita Experimental Range (SRER, Figure 2). This property was established in 1903 and was initially managed by the U.S. Forest Service until it was turned over to The University of Arizona in 1987 (Sayre 2003). SRER total land area is 215 km² and is situated in the Sonoran Desert northwest of the Santa Rita Mountains in Pima County, Arizona, at an elevation of about 950 m. The study site for this research is located in the northern portion of SRER (31.9083N, 110.8395W) in an area dominated by *L. tridentata* and characterized by a sandy loam soil (Breckenfeld and Robinett 2003). Mean annual precipitation for the immediately surrounding area is approximately 328 mm, with an average annual maximum temperature of 22.8 °C and average annual minimum temperature of 4.6 °C (WRCC 2007). Rainfall distribution is bimodal, with approximately 50% of annual precipitation falling in July-September (monsoon) and 45% during October-December (winter).

A fall 2008 field survey indicated a total percent vegetation cover at this site of approximately 24%, with *L. tridentata* as the dominant plant (14%) and a variety of grasses, forbs and cactuses comprising the remaining 10% vegetation cover.
Figure 2. Site map of the Santa Rita Experimental Range (SRER) in Pima County, Arizona.
1.3 Objectives

This thesis research addresses the application of repeat digital photography for monitoring plant phenology within a *L. tridentata*-dominated ecosystem, with expanded relevance across many other landscape types. There are two objectives to this study. The first was to compare several different image analysis techniques in order to determine which approach works best for automated detection of various flowering metrics (i.e., dates of start, peak, and end of flowering and flower abundance). The second objective was to assess the application of these different monitoring and analysis techniques for use by both researchers and interested citizen scientists as a simple and effective means of monitoring plant phenology.

1.4 Structure of the Following Chapters

This Masters research is presented as an individual paper that is placed in its entirety in Appendix A of this document. The paper titled *Automated repeat digital photography for continuous phenological monitoring: an analysis of flowering in a semiarid shrubland* is intended for submission to *Journal of Arid Environments* for peer review and publication in May 2009. Tables and figures associated with this manuscript appear at the end of Appendix A. Preparation of Appendix A was completed by the author herself, with guidance and review provided by the second author and those noted in the Acknowledgements section of Appendix A.
The following section, Present Study, summarizes the methods, results, and conclusions of this thesis research.
2. PRESENT STUDY

The methods, results, discussion, and conclusions of this study are appended to the thesis. The following abstract summarizes the major findings and conclusions from Appendix A.

2.1 Abstract of Appendix A: *Automated repeat digital photography for continuous phenological monitoring: an analysis of flowering in a semiarid shrubland*

Monitoring plant phenology with automated repeat digital photography has become increasingly popular due to the low cost, high accuracy, and archival capabilities that allow for continuous records of phenological data to be directly compared to climate data. While many studies that have used digital images to track green-up and vegetative growth, very few have used this method to monitor flowering phenology, especially within shrubland communities. Our approach uses low-cost digital game cameras (Figure 3) manufactured to withstand inclement field conditions to track important flowering metrics (start, end, peak flowering, and number of flowers) in a semiarid shrubland dominated by *Larrea tridentata* (creosotebush) in southern Arizona. Capturing images at three different lens-to-subject distances, we analyze and compare four image analysis methods: 1) *manual* counts, 2) *RGB* color format analysis, 3) *HSV* color format analysis and 4) a *yellow index* method. We found that mid-range lens-to-subject lengths (approximately 3 m) provided the best estimate of flowering phenology metrics for this
study, and that the accuracy of each image analysis technique varied according to the distance at which the plants were observed. Camera set-up and materials employed in this study worked well in a sparsely vegetated shrubland ecosystem. The methods and tools presented here offer an effective means for monitoring plant flowering phenology in both science-intensive and non-research citizen science ventures.
Figure 3. Photograph of the camera set-up used for this research. A *Larrea tridentata* shrub is located behind and to the right of the camera in this photo.
3. REFERENCES


APPENDIX A: AUTOMATED REPEAT DIGITAL PHOTOGRAPHY FOR CONTINUOUS PHENOLOGICAL MONITORING: AN ANALYSIS OF FLOWERING IN A SEMIARID SHRUBLAND

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1. Introduction

Phenology is the study of life cycle phases of plants and animals, which are triggered by changes in environmental conditions and weather patterns that occur throughout the seasons (Lieth 1974; Schwartz 2003). The observation and analysis of phenological patterns is a robust and effective means of detecting how climate patterns influence ecological systems at multiple scales (Chuine et al. 2000; Penuelas et al. 2004), and is therefore important for better understanding the possible effects of global change on terrestrial ecosystems (Menzel 2002; IPCC 2007). Accurate information on plant phenology is vital for understanding numerous aspects of plant-scale and ecosystem-level dynamics. Applications include seed and fruit production management in agriculturally important plants (Olasantan and Bello 2004), validation of land surface phenology remote sensing products (Schwartz 1997), and creation of reliable climate models (Lu et al. 2001; Arora and Boer 2004). As global climate patterns change (IPCC 2001; IPCC 2007), collection of phenology data at a variety of scales will lead to a better understanding of how specific vegetation regimes respond to climatic fluctuations, and in turn aid in the development of effective management and adaptation strategies.

Traditionally, phenological events in plants at the plot-scale were monitored manually using recorded human observations at discrete intervals. Using this technique, the quality of the phenology data depends heavily upon the observational skills and effort of the observers and is susceptible to a degree of subjective inaccuracy (Menzel 2002; Booth, Cox et al. 2005). Furthermore, human observations of plant
phenology are typically infrequent and geographically limited due to the labor intensive methods that are involved. To address this problem, researchers have begun to utilize “pheno-cams” (e.g., Kurc and Benton, in review; Crimmins and Crimmins 2008; Richardson et al. 2007), which are in situ cameras set up to capture digital images across time as a means to monitor phenology (see Table 1). This methodology has many advantages over the traditional observation-based recording, including (1) continuous, regular monitoring across time (Richardson et al. 2007; Ahrends et al. 2008; Crimmins and Crimmins 2008), (2) a permanent data record of the phenological stages (Richardson, Jenkins et al. 2007), (3) reduced labor and costs (Seefeldt and Booth 2006; Przeszlowska et al. 2006), (4) decreased observer-based bias and (5) allowing for quantitative digital analyses of phenological patterns (Neeser et al. 2000; Kercher et al. 2003).

Many recent studies have shown that detecting metrics of greenness and senescence can be performed via on-ground digital photography (Adamsen et al. 1999; Richardson et al. 2007; Ahrends et al. 2008), but few have focused on detecting the metric of flowering (Table 1). In fact, to the knowledge of the authors, there have been no studies using ground-based digital photography to monitor flowering in non-herbaceous woody species (i.e., shrubs or trees), which have become increasingly abundant in the southwestern United States (Archer 1994) and many other temperate regions of the globe (Roques et al. 2001). The timing and abundance of flowering affects critical aspects of plant life cycles, particularly pollination and seed production (Jennersten and Nilsson 1993; Norberg et al. 1993). Flowering time is also important
for avoiding flower herbivory and later seed predation by insects (Pettersson 1991; English-Loeb and Karban 1992) and circumventing water and resource limitation (Sharifi et al. 1988; Prieto et al. 2008), which is particularly crucial in dryland ecosystems (Beatley 1974; Barbour et al. 1977; West and Skujins 1978). Long-term flowering phenology data within shrub-dominated ecosystems is valuable for understanding overall reproductive success (Keeley 1992) and gaining an understanding of how climate influences the phenology of plants (Rathcke and Lacey 1985; Menzel 2002).

In perhaps the first study to estimate flower numbers via digital analysis, Adamsen et al. (2000) took nadir-view images of a yellow-flowered crop species and converted them from red, green, blue (RGB) color space format to binary images in which pixels containing yellow flowers were represented by white and non-flower pixels were black. They automated flower counts for each acquired image using readily available image-processing software. More recently, Crimmins and Crimmins (2008) captured oblique-angle RGB images of wildflower species, converted them to a hue, saturation, value (HSV) color space, and then determined pixels that contained flowers and those pixels that did not based on threshold values of hue and saturation. They acquired flower counts after several image processing steps to detect flower pixel aggregations. Conversion of RGB images to an HSV color scheme was performed by Crimmins and Crimmins (2008) because HSV is considered, to a large extent, closer to the way in which humans experience and describe color (Gonzalez et al. 2004), but it
remains unknown whether conversion of RGB-based images to the HSV color scheme results in more accurate flowering estimations.

In this study, *Larrea tridentata* (creosotebush), the most dominant and widely-distributed perennial plant in the North American warm deserts (Barbour et al. 1977; Turner et al. 1995), was chosen as the subject species because of the spatially-extensive and crucial role that it plays within these dryland ecosystems. *L. tridentata* is a repeat-blooming shrub (i.e., usually blooms more than once per calendar year) that has yellow, radial flowers which attract over 120 native species of bees, 22 of which are specialists and depend solely on the pollen of the creosotebush for their food source (Mabry et al. 1977; Minckley et al. 1999). Bees, the most efficient insect pollinators, are able to perceive flowers that reflect yellow-green (Glimn-Lacy and Kaufman 2006), one of the most common flower colors throughout North America and the southwestern United States (Figure 1). Monitoring yellow-blooming species is likely to be important in many other phenological and/or pollination studies, and therefore this *L. tridentata* example will be widely applicable. One of the potential effects of climate change is the asynchrony that could arise between plant flowering and pollinator emergence (Biesmeijer, Roberts et al. 2006; Hegland, Nielsen et al. 2009), which could pose a serious threat to the functioning of these dryland ecosystems. Furthermore, *L. tridentata* has expanded its range in recent times (Grover and Musick 1990; Schlesinger et al. 1990) and accurate monitoring of the species’ flowering phenology could help elucidate why this has occurred.
For the research presented here, daily digital images are captured from a *L. tridentata* ecosystem in the Sonoran Desert to assess blooming patterns across the spring and summer months of year 2008. Using three pheno-cams with different lens-to-subject distances (*close-range, mid-range* and *long-range*) four methods are used to detect timing and abundance of flowers throughout the study period. These include 1) a *manual* count of flowers from each image; 2) a *RGB* automation method that takes images in their original RGB format, converts them into binary images, and identifies pixel aggregates that are then counted as flowers; 3) a *HSV* automated analysis that converts RGB images to HSV format and then proceeds to make a binary image and count flowers as is carried out in the *RGB* method; and 4) an indexing method (*yellow index*) that attempts to quantify changes in the amount of yellow (the color of *L. tridentata* flowers) over time.

There were two objectives for this study. The first was to compare the above image analysis techniques, which are similar to those employed in previous studies (i.e. Ahrends et al. 2008; Crimmins and Crimmins 2008) in order to determine which approach works best for detecting various flowering metrics (i.e., dates of start, peak, and end of flowering and flower abundance). The second objective was to assess the application of these different monitoring and analysis techniques for use by both interested citizen scientists and researchers as a simple and effective means of monitoring phenology at the plot-scale (<10 km²; Morisette et al. 2009).

2. Materials and Methods
2.1 Site Description

Research for this study was carried out at the Santa Rita Experimental Range (SRER) located approximately 56 km south of Tucson, Arizona (31°46′N, 110°51′W) and northwest of the Santa Rita Mountains in an ecosystem dominated by *L. tridentata*. The research site is located in the northernmost central portion of SRER (Figure 2) at an elevation of about 950 m above sea level. A 4.25 m eddy covariance tower has been in place at this site since the beginning of March 2008, providing estimates of the carbon dioxide and water fluxes between the atmosphere and ecosystem. Continuously collected site-specific measurements include micrometeorological variables of precipitation, air temperature, soil temperature, net radiation, wind speed, wind direction, and relative humidity. Water content reflectometers (Campbell Scientific, CS616) collect soil moisture data under three profiles of both bare ground and canopy surfaces at depths of 2.5, 12.5, 22.5, 37.5, 52.5, 67.5, and 82.5 cm at the site.

Using long-term data (1971-2000) collected in the nearby town of Sahuarita, AZ, it is estimated that the study site has an average annual maximum temperature of 22.8 °C, an average annual minimum temperature of 4.6 °C, and mean annual precipitation of 327.9 mm (WRCC 2007). The majority of the precipitation in this area of southern Arizona falls during two periods: July-September (monsoon season) and October – December (winter season), with approximately half of the annual precipitation falling during each season.

A particle size analysis performed in 2008 shows that soil at the site is sandy loam for depths up to at least 1 m (Kurc, unpublished data). Previous studies have shown that
a very high percentage of the root area for *L. tridentata* can be found between approximately 12 and 45 cm beneath the soil surface (Kurc and Small 2004; Ogle, Wolpert et al. 2004). Percent cover at the site was estimated to be 24%, with 14% of that as *L. tridentata* and the other a mix of grasses, cactus, *Prosopis glandulosa*, *Ferocactus wislizenii* and *Zinnia acerosa*. On average, the *L. tridentata* shrubs reached 1.7 meters in height.

### 2.2 Pheno-cams

For this study, commercially available Moultrie I-60 digital game cameras (Moultrie Feeders, EBSCO Industries, Inc., www.moultriefeeders.com) were utilized to collect phenology data at the site. These cameras were chosen because of their low cost ($300), user-friendly settings that required no additional programming to facilitate time-lapse photo capture, explicit design for outdoor use in remote locations, and deep depth-of-field (a measure of the range within which a camera can focus). Cameras are battery operated (six D-cell batteries needing replacement approximately every 4 months). Optical field of view, which is the angle of view that can be seen through the camera lens, is 52 degrees. Focal length and spectral sensitivity for this camera model were not disclosed by the manufacturer. Resolution was manually set to 6 megapixels (“enhanced” mode) yielding an image size of 2848 x 2136 pixels. Images were saved on a 4.0 gigabyte SD memory card (SanDisk Corporation, www.sandisk.com) that was purchased separately to increase image storage capacity of the camera.
A total of three Moultrie cameras were installed within the footprint of the eddy covariance tower at the study site so that photos could be easily compared to the tower data in ancillary studies. All cameras were oriented vertically (field of view parallel to the ground surface) facing north to maximize sunlight exposure on the subject plants and minimize effects of shading. Cameras were enclosed in a black metal security box manufactured for the game cameras by Moultrie Feeders and were secured using a lock to protect against theft and direct exposure to the elements. This camera set-up was then mounted on a pole at an approximate height of 1 m above the ground surface. While the ecosystem within the footprint of the eddy covariance tower is fairly uniform, semi-random locations were selected for placement of the cameras to capture the different sizes of, aggregate structure of, and microtopography surrounding the shrubs that might occur.

Images were captured every hour on a daily basis and data was downloaded directly from the camera every two weeks throughout the study using a USB port on a portable laptop computer as jpeg (Joint Photographic Experts Group) image files. One photo for each date was manually chosen with time stamps between 1100 and 1300 hours (time range during which sun is high in the sky, so as to minimize shading effects). Images were manually renamed to the format cameraID_time_date (e.g., SRER1_1200_021408.jpg) for easy identification and analysis, and then organized in a time series according to date.
2.3 Image Analysis

2.3.1 Region of Interest Selection

Regions of interest (ROIs) were chosen for each of the image time series so that a static region of each photo was analyzed throughout the study (Figure 3). These particular regions were chosen to 1) reflect areas of high flower abundance across time and 2) to assess different lens-to-subject distances associated with each camera, i.e. 0.9 meters separate the close-range camera from the ROI for that time series, 3.1 meters lie between the mid-range camera and the ROI, and there is 6.7-m distance between the long-range camera and the ROI. Pixel areas for the three separate regions of interest included a 300 x 264 (79200 total pixels) for the close-range images (Figure 3B), 200 x 168 pixel area (33600 total pixels) for the mid-range images (Figure 3D), and 273 x 177 (48321 total pixels) for the long-range camera images (Figure 3F).

2.3.2 Manual Flower Count

In order to have a base-line flower count for each image analysis technique utilized in this study, a manual count of recognizable flowers was performed for each camera ROI. This allowed for a validation and comparison of subsequent analyses. The manual count was performed by opening each jpeg image and then projecting them, one-by-one, onto a whiteboard (as in Crimmins and Crimmins 2008) where the defined ROI was clearly outlined and static throughout the time series. Aggregations of multiple
yellow pixels that resembled the radial *L. tridentata* flowers were counted if a recognizable portion of the yellow petals were within the ROI. Small aggregates of yellow pixels were often considered to be buds based upon their round shape and small size and were not counted as open flowers. A tally of total open flowers per image was calculated for each time series within the static ROIs (see Table 2).

2.3.3 *Automated Flower Count*

Using the Image Analysis Toolbox associated with MATLAB® (The MathWorks, Inc., version 7.6.0.324 [R2008a]), we automated two different methods of detecting flowers within the ROIs. First, we adopted a *HSV* method based on the work presented in Crimmins and Crimmins (2008). In this method, the RGB ROIs are converted to an *HSV* color scheme, which requires translating equations used to map Cartesian-based RGB values into cylindrical coordinates utilized in the HSV scheme (Rogers 1997). After testing the images to determine the range of yellow values that best represented flower pixels, we set hue values to a range appropriate for yellow, 0.13 to 0.17, and saturation values for yellow in the images were specified to be greater than 0.8. (These values for hue and saturation were also used by Crimmins and Crimmins (2008) in their flower count analysis). Then, a binary image was created where all pixels with hue and saturation values within the specified range were set to the value 1 and displayed as white, and all other pixels were set to the values of 0 and displayed as black (Figure 4: A-HSV1, B-HSV1, C-HSV1). In this way, the pixels with a value of 1 represented yellow pixels detected within the ROI. We expected that one pixel is likely
to represent less area than an actual flower. Therefore, connected pixels of value 1 were aggregated to better represent flowers. Prior to this aggregation, the binary ROIs were cleaned and filtered in the following way. If single pixels of value 1 were not connected to any other pixels of value 1, these pixels were eliminated. Then, if a single pixel of value 0 was surrounded by pixels of value 1, that pixel value was changed to a value of 1. After the cleaning, aggregated yellow pixels were counted as individual flowers (Figure 4: A-HSV4, B-HSV4, C-HSV4).

The RGB flower count was conducted in a similar fashion. For this method of flower detection, images were left in their original RGB format (i.e., not converted to HSV as in previous method). Using MATLAB, red, green, and blue channels were given set bounds to capture those pixels characterized by the color yellow. In the RGB color scheme, yellow is limited in blue but strong in red and green; therefore, we set the following limits: to be considered yellow, a pixel had to have blue values less than 85 out of 255, red values greater than 150 out of 255 and green values greater than 150 out of 255. Then, as in the HSV method, yellow pixels were given a value of 1 and non-yellow pixels were given a value of 0 (Figure 4: A-RGB1, B-RGB1, C-RGB1). Each binary image was then cleaned and pixels were aggregated in the same manner as was conducted for the HSV method (Figure 4: A-RGB4, B-RGB4, C-RGB4).

We developed four phenological metrics to assess the quality of the automated analyses: (1) start of flowering, (2) peak flowering date, (3) end of flowering, and (4) count of flowers per blooming period (Table 2). Metrics determined from the automated analyses (i.e., HSV and RGB) were compared to metrics obtained from the manual count
to determine level of accuracy. Start of flowering, peak flowering date, and end of flowering were considered to “best” match the manual count if they fell within a 5-day margin of error from the manually-counted date for that lens-to-subject distance and filter level, and a “somewhat accurate” match being within a 10-day time frame of the manual value. These bounds were determined based upon how often a monitoring site is usually visited by human observers throughout the year, which is typically every two weeks (Bowers and Dimmitt 1994; Wetherill, personal communication). Thus, a 7 - 10 day margin of error for start, end, and/or peak flowering would be a better approximation of these phenology metrics than that of observer-based data records. An automated count of flowers was considered a “best” approximation in each blooming period if the count corresponded to a value within +/- 30% of manual flower counts for that particular flowering cycle (period 1 or 2); an acceptable automated count of flowers was inside a +/- 40% range of manually-determined values. The limits placed on these values were specified so that the most accurate analyses reflected a count of more than half of manually-counted flowers.

2.3.4 Yellow Index

Based upon previous studies that have successfully captured plant green-up using an RGB-based indexing method (Richardson et al. 2007; Ahrends et al. 2008; Crimmins and Crimmins 2008), we developed an index designed to capture amount of yellow appearing through time in the images. This “yellow” index approach does not allow for daily flower counts to be tallied from each image but rather tracks the number of yellow
pixels, or relative amount of yellow within every image in the time series. Images were cropped into their specific ROI as outlined above, and normalized brightness values for each RGB channel were calculated. A yellow index (Equation 1) was computed to determine the change in amount of yellow pixels across all three image time series.

\[ \text{Yellow Index} = \frac{[(2 \times \text{red} – \text{green} – \text{blue}) + (2 \times \text{green} – \text{red} – \text{blue})]}{510} \quad (1) \]

This index was calculated using mean brightness values for red, green and blue channels. There are 255 color values in the RGB color model; therefore the equation is divided by 510 to allow for ease of comparison across all three camera repeats.

3. Results

3.1 Micrometeorological Data

Precipitation, soil moisture, and temperature data are reported alongside image time series to show how they relate to the timing of bloom events (Figure 5). Peak blooming during the spring occurred between April 6-10 (DOY 97-101) and in the summer on July 25-27 (DOY 207-209). On March 20 (DOY 80), shallow soil moisture (2.5 cm depth) was drying down from the preceding 2.54-mm rain event. As expected, shallow soil moisture was responsive to rainfall events that were recorded, with the exception of a 1.52-mm event on April 1 (day 92). Deep soil moisture (37.5 cm depth) did not significantly change until a series of monsoon rain events occurred around June 28 (day 180) and remained relatively moist throughout the second blooming event. A
large 40 mm precipitation event occurred on August 25 (DOY 238) that substantially increased the moisture content at the 37.5 cm depth from 0.09 before the event to 0.12 around August 31 (DOY 244). Air and soil temperatures are displayed as daily averages (Figure 5). Concurrent with recorded precipitation events were drops in both soil and air temperatures at the site, and even with periods of missing data, we are able to observe the overall increase in mean daily temperatures across the time series.

3.2 *Manual Flower Counts*

At this southern Arizona study site, *L. tridentata* flowering periods for the year 2008, as determined via *manual* count, occurred from March 29 through May 2 (DOY 89 to 123, where DOY is “day of year”) and then again from July 14 to August 3 (DOY 196-216) (Figure 5, Table 2). These blooming days correspond to the timing of the first flower observed within all ROIs until the last visible yellow flowers were detected. Comparatively, the first blooming event was not as prolific as the later summer flowering episode, but lasted longer at all three camera locations (an average of 25 days in the first bloom period and only 15 days on average for the second flowering event, Figure 5). For *manual* counts, the *close-range* ROIs had the smallest numbers of visible flowers, i.e., exactly 14 each for both the first and second blooming periods. For *mid-range* ROIs, the first blooming event was manually counted to have a total of 175 flowers and the second blooming event had 128 total flowers within the ROI. *Long-range* ROIs
contained the most flowers of any ROI with 303 total flowers in the first blooming period and 228 in the second blooming event.

3.3 RGB and HSV Flower Counts

Automated flower counts using RGB and HSV methods are displayed in Figure 6 alongside manual counts, with a quantitative summary of these results and the derived phenological metrics presented in Table 2. The outcome of each automated analysis method depended upon the amount of filtering, or pixel aggregation that was performed on the ROIs (see Figure 4). In Figure 6 we demonstrate the effect of the filter process on the flower count, i.e. in filter 1 the image has been processed the least and in filter 4 the image has been processed the most. Consequently, flower counts decrease as filter number increases (Figures 4 and 6). Results for each lens-to-subject distance are varied and explained in the following sections.

3.3.1 Close-Range ROI

RGB and HSV image processing for short lens-to-subject distances (close-range) result in near continuous flowering throughout the time series (Figure 6A). Therefore, in order to compare manual flowering patterns to these automated pattern results, the midpoint between the two manually-counted peak blooming days for the close-range time series (April 9 in first period and July 3 in second period) was determined to be May
21 (DOY 142), which was used as the cut-off date between flowering period one and two. For close-range ROIs, the HSV method was not as accurate as the RGB analysis for all metrics of interest (Figure 6A, Table 3). While the manual count revealed only 14 flowers in the first flowering period (Table 2), HSV image processing detected from 4,553 (32,521% of manual) in the first filter to 378 (2,700% of manual) at the least filtered level. In the second flowering period we see similar results: only 14 manually-detected flowers compared to 11,935 flowers in HSV filter 1 (85,250% of manual) and 839 flowers in HSV filter 2 (5,993% of manual). Peak blooming dates tended to be inaccurately detected by HSV with an error of at least one to two months for all filters. Dates of first and last detected flowers in the close-range HSV analysis were also incorrectly approximated by one month before or one month after manual dates (Table 2).

The most filtered versions (i.e., filters 3 and 4) of RGB images in the close-range ROI resulted in best approximations of manual dates for start of flowering and peak flowering date (Table 3), meaning RGB filters 3 and 4 detected first and peak flowers within a 5-day time period of reported manual dates. RGB filter 4 also performed relatively well for flower counts in both the first (171% of manual) and second (71% of manual) flowering periods, and precisely counted number of peak flowers during the second peak bloom event (100% of manual) that occurred on July 26 (DOY 208).

3.3.2 Mid-Range ROI
At a mid-range lens-to-subject distance of approximately 3 m, both HSV and RGB automated analyses recorded two relatively distinct blooming periods (Figure 6B) for *L. tridentata*. In a few instances the HSV filters 1 through 3 detected extraneous flowers as compared to the manual counts; however, the majority of flowers were in fact counted within the manual blooming time-range. HSV filter 2 was most accurate in counting total flowers during the first bloom period, detecting 122 out of the manually estimated 175 flowers (70%), but total flowers were grossly under- or overestimated by all other HSV filters for both blooming cycles (Table 2, Table 3). For the first peak blooming day on April 7 (DOY 98), the HSV filter 2 detected 15 total peak flowers which was close in value to the manual count for the mid-range ROIs of 17 flowers, and although this peak occurred two days later than the manual peak these results still warrant a “best” approximation (Table 3). Peak flower timing and counts were also best captured by HSV filter 2 in the second blooming period, with 18 flowers detected (95% of manual). In this case, both manual and HSV filter 2 peak dates correspond to the same day, July 27 (DOY 209). Date of first flower counted by the least filtered versions of HSV was early by approximately two weeks in the first flowering cycle, but HSV filters 3 and 4 were relatively close to the March 29 (DOY 89) manual start date. The days on which last flowers were detected by HSV for all filters in both blooming periods were different than manual last bloom dates by anywhere from two days to slightly under five months (Table 2).

The RGB analysis for the first blooming period in the mid-range time series detected only 24% of manual flowers with filter 1, and progressively lower and less
accurate counts in subsequent filter applications. For the second blooming period captured in mid-range ROIs, RGB filter 1 was closest to the manual count by detecting 75 out of 128 total flowers (59%). RGB filter 1 performed second best for peak flowering date and peak flower, with 12 of the 19 flowers (63%) detected on July 27 (DOY 209), the same date as manual peak for the second flowering time period.

Overall, for both blooming periods captured by the mid-range ROI, the flower counts and peak flowering dates were best represented by HSV filter 2. For the phenologic metrics of start and end of flowering, however, RGB filter 1 and filter 2 presented the best results compared to manual dates.

3.3.3 Long-Range ROI

The first flowering period documented by the long-range ROIs was very weakly detected by both HSV and RGB analyses; however, filters 1 through 3 showed a distinct flowering event during the second manual bloom period (Figure 6C). HSV filter 1 was the most accurate method and filter level for total flowers counted, although this filter greatly under-estimated flower count with 45 out of 303 flowers detected (15%) in the first blooming event and 147 out of 228 flowers detected (65%) in the second blooming event. The peak blooming date for HSV filter 1 was on July 27 (DOY 209) with 46 total flowers detected, which was 2 days later and 7 flowers more than manual (18% overestimation). Peak flowering date was skewed for all filter levels and methods, occurring 23 days earlier in the HSV filters and 5 days earlier for the one flower detected
by the *RGB* count. Dates of first flower detected by *HSV* filters 1 and 2 were early by approximately two to four weeks. *HSV* filter 3 detected start of flowering only six days later than *manual* in the second flowering period; however, this was the only flower counted for the entire time series by that filter (Table 2).

In the first blooming event for the *long-range* time series, *RGB* analysis detected only one flower out of 303 in the first filter and no flowers were detected after subsequent pixel aggregation (Table 2). The second flowering period was also weakly documented by the *RGB* method with only 6% of flowers in the lowest filter level and 0.4%-0% thereafter. Peak flowering dates were best approximated by *RGB* filter 1, being within a 5-day time range of the *manual* dates of peak flowers.

### 3.4 Yellow index

A comparison of the *yellow index* (Equation 1) to the *manual* flower counts is displayed in Figure 7. Similar to the *RGB* and *HSV* flower counts, the *close-range* ROIs have a highly variable number of yellow pixels detected for each day in the time series (Figure 7A). In addition, at all lens-to-subject distances the *yellow index* does not show clear increases in the amount of yellow corresponding to the manually-detected blooming periods. The one obvious exception to this occurred on July 25 (DOY 207) during the second blooming period for the *long-range* ROIs (Figure 7C) when the peak amount of yellow in the index value corresponded to the peak day of bloom in the *manual*. In general, with the *yellow index* we see slight increases in yellow amounts during times
when blooming events are manually documented and slight decreases in the overall trend of the index during non-bloom times (especially for the second bloom event in long-range images, Figure 7C). But detection of the start, end and peak flowering dates was not readily possible using the yellow index due to the abundance of “yellow” pixels counted during non-bloom times.

4. Discussion and Conclusions

4.1 Detecting Flowers with Automated Image Analysis

Several key findings can be drawn from this study. First, mid-range distance (3.1 m) was the most ideal lens-to-subject range out of the three ROIs for analyzing images with the Moultrie game camera model used in this study. Because information on certain camera specifications (e.g., focal length, aperture) was not provided by the manufacturer, determining the best distance between lens and subject ROI for this camera was necessary. Perspective (the representation of three-dimensional objects on a flat surface) is largely controlled by the lens-to-subject distance (London and Upton 1998), making it an important factor to consider in any pheno-cam study. The number of pixels representing any subject (in this case the subject is a flower) within a digital image is a function of both the resolution of the camera being used, the size of the subject, and the distance that subject is from the camera lens (Figure 8). The mid-range ROI represented an ideal range for this camera set-up, where resolution was acceptable enough to separate flowers from background “yellow” noise given a minimal amount of filtering (most
notably for RGB analyses), and sizes of most flower aggregations were large enough to avoid re-classification as non-flower pixels in filters 1-3 (Figure 6B). This information may serve to inform potential future pheno-cam studies using this camera model or similar models with comparable resolution and camera specifications.

The second major finding relates to image analysis results for the three lens-to-subject distances. Close-range images required much more filtering (i.e., removal or aggregation of pixels) in order to accurately portray flowering events and flower counts, mid-range images required intermediate levels of filtering, and long-range accuracy for the phenology metrics was best achieved via the least amount of filtering (Figure 6).

With subsequent image processing and removal of pixels that were not part of a larger aggregation of “yellow” in the image, attempts were made to filter out those pixels that were not flowers (e.g., yellowed leaves). This resulted in progressively lower flower counts with each successive filtering. Due to the perspective given by the short lens-to-subject distance, close-range images exhibited larger flowers and therefore had larger pixel aggregations of flowers (Figure 8). However, often an area representing one flower by visual (manual) inspection in the close-range images was not automatically recorded as a single flower when images in the RGB and HSV color schemes were converted to binary. This is possibly due to shading of petals that served to disconnect representative single flower aggregates in the automated analysis because these shaded regions were no longer within the pre-determined yellow bounds. Flower morphology of L. tridentata could also play a role in pixel aggregation errors due to the actinomorphic (radially symmetrical) and apopetalous (separated petals) structure of the rather small flowers
(typically 7-13 mm in size). For the long-range ROI, pixel aggregation errors occurred due to the clustering of many individual flowers into one region, causing only one flower to be counted where two or more were present.

The final result standing out in this study is that the HSV and RGB analyses yielded mixed results for each of the phenology metrics. When comparing both approaches to manual flower dates of flowering events (i.e., start, end, and peak flowering dates), maintaining pictures in the original RGB color scheme resulted in increased overall accuracy (Table 3). RGB did a relatively better job than HSV at identifying flowers during the same blooming periods as detected by manual analysis, while HSV often detected “flowers” during non-bloom time periods (see Figure 6A, 6B). Results show that the chosen hue, saturation and value bounds of “yellow” in this study resulted in HSV analyses that were more sensitive to a larger range of yellow values than the chosen RGB “yellow” values. This sensitivity of the HSV analyses did increase inaccurate detection of flowers during non-blooming times, as noted above, yet also contributed to the fact that HSV flower count values were often closer to manual counts than RGB estimations (far right side of Table 2). Furthermore, RGB analyses tended to underestimate flower counts resulting in very dampened or non existent flower detection as more filtering occurred, especially within the mid-range and long-range ROIs (Figure 6B, 6C).

These results show that ideally, a mid-range (~3 m) lens-to-subject distance should be used for flower detection using a camera with comparable resolution (~6
megapixels) and depth-of-field to the game camera model used in this study. Given that the alternative method for determining these metrics is infrequent observer-based field observations, the advantages of using pheno-cams to track flowering patterns are numerous (Table 3). In this remote and harsh shrubland ecosystem and other similarly isolated field sites, visiting a site and making phenological observations at frequent intervals (i.e., more than once per week) is impractical and costly. Therefore, an automated image analysis of repeat digital photographs using the methods presented here could serve as a more objective and efficient alternative for monitoring flowering phenology.

4.2 Flowering Phenology and Climate

Several different abiotic factors may influence the frequency, timing and duration of plant flowering. Frost, seasonal rainfall, and other abiotic influences may limit the flowering seasons directly by affecting the ability to produce flowers or indirectly by having an effect on pollinators (Rathcke and Lacey 1985). Water is the major factor influencing productivity and resource allocation between vegetative growth and reproductive flowering for several plants in water-limited ecosystems (Kemp 1983; Prieto et al. 2008), including *L. tridentata* (Sharifi et al. 1988; Franco et al. 1994). Under water stress, semiarid plant species often shift resources to produce flowers rather than vegetative growth (Cunningham et al. 1979; Sharifi et al. 1988; Evans 1993). Differences in topography and soil can also cause variations in the flowering phenology
of *L. tridentata*, and reproductive development is a function of the microenvironment of the plant rather than of wider environmental conditions (Burk and Dick-Peddie 1973). For the dominant warm desert plant *L. tridentata*, its capacity to take advantage of fluctuations in resource availability by altering its physiological activity and utilizing different depths of soil water (Reynolds et al. 1999) is a dominant force in the plant’s ability to increase in abundance throughout its range (York and Dick-Peddie 1969; Grover and Musick 1990) and perhaps to adjust to the warmer and drier conditions expected to occur throughout the southwestern United States (Seager 2007; Seager et al. 2007).

Biotic forces also play a role in affecting flowering phenology within vegetation communities. In tropical regions phylogeny significantly constrains variations in flowering frequency among family groups (Bawa et al. 2003); however, in dryland ecosystems phylogenetic constraints have shown to be of minor consequence in influencing flowering (Bowers and Dimmitt 1994; Petanidou et al. 1995), especially as compared to the effects of surrounding climatic forces (Bowers and Dimmitt 1994). Plant biotic factors reported to have impacts on flowering include plant size (Schmitt 1983; O’Neil 1997; Bishop and Schemske 1998; Bowers 2006), timing of flower development (Kochmer and Handel 1986; Dorn and Mitchell-Olds 1991; Harvey and Pagel 1991), competition for pollinators (Mosquin 1971; Rathcke and Lacey 1985) and the amount of seed predation (Ollerton and Lack 1992; Mduma et al. 2007). These factors can play a role in plant flowering phenology at the individual, population, and/or species level, but in general, abiotic factors (as opposed to purely biotic factors) have
been found to be the primary determinants of reproductive timing and characterization in many plant species (Mduma et al. 2007).

Many plants are experiencing advanced springtime phenology activity across large portions of the globe due to changes in climate, especially temperature (Menzel and Fabian 1999; Schwartz and Reiter 2000; Fitter and Fitter 2002; Moza and Bhatnagar 2005; Wolfe et al. 2005; Cleland et al. 2006; Schwartz et al. 2006; Miller-Rushing and Primack 2008). In order to understand the full implications of this earlier trend in phenological events, development of improved methods for monitoring plant phenology is imperative. Changes in climate patterns and subsequent shifts in phenological cycles have the potential to disrupt complex linkages between different trophic levels in nature (Moza and Bhatnagar 2005) and this is particularly true for communities dominated by longer-lived plant species that are not able to evolve adaptive responses (i.e., changes in the genetic composition of the population) in the face of a rapidly-changing climate (Kramer et al. 2000).

By installing pheno-cams in the most dominant vegetation type of the U.S. desert southwest (Barbour et al. 1977; Turner et al. 1995) alongside site-specific environmental data collection, we strengthen the results of previous studies that have used pheno-cams within other vegetation communities (Adamsen et al. 2000; Richardson et al. 2007; Ahrends et al. 2008; Crimmins and Crimmins 2008) and set the stage for continued phenological monitoring in this shrub-dominated ecosystem and other vegetation communities.
4.3  *Research and Non-Research Applications*

The camera set-up that was used in this study allowed for monitoring of *L. tridentata* in a remote location with relatively infrequent site visitation. In the harsh southern Arizona climate, the Moultrie I-60 game cameras performed well and facilitated the recording of continuous records of phenological data for an extended length of time. Unlike other studies that required equipment to be contained within a building (e.g., Crimmins and Crimmins 2008) or images to be acquired via non-automated non-continuous capture (e.g., Adamsen et al. 2000), the method demonstrated here requires minimal set-up and maintenance even within the remote field site where this study was based. The camera set-up was inexpensive, required no additional camera programming or weatherproofing, and collected over 30 days of high-resolution images without requiring attention.

Pheno-cams offer a variety of applications for both research-based initiatives (e.g., PHENOCAM 2009) and less formal “citizen science”-based phenology monitoring projects (Morisette et al. 2009; National Phenology Network 2009; Project BudBurst 2009). At the research level, pheno-cams offer promising advances in phenology monitoring capabilities ranging from carbon flux monitoring and validation (Baldocchi et al. 2005; Wingate et al. 2008) to improving remote sensing products (Fisher et al. 2006) and phenological models (Chuine et al. 2000). In addition, using automated repeat digital photography to monitor phenology reduces labor, costs, and time associated with field
site visitation. Using data collected at the *L. tridentata* field site for this research, Figure 5 demonstrates the value of co-locating pheno-cams and micrometeorological stations. Measurements of soil moisture, precipitation, and temperature are plotted alongside *manual* flower counts for the three lens-to-subject distances. The continuous records that result from such a set-up show great promise in elucidating environmental mechanisms influencing reproductive phenology at the plot-scale in this shrub-dominated landscape and beyond.

For citizen science applications, affordable camera set-ups such as the one used in this study could increase the temporal frequency of observations collected by citizens, which would allow for detection of phenological events on the exact dates when they occur and increase the overall amount of data being collected. Pheno-cams provide an easy way to monitor plants on a daily basis without worry of missing a key phenological event and also provide opportunities for citizen phenology observers to understand both the temporal patterns of flowering in their plant species of interest. The enhanced digital data collected by citizens in turn can offer advantages back to the scientific community by providing more accurate records to be used in climate change research initiatives (see Schwartz and Reiter (2000) for an example of how such data can be used).

Methods outlined for *manual* counts of phenologic metrics used in this study could be easily employed by researchers and citizens alike. Utilizing basic image processing software can allow for further image processing as carried out in this study to provide automated, continuous phenological metric records across long time spans. Before employing these methods, several considerations should be taken into account. A
considerable amount of storage space is needed, as images acquired are large (~1.5 megabytes) and depending upon the time-lapse frequency settings of the camera and length of time the monitoring takes place, extra storage devices (i.e. SD camera cards, external hard drives, etc.) may be required. Also, resolution of the camera, shaded and non-shaded pixel regions within the images, height of the plants being monitored, size of the flowers, and lens-to-subject distance need to be considered in the set-up of future studies. Custom specifications for focal length, range of RGB and HSV color values used in image processing, pixel resolution of the camera being used, and amount of pixel aggregation or filtering that occurs all depend upon the particular vegetation type being observed and the location in which it exists.

5. Conclusions

Repeat digital photography and subsequent image analysis proved to be valuable tools for tracking flowering phenology within this water-limited *L. tridentata* ecosystem. With this rather simple and straightforward approach to automated phenological monitoring, methods presented in this study and others (Adamsen et al. 2000; Crimmins and Crimmins 2008) can be used by researchers and citizens with varied backgrounds to detect a range of phenological metrics without having to visit field sites or vegetation plots on a frequent basis. One of the most important aspects of using repeat digital photography for phenology monitoring is that it creates a continuous dataset that can be enriched and further interpreted alongside site-specific climatic data. This study was conducted over a short time-period of one growing season, but with continued ecosystem
monitoring and digital image archiving, many more questions can be asked in the future about the interactions between phenology and climate in this water-limited ecosystem and beyond. Increased efficiency, robustness, and spatial coverage of phenology data collection using the pheno-cam methods employed here, translates to increased understanding of phenology-climate interactions and better ecological management and policy decisions.

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References


Table Legends

Table 1. Studies employing digital image photography to capture a variety of phenological metrics for use in different ecological applications.

Table 2. Phenology metrics of interest to this study and the results of manual, RGB, and HSV analyses displayed for each lens-to-subject distance.

Table 3. An assessment of the phenological metrics detected by the RGB and HSV analyses and how they compare to manual data. The best accuracy level in reference to flowering dates (start, end, and peak) refers to HSV or RGB values that are within a 5-day time range of manual dates for the metric of interest. Somewhat accurate for these dates corresponds to a 10-day time range from manual. For flower counts, best refers to those flower counts that are +/- 30% of manual, with somewhat accurate being +/- 40% of manually-detected counts.
Figure Legends

Figure 1. Percentage of different flower colors within (A) all regions in North America (Niering 1998) and (B) desert ecosystems of North America (Ward and Ward 1978). Note the relatively large percentages of yellow flowers.

Figure 2. A map of Arizona showing the location of the Santa Rita Experimental Range (SRER) (grey region). The northern portion of the SRER (black polygon) is where the research site is located. (Courtesy of Michelle Cavanaugh)

Figure 3. Regions of interest (ROIs) outlined in red boxes for the three camera replicates. Close-range image (A) from July 27, 2008 (day 209) and the zoomed-in ROI (B) showing 3 flowers. Mid-range image (C) from July 26 (day 208) and the ROI (D). Long-range image (E) from July 27 and the isolated ROI (F).

Figure 4. ROIs for the close-range (A1), mid-range (B1), and long-range images (C1). Visualization of HSV filter 1 is given for each ROI (A-HSV1 through C-HSV1), with the final HSV filter 4 results (HSV4) placed below. Using RGB analysis with the same images, A-RGB1 through C-RGB1 represent the first RGB filter, with filter 4 binary images in the last row.

Figure 5. Number of flowers detected by human eye on a daily basis for each image time series (top panel). Climatic variables of soil moisture and precipitation were also recorded throughout the blooming events (middle). Notice the high rain levels between days 170 and 200 and the subsequent flowering episode. Air and soil temperature from the study site are also reported (bottom).

Figure 6. Visualization of image processing results for RGB (dark dashed lines) and HSV (light grey dashed lines) analysis for all focal lengths. Shaded regions represent manual bloom periods (black lines). Filter levels 1, 2, 3 and 4 represent amount of pixel aggregation, with filter 1 images being the least “cleaned” and aggregated and filter 4 images being the most processed.

Figure 7. Yellow index values and manual flower counts for each day across the length of the study.

Figure 8. A visualization of the effects of perspective on objects within a digital image.
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<td>Leaffing-out progression from bud development to full leaf growth</td>
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<td>Monoculture moss species</td>
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<td>Detect greenness as a proxy for CO₂ uptake</td>
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<td>Karcher and Richardson 2003</td>
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Table 3.

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