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(BIOLOGIA VEGETAL)....**

**FENOLOGIA REMOTA: USO DE IMAGENS DIGITAIS NO ACOMPANHAMENTO
FENOLÓGICO DE PLANTAS EM UMA ÁREA DE CERRADO *SENSU STRICTO*, NO
MUNICÍPIO DE ITIRAPINA, SÃO PAULO.**

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Dissertação apresentada ao Instituto de Biociências do Câmpus de Rio Claro, Universidade Estadual Paulista, como parte dos requisitos para obtenção do título de Mestre em Ciências Biológicas (Biologia Vegetal).

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Bernardo é quase árvore

Bernardo é quase árvore.

Silêncio dele é tão alto que os passarinhos ouvem de longe.

E vêm pousar em seu ombro.

Seu olho renova as tardes.

Guarda num velho baú seus instrumentos de trabalho:

um abridor de amanhecer

um prego que farfalha

um encolhedor de rios – e

um esticador de horizontes.

(Bernardo consegue esticar o horizonte usando três fios de teias de aranha. A coisa fica bem esticada). Bernardo desregula a natureza:

Seu olho aumenta o poente.

(Pode um homem enriquecer a natureza com a sua incompletude?)

(Manoel de Barros)

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RESUMO

Fenologia é uma ciência tradicional que estuda os eventos recorrentes dos ciclos de vida de plantas e animais e da sua relação com o clima, bem como com fatores bióticos e filogenia. O brotamento foliar define a estação de crescimento das plantas e controla processos cruciais dos ecossistemas, tais como: ciclagem de nutrientes, o armazenamento de água e balanço de carbono, regula a produtividade dos ecossistemas terrestres e as dinâmicas de trocas de carbono. Estudos fenológicos têm sido aplicados de forma eficiente no controle de distúrbios ambientais, respondendo a perguntas sobre o atual cenário de mudanças climáticas globais e estimulando a busca de ferramentas inovadoras no monitoramento de plantas. O uso de imagens de satélite e câmeras digitais vem sendo considerado métodos alternativos de observação das mudanças fenológicas. A técnica de fotografias repetidas utilizando câmeras digitais tem aumentado devido ao seu baixo custo, redução no tamanho, facilidade de instalação, e alta resolução dos dados obtidos tornando as câmeras ferramentas confiáveis para uma variedade de aplicações ecológicas. Estas ferramentas vêm sendo efetivamente utilizadas como sensores dos três canais de cor, fornecendo padrões de mudança de cor em folhas e mudanças fenológicas em plantas, principalmente no Hemisfério Norte e em vegetações temperadas. Acompanhamos com câmeras uma área de cerrado para avaliar a confiabilidade de imagens digitais para detectar padrões de mudança foliar com o objetivo de responder às seguintes perguntas: (i) as câmeras digitais são capazes de capturar as trocas foliares numa comunidade tropical de cerrado? (ii) podemos detectar diferenças nas mudanças fenológicas entre espécies e a comunidade de cerrado? (iii) o padrão de verde detectado para cada espécie pelas câmeras pode ser validado pelos dados fenológicos do chão (observação direta das mudanças de folhas das árvores)? Já que câmeras digitais geram uma grande quantidade de dados, exploramos ferramentas computacionais que poderiam auxiliar estudos fenológicos através de aprendizado de máquina, visando: (i) testar se as informações de

mudança de cor são capazes de caracterizar o padrão fenológico de um grupo de espécies; (ii) testar se a variação temporal da imagem de textura é útil para distinguir as espécies de plantas, e (iii) testar se os indivíduos da mesma espécie podem ser identificados automaticamente usando imagens digitais. Demonstramos que as câmeras digitais são ferramentas confiáveis para capturar mudanças foliares em uma vegetação tropical de cerrado. Detectamos três estratégias de trocas foliares entre as espécies estudadas através dos padrões de mudança de verde; tais padrões e a determinação de grupos funcionais foram validados pelos dados de fenologia do chão. Também desenvolvemos um método capaz de distinguir as espécies e grupos funcionais de plantas em imagens digitais através da aplicação de aprendizagem de máquina baseado em classificadores multi-escala, e o uso desta nova ferramenta pode ajudar os especialistas em fenologia na identificação de espécies na imagem e, conseqüentemente, na área de estudo. Concluimos que a fenologia remota é uma ótima ferramenta para obter uma avaliação imparcial das mudanças foliares sazonais em ambientes tropicais. A fenologia remota próxima da superfície está se tornando uma aplicação importante para a pesquisa fenológica. A chegada de novas tecnologias seguida pelo avanço de métodos em *e-Science* para lidar com grandes conjuntos de dados estão mudando o cenário dos estudos em ecologia vegetal.

Palavras-chave: fenologia remota; câmeras digitais, cerrado; brotamento foliar; análise de imagens.

ABSTRACT

Plant phenology is a traditional science to observe recurring events in plant life cycles and their relation mainly to climate, as well as to biotic factors and phylogeny. Leafing in plants defines the growth season and controls crucial ecosystems processes such as nutrient cycling, water storage, and carbon balance, regulating the productivity in terrestrial ecosystems and the dynamics of carbon sequestration. Phenological studies have been efficiently applied to track environmental changes, answering questions about the current scenario of global climate change and stimulating the search for innovative tools of plant monitoring. The use of satellite imagery and digital cameras has been considered as alternative methods of observation of phenological changes. The technique of taken repeated photographs using digital cameras has increased due to the low cost investment, reduction in size to set up installation, and the possibility of dealing with high resolution data, making digital cameras reliable tools for a range of ecological applications. Therefore, regular digital cameras have been effectively used as three-channel imaging sensors, providing measures of leaf color change or phenological shifts in plants largely on North Hemisphere and in temperate vegetation types. We monitored a species rich Brazilian cerrado savanna to assess the reliability of digital images to detect leaf-changing patterns aiming to answer the following questions: (i) Do digital cameras capture leaf changes in tropical cerrado savanna vegetation? (ii) Can we detect differences on phenological changes among species crowns and the cerrado community? (iii) Is the greening pattern detected for each species crown by digital cameras validated by our on-the-ground leafing phenology (direct observation of tree leaf changes)? Since digital camera phenology generate a large amount of data, to explore computational tools that could support phenology studies we applied machine learning, aiming: (i) to test if color change information is able to characterize the phenological pattern of a group of species; (ii) to test if the temporal variation in image texture is useful to

distinguish plant species; and (iii) to test if individuals from the same species may be automatically identified using digital images. We demonstrated that digital cameras are reliable tools to capture leaf changes in tropical cerrado savanna vegetation. We detected three leaf exchange strategies from the species patterns of green color change from digital images and the greening patterns and leaf functional groups were validated by our on-the-ground phenology. We also developed a method capable to distinguish species and functional groups of plants in digital images by applying machine learning based on multiscale classifiers, and we demonstrate the use of this new tool can help phenology experts to identify the similar species in the image and, therefore, on-the-ground. We conclude that near-remote phenology is a great tool to obtain an impartial assessment of seasonal leaf changes in tropical environments. Near-surface remote phenology is becoming an important application for phenological research. The arrivals of novel technologies followed by the advance of e-science methods for dealing with large data sets are changing the scenario of plant ecology studies.

Key words: remote phenology; digital cameras; leafing; image analysis.

1 INTRODUCTION

Plant phenology is a traditional science to observe recurring events in plant life cycles and their relation mainly to climate, as well as to biotic factors and phylogeny (Rathcke & Lacey 1985, Schwartz 2013, Staggemeier *et al.* 2010).

Leafing is the plant phenological event that defines the growth season and controls crucial ecosystems processes such as nutrient cycling, water storage and carbon balance, regulating the productivity in terrestrial ecosystems and the dynamics of carbon sequestration (Reich 1995, Rotzer *et al.* 2004, Negi 2006, Malhado *et al.* 2009). The time, length, and intensity of the leaf growing season are closely linked to the proportion of leaf exchange functional types (e.g. evergreen, deciduous and semi-deciduous species) (Reich 1995, Singh & Kushwaha 2005). Those plant functional types define the seasonal patterns of leaf changes and the dynamics of the ecosystem processes (Negi 2006, Shaver 1981, Gholz *et al.* 1976, Reich *et al.* 1997, Singh & Kushwaha 2005, Kushwaha & Singh 2005).

For plants of tropical forests, the periodic pattern is more common than the continuous pattern of leafing, even if the environmental conditions favor plant growth in most seasons (Borchert 2002, Morellato *et al.* 2000, Myneni *et al.* 2007). Nevertheless, the physiological mechanisms and interactions with external factors controlling plant development responses are not yet determined for the majority tropical environments. Tropical vegetation under seasonal climates may have a higher periodicity in the production of flowers, fruits and leaves, with the alternation of the wet and dry seasons being the major factor involving the triggering phenophases (Morellato *et al.* 1989, Morellato & Leitao-Filho 1990, van Schaik *et al.* 1993, Morellato & Leitao-Filho 1996, Lenza & Klink 2006, Morellato *et al.* 2013). Important results also suggest the influence of the small photoperiod or insolation variations serving as a trigger for the onset of leaf budding and flowering in tropical regions (Rivera *et al.* 2002, Elliot *et al.* 2006, Calle *et al.* 2010).

Phenological studies have been efficiently applied to track effects of environmental changes on plants and animals in temperate regions, answering questions about the current scenario of global climate change and stimulating the search for innovative tools of plant monitoring. Detect plant responses to environmental changes across tropical systems, especially in the Southern Hemisphere, is an important question in the global agenda, since few studies have addressed trends related to global warming (Rosenzweig *et al.* 2008, Morellato *et al.* 2013, Chambers *et al.* 2013). A comprehensive survey of phenology data and trends over the Southern Hemisphere (SH) highlights the gaps in the phenology knowledge of tropical species and ecosystems (Chambers *et al.* 2013). For many regions and taxa the trends and shifts, when detected, although coherent with Northern Hemisphere findings, come from SH temperate regions and species (Chambers *et al.* 2013).

Human labor and high diversity of species make it difficult the establishment of an extensive system of direct phenological observations at several sites to track trends and determinants that controls plant phenology and ecosystems process. The use of satellite imagery and digital cameras has being considered as alternative methods of observation of plant phenological changes (Richardson *et al.* 2007, Ahrends *et al.* 2009, Richardson *et al.* 2009, Morissette *et al.* 2009, Migliavacca *et al.* 2011), and can successful monitor plant phenology continuously across the landscape.

1.1 Digital cameras monitoring leaf phenology

1.1.1 Use of digital cameras in plants

The use of digital cameras to document plant changes is not novel. Cameras have been used to capture plants images for several kinds of studies, including changes in ecosystems dynamics and structure presented in the year of 1967 by Hastings and Turner, and more recently by Peñuelas and Boada (2003) and Webb *et al.* (2007); to document changes in

cultural landscapes (Nusser 2001) and for glacial retreat (Thompson *et al.* 2002). However, just recently repeated digital images has been used to measure vegetation growth and biomass (Crimmins & Crimmins 2008, Graham *et al.* 2009), to detect plant stress and nitrogen status (Wang *et al.* 2004), and for crop monitoring (Slaughter *et al.* 2008) as well as for monitor leaf phenology (Richardson *et al.* 2007, 2009).

The technique of repeated photographs using digital cameras has increased due it's low cost investment, reduction in size to set up installation, and the possibility of handling high resolution data, making digital cameras reliable tools for a range of ecological applications (Crimmins & Crimmins 2008, Morisette *et al.* 2009, Graham *et al.* 2010).

Digital images allow the detection of phenological events according to the changes of red, green, and blue (RGB) channels along time. By quantifying the RGB color channels it is possible to estimate, for instance, leaf flushing and senescence, using the green and red channels, respectively (Ahrends *et al.* 2009, Morisette *et al.* 2009, Richardson *et al.* 2009, Henneken *et al.* 2013). Several indexes have been applied to detect leaf color changes in temporal time series of digital images exploring the three color channels (Richardson *et al.* 2007, Nagai *et al.* 2010, Sonnentag *et al.* 2012, Zhao *et al.* 2012, Zhou *et al.* 2013). Woebbecke (1995) was one of the first to calculated several indexes using RGB channels of digital images to evaluate which could better detect weeds in different types of soil, residue and light conditions. A normalized index called RGB chromatic coordinates (RGB_{cc}) was developed by Gilespe *et al.* (1987) and it is considered up to now the most efficient to detect the color of plants in relation to their background (Sonnentag *et al.* 2012).

Digital images have not been explored to monitor other phenophases. In a first approach, Adamsem (2000) estimated duration and number of flowers of the species *Lesquerella* using color digital images taken in fixed plots of a controlling experiment. Recently, not only fixed cameras, but also pan-tilt-zoom cameras (see more in Granados *et al.*

2013) on a mobile platform have been used to identify and count individual flowers of *Rhododendrom* in a temperate forest (see Morisette *et al.* 2009).

The first application of digital cameras to track a phenological event as the green-up in a community was made by Richardson *et al.* (2007), in a temperate forest at New Hampshire. Afterwards, several examples demonstrating the applicability of digital images to monitor leaf phenology emerged, at least for the North hemisphere (e.g. Richardson *et al.* 2009, Ahrends *et al.* 2008, 2009, Graham *et al.* 2009, Ide & Oguma 2010, Nagai *et al.* 2010, Bater *et al.* 2011, Miglivacca *et al.* 2012, Henneken *et al.* 2013, Zhao *et al.* 2012, Zhou *et al.* 2013)

1.1.2 Application of near-surface remote phenology in the tropics

The traditional on-the-ground phenology, the direct observations of individual plants, preclude large spatial areas, and the interference of the observer is high due to the inherent difficulties to detect the variations on leaf color patterns from leaf budding to senescence in the tropics (Richardson *et al.* 2007, Morisette *et al.* 2009, Morellato *et al.* 2010). Satellite remote sensing provides spatially extensive information of vegetation changes; however, it is difficult to detect phenological events at species and community levels (Ide & Oguma 2010). In addition, the temporal resolution and the quality of satellite observations are limited due to clouds and atmospheric disturbances (Ahl *et al.* 2006, Zhang *et al.* 2006) and still needs ground validation (Chambers *et al.* 2007). The set-up of digital cameras to monitor vegetation systems can be a solution for these limitations.

The method of applying digital cameras to monitor plant phenology has been described as “near” remote sensing (Richardson *et al.* 2007). “Near-surface remote phenology” using digital cameras set up at the top of towers reduces the temporal and spatial constraints of on-the-ground human observations, and eliminates the uncertainty of cloud

cover, enhancing the resolution of information at individual tree, species, and community scales (Polgar & Primack 2011).

The focus of near-surface monitoring systems is leaf phenology, mainly leaf flushing, also referred to as leafing, leaf out, the time of first leaf bud appearance, or leaf budding (Crimmins & Crimmins 2008, Richardson *et al.* 2007, Polgar & Primack 2011). To enhance the interpretation of phenological events, take meteorological site-specific data measurements are important to correlate with color time series and precisely define phenological triggers (Crimmins & Crimmins 2008).

The applicability of this new technology has been demonstrated in temperate ecosystems (e.g. Richardson *et al.* 2007, 2009, Ahrends *et al.* 2008, 2009, Nagai *et al.* 2010, Ide & Oguma 2010, Migliavacca *et al.* 2011, Sonnentag *et al.* 2012, Zhao *et al.* 2012, Henneken *et al.* 2013, Zhou *et al.* 2013), with relevant studies coming from camera's networks developed in the US (PhenoCam Network - <http://phenocam.sr.unh.edu/webcam/>) and Japan (Phenological Eyes Network-PEN - <http://pen.agbi.tsukuba.ac.jp/> and Japan long-term Ecological Research Network-JaLTER - www.jalter.org).

The present study is part of a multidisciplinary project called “e-phenology: The application of new technologies to monitor plant phenology and track climate changes in the tropics” (FAPESP grant 2010/52113-5) which comprehends the application of new technologies for plant phenology monitoring and creates a protocol to include digital cameras as tools to detect leaf flushing and senescence in tropical systems. The project also integrates research in computer science with development of method and algorithms for data mining and analysis of time series. This project is innovative and puts Brazil in the state of the art of near remote phenology monitoring, already established in areas of temperate forests in northern hemisphere.

Near-surface monitoring systems in the tropics are necessarily complex since the environmental conditions are harsh and the diversity of species is usually high. Since image information from digital cameras is still sparse for high-diverse tropical vegetation, we aim to develop in the first chapter of this study, a protocol of installation of a digital camera and analysis of images in a tropical cerrado savanna during the main leafing season, based on an approach at community and species levels. We aim to test the reliability of the near-surface system and answer: (i) Do digital cameras capture leaf changes in tropical cerrado savanna vegetation? (ii) Can we detect differences on phenological changes among species crowns and the cerrado community? (iii) Is the greening pattern detected for each species crown by digital cameras validated by our on-the-ground leafing phenology (direct observation of tree leaf changes)?

The second chapter of this study explores computational techniques of machine learning to identify species in the image based on phenological features, and our goals were: (i) to test if color change information is able to characterize the phenological pattern of a group of species; (ii) to test if the temporal variation in image texture is useful to distinguish plant species; and (iii) to test if individuals from the same species may be automatically identified using digital images.

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3 CHAPTER 1

USING PHENOLOGICAL CAMERAS TO TRACK THE GREEN UP IN A CERRADO SAVANNA AND ITS ON-THE-GROUND VALIDATION¹

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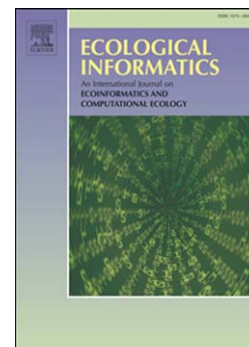
Using phenological cameras to track the green up in a cerrado savanna and its on-the-ground validation

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Using phenological cameras to track the green up in a cerrado savanna and its on-the-ground validation

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Abstract: Plant phenology has gained new importance in the context of global change research, stimulating the development of novel technologies for phenological observations. Regular digital cameras have been effectively used as three-channel imaging sensors, providing measures of leaf color change or phenological shifts in plants. We monitored a species rich

Brazilian cerrado savanna to assess the reliability of digital images to detect leaf-changing patterns. Analysis was conducted by extracting color information from selected parts of the image named regions of interest (ROI). We aimed to answer: (i) do digital cameras capture leaf changes in cerrado savanna vegetation? (ii) Can we detect differences in phenological changes among species crowns and the cerrado community? (iii) Is the greening pattern detected for each species by digital camera validated by our on-the-ground leafing phenology (direct observation of tree leaf changes)? We analyzed daily sequences of five images per hour, taken from 6:00 to 18:00h, recorded during the cerrado main leaf flushing season. We defined 24 ROIs in the original digital image, including total or partial regions and crowns of six plant species. Our results indicated that: (i) for the studied period, single plant species ROIs were more sensitive to changes in relative green values than the community ROIs, (ii) three leaf strategies could be depicted from the species' ROI patterns of green color change; (iii) the greening patterns and leaf functional groups were validated by our on-the-ground phenology. We concluded that digital cameras are reliable tools to monitor high diverse tropical seasonal vegetation and it is sensitive to inter-species differences of leaf patterns.

Key words: leafing, leaf traits, cerrado, data validation, digital camera, phenology

1. Introduction

Leaf flushing and senescence are important events in plants life cycles and fundamental to understand a range of processes in the ecosystem due to their impact on growth, water status, gas exchange and nutrient cycling (Reich 1995; Negi 2006; Morisette et al. 2009). The plants' growing season plays a crucial role in the carbon balance and in the productivity of terrestrial ecosystems (Keeling et al. 1996; Rotzer et al. 2004; Loustau et al. 2005), controlling spatial and temporal patterns of carbon and water exchange between the forest and atmosphere (White et al. 1999; Schwartz et al. 2002). The time, length, and intensity of the leaf growing season are closely linked to the proportion of leaf exchange functional types (e.g. evergreen, deciduous and semi-deciduous species). Those plant functional types define the seasonal patterns of leaf changes and the dynamics of the ecosystem processes (Gholz et al. 1976, Shaver 1981, Reich et al. 1997, Negi 2006).

The relevance of plant phenology as a reliable indicator of species' responses to global climate change has stimulated the development of new technologies for phenological monitoring (Walther et al. 2002, Parmesan and Yohe 2003, Walther 2004, Rosenzweig et al. 2008; Richardson et al. 2009). To better understand seasonal patterns and responses of leafing to inter-annual and long-term variation in climate, a variety of approaches to describe temporal changes in the plant canopy have been employed. The traditional on-the-ground phenology, the

direct observations of individual plants, preclude large spatial areas, and the interference of the observer is high due to the inherent difficulties to detect the variations on leaf color patterns from leaf budding to senescence in the tropics (Richardson et al. 2007, Morisette et al. 2009, Morellato et al. 2010a). Satellite remote sensing provides spatially extensive information of vegetation changes; however, it is difficult to detect phenological events at species and community levels (Ide and Oguma 2010). In addition, the temporal resolution and the quality of satellite observations are limited due to clouds and atmospheric disturbances (Ahl et al. 2006; Zhang et al. 2006) and still needs ground validation (Chambers et al. 2007).

The technique of repeated photographs using digital cameras has been increasingly used for several ecological applications (Crimmins and Crimmins 2008; Graham et al. 2010). Low cost investment, reduction in size to set up installation, and high resolution data make digital cameras a reliable tool for a range of applications (Morisette et al. 2009), including changes in ecosystem dynamics and structure (Peñuelas and Boada 2003), growth vegetation and biomass (Crimmins and Crimmins 2008; Graham et al. 2009), plant stress and nitrogen status (Wang et al. 2004), and for crop monitoring (Slaughter et al. 2008).

Recently, “near-surface” remote monitoring with digital cameras has been successfully used as multi-channel imaging sensor to characterize leaf change patterns in temperate ecosystems, such as: Northern hardwood and conifer forests (Richardson et al. 2007, 2009; Graham et al. 2009), Mixed beech forest and Temperate deciduous forests (Ahrends et al. 2009; Ide and Oguma 2010; Henneken et al. 2013), Deciduous broad-leaved forest (Nagai et al. 2011), Subalpine grasslands (Migliavacca et al. 2011) and temperate dry land ecosystems (Kurc and Benton 2010). After quantifying the RGB (red, green, and blue) color channels, it is possible to estimate, for instance, leaf flushing and senescence, using the green and red channels, respectively (Ahrends et al. 2009; Morisette et al. 2009; Richardson et al. 2009; Henneken et al. 2013). Another important feature is the precise estimation of the starting date of leaf flush season, due to the daily frequency of data acquisition (Morisette et al. 2009; Richardson et al. 2009).

However, image information from digital cameras is still sparse for high-diverse tropical vegetation. In those ecosystems, one image may encompass dozens to more than a hundred of species, whereas temperate vegetation includes a much lower number of species. In this context, we monitored a cerrado savanna during the leafing season to assess the reliability of digital images to detect leaf change patterns in this species rich vegetation. We used our on-the-ground direct plant phenological observations at the same study site to validate the digital data. We aim to answer: (i) Do digital cameras capture leaf changes in a cerrado savanna vegetation? (ii) Can we detect differences on phenological changes among species crowns and the cerrado community? (iii) Is the greening pattern detected for each species crown by digital cameras validated by our on-the-ground leafing phenology (direct observation of tree leaf

changes)? We discuss the implications of our findings for monitoring the dynamics of seasonal tropical vegetations.

2. Materials and methods

2.1 Study Area and Camera Setup

The near-remote phenological system was set up in an 18 m tower (phenology tower) in a Cerrado *sensu stricto*, a savanna vegetation located at Itirapina (22°10'49.18"S; 47°52'16.54"W, 610 m a.s.l), São Paulo State, Brazil (Figure S1, Supplementary material). The cerrado *sensu stricto* (Coutinho 1978) vegetation does not form a continuous canopy, but presents a dominant woody component six to seven meters high, with some trees reaching up to 12 m high and a continuous herbaceous layer.

The regional climate is Cwa type (i.e., humid subtropical climate) according to Köppen (1931) classification. The average local climate (1972 to 2002) shows a mean annual total rainfall of 1524 mm and mean annual temperature of 20.7°C, with one warm, wet season from October to March (average of 22°C and 78% of annual precipitation) and one cold, dry season (average of 18°C and 16% of annual precipitation) from April to September (Figure S2). During the year of study (2011) the climate seasonality was similar to the average pattern, with a mean temperature of 21.2°C, but a higher annual total rainfall of 1891 mm due to a very humid January with precipitation over 500 mm (Fig. 1). Climatic data were obtained from the adjacent Climatological Station of the Center for Water Resources and Applied Ecology (CRHEA) of the University of São Paulo, located 4 km from the study site.

A digital hemispherical lens camera Mobotix Q 24 (Mobotix AG - Germany) was placed at the top of the tower attached to an extension arm facing northeast at a mean vertical distance of 10 meters from the tree canopy (Figure S1). The camera was well fixed to prevent any movement that could cause shifts in the camera position and thus image mismatches from one day to another. A timer controlled the camera activity. Camera was set in automatic exposure and white balance, as suggested by Zhao et al. (2013). The energy source was a 12 Volt Battery charged by a solar panel. We set up the camera to automatically take a daily sequence of five JPEG images (at 1280 x 960 pixels of resolution) in the first 10 minutes of each hour, from 6:00 to 18:00 h (UTC -3; Universal Time Coordinated). The present study is based on the analysis of over 2470 images, recorded at the end of the dry season, between August 29th and October 5th 2011, day of year (DOY) 241 to 278, during the main leaf flushing season (Camargo et al. 2013, Morellato et al., *unpublished data*, Fig. 1). Sunrise, sunset, and solar elevation angle were 6:03 h, 17:38 h, 58° (DOY 241), and 5:26 h, 17:48 h, 72° (DOY 278), respectively.

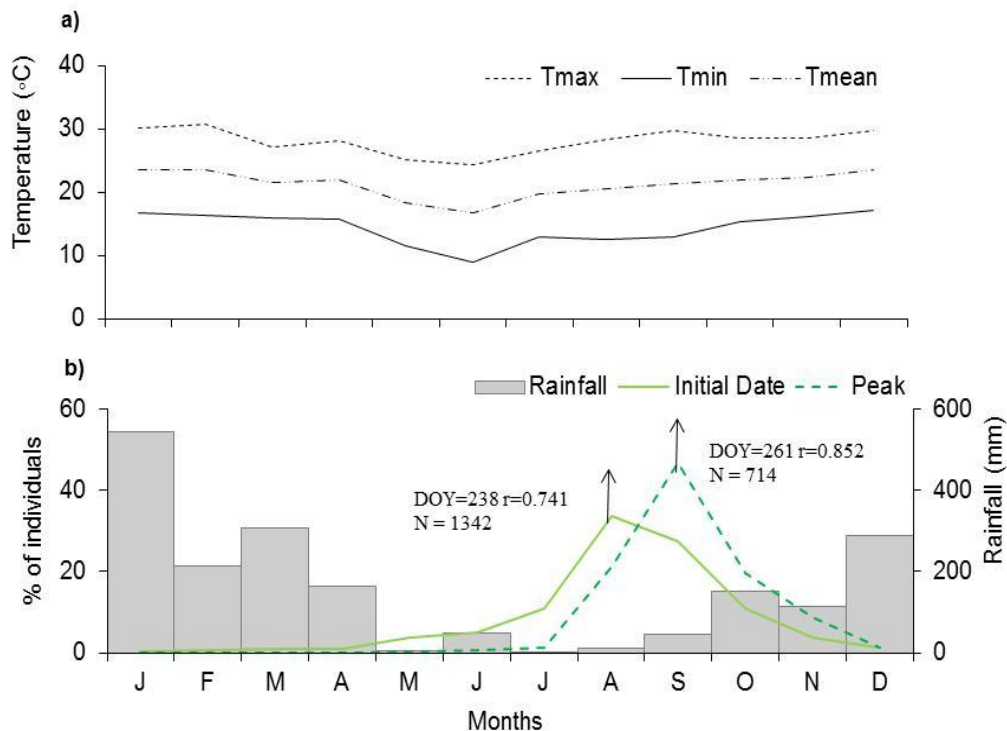


Fig. 1 Temperature, precipitation, and the leaf flushing pattern derived from on-the-ground direct observations of phenology during 2011 at the cerrado study site, Southeastern Brazil. (a) Maximum, mean, and minimum temperature, (b) Bars represent rainfall and lines represent the proportion of individuals at initial date (continuous line) and on the peak date (dotted line) of leaf flushing at the cerrado community. Arrows show the mean start date and peak date of leaf flushing along the year, indicated as the DOY (day of year) and N indicates number of individuals in the analyses. Rayleigh test was significant ($p < 0.01$), and the value of r has no units and indicates the amount of concentration in the data around the mean angle, from zero (when there is so much dispersion that a mean angle cannot be described) to one (when all the data are concentrated at the same direction or angle).

2.2 Image Analysis

The image analysis was conducted by defining different regions of interest (ROI) in the image, as described by Richardson et al. (2007, 2009), Ahrends et al. (2009) and Henneken et al. (2013). We identified at species level all crowns monitored in the hemispherical image, excluding just the trees on the very edge (Fig. 2d) where the distortion made the tree identification unreliable. The plant identifications were done in the field by directly matching the tree crown in the image with the tree on the ground.

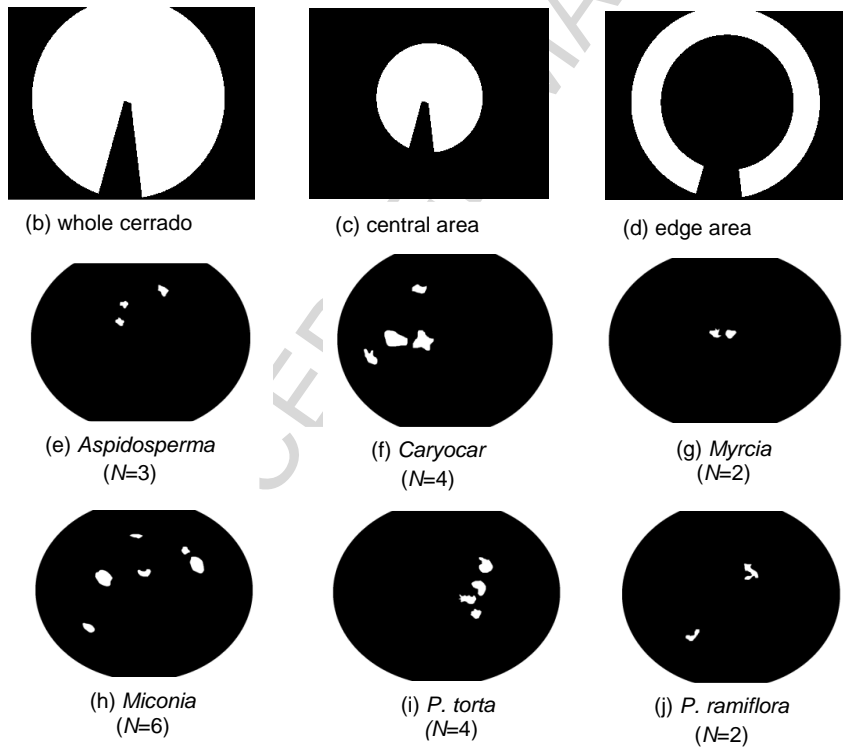
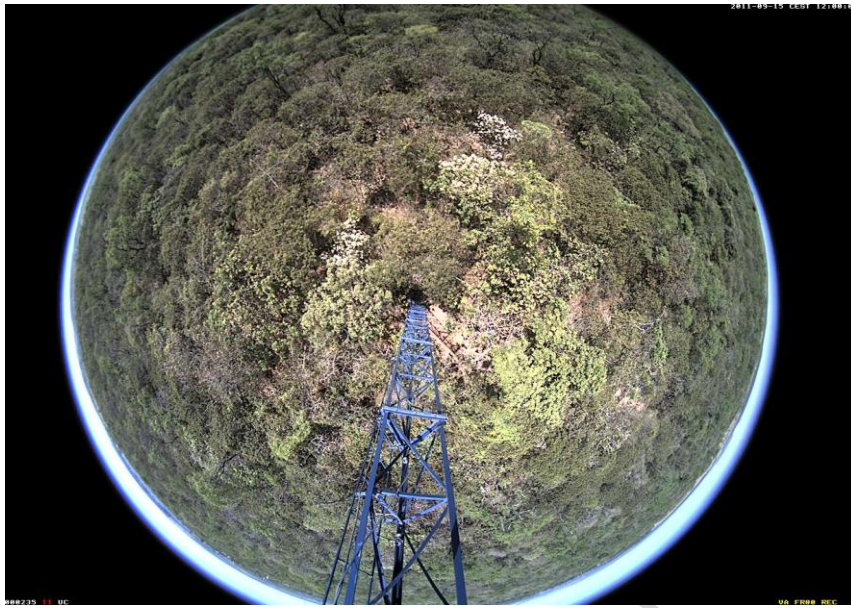


Fig. 2 Sample image of the cerrado savanna (a) recorded by the digital camera on October 15th 2011. Below (b-j) the masks indicating the regions of interest (ROI) visualized as white areas: (b) whole cerrado savanna, excluding the tower; (c) central area of (b), excluding the distorted edge; (d) distorted edge as seen on (b); (e) *Aspidosperma*; (f) *Caryocar*; (g) *Myrcia*; (h) *Miconia*; (i) *P. torta*; and (j) *P. ramiflora*. Number of ROIs are in parentheses.

We defined 24 ROIs (Figure 2b-j), described as follow: (b) whole cerrado: we took the complete image area, excluding just the tower; (c) central area of the whole cerrado image,

excluding the edge (radius 30m); (d) edge area: periphery of the whole cerrado image; (e) to (j) ROIs based on the random selection of six plant species crowns in the hemispheric image, taking into account the smallest overlap with neighboring crowns: (e) *Aspidosperma tomentosum* (N= 3 ROIs); (f) *Caryocar brasiliensis* (N= 4 ROIs); (g) *Myrcia guianensis* (N= 2 ROIs); (h) *Miconia rubiginosa* (N= 6 ROIs); (i) *Pouteria torta* (N= 4 ROIs) and (j) *Pouteria ramiflora* (N= 2 ROIs). The number of ROIs for each species was limited by the occurrence of the individuals in the hemispheric image. Hereafter, the species will be named by their genus, except for *P. torta* and *P. ramiflora*.

For each ROI, a binary image with the same dimensions as the original image was created as a mask. White pixels of a mask indicate the ROI, while the remaining area was filled by black pixels (Fig. 2b-j). We analyzed each ROI in terms of the contribution of the relative brightness of the green color channel (RGB chromatic coordinates in Woebbecke et al. 1995) in relation to the primary colors (red, green, and blue). The normalized RGB chromatic coordinate index used in our analysis is referred as the most suitable index to detect leaf color changes and the most efficient to suppress light variation (Gillespie et al. 1987; Woebbecke et al. 1995; Sonnentag et al. 2012). A custom script was used to analyze each color channel and to compute the average value of the pixels' intensity. We calculated normalized colors of the green color channel, as:

$$Total_{avg} = Red_{avg} + Green_{avg} + Blue_{avg}$$

$$Green \% = \frac{Green_{avg}}{Total_{avg}}$$

Although the index Green % is actually calculated as a proportion, we call it “percent” for convenience.

2.3 Image quality control

To assess the day-to-day stability of the image data acquisition along the growing season, we defined an additional ROI from the tower structure as a reference (Fig. S3) and extracted their averaged RGB color channels. Then, we calculated the coefficient of variation for the red, green and blue color channels time series.

Variation along the hours of the day was verified for each ROI. Mean time series for all period along the hours of the day (from 6 h to 18 h) were plotted for the community and individuals species. In general, ROIs presented the highest green values and more stability within midday hours (from 10h to 14h, Fig. 3) as previous detected by other authors (Ahrends et al. 2008, 2009, Richardson et al. 2009, Ide and Oguma 2010, Zhao et al. 2012). Since we analyzed a short time frame during the dry season, and weather conditions were relatively

constant in that period, we did not detect diurnal variations related to overcast and sunny days as described by Sonnentag et al. (2012).

To minimize the solar angle effect, avoiding problems in the green values related to seasonal changes and time of the day, we applied the *per90* method proposed by Sonnentag et al. (2012). We considered all daytime % green values within a moving window of three days, for calculating the 90th percentile of the % green values (Sonnentag et al. 2012).

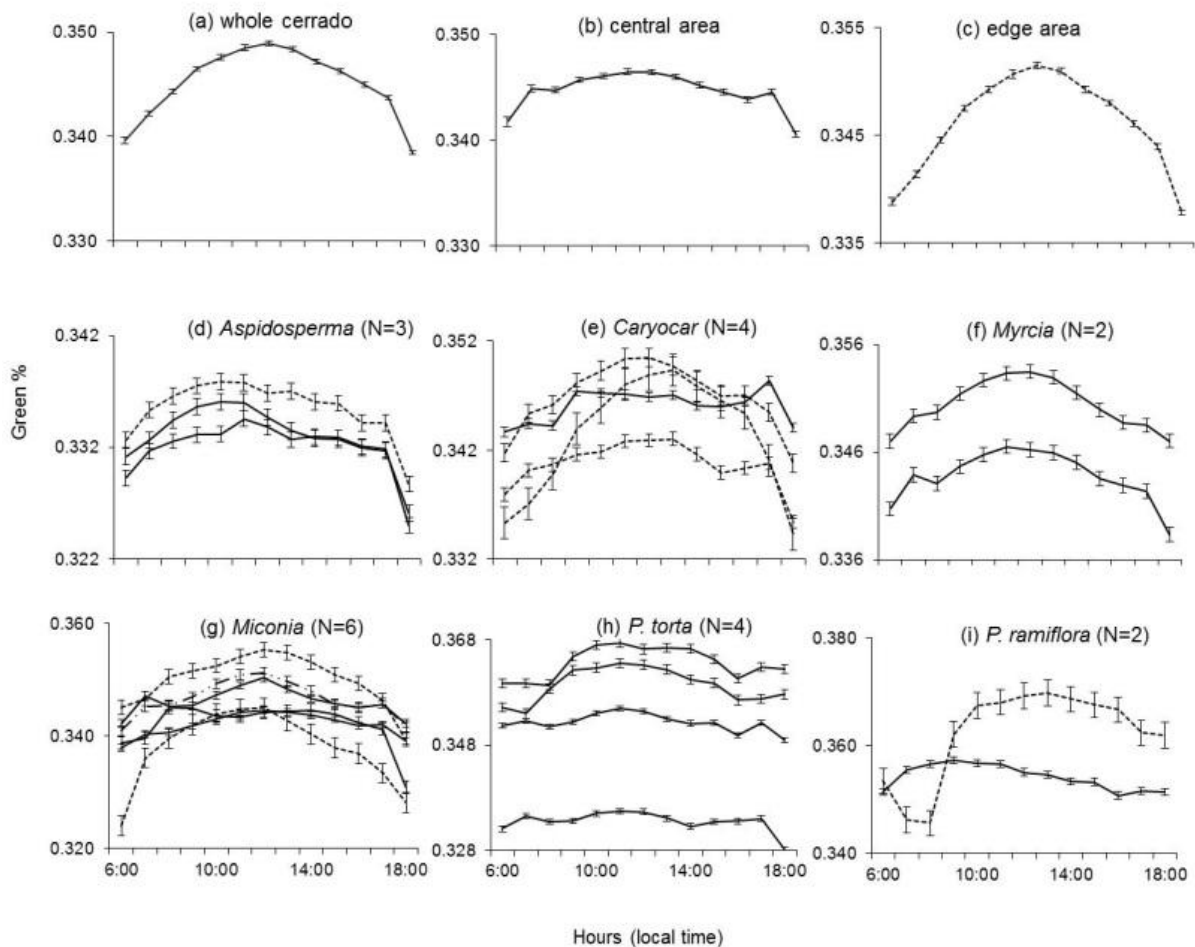


Fig. 3 Mean diurnal patterns of Green % from day of year (DOY) 241 to 278 for all the 24 regions of interest (ROIs). Error bars show 95% of confidence intervals. Black thick lines represent ROIs positioned in the central area of the image, and dashed lines represent the ROIs positioned near the edge of the digital image. *N* indicates number of ROIs

To check the precision in location of ROIs over time and consequently, if the masks were dislocated in the image or covered by other crowns we made a video with the sequence of images for the studied period. There was no evidence of image mismatch over the time span analyzed (video is available in the Electronic Supplementary Material (ESM) and through our web page <http://www.recod.ic.unicamp.br/ephenology/index.php?id=3>).

2.4 On the ground validation of digital image phenology

To evaluate the performance of the method and verify the efficiency for monitoring phenological events in the cerrado savanna, we validated our data with monthly on-the-ground direct observations of leaf flushing on 2016 marked individuals in the cerrado savanna study site (see Camargo et al. 2011, 2013, for details on methods).

To verify if the camera-based greening pattern for each ROIs species matches the on-the-ground leaf flushing phenology, we analyzed the frequency of individuals of each species producing new leaves in 2011. To verify if our near-surface phenology fell into the main leafing season, we plotted the on-the-ground leaf flushing phenology for all the community and applied circular statistics analyses to define the mean date and mean start and peak of leaf flushing as proposed by Morellato et al. (2000, 2010b). We use the Rayleigh test to check the significance of mean angle or mean date and, when the mean angle was significant, we use r as a measure of degree of seasonality (Morellato et al. 2000, 2010b). The mean angle or date represents the time around with most individuals was flushing new leaves; the value of r represents the concentration of trees leafing around the mean date. The value of r has no units and indicates the concentration in the data, from zero (when there is so much dispersion that a mean angle cannot be described, – e.g., Fig. 6 c and d) to one (when all the data are concentrated at the same direction or angle, – e.g., Fig.6 a and b). We define the leaf change strategy for each studied species based on the long-term on-the-ground savanna phenology data series at our study site (Morellato et al., *unpublished data*).

3. Results

3.1 Growing season patterns

The reference RGB values from the tower's ROI did not show a strong variation, except for the early (6-8) and late (16-18) hours of the day (Fig. S3a). Likewise, the low coefficients of variation of the RGB % values from the tower's ROI during the growing season (1.45%, 1.07% and 1.60% for R, G and B, respectively) indicate only small changes along the period of study (Fig. S3b), which did not affect the observed leaf color changes.

In general, the ROIs selected for the cerrado vegetation showed a variation in the green channel along the daily hours (see Fig. 3) as well as in their green pattern along the main leafing season (Fig. 4). The green area in Figure 4 represents changes in the % of green, and the increase in green % indicates the flush of new leaves which differed not only among the different species (see Fig. 5), but explicitly also among individuals of the same species which are plotted in Fig. 4.

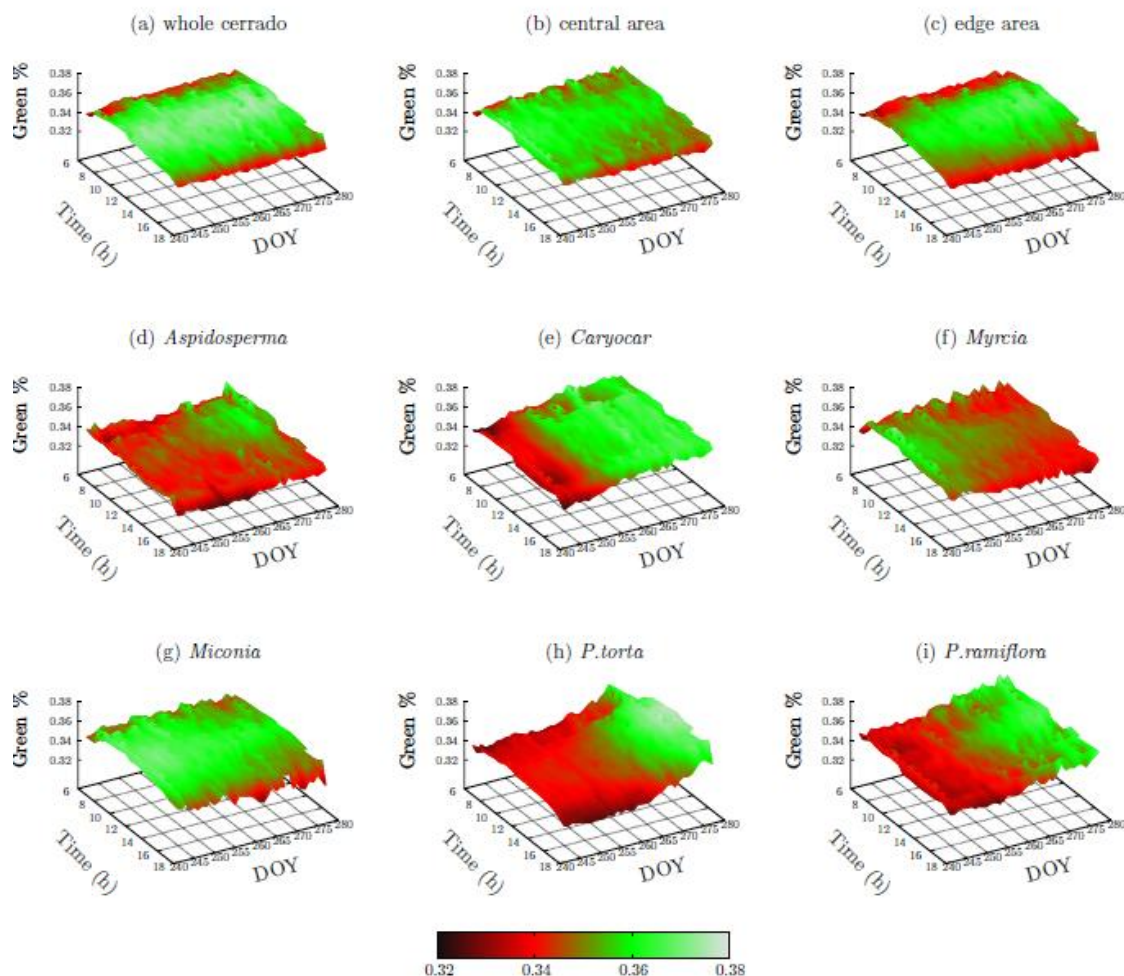


Fig. 4 Changes of the green % values from digital images taken every hour (6:00 h to 18 h) during the growing season, from day of the year (DOY) 241 to 278 (August 28th to October 3rd, 2011), for individual trees' regions of interest (ROIs) at the cerrado savanna vegetation, Southeastern Brazil

Results based on the 90th percentiles allowed us to identify changes in the green % pattern for each species' ROI along the growing season. The species' crowns showed different patterns for leaf color change (Fig. 5). *Aspidosperma* and *Caryocar* presented an increase in the green channel along the observed period (Fig. 5a-b), while the opposite pattern was observed for *Myrcia*, *Miconia*, *P. torta* and *P. ramiflora*, with a decreasing of greening over time (Fig. 5c-f). However, we observed a within-species variation in the 90th percentile of green %, with individual ROIs of the same species showing divergent patterns over the leafing season (Fig. S4). For instance, ROIs of individual crowns of *P. torta* and *P. ramiflora* showed either increase or decrease patterns of green % (Fig.S4 o-t). On the other hand ROIs of *Myrcia* and *Miconia* demonstrated the same pattern of green % decrease during the main leafing season (Fig. S4 h-n).

However, the 90th percentile (*per90*) of green % values (Sonnentag et al. 2012) differed between the community and the species ROIs along the study period. For the community ROIs, we did not detect evident color changes in the short period analyzed, even considering that all images were taken during the peak of the leafing season (Fig. S5).

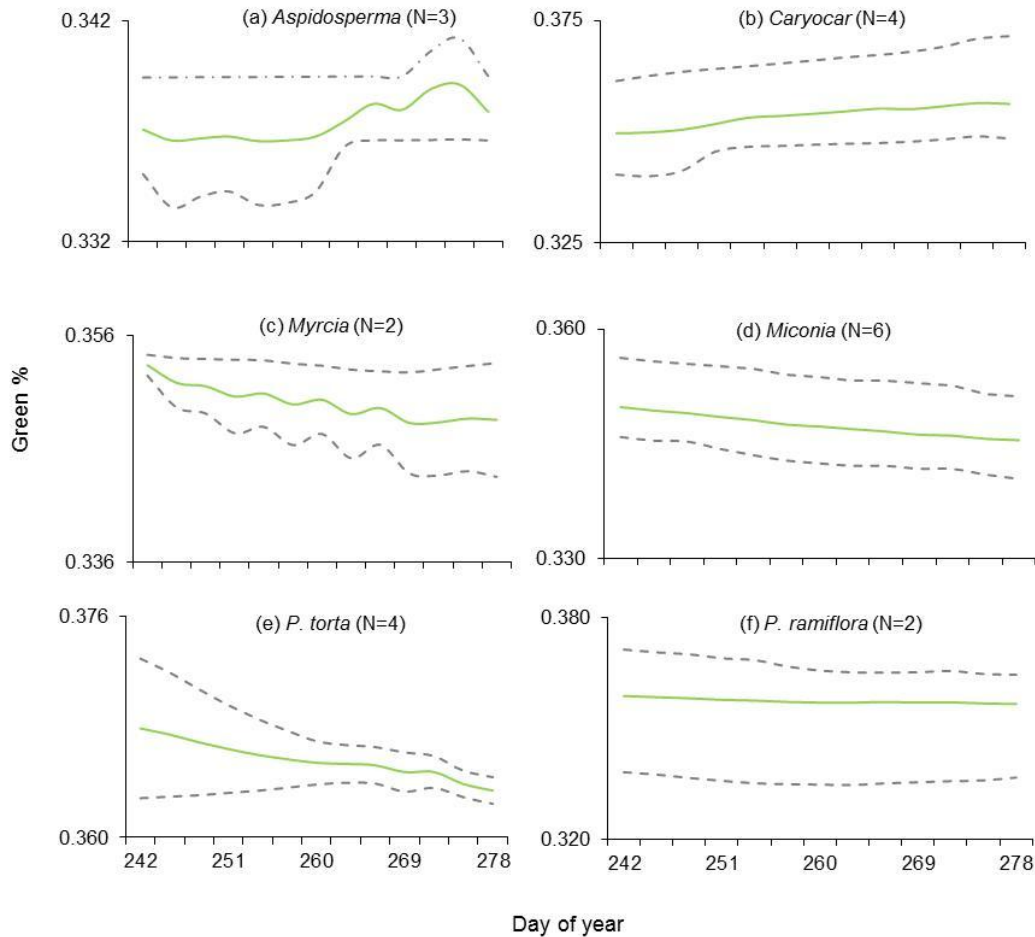


Fig. 5 Mean three-day 90th percentiles of Green % during the leafing season for each species' ROIs in the cerrado savanna, Southeastern Brazil. (a) *Aspidosperma*; (b) *Caryocar*; (c) *Miconia*; (d) *Myrcia*; (e) *P. torta*; (f) *P. ramiflora*. Green lines represent the mean 90th percentiles of Green % for the species; dashed lines represent the maximum and minimum values, respectively (for the masks of each ROI see Fig. 2).

3.2 Leafing, leaf strategies and on-the-ground validation

The on-the-ground observations of cerrado community leaf phenology in 2011 demonstrated that the leafing season was significantly seasonal, with most individuals starting to flush new leaves in August (mean date of 26-Aug-2011 or DOY 238) and a peak of leaf flush in middle September (mean date of 18-Sep-2011 or DOY 261; Fig. 1). Therefore, our study period (DOY 241 to 278) fell within the main leafing season, even considering the community green % did not changed over the dry season.

For the six plant species analyzed in the digital images the on-the-ground observations showed different leafing patterns (Fig. 6). Based on the leaf color changes (Fig. 4) and the 90th percentile analyses (Fig. 5), combined with the on-the-ground phenology, we classified the species into three leaf change functional groups: (i) deciduous - species that lose all leaves in the dry season, and flush new ones seasonally and synchronously at the end of the dry season (*Aspidosperma* and *Caryocar*, Fig.6 a-b); (ii) evergreen - species flushing new leaves continuously along all the year (*Myrcia* and *Miconia*, Fig. 6 c-d); and (iii) semi-deciduous - species that lose part of their leaves in the dry season, and may flush new leaves through the year or more concentrated at the end of dry season or beginning of the wet season (*P. torta* and *P. ramiflora*, Fig.6 e-f).

Deciduous species presented a marked leaf change, with a seasonal peak of leaf flushing in August (Fig. 6a-b). An opposite pattern was observed for evergreen species for which new leaves were flushing all year and the concentration around the mean date was lower, but also peaking in July and August (Fig. 6c-d). The individuals of semi-deciduous species flushed new leaves all year round (Fig. 6e-f).

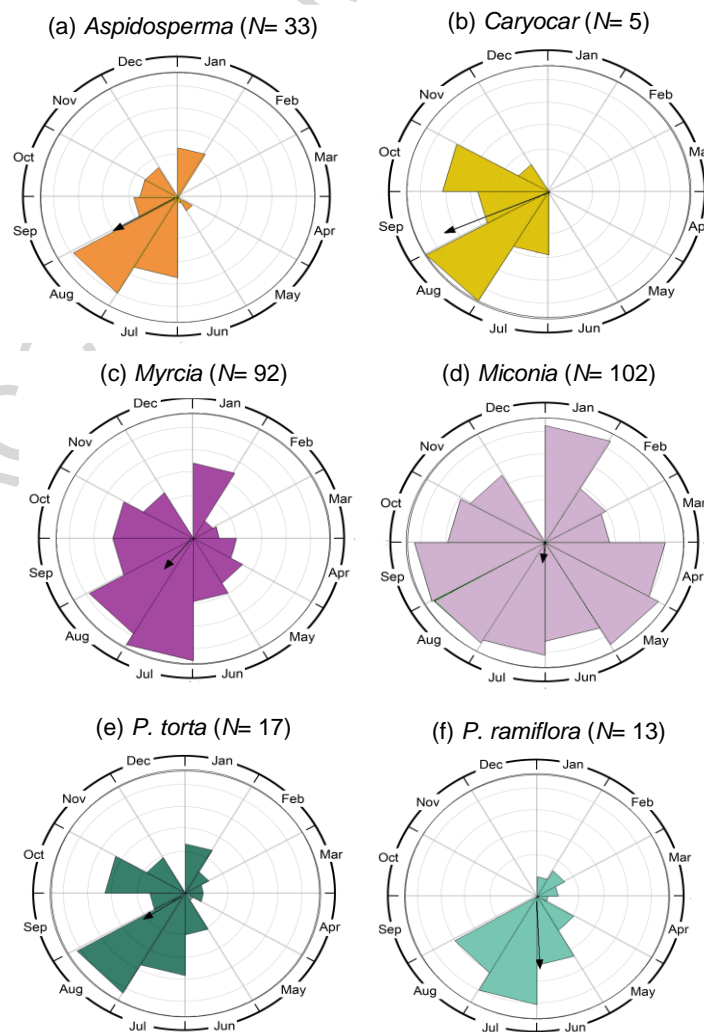


Fig. 6 Circular histograms of the leaf flushing on-the-ground phenology during the year of study (2011) for the six species analyzed in the cerrado savanna study site, Southeastern Brazil. Frequency of individuals in the peak flushing of new leaves for (a) *Aspidosperma*.; (b) *Caryocar*; (c) *Miconia*; (d) *Myrcia* (e) *P. torta*; (f) *P. ramiflora*. The arrows point to the mean angle or date around with most individuals was flushing new leaves; the length of the arrow indicates the value of r , and represents the concentration of trees leafing around the mean date. The r has no units and varies from zero to one (when all the data are concentrated at the same direction or angle; see Methods for details). Within parentheses: number of trees observed on the ground.

4. Discussion

4.1 Digital cameras and the near-remote phenology of cerrado savanna

Digital camera was a reliable tool to monitor leaf phenological changes in the highly-diverse cerrado vegetation. ROIs time series present the highest values for the green curves during the midday hours (noon) (Ahrends et al. 2008, 2009; Sonnentag et al. 2012), except for *Aspidosperma* with the highest green values around 9:00 and 10:00 hours. The hours from 8:00 to 11:00 were suggested as the best daytime to perform automatic species recognition in the digital images based on the analyses of the RGB channels and texture features of same ROIs (Almeida et al. 2013).

We did not detect within-species variations in green % related to the position of the species crown in the image. However, for *P. torta* and some crowns of *Caryocar* in multiple positions differed in their daily green %. These variations may be explained by modifications in leaf position due to wind, and also by individual specific attributes such as leaf angle inclination, type of leaf protection, and discolored leaves. Also, reflectance patterns of the leaves in different wavelengths may be considered (Ahrends et al. 2008; pers. obs.). In these cases, field observations will be important to combine image data processed with complementing observation of different trees and species.

4.2 Green patterns and on-the-ground phenology

We verified leaf color changes along the main leafing season, in particular for each species' ROIs. The on-the-ground observations validated the phenological pattern derived from the digital images and also the species classification in the leafing functional groups: deciduous, semi-deciduous, and evergreen.

Cerrado community ROIs were not sensitive to changes in greenness within the time span analyzed here. Longer data series may be needed to perceive changes at the community level. ROIs integrating major parts of the community carry too much information, due to the high heterogeneity and diversity of tropical ecosystems (Woebbecke et al. 1995).

However, species' ROIs indicated distinctive leaf color changes, which allowed us to distinguish tree main leaf functional groups (deciduous, semi-deciduous, and evergreen species). Data from our on-the-ground local phenology was essential to identify the groups and validate the trends of greenness of the digital images' ROIs. Species with deciduous and evergreen leaf patterns typically differ in leaf life span (Van Ommen Kloeke et al. 2012). Deciduous trees usually have short leaf life span, and put out the new crop of leaves either just before the onset or in the beginning of the wet season in southeastern Brazil and cerrado savannas (Morellato et al. 1989; Lenza & Klink 2006; Rubim et al. 2010; Morellato et al. *unpublished data*). A decrease for the green % values occurring in the peak of the leaf season was detected for evergreen and some semi-deciduous species, such as *Myrcia*, *Miconia* and *P. torta*. Those species may renew their foliage along the year or eventually during the dry season, when both, leaf flush and leaf fall, can proceed simultaneously (Monasterio and Sarmiento 1976; Lenza and Klink 2006; Rubim et al. 2010). Evergreen species keep the same foliage longer than deciduous species, but the color of the leaves change during the leaf life span, with degradation of chlorophyll and different levels of carotenoids (Billow et al. 1994; Merzlyak et al. 1999). Moreover the green % values also represent optical leaf color changes due to leaf maturity and aging processes (Richardson et al. 2009).

Although the three leaf functional groups as ecological strategies are very useful and largely applied to understand cerrado leaf change, this simplification leads to considerable loss of information (Petchey and Gaston 2002). Single specimen can considerably vary in their flushing or greening pattern, for instance a single individual of *P. torta* increased in green % whereas the average pattern based on four ROIs is clearly decreasing (Fig. 4 vs. Fig. 5) which also matches the on-the-ground observations based on 17 individuals (Fig. 6). In addition, single species inside those leaf functional groups differ in their mean greening pattern (see Fig. 5) and species belonging to different groups are not equally different.

Future research should use digital cameras images to explore cerrado savanna deciduousness as a continuous variable, by combining the analysis of green and red color channels, and the leaf color spectral changes over season.

5. Conclusions

This is the first study addressing the applicability of near-surface remote phenology to track leaf changes along the leafing season in tropical seasonal vegetation, the cerrado, and innovates by integrating on-the-ground validation by direct plant phenological observations. The digital camera turned out to be a reliable tool to monitor the phenology of cerrado savanna species; leaf functional groups were detected by analyses of the green channel, averaged over individual crowns' ROIs. Ground direct phenological observations were important to validate camera data and to develop a trustworthy methodology to be set up at new sites and in different ecosystems. There is a large range of ecological questions to be answered regarding leafing behavior (Polgar and Primack 2011).

Near-surface monitoring systems in the tropics are necessarily complex since the environmental conditions are harsh and the diversity of species is usually high. The traditional method of the on-the-ground phenology, the direct observations of individual plants, preclude large spatial areas, human labor and the interference of the observer is high due to the inherent difficulties to detect the variations on leaf color patterns from leaf budding to senescence, especially in the tropics (Richardson et al. 2007, Morisette et al. 2009, Morellato et al. 2010a). However, on-the-ground phenology is still the most widely applied method of observation in the tropics. Additionally, it is a very confident technique to monitor individual based phenology and offers key information for validation of near-remote generated patterns. Image information from digital cameras is still sparse for high-diverse tropical vegetation, and allows us to obtain an impartial and comparable data of leaf seasonal changes. We consider that these two approaches are complementary to each other and the application will depend on the study goals. Near-surface remote phenology has becoming more and more common for phenological research and the arrivals of novel technologies followed by the advance of e-science methods for dealing with large data sets are changing the scenario of plant ecology studies.

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Highlights

Using phenological cameras to track the green up in tropical cerrado savanna and its on-the-ground validation

- digital cameras are reliable tool to capture leaf changes in tropical cerrado savanna vegetation
- three leaf exchange strategies were depicted from the species patterns of green color change
- the greening patterns and leaf functional groups were validated by our on-the-ground phenology

4 CHAPTER 2

APPLYING MACHINE LEARNING BASED ON MULTISCALE CLASSIFIERS TO DETECT REMOTE PHENOLOGY PATTERNS IN CERRADO SAVANNA TREES¹

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Applying machine learning based on multiscale classifiers to detect remote phenology patterns in Cerrado savanna trees

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Tropical forests

ABSTRACT

Plant phenology is one of the most reliable indicators of species responses to global climate change, motivating the development of new technologies for phenological monitoring. Digital cameras or near remote systems have been efficiently applied as multi-channel imaging sensors, where leaf color information is extracted from the RGB (Red, Green, and Blue) color channels, and the changes in green levels are used to infer leafing patterns of plant species. In this scenario, texture information is a great ally for image analysis that has been little used in phenology studies. We monitored leaf-changing patterns of Cerrado savanna vegetation by taking daily digital images. We extract RGB channels from the digital images and correlate them with phenological changes. Additionally, we benefit from the inclusion of textural metrics for quantifying spatial heterogeneity. Our first goals are: (1) to test if color change information is able to characterize the phenological pattern of a group of species; (2) to test if the temporal variation in image texture is useful to distinguish plant species; and (3) to test if individuals from the same species may be automatically identified using digital images. In this paper, we present a machine learning approach based on multiscale classifiers to detect phenological patterns in the digital images. Our results indicate that: (1) extreme hours (morning and afternoon) are the best for identifying plant species; (2) different plant species present a different behavior with respect to the color change information; and (3) texture variation along temporal images is promising information for capturing phenological patterns. Based on those results, we suggest that individuals from the same species and functional group might be identified using digital images, and introduce a new tool to help phenology experts in the identification of new individuals from the same species in the image and their location on the ground.

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1. Introduction

Phenology, the study of natural recurring phenomena and its relation to climate (Schwartz, 2003), is a traditional science dedicated to the observation of the cycles of plants and animals and relate mainly to local meteorological data, as well as to biotic interactions and phylogeny (Staggemeier et al., 2010).

The leaf exchange patterns from leaf flush to senescence are key events to understand a range of ecosystem processes, considering its prominence on growth, water status, gas exchange, and nutrient cycling (Negi, 2006; Reich, 1995). The carbon balance and the productivity of terrestrial ecosystems are essentially defined by the dynamics of plant growing seasons (Keeling et al., 1996; Loustau et al., 2005; Rotzer et al., 2004), controlling spatial and temporal patterns of carbon and

water exchange between forest and atmosphere (Schwartz et al., 2002; White et al., 1999).

Plant phenology has gained importance as the simplest and most reliable indicator of species responses in the context of global change research, stimulating the development of new technologies for phenological observation (Parmesan and Yohe, 2003; Richardson et al., 2009; Rosenzweig et al., 2008; Walther, 2004; Walther et al., 2002). Digital cameras have been successfully used as multi-channel imaging sensors, and the measurements of color change information (RGB channels) from digital images allow one to detect phenological changes in plants (Ahrends et al., 2009; Ide and Oguma, 2010; Kurc and Benton, 2010; Nagai et al., 2011; Richardson et al., 2007, 2009).

After quantifying the color channels, it is possible to estimate changes on phenological events, such as leaf flushing when analyzing the green channel, or leaf color change and senescence using values from the red channel (Ahrends et al., 2009; Richardson et al., 2009). However, image information from digital cameras is sparse for a highly diverse tropical forest, where one image may encompass dozens to more than a hundred species, compared to the low number of species in temperate vegetations.

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Another important feature that can be extracted from digital images is the spatial arrangement of the pixel intensities, known as texture (Torres and Falcão, 2006). The appearance of texture can help an observer to determine whether different regions from a digital image of a given vegetation have a same structure. Due to difficulties in measurement and interpretation, texture has been little used in phenology studies (Culbert et al., 2009).

We monitored a tropical Cerrado savanna vegetation to assess the reliability of digital images to detect leaf changes and validate the digital data with on the ground direct phenological observation (Alberston et al., 2012). In this paper, we investigate the use of machine learning based on multiscale classifiers to detect phenological patterns in a Cerrado savanna by using color and texture information of digital images. The key contribution of this study is the analysis of intra-species variations.

The primary goal of our research is to determine how good is the color change information to characterize the phenological pattern of a group of species. Moreover, we are interested in analyzing how promising is the temporal variation in image texture to distinguish different individuals that have similar spectral characteristics but different spatial patterns. Finally, we use machine learning based on multiscale classifiers to find similar textures in the digital image and we checked if they correspond to similar species or functional groups.

Based on those studies, we expect to open new venues on the automatic identification of plants from the same species or functional group using machine learning. Most of existing methods for species identification have focused on morphological features of a single organ (mainly leaf, rarely flower), often considering ideal conditions, such as noise-free images with a uniform background, taken at specific periods (Cope et al., 2012; Kumar et al., 2012).

Unlike previous works in the literature, we address the problem of identifying plant species by using phenology instead of morphometrics. Our strategy integrates a high degree of diversity in terms of locations, periods, and illumination conditions, which is a prerequisite to build modern plant identification systems.

A preliminary version of this work was presented at eScience 2012 (Almeida et al., 2012). Here, we include the analysis of texture information to characterize phenological patterns. The new reported results show the potential of texture change information for species identification.

The remainder of this paper is organized as follows. Section 2 presents our learning strategy and shows how to apply it to identify plant species. Section 3 describes materials and methods of our experimental protocol. Section 4 reports our experimental results and discuss how they can be applied in phenology studies. Finally, we offer our conclusions and directions for future work in Section 5.

2. Machine learning

In machine learning, classification is the task of assigning objects to one of several predefined classes. The input data for a classification task is a collection of records. Each record, also known as a *sample*, is characterized by a tuple (\mathcal{F}, Y) , where \mathcal{F} is the attribute set and Y is a special attribute, called *label*, which indicates the class that belongs each sample (Tan et al., 2005).

The attribute set \mathcal{F} , also known as a *feature vector*, is a sequence of continuous or discrete values obtained from measures over a given object and it is used for computationally describing each sample concerning a specific property. The label, on the other hand, must be a discrete attribute (Tan et al., 2005).

A *detector* or *classifier* is a systematic approach to building classification models from an input data set. Each technique employs a *learning strategy* to identify a model that best fits the relationship between the feature vector and label of the input data (Tan et al., 2005).

For that, a *training set* consisting of records whose labels are known must be provided. The training set is used to build a classification model,

which is subsequently applied to predict the labels of records it has never seen before (Tan et al., 2005). For more details concerning machine learning concepts, refer to (Alpaydin, 2010; Rostamizadeh and Talwalker, 2012).

In this paper, we use machine learning to detect phenological patterns. For this purpose, we adopted the *multiscale classifier* (MSC) approach (dos Santos et al., 2012b) to learn phenological patterns and build phenological pattern detectors. It was chosen due to its ability of combining different features by weighting the ones more suitable for each plant species. Moreover, it also allows the combination of features from different segmentation scales, which increases the power of the final detector (dos Santos et al., 2012a).

2.1. Multiscale classifier

The *multiscale classifier* (MSC) (dos Santos et al., 2012b) is a learning strategy based on boosting of weak learners. It is based on the Adaboost algorithm proposed by Schapire (1999), which builds a linear combination of weak classifiers to compose a final strong one. A weak learner is a classifier slightly better than the random. Boosting-based classification strategies have been extensively used in applications that need to combine a large sets of different features or classifiers (Grabner and Bischof, 2006; Lechervy et al., 2013; Viola and Jones, 2001).

Let H be a hierarchy of segmented regions, P_λ is a partition, which is the segmentation result at a given scale λ . A partition P is obtained by cutting the hierarchy H . In this sense, $R \in P$ refers to any region R that belongs to the partition P . The MSC aims at assigning a label (+1, for relevant class; and -1, otherwise) to each pixel p of P_0 taking advantage of various features computed on regions of various levels from a segmentation hierarchy H . The final classifier is a linear combination MSC(p) of T weak classifiers $h_t(p)$:

$$MSC(p) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(p) \right), \quad (1)$$

where α_t is the weight assigned to the weak classifier $h_t(p)$ at the iteration t .

The training consists of testing *weak learners* in a sequence of rounds $t = 1, \dots, T$. Each weak learner builds a weak classifier that reduces the expected classification error of the final classifier. For each round t , MSC selects the weak classifier that most decreases the error.

The algorithm keeps a set of weights over the training set. The weights can be understood as a measure of difficulty of each sample. The pixels start with the same weights. But along the rounds, the weights of the misclassified pixels are increased. Thus, the weak learners are forced to focus on the most difficult samples. We note $W_t(p)$ the weight of pixel p in round t , and $D_{t,\lambda}(R)$ the misclassification rate of region R in round t at scale λ which is the mean of the weights of its pixels:

$$D_{t,\lambda}(R) = \left(\frac{1}{|R|} \sum_{p \in R} W_t(p) \right). \quad (2)$$

Algorithm 1 presents the training process of the MSC. Let $Y_\lambda(R)$, the set of labels of regions R at scale λ , be the training set. In a series of rounds $t = 1, \dots, T$, for all scales λ , the weight of each region $D_{t,\lambda}(R)$ is computed (line 3). The selection of regions is based on this piece of information to create a subset of labeled regions $\hat{Y}_{t,\lambda}$ (line 6). This subset is used to train weak learners: each features \mathcal{F} at scale λ (line 9). Each weak learner produces a weak classifier $h_{t,(\mathcal{F},\lambda)}$ (line 10). The algorithm then selects the weak classifier h_t that most reduces the error Err_{h_t} (line 12). The level of error of h_t is used to compute the coefficient α_t , which indicates the degree of importance of h_t in the final classifier (line 13). The selected weak classifier h_t and the coefficient α_t are used to update the weights of the pixels $W_{(t+1)}(p)$ which can be used in the next round (line 14).

Algorithm 1. Multiscale classifier.

Input:
 Training labels $Y_\lambda(R)$ = labels of regions R at scale λ
 Initialize:
 For all pixels p , $W_1(p) \leftarrow \frac{1}{|Y_0|}$, where $|Y_0|$ is the number of pixels in the image level
 1 For $t \leftarrow 1$ to T do
 2 For all scales λ do
 3 For all $R \in P_\lambda$ do
 4 Compute $D_{t,\lambda}(R)$
 5 End for
 6 Build $\hat{Y}_{t,\lambda}$ (a training subset based on $D_{t,\lambda}(R)$)
 7 End for
 8 For each pair feature/scale (\mathcal{F}, λ) do
 9 Train weak learners using features (\mathcal{F}, λ) and training set $\hat{Y}_{t,\lambda}$.
 10 Evaluate resulting classifier $h_{t,(\mathcal{F},\lambda)}$; compute $\text{Err}(h_{t,(\mathcal{F},\lambda)}, W)$ (Eq. (3))
 11 End for
 12 Select weak classifier $h_t = \underset{h_{t,(\mathcal{F},\lambda)}}{\text{argmin}} \text{Err}(h_{t,(\mathcal{F},\lambda)}, W_{t,\lambda})$
 13 Compute $\alpha_t \leftarrow \frac{1}{2} \ln \left(\frac{1+\text{Err}_t}{1-\text{Err}_t} \right)$ with $\text{Err}_t \leftarrow \sum_p c Y_0(p) h_t(p)$
 14 Update $W_{t+1}(p) \leftarrow \frac{W_t(p) \exp(-\alpha_t Y_0(p) h_t(p))}{\sum_p W_t(p) \exp(-\alpha_t Y_0(p) h_t(p))}$
 15 End for
 Output: Multi-Scale Classifier $MSC(p)$

The training set labels Y_0 corresponds to the samples at the pixel level. The training sets labels Y_λ with $\lambda > 0$ are defined according to the percentage of pixels that belongs to each of the two classes (for example, at least 80% of one region). The learning is performed over a training set Y_λ corresponding to the same scale λ . The weak learners use the subset $\hat{Y}_{t,\lambda}$ for training and produce a weak classifier $h_{t,(\mathcal{F},\lambda)}$.

The classification error of the classifier h is:

$$\text{Err}(h, W) = \sum_{p|h(p)Y_0(p)<0} W(p). \tag{3}$$

2.2. SVM-based weak learner

In this work, we used a linear SVM (support vector machine) as weak learner, which is an SVM trainer based on a specific feature type \mathcal{F} and a specific scale λ . Given the training subset labels \hat{Y}_λ , the method finds the best linear hyperplane of separation, trying to maximize the data separation between the regions according to their classes. The sample regions in the margin are called support vectors and are found during the training.

Once the support vectors and the decision coefficients (α_i , $i = 1, \dots, N$) are found, the SVM weak classifier can be defined as:

$$\text{SVM}_{(\mathcal{F},\lambda)}(R) = \text{sign} \left(\sum_i^N y_i \alpha_i (f_R \cdot f_i) + b \right), \tag{4}$$

where b is a parameter found during the training. The support vectors are the f_i such that $\alpha_i > 0$, y_i is the support vector class and f_R is the feature vector of the region.

Only the most difficult regions are supposed to be used for training. Thus, the training subset $\hat{Y}_{t,\lambda}$ is composed by n labels from Y_λ with values of $D_{t,\lambda}(R)$ larger or equal to $\frac{1}{|Y_0|}$.

3. Materials and methods

3.1. Study area and camera setup

The near-remote phenological system was set up in an 18 m tower in a Cerrado sensu stricto, a savanna-like vegetation located at Itirapina (22° 10' 49.18" S / 47° 52' 16.54" O), São Paulo State, Brazil. The Cerrado stricto sensu (Coutinho, 1978) is a savanna-like vegetation presenting a

discontinuous canopy and woody component reaching six to seven meters high and a continuous herbaceous layer (Alberton et al., 2012). In some parts, the vegetation is denser, with some trees reaching up to 12 m high. The Cerrado savanna study site is about 260 ha, 610 m altitude and the regional climate is Cwa type (i.e., humid subtropical climate) according to Köppen classification.

The average climate (1972 to 2002) shows a mean annual total rainfall of 1524 mm and mean temperature of 20.7 °C, with one warm, humid season from October to March (average of 22 °C and 78% of annual precipitation) and one cool, dry season from April to September (average of 18 °C and 16% of annual precipitation). During the year of study (2011) the climate seasonality was similar to the average pattern, with a mean temperature of 21.2 °C, but a higher annual total rainfall of 1891 mm due to a very humid January with precipitation over 500 mm. Climatic data were obtained from the Climatological Station of the Center for Water Resources and Applied Ecology (CRHEA) of the University of Sao Paulo, located 4 km from the study site.

A digital hemispherical lens camera (Mobotix Q24) was set up at the top of the phenology tower, attached to an iron arm facing northeast (Fig. 1). The camera activity is controlled by a timer and the energy source is a 12 V battery charged by a solar panel.

The first data collection from the digital camera started on 18th August 2011. We set up the camera to automatically take a daily sequence of five JPEG images (at 1280 × 960 pixels of resolution) per hour, from 6:00 to 18:00 h (UTC-3). The present study was based on the analysis of over 2700 images (Fig. 2), recorded at the end of the dry season, between August 29th and October 3rd 2011, day of year 241 to 278 (DOY), during the main leaf flushing season (Alberton et al., 2012; Reys, 2008). Sunrise, sunset, and solar elevation angles were 6:03 h, 17:38 h, 58° (DOY 241); and 5:26 h, 17:48 h, 72° (DOY 278), respectively.



Fig. 1. The Cerrado-savanna phenology tower (18 m tall) at Itirapina, São Paulo, South-eastern Brazil, where the digital hemispherical lens camera was set up (red arrow) attached to an iron arm facing northeast. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Image analysis

3.2.1. Regions of interest

The image analysis was conducted by defining different regions of interest (ROI), as described by Ahrends et al. (2009); Alberton et al. (2012); Richardson et al. (2007, 2009). For each ROI, a binary image with the same dimensions of the original image was created as a mask. White pixels of a mask indicate the ROI, while the remaining area was filled by black pixels. We defined six ROIs (Fig. 3) based on the random selection of six plant species identified manually by phenology experts in the hemispheric image: (1) *Aspidosperma tomentosum* (Fig. 3(a)), (2) *Caryocar brasiliensis* (Fig. 3(b)), (3) *Myrcia guianensis* (Fig. 3(c)), (4) *Miconia rubiginosa* (Fig. 3(d)), (5) *Pouteria ramiflora* (Fig. 3(e)), and (6) *Pouteria torta* (Fig. 3(f)).

According to the leaf exchange data from the on-the-ground field observations on leaf fall and leaf flush at our study site, those species were classified on three functional groups (Alberton et al., 2012; Morellato et al., 1989; Reys, 2008): (i) deciduous, *A. tomentosum* and *C. brasiliensis*; (ii) evergreen, *M. guianensis* and *M. rubiginosa*; and (iii) semideciduous, *P. ramiflora* and *P. torta*.

3.2.2. Color features

We analyzed each ROI in terms of the contribution of the primary colors (red, green, and blue), as proposed by (Richardson et al., 2007). Initially, a custom script was used to analyze each color channel and to compute the average value of the pixel intensity. After that, we calculated the relative (or normalized) brightness of each color channel, as:

$$\begin{aligned} Total_{avg.} &= Red_{avg.} + Green_{avg.} + Blue_{avg.} \\ \% \text{ of Red} &= \frac{Red_{avg.}}{Total_{avg.}} \\ \% \text{ of Green} &= \frac{Green_{avg.}}{Total_{avg.}} \\ \% \text{ of Blue} &= \frac{Blue_{avg.}}{Total_{avg.}} \end{aligned} \tag{5}$$

where $Red_{avg.}$, $Green_{avg.}$, and $Blue_{avg.}$ are the average pixel intensities of the red, green, and blue bands, respectively. The normalization of those values reduces the influence of the incident light, decreasing the color variability due to changes on illumination conditions (Cheng et al., 2001).

Fig. 4 shows the behavior of those values for each ROI along the whole period, considering only the digital images taken at midday. Each line corresponds to a time series for the variation of the normalized brightness of each color channel. Notice the differences between

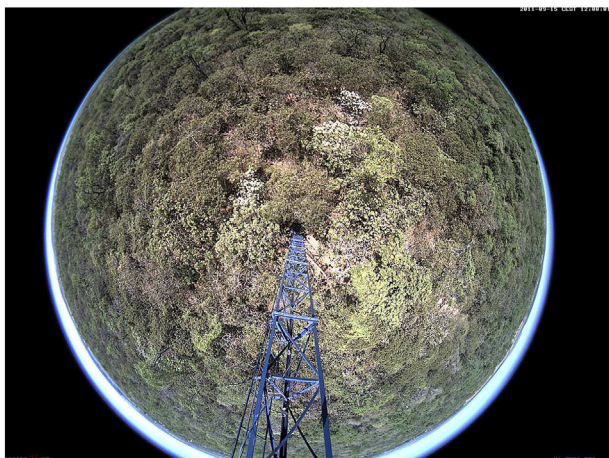


Fig. 2. Sample image of the Cerrado savanna recorded by the digital camera on October 15th, 2011.

the behavior of each species individually, reflecting the leaf color changes over the leaf life cycle or aging process.

3.2.3. Texture features

One of the most traditional techniques for extracting and representing texture information is the Co-occurrence matrix (Haralick et al., 1973). It describes spatial relationships among pixel intensities in an image. Each position (i,j) in this matrix indicates the probability at which pixels of intensity values i and j occur at a user specified distance and direction. There are four commonly used directions: 0° (horizontal), 45° (right diagonal), 90° (vertical), and 135° (left diagonal). The distance parameter is typically set to 1, thus comparing adjacent pixels. From this matrix, we can compute properties such as contrast, entropy, and homogeneity.

A simplification of the aforementioned method consists replacing the usual co-occurrence matrices by their associated sum and difference histograms (Unser, 1986). The non-normalized sum s and difference d associated with a relative displacement (δ_1, δ_2) on the position (k,l) of an image I are defined as:

$$\begin{aligned} S_{k,l} &= I_{k,l} + I_{k+\delta_1, l+\delta_2}, \\ d_{k,l} &= I_{k,l} - I_{k+\delta_1, l+\delta_2}. \end{aligned} \tag{6}$$

Let D be a subset of indexes specifying a region to be analyzed and $G = \{1, 2, \dots, N_g\}$ be the set of the N_g pixel levels. The sum (h_s) and difference (h_d) histograms for the intensity values i and j over the domain D are defined by:

$$\begin{aligned} h_s(i; \delta_1, \delta_2) &= h_s(i) = \text{Card}\{(k, l) \in D, s_{k,l} = i\}, \\ h_d(j; \delta_1, \delta_2) &= h_d(j) = \text{Card}\{(k, l) \in D, d_{k,l} = j\}. \end{aligned} \tag{7}$$

The normalized sum (P_s) and differences (P_d) histograms are given by

$$\begin{aligned} P_s(i) &= h_s(i)/N & i &= 2, \dots, 2N_g, \\ P_d(j) &= h_d(j)/N & j &= -N_g + 1, \dots, N_g - 1, \end{aligned} \tag{8}$$

where N is the total number of counts,

$$N = \text{Card}\{D\} = \sum_i h_s(i) = \sum_j h_d(j). \tag{9}$$

Statistical information can be extracted from those histograms by computing quantities such as mean, variance, and entropy. Unser (1986) has presented a variety of statistical measures that can be employed to extract useful information from both sum and difference histograms, as shown in Table 1. Such measures were computed from the sum and difference histograms obtained from the green color band by considering the domain D defined by each ROI.

Fig. 5 shows the behavior of those measures for each ROI along the whole period, considering only the digital images taken at the midday. Each line corresponds to a time series for the variation of the normalized value of each textural metric. The behavior of those curves is equivalent for the different orientations. For that reason, we report the average results of the all the directions (0° , 45° , 90° , and 135°).

3.3. Classification

Fig. 6 illustrates the steps of our MSC approach. The first step is to build a hierarchy of regions H . We have used the Guigues algorithm (Guigues et al., 2006) to perform the segmentation. In the remainder of this paper, when we refer to regions of interest related to tree crowns of plant species identified manually in the digital image, we use the acronym ROI; and when we refer to segmented regions obtained from the segmentation algorithm, we use the acronym SR.

The image used to obtain the hierarchy of segmented regions (SR) was taken at noon on October 15th, 2011 (Fig. 2). We have selected 5

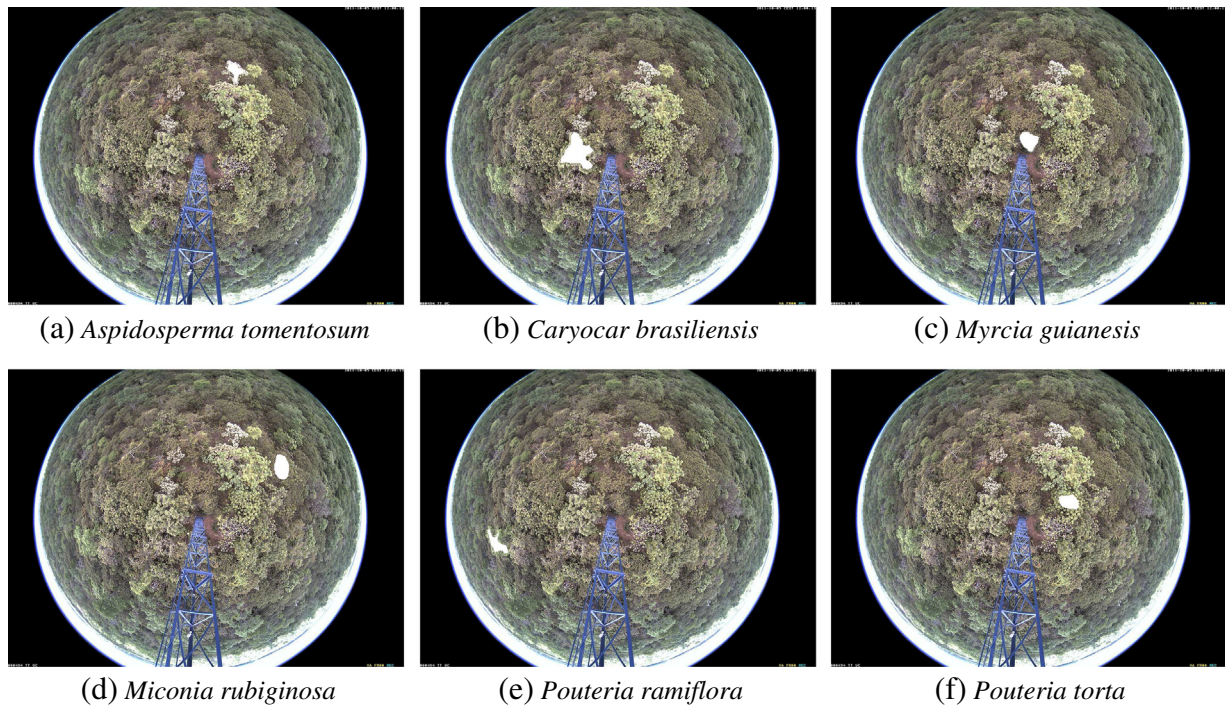


Fig. 3. Regions of interest (ROIs) defined for the analysis of Cerrado-savanna digital images: (a) *Aspidosperma tomentosum*, (b) *Caryocar brasiliensis*, (c) *Myrcia guianensis*, (d) *Miconia rubiginosa*, (e) *Pouteria ramiflora*, and (f) *Pouteria torta*.

segmentation scales from the hierarchy to perform feature extraction. The finest scale is composed of 27,380 SRs and the coarsest scale contains 8849 SRs. Fig. 7 illustrates the segmented scales in a subimage sample from Fig. 2.

The second step is the feature extraction, which is carried out on the SRs at different segmentation scales. For each plant species, we

have tested 39 different color features by considering the available periods during the day (13 h: from 6:00 to 18:00 h) and the color channels (3 bands: R, G, and B). Also, we have tested 91 different texture features by considering the available periods during the day (13 h: from 6:00 to 18:00 h) and the texture metrics (7 statistical measures: mean, variance, contrast, correlation, entropy, homogeneity, and maximum probability).

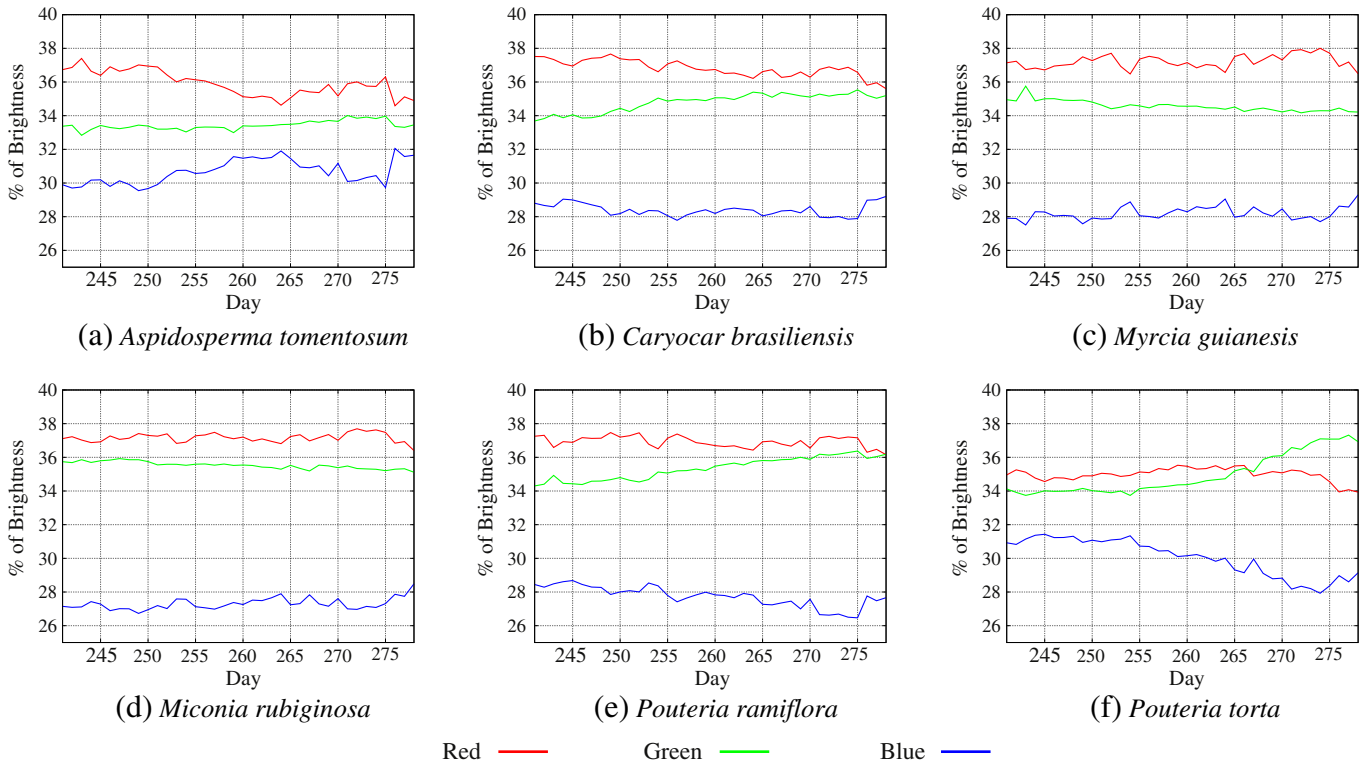


Fig. 4. The variance of the normalized brightness of each color channel from the digital images taken at the midday, each Julian day (August 28th to October 3rd, 2011), in the Cerrado savanna using different regions of interest (ROIs), as described in Fig. 3.

Table 1
Textural metrics extracted from each ROI.

Feature	Formula
Mean	$\mu = \frac{1}{2} \sum_i i \cdot P_s(i)$
Contrast	$C_n = \sum_j j^2 \cdot P_d(j)$
Homogeneity	$H_g = \sum_{j=1}^p \frac{1}{j} \cdot P_d(j)$
Variance	$\sigma^2 = \frac{1}{2} \left(\sum_i (i-2\mu)^2 \cdot P_s(i) + \sum_j j^2 \cdot P_d(j) \right)$
Correlation	$C_r = \frac{1}{2} \left(\sum_i (i-2\mu)^2 \cdot P_s(i) - \sum_j j^2 \cdot P_d(j) \right)$
Entropy	$H_n = - \sum_i h_s(i) \cdot \log P_s(i) - \sum_j P_d(j) \cdot \log P_d(j)$
Maximum	$M_p = \max_i P_s(i)$

For each feature, we take the average value obtained for the five images of each hour of the day. Time series are obtained by computing those values along the whole period (August 28th to October 3rd, 2011), forming the feature vector.

Finally, we use the MSC (Algorithm 1) to build a linear combination of weak classifiers, each of them related to a specific scale and feature. This step was performed for each plant species by using their ROIs (Fig. 3). To build a classifier for a given species, we used the SRs from its corresponding ROI as positive samples and from ROIs of the other species as negative samples. At the end, the final classifier was applied to classify the remaining SRs of the image.

3.4. Effectiveness measures

We carried out experiments to classify the plant species in the image. For that, we selected two species from different functional groups: *A. tomentosum* (deciduous) and *M. rubiginosa* (evergreen). Next, we built a classifier for each species using the approach described in Section 2.

Fig. 8 shows the ROIs identified by phenology experts, which we used to build and analyze each of the classifiers. In this figure, green areas indicate individuals of the analyzed species, whose SRs obtained from the segmentation were used as positive samples; while red

areas represent individuals from the other species, whose SRs were considered as negative samples.

To assess the effectiveness of each classifier, other individuals (yellow areas; Fig. 8) from each of the analyzed species were chosen as a validation set. Then, we used the SRs extracted from those ROIs as input samples for each classifier. Thus, we can measure the classification accuracy as the ratio of the number of samples correctly classified as belonging to the analyzed species to the total number of samples in the validation set.

4. Results and discussion

4.1. Classification accuracy

4.1.1. Color change information

Fig. 9 shows the classification accuracy for each of the color channels (3 bands: R, G, and B) along all the available periods of the day (13 h: from 6:00 to 18:00 h), totaling 39 different features for each of the analyzed species.

Fig. 10 shows a different view of those results, including all feature combinations, totaling 56 different possibilities. They are: (i) 1 h of the day and 1 color channel (39 combinations); (ii) 1 h of the day and all the color channels (13 combinations); (iii) all the hours of the day and 1 color channel (3 combinations); and (iv) all the hours of the day and all the color channels (1 combination). In order to make the comparison easier, we sorted the results from higher to lower accuracy.

Observe that, with less sunshine (early in the morning and late in the afternoon), the classification accuracy is higher, characterizing better the analyzed species for that particular day (Fig. 9). It indicates that early and late hours are better to characterize the phenological pattern of plant species for the identification using machine learning. This finding disagrees with the general suggestion of extracting color information from midday hours for ecological studies (Ahrends et al.,

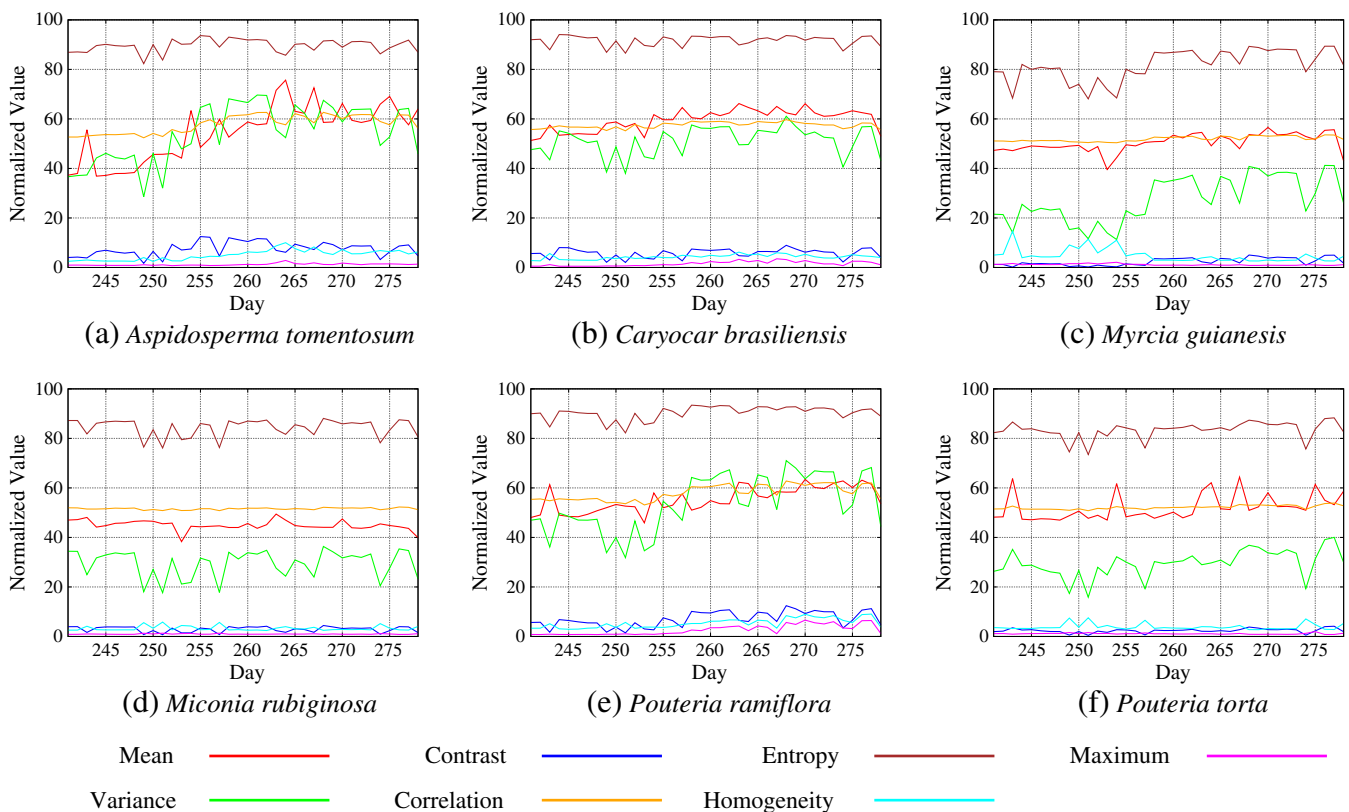


Fig. 5. The variance of the normalized value of each textural metric from the digital images taken at the midday, each Julian day (August 28th to October 3rd, 2011), in the Cerrado savanna using different regions of interest (ROIs), as described in Fig. 3.

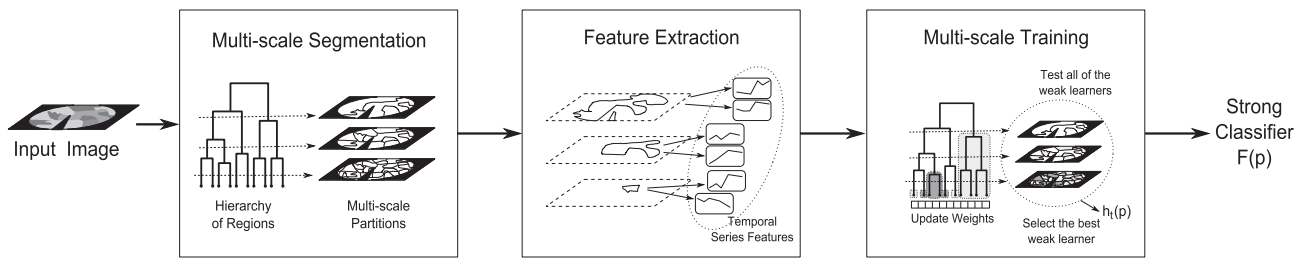


Fig. 6. Steps of the multi-scale learning process. Adapted from dos Santos et al. (2012b).

2009; Ide and Oguma, 2010; Richardson et al., 2007, 2009). Such differences are related to the type of data analyses being conducted, once those research works are interested in the variation among species (e.g., how different are the phenological patterns of individuals from different species), while the present study is focused on intra-species variations (e.g., how similar are the phenological patterns generated by different individuals of a same species).

Notice also the differences between the behavior of each of the species individually with respect to the color channels, indicating different patterns of leaf color change (Fig. 10). This behavior reflects their contrasting leaf phenology (Alberton et al., 2012): the *M. rubiginosa* is an evergreen species and, therefore, the leaf senescence is a continuous process and color changes are more subtle over time; in contrast, the *A. tomentosum* is deciduous, thus the color change reflects the rapid leaf senescence and the flush of new leaves.

As mentioned in Section 2.2, the MSC approach is based on boosting weak learners. In this paper, each weak learner is a linear

SVM classifier using features extracted from a given segmentation scale. In this way, each of the color channels along all the available periods of the day at one of the scales are used as a distinct feature. Table 2 presents the weak classifiers chosen by MSC training algorithm for the *A. tomentosum* and *M. rubiginosa* species.

Those results confirm that the extreme hours (morning, from 6:00 to 9:00 h; and afternoon, from 15:00 to 18:00 h) are better to characterize plant species. In addition, they also show that the *A. tomentosum* and *M. rubiginosa* species present a different behavior with respect to the color channels. Moreover, it is interesting to note that coarse scales provide better results than fine ones for the species identification.

A detailed analysis of the effects of the scale of segmentation on the descriptors is presented in dos Santos et al. (2012a). As pointed out by the authors, all scales are important in different ways: large regions offer more power of description, and the small ones can be used to refine the segmentation.

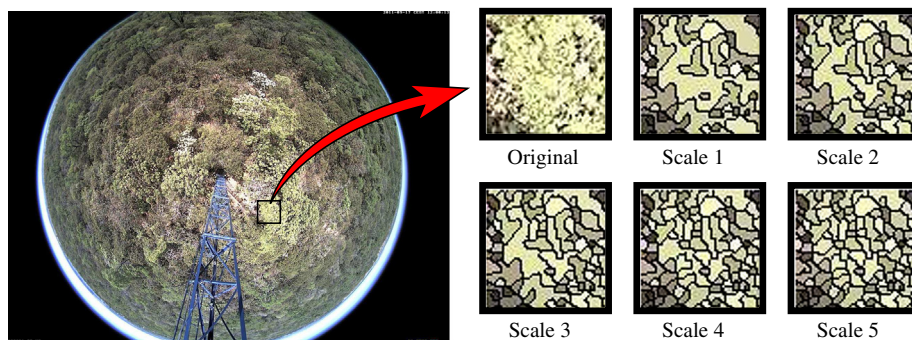


Fig. 7. The segmentation results for the selected scales in a subimage sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

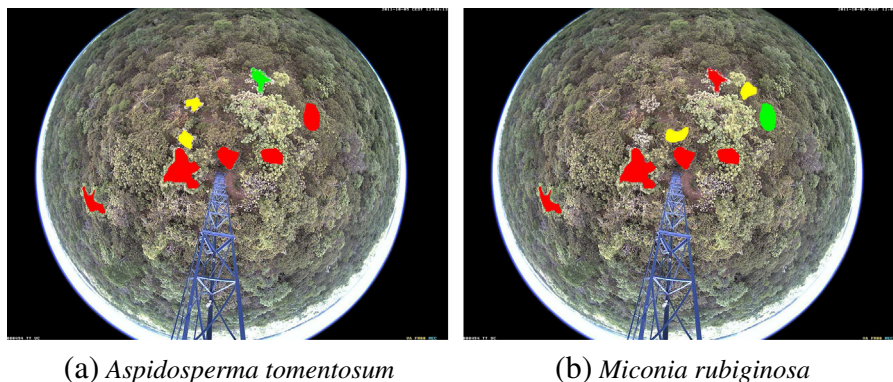


Fig. 8. Regions of interest (ROIs) used to build and analyze classifiers: green and red areas indicate individuals of plant species taken, respectively, as positive and negative samples for training; whereas yellow areas indicate individuals of plant species chosen for validation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The reason for the different behavior between the two species is probably related to the leaf change pattern and species functional group. These divergent leafing patterns indicated different behavior for the analyzed species that need further in-depth analyses considering their on-the-ground phenology (Alberton et al., 2012). Based on those results, our analysis suggests that individuals from the same species and functional group can be identified using digital images.

4.1.2. Texture change information

Fig. 11 shows the classification accuracy for each of the textural metrics (7 statistical measures: mean, variance, contrast, correlation, entropy, homogeneity, and maximum probability) along all the available periods of the day (13 h: from 6:00 to 18:00 h), totaling 91 different features for each of the analyzed species.

Fig. 12 shows a different view of those results, including all the feature combinations, totaling 112 different possibilities. They are: (i) 1 h of the day and 1 textural metric (91 combinations); (ii) 1 h of the day and all the textural metrics (13 combinations); (iii) all the hours of the day and 1 textural metric (7 combinations); and (iv) all the hours of the day and all the textural metrics (1 combination). In order to make the comparison easier, we sorted the results from higher to lower accuracy.

In general, the results indicate how promising is the use of textural metrics for capturing phenological patterns, achieving a high classification accuracy, comparable to that from the color features. This opens up a number of possibilities that deserve much deeper study, but an immediate consequence is that the variation in image texture contains important information which can be explored in phenology studies.

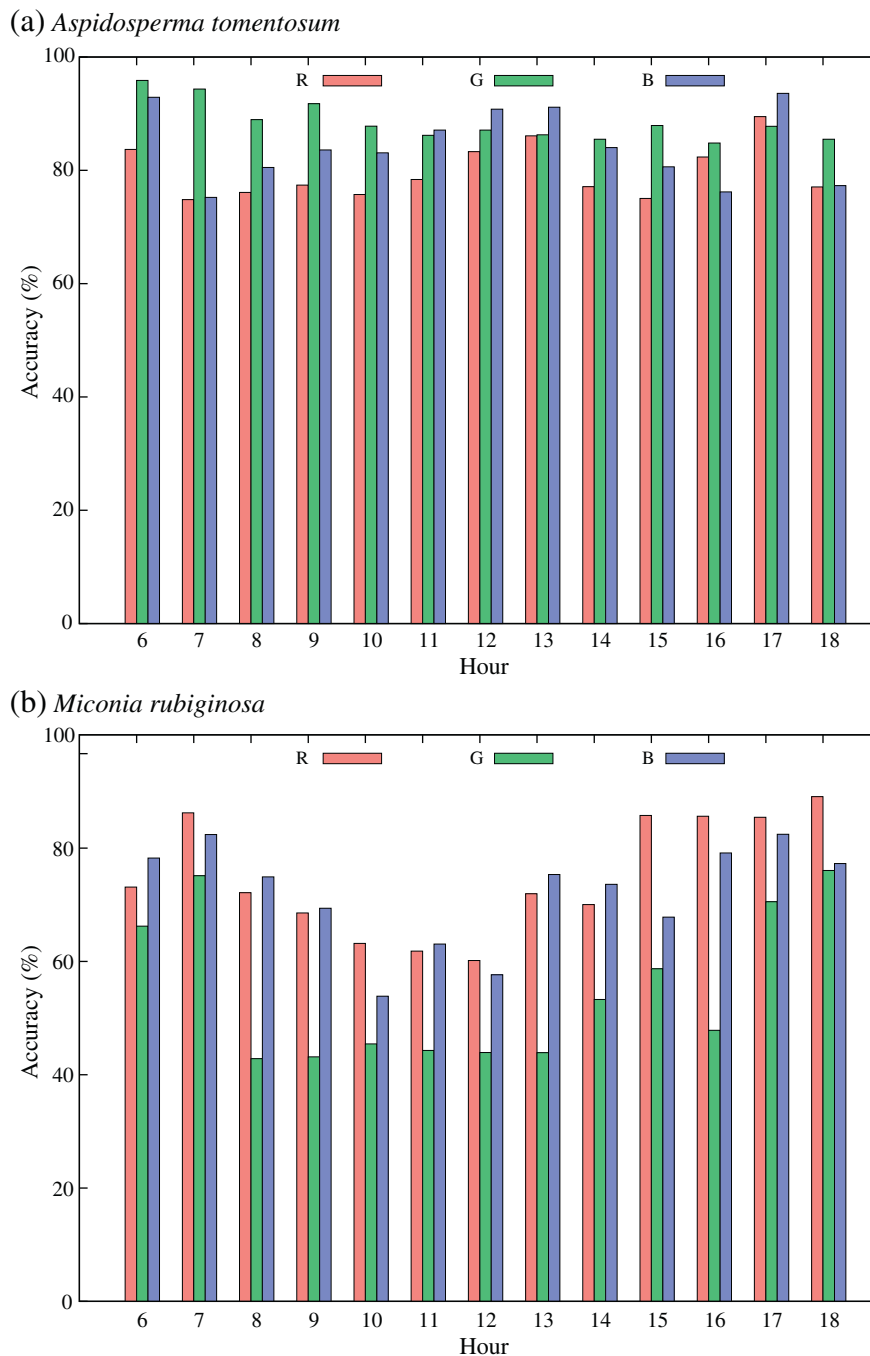


Fig. 9. Classification accuracy for each of the color channels along all the available periods of the day.

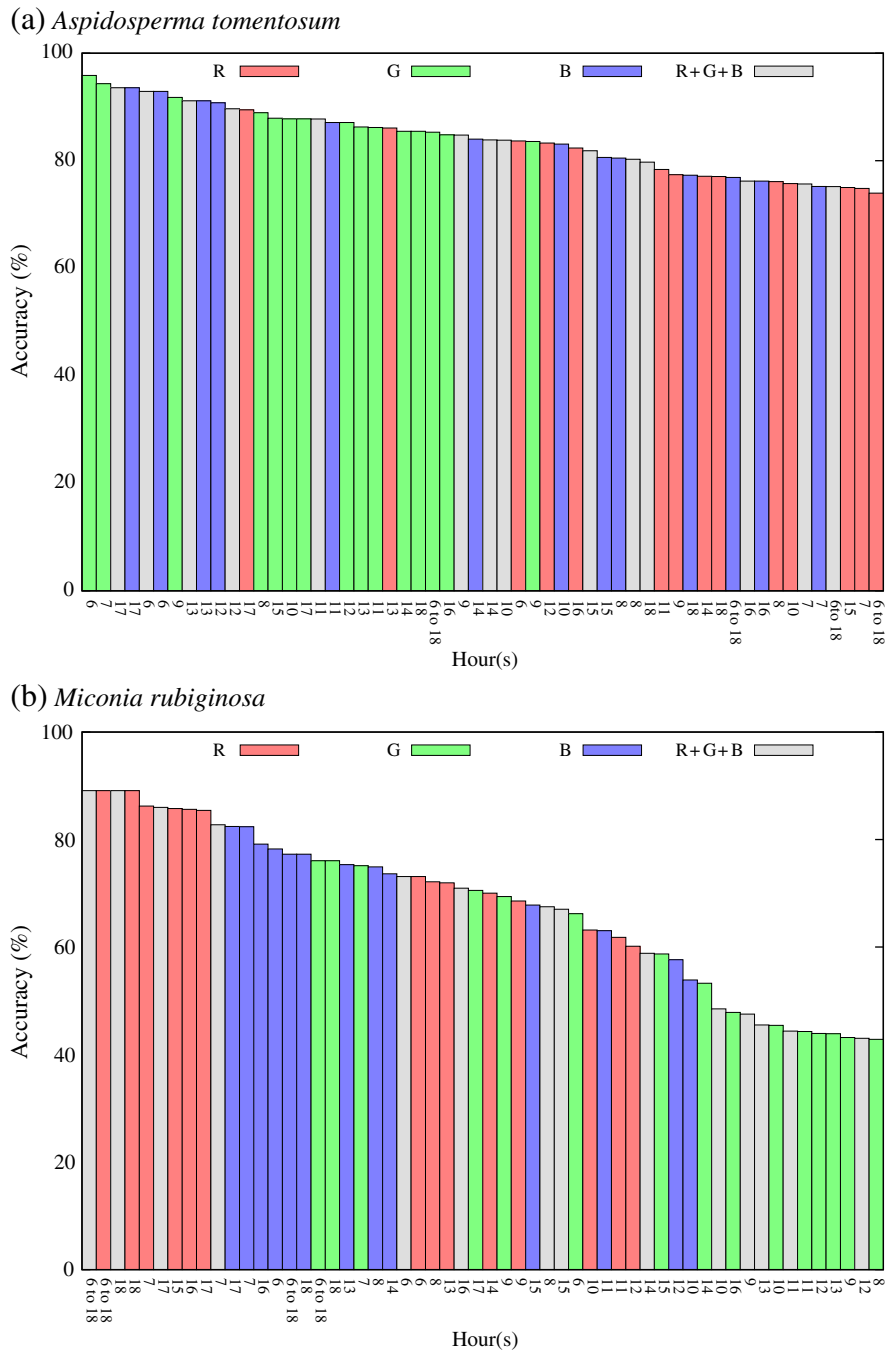


Fig. 10. Classification accuracy for each of the color channels along all the available periods of the day (among all the possible combinations).

Table 2

Weak classifiers chosen by the MSC for each round t . The classifier is composed by: color band, hour of the day and segmentation scale.

t	<i>Aspidosperma</i>		<i>Miconia rubiginosa</i>	
	Classifier	Weight	Classifier	Weight
0	7 h,R, λ_1	3.9	18 h,R, λ_4	4.0
1	16 h,B, λ_2	1.0	18 h,R, λ_3	3.7
2	16 h,B, λ_4	4.1	18 h,R, λ_1	1.0
3	16 h,R, λ_1	1.0	18 h,R, λ_1	1.0
4	7 h,B, λ_4	4.6	18 h,R, λ_1	1.0
5	7 h,B, λ_1	1.0	18 h,R, λ_1	1.0
6	7 h,B, λ_2	1.0	18 h,R, λ_1	1.0
7	16 h,B, λ_2	5.2	18 h,R, λ_1	1.0
8	7 h,B, λ_2	1.0	18 h,R, λ_1	1.0
9	7 h,B, λ_1	6.3	18 h,R, λ_1	1.0

Table 3

Weak classifiers chosen by the MSC for each round t . The classifier is composed by: textural metric, hour of the day and segmentation scale.

t	<i>Aspidosperma</i>		<i>Miconia rubiginosa</i>	
	Classifier	Weight	Classifier	Weight
0	8 h,Variance, λ_1	3.0	7 h,Mean, λ_1	1.9
1	7 h,Mean, λ_2	3.8	7 h,Entropy, λ_2	1.6
2	18 h,Mean, λ_1	2.9	17 h,Variance, λ_1	1.9
3	7 h,Mean, λ_1	4.5	6 h,Mean, λ_1	1.7
4	7 h,Mean, λ_1	1.0	6 h,Mean, λ_1	2.0
5	7 h,Mean, λ_1	1.0	6 h,Mean, λ_1	2.5
6	7 h,Mean, λ_1	1.0	15 h,Mean, λ_1	2.9
7	7 h,Mean, λ_1	1.0	6 h,Mean, λ_1	3.2
8	7 h,Mean, λ_1	1.0	6 h,Mean, λ_1	1.0
9	7 h,Mean, λ_1	1.0	18 h,Mean, λ_1	1.0

As we can observe, the statistical measures of mean, contrast, and variance achieve the best results for both the *A. tomentosum* and *M. rubiginosa* species. In contrast, it is interesting to note the differences in responsiveness of each of the species individually with respect to those textural metrics, indicating different patterns of temporal changes in their spatial distribution. The contrast captured better the deciduous leaf change pattern of the *A. tomentosum*, as previously described. On the other hand, the mean described better the continuous process of leaf senescence of the *M. rubiginosa*, an evergreen species.

The weak classifiers chosen by MSC training algorithm for the *A. tomentosum* and *M. rubiginosa* species are presented in Table 3. Those results confirm that the statistical measure of mean is better to characterize plant species. In addition, as for the color features,

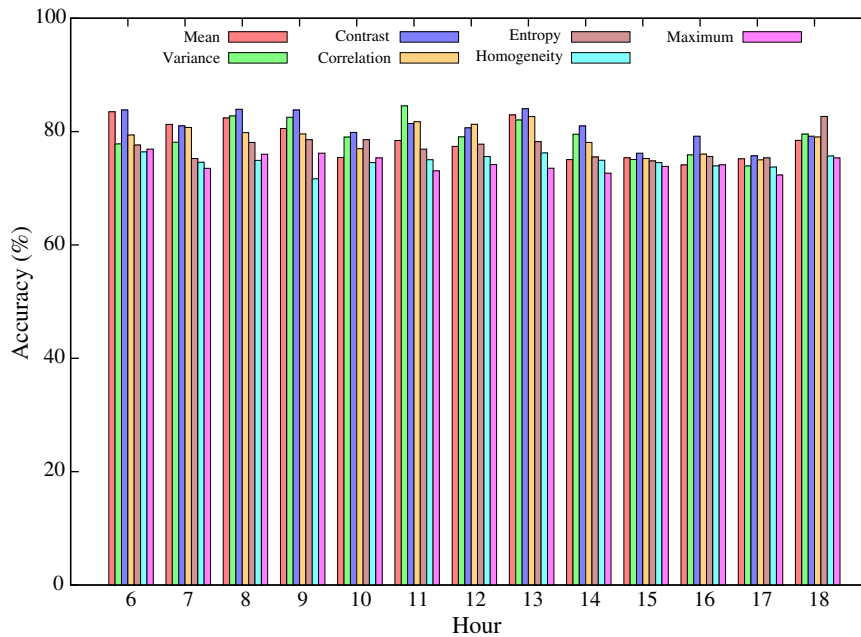
they also show that coarse scales provide better results than fine ones for the species identification.

The strong fine-scale variation in the vegetation leads to a high spectral variation, which is translated into higher variation of textural measures. For that reason, the temporal variation in image texture is useful information to distinguish plant species.

4.2. Application in phenology studies

The species identification in the digital image is a key issue for the near-remote phenological observation of tree crowns, especially in tropical vegetations where one single image may include a high number of species. Usually, this task is very time-consuming since it has to

(a) *Aspidosperma tomentosum*



(b) *Miconia rubiginosa*

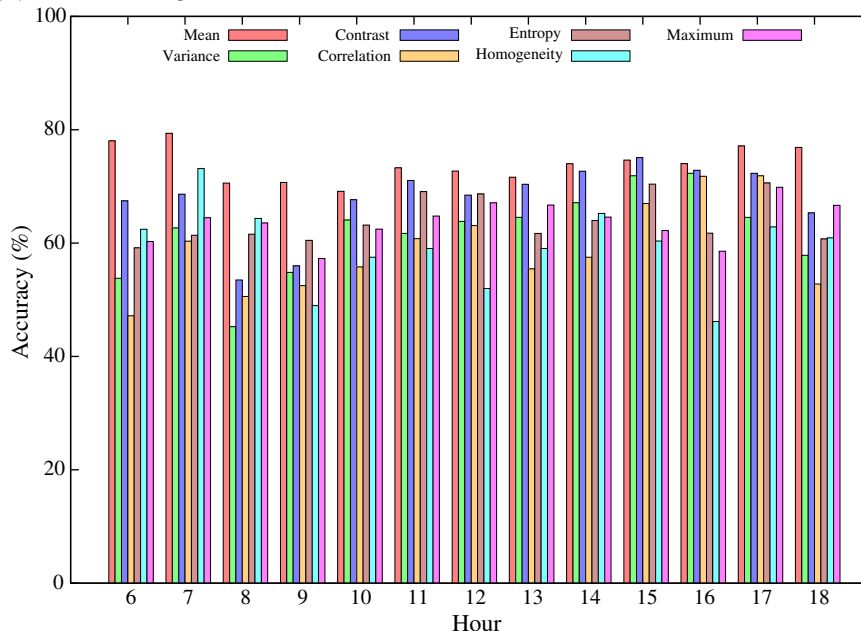


Fig. 11. Classification accuracy for each of the textural metrics along all the available periods of the day.

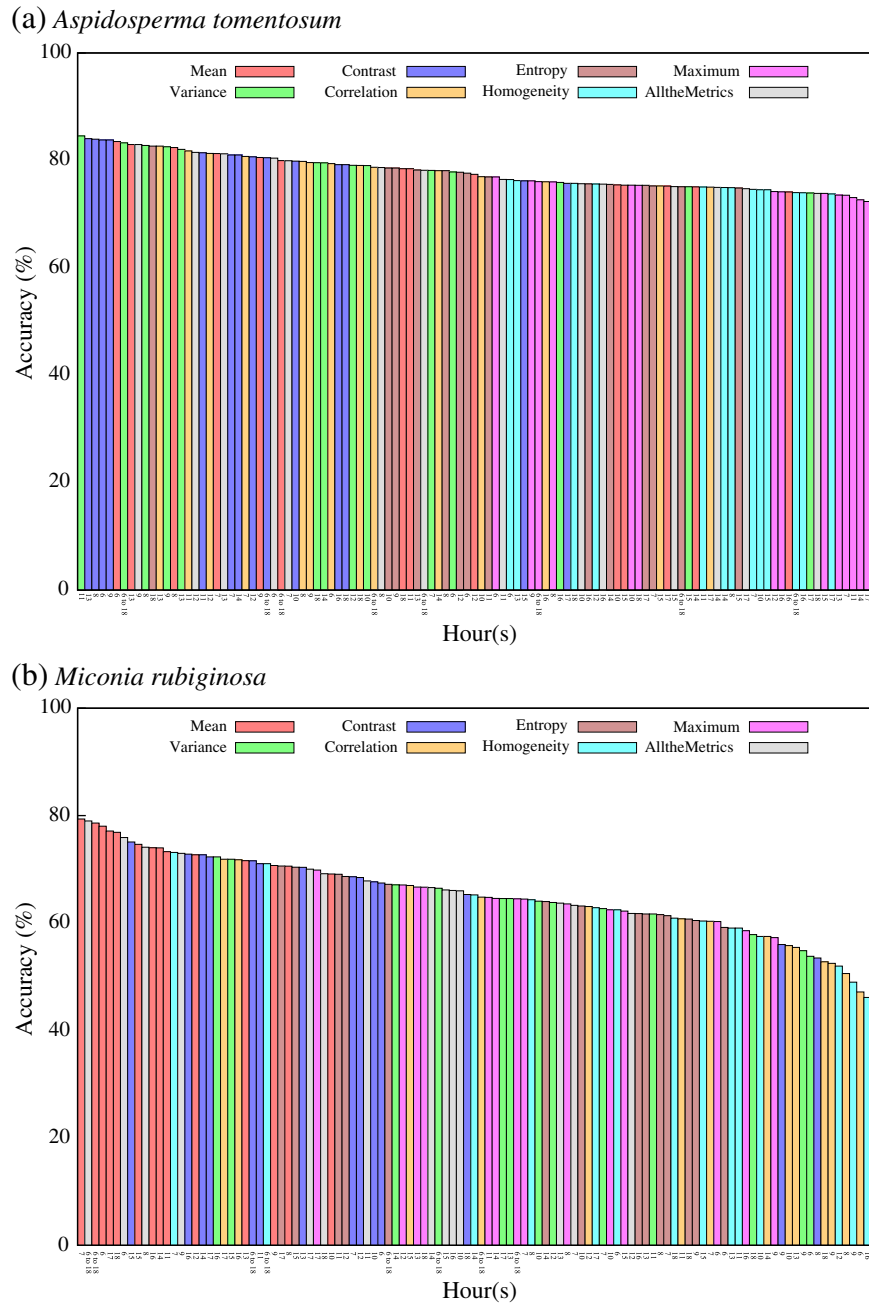


Fig. 12. Classification accuracy for each of the textural metrics along all the available periods of the day (among all the possible combinations).

be done in the field, first by matching each crown in the image to the tree in the soil and then by identifying the tree at species level.

In this sense, our framework can help phenology experts to find the species in the image, since we can use the MSC approach to automatically identify similar ROIs (tree crowns), reducing the area on the ground over which to look for a similar species' ROI, making such a task much easier and faster.

For that, we use the MSC approach to classify segmented regions from the digital images. Next, we create an image map based on the assigned labels, indicating graphically the areas where the probability of finding individuals from a given species is higher.

Fig. 13 presents the image maps produced for the analyzed species using the feature combination that achieved the highest classification accuracy (i.e., 6 h/G, for the *A. tomentosum*; and 6–18 h/RGB, for the *M. rubiginosa*). Different color scales were used to maximize the difference between the assigned labels: (i) a green scale, for similar

pattens (between +1.0 and +0.3); (ii) a gray scale, for undefined patterns (between +0.3 and -0.3); and (iii) a red scale, for inverted patterns¹ (between -0.3 and -1.0).

In this figure, the green areas indicate the segmented regions with a high probability of belonging to the same species. Notice how the search efforts can be greatly reduced by employing our approach. This opens up a number of possibilities that deserve much deeper study, but an immediate consequence is that we can help phenology experts with a new tool to identify plant species, increasing their accuracy on defining the relationship between phenology and climate.

The automatic identification of regions in the digital image with similar phenological patterns have allowed us to find more crowns of the analyzed species, which were validated by the on site

¹ For inverted patterns, we mean a behavior completely opposite of the expected one.

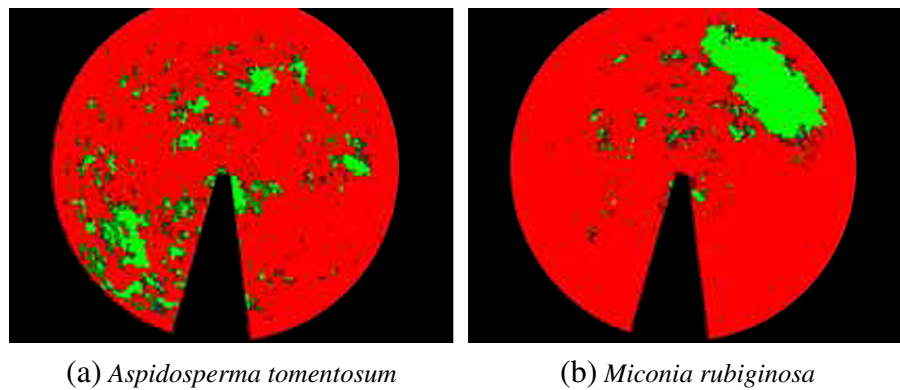


Fig. 13. Image maps produced for different species using the feature combination with the highest classification accuracy. Different color scales were used to maximize the difference between the assigned labels: (i) a green scale, for similar patterns; (ii) a gray scale, for undefined patterns; and (iii) a red scale, for inverted patterns. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

identification of the trees. Also, from the point of view of phenology, it has helped us to distinguish different regions in our study area regardless of their individual species and to understand the predominant phenology of a whole community.

5. Conclusions

We conclude that machine learning based on multiscale classifiers can be applied to detect phenological patterns in the high diversity of the tropical Cerrado savanna vegetation. Using a conventional tool to measure the color change information, we were able to define the best hours of the day for characterizing plant species. Different from the suggestion of using midday hours reported in ecological studies, the extreme hours (morning and afternoon) have shown the best results for the species identification using machine learning. Moreover, the data validation at species level has also revealed that different plant species present a different behavior with respect to the color change information. In this way, we were able to distinguish species and functional groups of plants using digital images. Another significant finding of our study was that textural measures exhibit a temporal-change pattern with respect to phenological changes. The potential upside of temporal variation in image texture is that texture differences among multitemporal images contain useful information to characterize plant species. Finally, based on those results, we have introduced a new tool to help phenology experts in the species identification on-the-ground, making such a task much easier and faster. Future work includes the evaluation of other visual features (e.g., color (Almeida et al., 2013) and shape (Torres et al., 2013)) and/or learning methods (e.g., genetic programming (Andrade et al., 2012)).

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5 CONCLUSIONS

In this project we intended to incorporate new technologies of phenological observations using digital cameras installed in the field and test them as an innovative and complementary tool for collecting phenological data of leaf flushing in a high diverse cerrado savanna.

In the first chapter, we concluded that: (i) digital cameras are reliable tools to capture leaf changes in tropical cerrado savanna vegetation; (ii) three leaf exchange strategies were depicted from the species patterns of green color change; and (iii) the greening patterns and leaf functional groups were validated by our on-the-ground phenology. In the second chapter, we presented: (i) a method capable of distinguishing species and functional groups of plants in images by a machine learning approach based on multiscale classifiers; and (ii) concluded that the use of this new tool can help phenology experts in the species identification on-the-ground.

As a next step to explore in the field of remote phenology, we plan to monitor leafing along a seasonal gradient of tropical vegetation. By monitoring from very seasonal areas such as caatinga, then the cerrado savanna to low seasonal communities as the Atlantic forest, we aim to verify the changes in community color patterns, and investigate which factors will affect most the growing season and ecosystems process for each vegetation type.

The so-called near-remote phenology is a great opportunity to obtain an impartial and comparable assessment of leaf seasonal changes in tropical environments. Near-surface remote phenology has becoming more and more common for phenological research. The arrivals of novel technologies follow by the advance of e-science methods for dealing with large data sets are changing the scenario of plant ecology studies.