UNIVERSIDADE FEDERAL DE LAVRAS

BRENO IZIDORO DOMINGOS

MAPEAMENTO DE DISTÚRBIOS ANTRÓPICOS NA VEGETAÇÃO UTILIZANDO MÉTRICAS FENOLÓGICAS

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Monografia apresentada à Universidade Federal de Lavras, como parte das exigências do Curso de Engenharia Florestal, para a obtenção do título de Bacharel.

Prof. Dr. Fausto Weimar Acerbi Júnior

Orientador

Mestre. Inácio Bueno Thomaz

Coorientador

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Resumo Geral

Diversos mapeamentos para monitoramento da vegetação e análise da cobertura do solo são realizados nos dias atuais devido ao grande acervo de imagens disponíveis nos últimos anos advindos de diferentes sensores remotos possibilitando cada vez mais processamentos de imagens e a aquisição de diferentes dados para análise. Este estudo teve como objetivo analisar o potencial da utilização de métricas fenológicas na detecção de mudanças na cobertura do solo, identificando e caracterizando pontos de mudança e não mudança nos biomas do Cerrado e Mata Atlântica. Para isso foi utilizado uma série temporal de imagens do satélite MODIS para detecção de pontos de desmatamento e pontos onde não houve mudanças, e também a extração das métricas fenológicas. A análise dos resultados revelou que as métricas fenológicas quando associadas a uma análise rigorosa dos dados e aplicado o método correto, pode melhorar significativamente a acurácia da detecção. Assim, pode-se concluir que o uso de métricas fenológicas para mapeamento das mudanças na cobertura vegetal deve ser realizado com cautela, recomendando-se análise da área anteriormente se apresenta fatores que possam auxiliar no uso das métricas, como a sazonalidade.

Palavras-chave: Mapeamento, métricas fenológicas, acurácia da classificação.

Sumário

PRIMEIRA PARTE

1. INTRODUÇÃO

Fenologia é o estudo dos estágios recorrentes do ciclo de vida da planta, principalmente relacionados ao tempo de ocorrência e as relações com o tempo e o clima, os principais eventos associados a fenologia são: germinação, crescimento das folhas, floração, frutificação e senescência (DUBÉ et al. 1984).

Sensoriamento remoto nos últimos anos tem sido uma importante ferramenta para a caracterização e monitoramento da dinâmica da vegetação em escalas regionais, continentais e globais (MELAAS et al., 2018; ZHANG et al., 2007). Com uma grande variedade de sensores fornecendo imagens de toda a superfície terrestre, tem possibilitado o desenvolvimento de estudos em diversas áreas do conhecimento com o auxílio do sensoriamento remoto (ZHU, 2017). Estudos fenológicos estão presentes constantemente na literatura, sendo abordados de diferentes formas como: caracterização do ciclo fenológico (ATZBERGER et al., 2013), mudanças fenológicas ao longo do tempo (VERBESSELT et al., 2010), fenologia como indicador de mudanças climáticas (GARONNA et al., 2018) e mapeamento (QADER et al., 2016).

O sensor Espectrorradiômetro de Imagem de Resolução Moderada (MODIS), é o mais utilizado nos estudos fenológicos, devido ao fornecimento diário de imagens cobrindo áreas em grandes escalas, também fornece produtos com composição de imagens de 16 dias, com indicies de vegetação, como o Índice de Vegetação por Diferença Normalizada (NDVI), que é o mais utilizado em estudos fenológicos (CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021). Na fenologia mudanças ocorrem rapidamente, sendo necessário a utilização de imagens com baixa resolução temporal, para captar bem as mudanças. Sensores que fornecem imagens com mais de 16 dias não é indicado para estes tipos de estudo.

Embora constantemente presente na literatura, estudos fenológicos comumente abordam a caracterização do ciclo fenológico como tema principal, no entanto há poucos estudos que utilizam as métricas fenológicas para associação e aplicação com outros fatores ambientais, como para o mapeamento de distúrbios antrópicos (CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021).

O objetivo deste trabalho foi explorar uma nova abordagem baseado em métricas fenológicas e índices de vegetação para mapear ações antrópicas de desmatamento nos biomas Cerrado e Mata Atlântica no estado de Minas Gerais. Através de uma série temporal de 10 anos de imagens do sensor MODIS (2008-2017), foi possível mapear as mudanças da cobertura do solo e extrair métricas fenológicas em ambos os biomas. Aplicamos o algoritmo do Random Forest para modelar e classificar amostras de mudança e não mudança na cobertura do solo, com o auxílio das métricas fenológicas e avaliar as acurácias fornecidas pelo algoritmo.

2. REFERENCIAL TEÓRICO

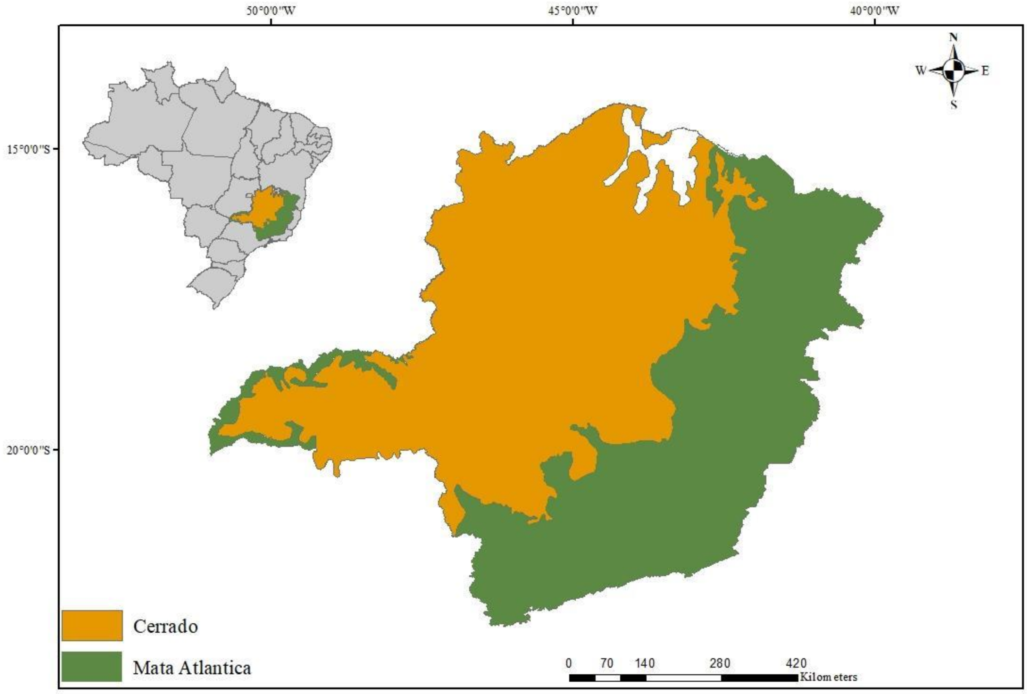
2.1. Cerrado e Mata Atlântica no estado de Minas Gerais

Minas Gerais é um dos 26 estados que compõe o Brasil, sendo o quarto maior em extensão territorial com área de 586 852 35 km², e o segundo mais populoso com população estimada em 2020 de 21,3 milhões de habitantes (IBGE., 2020), e está localizado na região sudeste do país. Suas paisagens são variadas devido a diferentes características edafoclimáticas, topográficas, tendo em sua composição grandes picos do Brasil e também é uma importante fonte de grandes Rios nacionais que nascem em Minas Gerais. A vegetação varia ao longo das paisagens e é característica por três biomas que cobrem o Estado: Cerrado, Mata Atlântica e Caatinga (Instituto Estadual de Florestas - IEF, 2020), (Figura 1).

Cerrado é a nominação para descrever diferentes tipos de ecossistemas que ocorrem em grande extensão do território brasileiro e é mundialmente classificado como Savana, no entanto possui particularidades que o faz ser diferente em diversos aspectos, apresenta diferentes fisionomias que são classificadas; campo limpo, campo sujo, cerrado sensu stricto e cerradão (PEREIRA et al., 2011). No estado de Minas Gerais está localizado na porção centro-ocidental, ocupa aproximadamente 54% da extensão territorial, sendo o maior bioma do Estado, aparece especialmente nas bacias dos Rios São Francisco e Jequitinhonha (Instituto Estadual de Florestas - IEF, 2019). É caracterizado por descontinuas formações florestais e densas ao longo de um contínuo campo, as estações secas e chuvosas são bem definidas, sendo as secas acentuadas e as chuvas sazonais, principalmente no verão de dezembro a março (SILVEIRA et al., 2018), a precipitação média anual varia de 1200 a 1880 mm. A fertilidade do solo é de moderada a baixa, com alta amplitude de topografia (declividade e altitude), esses fatores afetam as formações vegetais que são compostas por: pastagem, arbustos, florestas e savana densamente arborizada (SILVEIRA et al., 2018; TERRA et al., 2017), o Cerrado apresenta forte influência de sazonalidade. É considerado um dos hotspots de biodiversidade (MYERS et al., 2000), no entanto é o bioma mais degradado no Brasil nas últimas décadas (FRANÇOSO et al., 2015), tem sofrido principalmente com a expansão da agricultura e pecuária, desde a década de 1970 quando a agricultura começou a ser implantada no Cerrado, o bioma já perdeu aproximadamente 50% da sua área natural (MONTEIRO et al., 2020).

A Mata Atlântica é o segundo maior bioma no Estado, e o mais degradado ao longo da história do Brasil, é estimado que apenas 7% da Mata Atlântica se manteve preservado (PMDBBS - Projeto de Monitoramento do Desmatamento dos Biomas Brasileiros por Satélite, 2020), mesmo incluindo entre 1 % e 8 % da espécies mundiais de fauna e flora (RIBEIRO et al., 2009). É composta por florestas semi-decíduas, florestas ombrófilas e campos de altitude, a temperatura média anual é entre 22º C e 25º C. Em alguns locais de Mata Atlântica a época de seca ocorre durante 2 a 5 meses e mantem a temperatura com pouca variação, nesse caso é onde se encontra as florestas semi-decíduas (COLOMBO; JOLY, 2010), e a sazonalidade apresenta fortes influências sobre estas florestas. Já em sítios onde as estações de seca não são bem definidas, e recebe bons índices de pluviosidade distrubuído ao longo do ano, é onde se encontra as florestas ombrófilas, que são sempre verdes, e a sazonalidade apresenta baixa influência sobre elas. A precipitação média anual varia de 1500 mm em áreas próximo ao Cerrado (JUNQUEIRA et al., 2017), até 2000 mm em áreas ao sul do Estado (TERRA et al., 2015). Devido à alta biodiversidade a qual se encontra na Mata Atlântica e ao fato de possuir diversas espécies de endemismo, é também um dos hotspots de biodiversidade (MYERS et al., 2000).

Figura 1 – Localização dos biomas Cerrado e Mata Atlântica no estado de Minas Gerais.



Fonte: Do Autor (2021).

2.2. Estudos Fenológicos

A dinâmica da fenologia está associada a ciclos específicos que ocorrem durante um ciclo anual de vida da planta, tais como a germinação, aparecimento das folhas, floração, frutificação, e senescência, é guiado principalmente por fatores ambientais global e local (LIETH, 1974), o clima é o principal controlador de fatores que afetam as plantas, no entanto fatores não climáticos podem influenciar os ciclos das plantas e consequentemente a fenologia, tais como a profundidade e umidade do solo, condições topográficas como altitude, e relevo, e fatores biológicos como competição, genética e diversidade (MENZEL, 2002).

Nas últimas décadas, o estudo da fenologia vegetal tem atraído uma atenção significativa à medida em que mudanças ocorrem no ritmo do ciclo fenológico, estes eventos são considerados um indicador biológico chave para as mudanças climáticas (PEÑUELAS; FILELLA, 2001; GARONNA et al., 2018). Mudanças no tempo de duração dos eventos fenológicos podem influenciar a forma como os ecossistemas terrestres funcionam e controlam o ciclo do carbono, ciclo da água, fluxos de energia ou interação entre espécies. Portanto estudar dinâmica fenológica da vegetação é fundamental para importância de compreender respostar comportamentais de ecossistemas terrestres em face das mudanças que ocorrem na cobertura do solo.

Nos últimos quarenta anos, o sensoriamento remoto desempenhou um papel fundamental para monitoramento da vegetação, como ela responde as mudanças ambientais que ocorrem ao longo do tempo (DASH; OGUTU, 2016). A fenologia da superfície da terra, se refere a fenologia da vegetação derivado de dados de satélite (DE BEURS; HENEBRY, 2004), e é geralmente estimado a partir de índices de vegetação e séries temporais (ou seja, dados coletados ao longo de um período de tempo), pode ser usado para estudar fases e métricas fenológicas em análises funcionais. Portanto os estudos fenológicos para determinar variáveis ecologicamente significativas relacionadas a fenologia vegetal, a partir de observações de satélites multiespectrais, que podem estar associadas a mudanças ambientais, sendo possível a utilização para validação, ou comparação com outros dados fenológicos. Estudos de fenologia surgem como complemento para melhorar as análises de fenologia com o avanço da tecnologia, permitindo a realização de estudos em escala global fornecendo uma visão geral dos ecossistemas (RODRIGUEZ-GALIANO et al., 2015b).

O número de estudos utilizando dados de sensoriamento remoto para monitorar dinâmica da vegetação aumentou consideravelmente, até o ano 2000 foram realizados (10 estudos) e até o ano de 2021 após 2010 foram realizados aproximadamente (435 estudos), este aumento se deve principalmente ao crescente interesse em compreender a relação entre como os ecossistemas se comportam, e ao aumento da cobertura temporal de dados de satélite (CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021). Atualmente estes estudos relacionados a fenologia se encontram distribuídos em todos os continentes, porém concentrados em alguns países que apresentam maiores números de estudos, como por exemplo, na Ásia, 80 % das publicações são voltadas para a China, o segundo maior número de estudos é a Índia com 9 %. Na América do Norte 83% dos estudos se concentram nos Estados Unidos, na América do Sul, o Brasil tem 71 % das publicações, e na Oceania somente a Austrália apresenta publicações de estudos sobre LSP (CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021).

Os diferentes objetivos dos estudos fenológicos podem ser classificados em três principais categorias: caracterização, explicação e aplicação. A caracterização inclui estudos que focam na descrição dos fenômenos fenológicos (37 %), a explicação foca na dinâmica da vegetação e suas relações com fatores ambientais (52 %), muitos desses estudos foram focados na investigação de ciclos biológicos das plantas e como respondem a diferentes fatores climáticos. A categoria da aplicação é a menos explorada com (11 %), sendo a maioria deles focados na classificação da cobertura do solo usando dados fenológicos (CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021). Com grande potencial de exploração, estudos baseados em fenologia para a classificação da cobertura de solo, como em mapas de vegetação natural (QADER et al., 2016), expansão agrícola (KNAUER et al., 2017) e desmatamento (VALDERRAMA-LANDEROS; ESPA, 2016).

2.3. Obtenção de dados fenológicos

Os diferentes tipos de vegetação apresentam diferentes padrões fenológico, sendo possível distingui-los (PETTORELLI et al., 2005), é possível identificar o comportamento geral de cada tipo de superfície natural com base no comportamento dos dados ao longo da série temporal e estabelecer as características básicas de ciclo sazonal, fenologia da vegetação para o tipo de cobertura do solo.

O aumento nas pesquisas de fenologia muito se deve ao lançamento do sensor de Espectrorradiômetro de imagem de resolução moderada (MODIS), que desde 1999 tem sido o satélite mais utilizado para obtenção de dados de estudos sobre LSP (54 %) (ATZBERGER et al., 2013; JIANMIN WANG and ZHANG 2020), fornecido imagens diárias com resoluções espaciais de (250 m, 500 m, e 1 km) (WARDLOW; KASTENS; EGBERT, 2006). O MODIS apresenta alguns problemas nas imagens diárias como a, contaminação por nuvens, anglo solar, sombras e erros de pixel (DIDAN et al., 2015), devido a isto é comum a utilização de produtos do MODIS para monitoramento da vegetação, como o MOD13Q1 o que inclui uma composição de imagens NDVI de 16 dias, com resolução espacial de 250 m e qualidade de pixels (TESTA et al., 2018), no entando a composição de imagens pode levar a descontinuidades temporais e espaciais, como por exemplo pixels da mesma area no entanto em datas diferentes, a resoluçaõ temporal é degrada, e em estudos de fenologia as mudanças ocorrem em um curto periodo de tempo (AHL et al., 2006; DIDAN et al., 2015; TESTA et al., 2018), não sendo indicado a utilização de composição de imagens por longos períodos, principalmente em composições com mais de 16 dias.

Os dados de fenologia são extraídos principalmente dos índices de vegetação, sendo o NDVI o índice mais utilizado, em aproximadamente 75 % dos estudos de LSP

(CAPARROS-SANTIAGO; RODRIGUEZ-GALIANO; DASH, 2021), devido a ser sensível os pigmentos de clorofila presente na copa das arvores, além de diminuir efeitos de sombras de nuvens (GITELSON and MERZLYAK 1996; HUETE et al., 2002), entre as limitações do NDVI está a perda de sensibilidade em áreas que apresentam altos índices de biomassa, causando saturação ao índice (JUSTICE et al., 2002; HUETE et al., 2002).

Para a extração de parâmetros da fenologia, o Timesat é o software mais utilizado, para análise da série temporal e extração de métricas fenológicas (EKLUNDH; JÖNSSON, 2017). Sendo processado as imagens em três passos, o primeiro é a remoção de picos através de filtros, sendo mais comum a utilização de um filtro médio. O segundo passo é o ajuste da série temporal através de um modelo, o software fornece três modelos de ajuste sendo eles; Savitzky Gokay filtro, Gaussiano assimétrico e o duplo logístico, sendo indicado para diferentes tipos de dados, como por exemplo o Gaussiano assimétrico é indicado para dados com muito ruídos, e onde se procura melhores o padrão dos dados para encaixe na curva (UDELHOVEN; STELLMES; ACHIM, 2015), e por último é a extração das métricas fornecidas pelo Timesat.

2.4. Mapeamento de distúrbios antrópicos

Apesar da maioria dos estudos fenológicos serem focados na caracterização e explicação, as métricas fenológicas têm demonstrado em recentes estudos que sua aplicação é uma ferramenta confiável para predição e classificação da cobertura de solo, melhorando significantemente a acurácia dos produtos quando a combinação de métodos adequado por avaliação rigorosa é utilizada (ZHANG et al., 2020).

Métricas fenológicas já foram aplicas em estudo de mapeamento de desmatamento no México, onde foi proposto um método para construir um mapa de cobertura de solo, a partir de variáveis fenológicas, neste estudo foi extraído 11 métricas do Timesat, os coeficientes utilizados para calcular componentes obtidos a partir das variáveis originais, sendo possível classificar 17 263,59 ha de desmatamento, com o auxílio de métricas fenológicas (VALDERRAMA-LANDEROS; ESPA, 2016).

O seguinte estudo enfoca no uso de séries temporais de sensoriamento remoto com o auxílio de métricas fenológicas para classificação de tipos de vegetação no Iraque. Dados de série temporal tem o potencial de fornecer grande número de variáveis preditoras que podem ser exploradas com o auxilio do aprendizado máquinas, e fornecer uma classificação mais precisa e robusto, como foi realizada neste estudo. A precisão geral da classificação dos tipos de vegetação teve uma acurácia de 88,46 %, esta pesquisa mostrou que a fenologia da vegetação a partir do MODIS NDVI com resolução espacial pode fornecer mapeamento consistente e de alta precisão de cobertura do solo em escala regional (QADER et al., 2016).

Com o avanço recente da tecnologia associado ao sensoriamento remoto usado para o mapeamento de áreas de vegetação em uma paisagem dinâmica cobrindo amplas áreas em escalas globais, mas mantendo detalhes na distribuição espacial dos parâmetros alvo, a associação com dados fenológicos tem se mostrado uma ferramenta muito útil principalmente para classificação do tipo de cobertura, no entanto, outras pesquisas tem demonstrado a utilidade das métricas fenológicas aplicadas em outras situações como citado anteriormente na expansão da agricultura e desmatamento (QADER et al., 2016; VALDERRAMA-LANDEROS; ESPA, 2016), há ainda a aplicação em mapeamento de florestas naturais e plantadas (SENF et al., 2013). Combinado com as informações fenológicas para melhorar a classificação, particularmente o algoritmo Random Forest tem se mostrado útil capturando os padrões sazonais de cada tipo de vegetação (SENF et al., 2013).

CONSIDERAÇÕES FINAIS

Com este trabalho, foi possível analisar o potencial da utilização de métricas fenológicas para o mapeamento de distúrbios antrópicos nos biomas do Cerrado e Mata Atlântica no estado de Minas Gerais, além de abordar uma nova utilidade para as métricas fenológicas, que aplicado a outros fatores ambientais ainda não se tem muitos estudos relacionados. É importante destacar que a utilização das métricas fenológicas devem estar associadas a uma rigorosa análise dos dados, a fim de se obter uma classificação confiável.

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SEGUNDA PARTE – ARTIGO

MAPPING ANTHROPIC DISTURBANCES IN VEGETATION USING PHENOLOGICAL METRICS

Breno Izidoro Domingos, Inácio Thomaz Bueno[a], Fausto Weimar Acerbi Júnior[a]

[a]*Forest Science Department, Federal University of Lavras (UFLA), Lavras, Brazil, 3037, brenodomingos234@gmail.com; fausto@ufla.br;* inaciotbueno@gmail.com

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ABSTRACT

Several maps for monitoring vegetation and analyzing land cover are carried out nowadays due to the large collection of images available in recent years coming from different remote sensors, enabling increasingly more image processing and the acquisition of different data for analysis. This study aimed to analyze the potential of using phenological metrics to detect land use changes in the Cerrado and Atlantic forest biomes. For this, a time series of images from the MODIS sensor were used to extract the phenological metrics and to detect deforestation areas and areas where there were no changes. The analysis of the results revealed that the phenological metrics when associated with a rigorous analysis of the data and applied the correct method, can significantly improve the accuracy of the detection. Thus, it can be concluded that the use of phenological metrics for mapping vegetation cover changes should be carried out with caution, recommending an analysis of the area previously if it presents factors that can assist in the use of metrics, such as seasonality.

Key words: Mapping, phenological metrics, accuracy assessment.

1. Introduction

Phenology is defined by the United States International Biological Program Committee as the study of the timing of recurring biological events, their causes along with biotic and abiotic forces, and the relation with the environment (Lieth 1974). The phenology expression in forested ecosystems is based on the observation of dynamics in trees, such as germination, growing leaves, flowering, fruiting, changes in the leaf color or senescence, also characterized by the biological cycle (Liang and Schwartz 2009; Polgar and Primack 2011; Richardson et al. 2013; Tooke and Battey 2010). These dynamics occurs in different plant species during an annual life period, and it is common defined by their local, regional and global environmental conditions. Climate is the main factor in the phenological cycle of forests, followed by secondary events as soil fertility, water availability, topography conditions, and biological factors (Menzel Annette 2002; Peñuelas and Filella 2001; Richardson et al. 2013).

Remote sensing is an important tool in global vegetation monitoring. Several satellites provide periodic observation of the Earth's surface, enabling studies about forest dynamics, structure, anthropic changes, and phenology (Zhu 2017). In the last decade the number of phenology researches have growing (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021; Richardson et al. 2009; Testa et al. 2018). Monitoring vegetation phenology using remote sensing techniques is generally supported by the spectral information of the target, where vegetation indices and satellite time series are very popular in such studies (Palareti et al. 2016; Sakamoto et al. 2005; Zhang et al. 2003; Jönsson and Eklundh 2002). The Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1973) is the most common vegetation index used in phenology studies by the scientific community (Atzberger et al. 2013; Ivits et al. 2014). By analyzing the spectral information through time, phenological metrics can be computed based on yearly information such as the start of the season, also referred as green-up date, end of the season, referred as senescence, and length of the season, which is the time between the start and end of a season (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021). . Primary statistical metrics based on phenology information are also used to analyze vegetation dynamics in time, i.e. the average value of start of season in a particular time period (Xu et al. 2016; Tan et al. 2011). These phenological information supports the monitoring of vegetation dynamics of different biomes at large scales since different types of vegetation domain have different phenological patterns. The increase of phenologyrelated studies in the scientific community is associated with the data availability from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, which is the most used sensor in vegetation phenology studies (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021). MODIS sensor provides daily images at the spatial resolution of 250 m, 500 m, and 1 km, covering large scale areas (Wardlow, Kastens, and Egbert 2006). Another advantage of MODIS products in phenology studies are the image composites of 8-day, 16-day or monthly, providing noise free imagery in short periods of time, and enabling a more proper observation of vegetation dynamics (Adami et al. 2018; Didan et al. 2015; Justice et al. 2002).

In addition to monitor the dynamics of vegetation, another important purpose of remote sensing technique is the detection and mapping of anthropic disturbances on those environments, to understand anthropic process that affect natural land cover surface, require the analyses of time series to detect changes (Verbesselt, Zeileis, and Herold 2012), the most common anthropic changes are: agriculture, forestry and urbanization, which has affect environment in large scales. The detection of anthropic disturbances through time series and phenological metrics, have present potential to map and classify different types of anthropic disturbances such as agricultural expansion (Knauer et al. 2017) and deforestation (Valderrama-landeros and Espa 2016). However, quantify those disturbance is not a simple task, temporal series present phenological changes, atmospheric scatter, different pixels values and cloud noise, it happens due to the different acquisition of satellite images from different days.

Research into disturbance mapping is comprehensive and several studies have mapped disturbances using algorithms capable of detecting changes from spectral signal such as Vegetation Change Tracker (Huang et al. 2010) and Continuous Change Detection and Classification (Zhu, Woodcock, and Olofsson 2012), phenological metrics (Senf et al. 2013), phenology-based on vegetation index (Yihua Jin et al. 2016) and biophysical variables (Valderrama-landeros and Espa 2016).

Despite the phenology studies be often present in the literature, just a small percentage of these studies are focus on the use of phenological parameters to environmental applications, which contribute to a lack of information of explanatory factors. However the integration of disturbance maps and phenological information is barely explored. A study accomplished by (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021) concluded that most of phenology studies used phenological metrics to explore the vegetation behavior, and only 11% used them as explanatory factors. Besides, this small group of studies focused on land cover classification (Yihua Jin et al. 2016; Qader et al. 2016), climate change (Garonna et al. 2018; Menzel et al. 2006), water cycle (Arantes, Ferreira, and Coe 2016). No study has examined how phenological information can perform on disturbance map algorithms and how the information from particular biomes impacts on map accuracies.

In this study, we mapped anthropic disturbances in different biomes using phonological metrics from MODIS time series. This study addressed the following questions: (a) phenological metrics can map anthropic disturbances in vegetation environments? (b) which metrics are important to improve disturbance map models? (c) how distinct biomes impact on final map accuracies? To answer these questions, we used MODIS time series from 2008 to 2017 to extract 54 phenological metrics, using them as input data in the Random Forest algorithm, then classifying anthropic disturbances from stable vegetation. We evaluated disturbance maps accuracies in two distinct biomes in Brazil: Atlantic forest and Cerrado.

2. Material and methods

2.1. Study area

The study area comprises two biomes in the state of Minas Gerais, Brazil: savanna and Atlantic forest. The Brazilian savanna vegetation, also known as *Cerrado*, is characterized by a discontinuous forested formations to continuous grassland extensions (Klink et al. 2005). Climate indicates two distinct rainy periods: one wet season from December to March where 90% of the rains are concentrated, and one dry season where monthly precipitations can reach zero millimeters (Klink et al. 2005). The topography across the Cerrado in Minas Gerais presents high heterogeneity, followed by a soil fertility ranging from moderate to low.

The Cerrado species present leaf budding and flower productions periodic variations, which represent adaptions to biotic and abiotic factors (Schaik 1993). A striking feature of Cerrado vegetation is the occurrence of different phenological groups in relation to leaf production and fall (Lenza and Klink 2006). In the dry season occurs the leaf fall and a major proportion of deciduous species, while, budding, flowering and fruiting may occur, in wet and dry season (Batalha and Mantovani 2000). These factors affect the vertical structure of Cerrado vegetation, mainly composed by grasslands, shrublands, woodlands, and dense wooded savanna (Silva de Miranda et al. 2018; Terra et al. 2017). This high heterogeneity also induced Cerrado as a hotspot of biodiversity presenting the richest flora among savannas worldwide (Myers et al. 2000). However, the deforestation scenario in the biome is represented by large losses of vegetated area due to anthropic pressure, remaining approximately 47% of its natural vegetation (Beuchle et al. 2015).

The Atlantic forest is another hotspot of biodiversity in the state with high specie endemism (Myers et al. 2000), mainly composed by rainforests, semi-deciduous forests, and high altitude grasslands. Annual rainfall is higher compared to Cerrado varying from 1500 mm in northern regions (Junqueira et al. 2017) to 2000 mm in the south with higher values found at montane areas (Terra et al. 2015). The Atlantic forest is mainly composed by semi-deciduous forests and rainforests with different species presenting different phenology effects (Oliveira-Filho and Fontes 2000). The variation of rainfall and the length of dry season influences the floristic composition and seasonal patterns for different vegetation forms in the Atlantic forest (Morellato and Haddad 2000). Temperature is the main factor to seasonal patterns of rainforests, while rainfall and low temperatures are the main factors to affect the phenology in the Atlantic semi-deciduous forests (Morellato et al. 1989). The Atlantic forest remaining approximately 7% of the natural vegetation (Morellato and Haddad 2000).

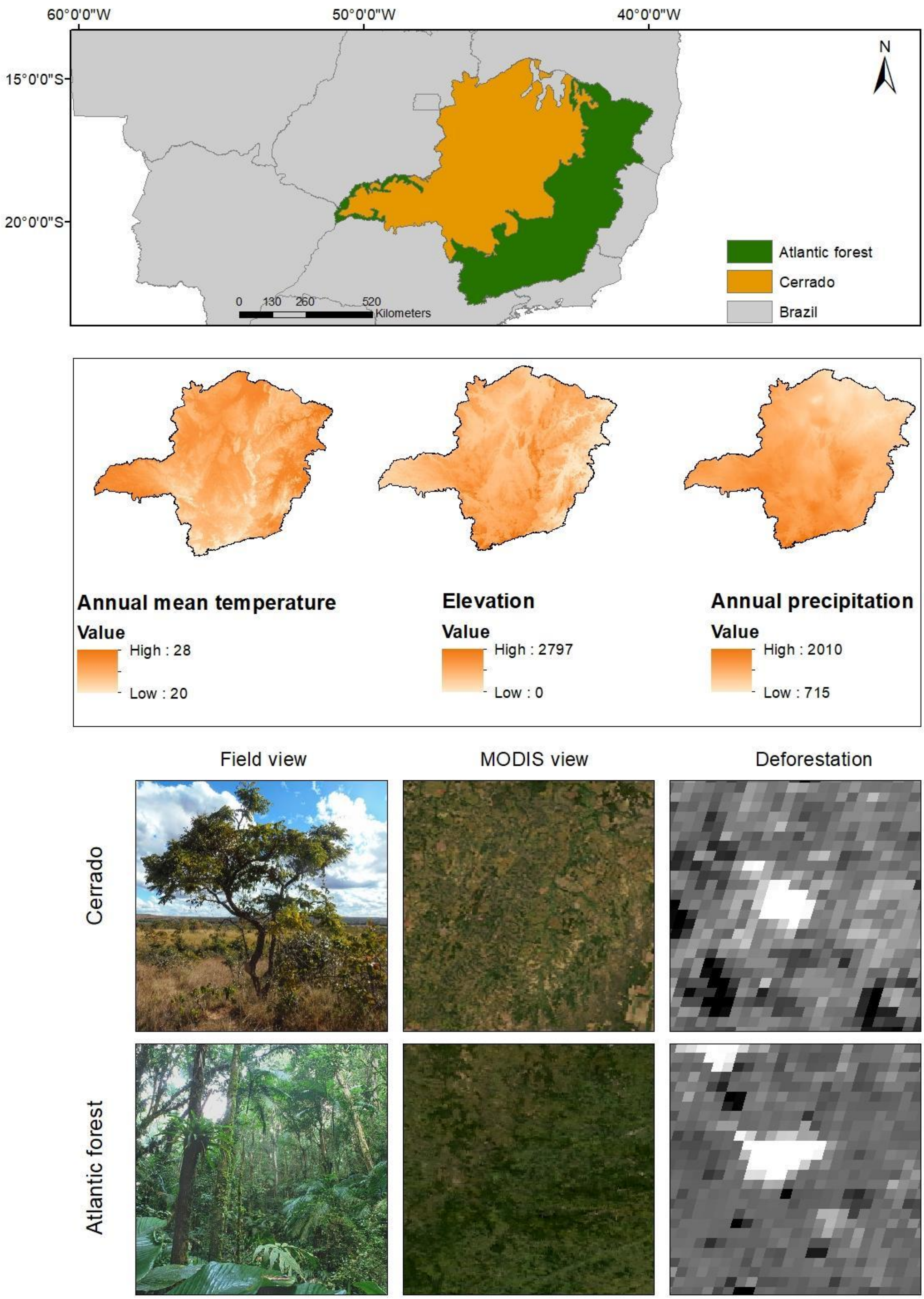

Figure 1. The study area.

2.2. Image data

We acquired MODIS images from 2008 to 2017 provided by the United States Geological Survey's Earth Resources Observation and Science Center (USGS/EROS). We used MOD13Q1 product which provides 16-day NDVI image composite at 250 m of spatial resolution. The 16-day image composites returned 22 images per year, a total of 220 in the study period, which represented a suitable number of observations in order to capture the vegetation phenology and proceed with further analysis. However, the spatial resolution of 250m excluded the analysis of disturbed areas smaller than 25 hectares (approximately four pixels). This minimum unit of analysis provided a more certain analysis of disturbed pixel avoiding spectral mixture.

2.3. *Reference data collection*

We sampled pixels throughout the area based on NDVI difference images and visual interpretation by manually selection. We set two classes of disturbance events in the reference data collection step: disturbed vegetated pixels and non-disturbed vegetated pixels. Reference data collection was also stratified by biome, using a biome layer of (reference) to support sampling and to distinct pixels of Cerrado from Atlantic forest. A total of 270 pixels per biome were collected (totaling 540 in the entire dataset). From these, 135 were disturbance pixels and the other half non-disturbance pixels. Samples were equally collected along the period of study (60 samples per year interval) and well distributed throughout the area in order to capture the variability of disturbance and non-disturbance events.

Two sets of image data were used as auxiliary information to support reference data collection. First, Landsat imagery was chosen due its higher spatial resolution of 30m (compared to the 250m of MODIS images), where vegetation samples can be easily confirmed in data collection. In addition, Landsat provided satisfactory temporal consistency, which supported the confirmation of disturbance events in a higher spatial resolution. Unclear observations were submitted to a second round of confirmation. In this case, we used Google Earth platform due its spatial resolution higher than 2.5m, supporting the identification of vegetation cover, disturbance events, and other relevant attributes via visual interpretation. The visual interpretation was performed by interpreters with expertise of image interpretation of forest landscapes, and data collection passed through a multi-step quality control providing a reliable dataset.

2.4. Phenological metrics

Phenological metrics were computed from MODIS time series using the Timesat software (Eklundh and Jönsson 2017). We follow a three-step procedure to compute phenological metrics: 1) peak removal: we applied a median filter to remove outlier values from the time series signal due to the fact that the image composition may present noises such as cloud shadows (Eklundh and Jönsson 2015), mainly in the Atlantic Forest areas. 2) time series modelling: the model to smooth the curve can effectively suppress the data noise, where asymmetric Gaussian functions (Jönsson and Eklundh 2002, 2004), fit better in the vegetation with a seasonal behavior marked (deciduous broadleaf forests and grasslands) (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021). 3) metric computation: based on the Gaussian model, Timesat computed thirteen metrics (Table 1). Data smoothing methods are expected to remain the integrity of the vegetation dynamics while remove noises present in the time series. For an illustrated information about Timesat phenological metrics, see (Figure 2) of Timesat manual (Eklundh and Jönsson 2017).

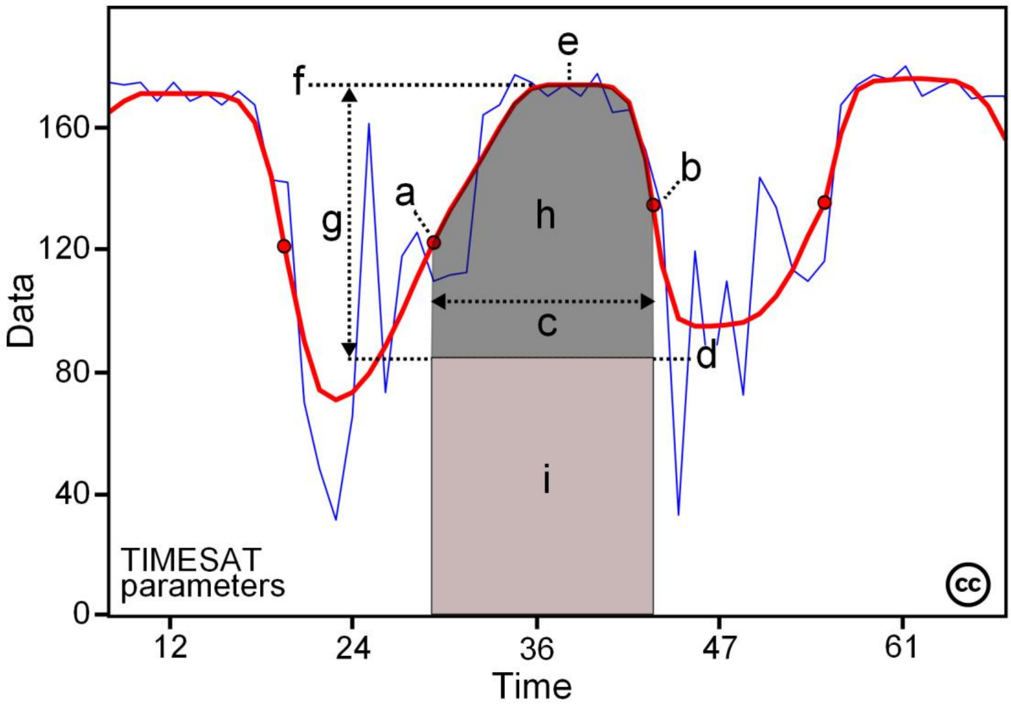

Figure 2. Some of the seasonality parameters generated in Timesat: (a) start of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value.

Table 1. Metrics extracted from timesat and their description.

Timesat phenological metrics	Abv.	Metrics description
Timing of the start of the season	T_{start}	Time for which the left edge was increased to a user defined level measured from the left minimum level.
Timing of the end of the season	T_{end}	Time for which the right edge has decreased to a user defined level measured from the right minimum level.
Duration of the season	Dur	Time from the start to the end of the season.
Base level	Bl	Given as the average of the left and right minimum values.
Time for the mid of the season	T_{mid}	Computed as the mean value of times for which, respectively, the left edge has increased to the 80% level and the right edge has decreased to the 80% level.
Largest data value for the fit function during the season	Large	Maximum data value reach in the season.
Seasonal amplitude	Amp	Difference between the maximum value and the base value.
Rate of increase at the beginning of the season	Inc	Calculated as the absolute value of the ratio of the difference between the right 20% and 80% levels and the corresponding time difference.
Rate of decrease at the end of the season	Dec	Calculated as the absolute value of the ratio of the difference between the right 20% and 80% levels and the corresponding time difference. The rate of decrease if thus given as a positive quantity.
Large seasonal integral	L_{int}	Integral of the function describing the season from the season start to the season end.
Small season integral	S_{int}	Integral of the difference between the function describing the season and the base level from season start to season end.
Value for the start of the season	V_{start}	Value of the function at the time of the start of the season.
Value for the end of the season	V_{end}	Value of the function at the time of the end of the season.

Phenological metrics were extracted as annual information from Timesat. In order to get a value that represents the period of study, we computed basic statistics values from these metrics. We computed median, maximum, minimum, and the standard deviation of each metric, totaling 52 variables (13 metrics x 4 stats).

2.5. Disturbance maps

Random Forest (RF) algorithm (Breiman, 2001) has been widely used in many fields of remote sensing (Belgiu and Drăgut 2016). It is an ensemble classification method, based on a combination of many decision tree classifiers and bootstrapped samples, providing a robust algorithm (Yuhao Jin et al. 2018). There are some advantages of RF over other classifiers reported in the scientific literature (Belgiu and Drăgut 2016), as the ability to accommodate a large number of predictor variables, and the robustness of a non-parametric method (Devries et al. 2016). This robustness is also presented in the input user information, which is basically the number of the decision trees (Ntree) created in the procedure, and the number of predictor sampled at each tree node (Mtry). In this study, we set Ntree to 500 and Mtry to 7, as reported as a standard RF tuning in remote sensing studies (Belgiu and Drăgut 2016).

We ran three different RF models with equal parameter settings: a) Using all 540 samples mixing Atlantic forest and Cerrado observations (hereafter labeled as "Blended observations"); b) using only Atlantic forest observations; and c) only Cerrado. The database with phenological information of disturbed and non-disturbed pixels was split into 70% to training the model, and 30% to validate. Overall, producer' and user's accuracy were calculated for each test.

The variable importance was evaluated by the average impurity decrease. In this method, RF shifts one the input random variables while keeping the others constant and rate the decrease in impurity by means of the Gini index (Bueno et al. 2019). In addition, it measures how much a variable reduces in relation the general average in a particular class. Thus, the higher the Gini value of a variable, the higher its importance in the dataset (Rodriguez-Galiano et al. 2012).

3. Results

3.1. Accuracy assessment

The RF models constructed 500 decision trees from disturbance and non-disturbance samples and phenological predictors. For the Blended observations, RF returned an overall accuracy of 86.1% and an error of 13.9%. By splitting the observations into vegetation domains, accuracy measures increase for the Cerrado biome, returning 89.0% of overall accuracy and 11.0% of error. However, Atlantic forest have shown a decrease of overall accuracy to 85.5%, then increasing the overall error to 14.5%.

Analyzing the accuracy measures of the disturbance class, the producer's accuracy and omission errors of isolated biomes outperformed the blended dataset. Cerrado biome returned 86.1% and Atlantic forest returned 86.4%, while the two sets of observations merged had 85.3% of producer's accuracy. With regards to user's accuracy and commission errors for the disturbance class, Cerrado outperformed the Blended dataset, 92.5% against 88.2%, while Atlantic forest had a loss in accuracy to 86.4%.

Table 2. Accuracy analysis of the three datasets evaluated in this study. OA: overall accuracy; OE: overall error; PA: producer's accuracy; and UA: user's accuracy.

			Disturbance class		Non-disturbance class	
Dataset	**OA (%)**	**OE (%)**	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**
Blended	86.1	13.9	85.3	88.2	87.1	85.2
Cerrado	89.0	11.0	86.1	92.5	92.3	85.7
Atlantic forest	85.5	14.5	86.4	86.4	84.6	84.6

3.2. *Variable importance*

RF models also returned the importance of each variable based on the Gini index (Figure 3). The three most important phenological variables for mapping disturbance in Cerrado were largest data value for the fitted function during the season standard deviation, Time for the end of the season mean and large season integral minimum, while for Atlantic forest were value for the start of the season maximum, value for the end of the season maximum, and Base level maximum. Merging biome observations returned a variable ranking of value for the end of the season maximum, value for the start of the season maximum and largest value for the fitted function during the season standard deviation.

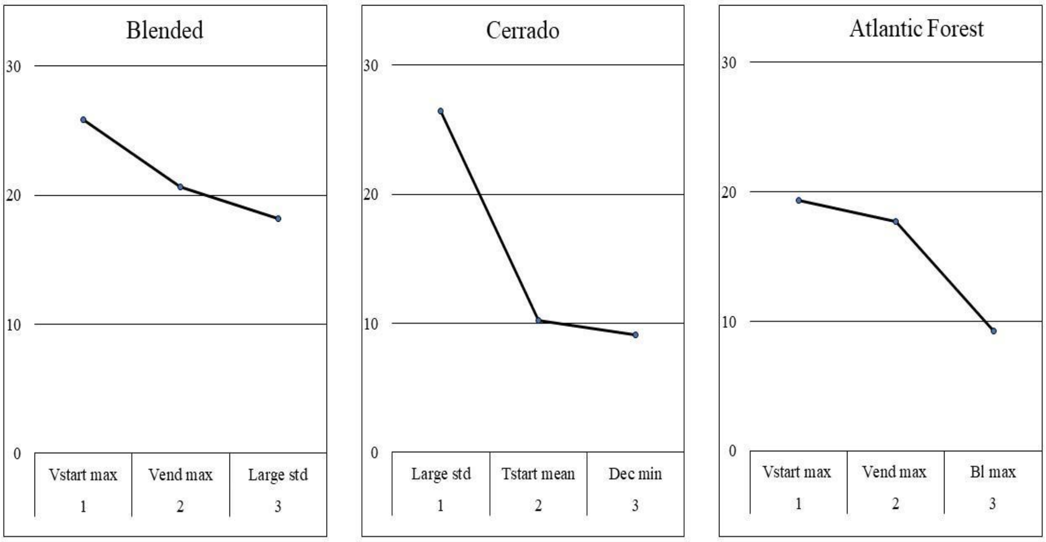

Figure 3. Three most important phenological variables by biome in the disturbance mapping. Vstart max (value for the start of the season maximum), Vend max (value for the end of the season maximum), Large std (largest data value for the fitted function during the season standard deviation), Tstart mean (time for the start of the season mean), Dec min (large seasonal integral minimum), Bl max (base level maximum).

4. Discussion

Phenological metrics have shown as an important predictor when combining a suitable method with rigorous evaluation (Xiaoxuan Zhang et al. 2020). (Valderrama-landeros and Espa 2016) mapped deforestation in Michigan and found right and left derivatives as important variables, while (Yihua Jin et al. 2016) reached 89% of accuracy in North Korea. Rubber plantations and natural forests in China were mapped with overall accuracy of 64% and 80% respectively (Senf et al. 2013).

Despite the use of land surface phenology metrics for land cover classification (Caparros-Santiago, Rodriguez-Galiano, and Dash 2021), we have demonstrated that phenological metrics are also a reliable predictor variable for detection of vegetation disturbances, with regards of anthropic changes such as deforestation. The results are in agreement with other studies that used phenological metrics to map distinct types of land cover and disturbances (Clark et al. 2010; Senf et al. 2013; Valderrama-landeros and Espa 2016).

The selection of the most suitable phenological metrics was an important step to map the disturbances, leading to satisfactory accuracies from the model. Our study demonstrated that the phenological metrics in association with vegetation domains improve accuracy measures due to the intrinsic phenological characteristic of each biome. This finding supports the idea of map disturbances in association with the vegetation type.

Cerrado observations returned the largest data value for the fitted function during the season as the most important variable of the disturbance model. Characterizes of Cerrado such as, well-defined and long dry season, high annual mean temperature and low mean annual precipitation, a considerable seasonal effect, is associated with the variable importance to this biome (Terra et al. 2017). On the other hand, Atlantic forest presented the value for the start of the season as the most important variable, due to the characteristics of the biome such as leaf fall in the dry season, which marks the start of the season. Using the entire dataset, the most important variable was the value for the end of the season. The end of the dry season is similar for both biomes, due to the wet season start around the same month (october), and characteristics such as growing leaf mark the end of the dry season.

There are limitations to this method, which should be considered for further analyses. MODIS imagery have demonstrated as a suitable source of information in phenological studies, however, its coarse spatial resolution unable the detection of disturbances smaller than 6.25 hectares. Regarding to biome characteristics, Atlantic forest presents a high cloud and cloud shadow contamination, even though in MODIS 16-day composites. Clouds and cloud shadows are a source of noise in disturbance mapping studies (Huete et al. 2002; Testa et al. 2018). In our study, this source of noise may affect the phenological modelling of pixel value trajectories, which directly affects accuracy measures and explains the decrease of accuracy compared to other datasets. Finally, another limitation is based on the transition area between biomes. Phenological metrics on this area is similar for both Cerrado and Atlantic forest, where biome boundaries are very subjective. There is a lack of information in the transition areas and further research is required to establish the viability of mapping disturbances with levels of accuracy.

5. Conclusions

This study set out to explore the information of phenological metrics extracted from MODIS time series to map vegetation disturbance in Cerrado and Atlantic forest biomes. We have demonstrated that phenological metrics are suitable to map anthropic disturbances with satisfactory values of accuracy. Phenological metrics fitted and computed by Timesat demonstrated a good potential do model anthropic disturbances, highlighting the largest data value for the fitted function during the season for Cerrado and the value for the start of the season for Atlantic forest, the most important variables for these biomes. Vegetation domains presented a considerable effect in the accuracies, where higher accuracies were found in isolated observations of Cerrado.

This study provided some information of phenological metrics and the potential to detect disturbances in areas affected by seasonal variations. This research has raised many questions in need more investigation, such as a deep analysis in transition areas. Future research should follow-up the approach of phenological metrics to detect disturbance in different vegetation domains and explore the limitations of this method.

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