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PROGRAMA DE PÓS-GRADUAÇÃO EM SENSORIAMENTO REMOTO

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ANÁLISE DO COMPORTAMENTO ESPAÇO-TEMPORAL DO FOGO EM FORMAÇÕES CAMPESTRES DO BIOMA MATA ATLÂNTICA NO ESTADO DO RIO GRANDE DO SUL

PORTO ALEGRE

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Orientador: Prof. Dr. Victor Fernandez Nascimento
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RESUMO

Avaliar o impacto do fogo em formações campestres requer uma compreensão das relações ambientais e antrópicas sobre a dinâmica da paisagem ao longo do tempo. Nos campos de altitude situados no sul do Brasil, o fogo tem sido um componente intrínseco da ecologia dos ecossistemas, afetando as políticas públicas, econômicas, sociais e até mesmo culturais das interações do homem com a natureza. O objetivo deste estudo foi analisar espacial e temporalmente o efeito do uso do fogo em formações campestres do Bioma Mata Atlântica (BMA) no estado do Rio Grande do Sul (RS) usando técnicas de sensoriamento remoto (RS). Para isso, este estudo foi dividido em quatro artigos com diferentes abordagens metodológicas: i) Aplicação do método do Itens de Relatório Preferidos para Revisões Sistemáticas e Meta-Análise (PRISMA) utilizando o software VOSviewer para analisar o estado da arte de como o Sensoriamento Remoto (SR) vem sendo aplicado para a análise de fogo em formações campestres; ii) Identificação da influência de variáveis ambientais e antropogênicas na ocorrência de focos de fogo e a sua resposta às mudanças do forçamento radiativo derivadas de cenários climáticos futuros utilizando o algoritmo *RandomForest*; iii) Identificação da frequência e distribuição de áreas queimadas para avaliar as ferramentas de gestão pública para controle do uso do fogo utilizando bandas espectrais e o índice ΔNBR na plataforma *Google Earth Engine* (GEE), assim como a análise da aplicabilidade do produto MapBiomas Fogo para os campos de altitude; e iv) Aplicação do Índice de Degradação de Campo (IDC) para avaliar o grau de degradação de formações campestre e sua sensibilidade ao manejo com fogo. Os resultados apresentados em cada artigo permitirem a inferência das interações do fogo, clima, uso da terra e vegetação, além de contribuir para a avaliação da eficiência das áreas protegidas e das políticas públicas para a conservação desses ecossistemas diante das mudanças climáticas globais.

Palavras-chave: Campos de altitude. Manejo de fogo. índices de vegetação. Aprendizado de máquina.

ABSTRACT

To assess the impact of fire on grasslands, it is necessary to comprehend the environmental and anthropogenic relationships of landscape dynamics over time. In the highlands of southern Brazil, fire has been an integral part of ecosystem ecology, influencing public, economic, social, and cultural policies of human interactions with nature. This study aims to analyze the effects of fire on grasslands of the Atlantic Forest Biome (BMA) in Rio Grande do Sul (RS) using remote sensing (RS) techniques. The study is divided into four articles, each with a distinct methodological approach. i) The Preferred Report Items method for Systematic Reviews and Meta-Analysis (PRISMA) was applied using the VOSviewer software to analyze the state of the art of how Remote Sensing (SR) has been utilized for analyzing fire in grasslands. II) The study identified the impact of environmental and anthropogenic variables on fire occurrence and their response to changes in radiative forcing using the RandomForest algorithm. Iii) The study identified the frequency and distribution of burned areas to evaluate public management tools for controlling fire using spectral bands and the ΔNBR index on the Google Earth Engine (GEE) platform, and the applicability of the MapBiomas Fogo product for the highland grasslands. iv) The Grassland Degradation Index (IDC) was applied to assess the degree of degradation of grasslands and their sensitivity to fire management. The results of each article contribute to understanding the interactions of fire, climate, land use, and vegetation and the evaluation of the efficiency of protected areas and public policies for the conservation of these ecosystems in the face of global climate change.

Keywords: Highland grasslands. Fire management. vegetation index. Machine learning.

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LISTA DE ABREVIATURAS E SIGLAS

AFB	*Atlantic Forest Biome*
BMA	Bioma Mata Atlântica
BZ	*Buffer Zone*
CART	*Classification and Regression Trees*
CBR	*CatBoost Regressor*
CMIP6	*Coupled Model Intercomparison Project - Phase 6*
CVC	Cobertura Vegetal de Campo
DTR	*Decision Tree Regressor*
ED	Extremamente degradada
EGB	*Extreme Gradient Boosting*
ETR	*Extra Trees Regressor*
EVI	*Enhanced Vegetation Index*
FOM	Floresta Ombrófila Mista
GBR	*Gradient Boosting Regressor*
GEE	*Google Earth Engine*
IDC	Índice de degradação de campo
IPCC	*Intergovernmental Panel on Climate Change*
LD	Levemente degradada
LGBM	*Light Gradient Boosting Machine*
MAE	*Mean Absolute Error*
MAPE	*Mean Absolute Percent Error*
MD	Moderadamente degradada
MODIS	*Moderate Resolution Imaging Spectroradiometer*
NBR	*Normalized Burn Ratio*
ND	Não degradada
NDVI	*Normalized Difference Vegetation Index*
NDWI	*Normalized Difference Water Index*
NIR	Infravermelho próximo
PET	Parque Estadual do Tainhas
PRISMA	Itens de Relatório Preferidos para Revisões Sistemáticas e Meta-Análise
R	Vermelho
R^2	*Coefficient of Determination*

RF	*Random Forest*
RFR	*Random Forest Regressor*
RMSE	*Mean Square Error*
RS	Rio Grande do Sul
SAVI	*Soil-Adjusted Vegetation Index*
SD	Severamente degradada
SHAP	*SHapley Additive exPlanations*
SSP	*Shared Socio-economic Pathway*
SR	Sensoriamento Remoto
SWIR	Infravermelho Médio
TIR	Infravermelho Termal
UC	Unidade de Conservação
V	Visível
ZA	Zona de Amortecimento

SUMÁRIO

1 INTRODUÇÃO

As formações campestres são um componente importante dos ecossistemas, cobrem mais de 30% da área terrestre global (SHOKO; MUTANGA; DUBE, 2016) e fornecem serviços ecossistêmicos essenciais, como a manutenção da biodiversidade vegetal e animal, controle da erosão do solo e regulação do ciclo do carbono (WANG et al., 2019). Entretanto, esse tipo de formação vegetal é altamente suscetível à fragmentação e os seus remanescentes são vulneráveis aos efeitos da mudança do uso da terra, variabilidade climática e regime de fogo (HE; YANG; GUO, 2020).

Pode-se dizer que o fogo é um dos principais responsáveis por distúrbios na dinâmica dos processos ecológicos em diversos ecossistemas, inclusive nas formações campestres (HOFFMANN et al., 2012), e configura-se como um importante agente nas transformações do comportamento do sistema terrestre (BOND; WOODWARD; MIDGLEY, 2005).

Em savanas tropicais, ainda que o fogo desempenhe um importante papel para a manutenção de biodiversidade e ciclagem de nutrientes (COUTINHO, 1990; STAVER; ARCHIBALD; LEVIN, 2011), o seu aumento, causado principalmente por pressões antrópicas nas últimas décadas, tem alterado significativamente o seu regime natural e, como consequência, impacta o funcionamento destes ecossistemas (PILLAR et al., 2009).

Os efeitos do fogo na vegetação e no solo podem ser perturbações de origens naturais e/ou antropogênicas, porém ambos influenciam mudanças ecossistêmicas (ADAGBASA; ADELABU; OKELLO, 2020). Compreender e caracterizar a história de como o fogo vem sendo usado é imprescindível para melhorar nosso conhecimento e gestão das interações do fogo, clima, uso da terra, e vegetação (GOODWIN; COLLETT, 2014), além de suas relações econômicas e sociais (DENNIS et al., 2005).

Neste contexto, é necessário caracterizar os padrões espaço-temporais de incidência de fogo existentes sobre distintos ecossistemas para uma melhor compreensão das relações ambientais e da influência dos fatores antrópicos incidentes sobre a dinâmica da paisagem. Para analisar o efeito da incidência de queimadas em múltiplas escalas espaciais, temporais e espectrais, o uso de produtos derivados de sensoriamento remoto (SR) se consolida como uma importante fonte de dados, ao dispor de informações de vastas áreas com um recobrimento multitemporal e multiespectral (ASNER et al., 2001; GIGLIO et al., 2010).

Ainda que as formações campestres sejam consideradas vulneráveis, a maioria dos estudos de SR se concentram em áreas de formações florestais, onde a vegetação é mais densa e contínua (EVA; FRITZ, 2003; NIOTI et al., 2015; TRAN; TANASE; BENNETT, 2018). Um dos fatores relacionados à concentração de estudos em formações florestais é o desafio de se quantificar a vegetação verde em formações campestres, pois essas apresentam muitas vezes cobertura descontínua, seja por estar intercalada com solo exposto em pastagens fortemente exploradas ou por material vegetativo não fotossintético em áreas preservadas (HE; YANG; GUO, 2020). Além disso, para se quantificar a vegetação campestre é necessário se conhecer a sua variação fenológica sazonal que pode variar de acordo com as condições climáticas (EDWARDS et al., 2013).

Recentemente, o *Intergovernmental Panel on Climate Change* (IPCC) lançou o seu sexto relatório sobre mudanças climáticas, em que aponta diversas consequências a respeito do aumento da temperatura da Terra, uma delas é o aumento da frequência e do tamanho dos incêndios que podem se tornar mais agressivos e recorrentes (IPCC, 2022). Assim, com a intensa atuação do fogo, há necessidade de se estimar a extensão das áreas atingidas e os locais de ocorrência. O SR pode fornecer dados para delinear estratégias, numa frequência temporal e espacial satisfatória para muitos estudos científicos, como é o caso da presente pesquisa.

Assim, a análise da frequência e dos efeitos do fogo em ecossistemas campestres por meio de produtos derivados de sensoriamento remoto pode auxiliar na compreensão das interações ambientais e antrópicas e na definição de estratégias de manejo, além de permitir a avaliação da eficiência das áreas protegidas e das políticas públicas para a conservação desses ecossistemas em face das mudanças climáticas globais

1.1 Objetivo geral

O objetivo deste estudo é analisar espacial e temporalmente o efeito do uso do fogo em formações campestres do Bioma Mata Atlântica (BMA) no estado do Rio Grande do Sul (RS) usando SR.

1.1.1 Objetivos específicos

a) Realizar uma revisão sistemática do tema de SR aplicado ao entendimento do uso do fogo em formações campestres no mundo.

b) Avaliar por meio de algoritmos de aprendizado de máquina a ocorrência do fogo e sua capacidade preditiva no Bioma Mata Atlântica no estado do RS com a análise da resposta do fogo às mudanças do forçamento radiativo obtidas a partir de cenários climáticos futuros

c) Analisar a ocorrência, frequência do fogo através de dados de SR orbitais e avaliar a sua correlação com a legislação ambiental ao longo do tempo para os campos de altitude do RS - Brasil.

d) Determinar, a partir de imagens orbitais e índices de vegetação, o grau de degradação de uma área em campos de altitude e a sua sensibilidade ao uso do fogo.

2 DESENVOLVIMENTO

Este trabalho está organizado em duas seções principais, sendo a primeira delas o referencial teórico sobre conceitos abordados e estudados para o desenvolvimento do trabalho. As referências desta seção serão apresentadas no final do documento.

A segunda parte apresenta o desenvolvimento do trabalho, onde será apresentada a metodologia, resultados e discussão, dividido em quatro artigos científicos, aqui denominados capítulos. As referências desta seção serão apresentadas no final de cada capítulo.

2.1 Referencial teórico

2.1.1 Definição de termos relacionados a formações campestres

As formações campestres do bioma Mata Atlântica, classificadas pelo Instituto Brasileiro de Geografia e Estatística como “Estepe” (IBGE, 2004), estão distribuídas desde o norte do RS até o Paraná. São denominadas “Campos de Altitude” pela Lei da Mata Atlântica e estudos clássicos sobre a região, e são popularmente conhecidas no RS como os “Campos de Cima da Serra” (SAFFORD, 1999; BRASIL, 2006; PILLAR; LANGE, 2015; PILLAR et al., 2009).

Estudos botânicos sobre a vegetação do RS e formações campestres no sul do Brasil costumam se referir a elas simplesmente como “Campos” (OLIVEIRA; PILLAR, 2004; OVERBECK et al., 2007; RAMBO, 1956).

Assim, pelas definições apresentadas até aqui, quando nos referirmos a formações campestres, sem qualquer qualificação adicional, estamos nos referindo ao tipo de formação vegetal, independentemente da localização geográfica. Ao nos referirmos a “Campos de Altitude”, ou somente “Campos”, consideramos a indicação de ocorrência na Mata Atlântica.

2.1.2 Formações campestres, degradação e uso do fogo

O fogo é comumente utilizado como ferramenta de manejo de formações campestres (OVERBECK et al., 2005) e está presente nos Campos de Altitude desde o início do Holoceno (BEHLING et al., 2007). Como são localizados em regiões climáticas que normalmente seriam florestais, na ausência de fogo e pastejo, há uma tendência para o adensamento de arbustos e a expansão florestal (MÜLLER et al., 2007).

As formações campestres vem sendo ameaçadas, devido à perda de habitat, pela fragmentação ocasionada por distúrbios humanos graves e de longo prazo, tanto pelo uso excessivo de fogo e sobrecarga de pastejo de gado, quanto pela disseminação da agricultura com conversão de grandes áreas ou pela introdução de espécies exóticas (BARROS et al., 2015; OVERBECK et al., 2007).

A compreensão das relações entre estes fatores tem implicações substanciais para a base intelectual de gerenciamento de fogo, que se estende na integração da conservação da biodiversidade com valores culturais, sociais e econômicos (BOWMAN et al., 2011).

As formações campestres são importantes para a produção pecuária, especialmente em áreas onde outras atividades agrícolas não são viáveis. A prática do manejo de campo com fogo no período do inverno se torna comum e é utilizada para retirada de biomassa seca, com o intuito de propiciar o rebrote da vegetação que será utilizada na alimentação do rebanho bovino na primavera e verão (BOLDRINI, 1997). A remoção da biomassa acima do solo pelo fogo estimula a regeneração e fornece microssítios para o estabelecimento de novas espécies, remoção de concorrentes dominantes e favorece o surgimento de bancos de sementes (FIDELIS et al., 2012).

Por muito tempo, a degradação destas formações campestres foi associada a fatores antropogênicos como as práticas de manejo com fogo e pastejo excessivo (ZHOU et al., 2017). As formações campestres degradadas mostraram principalmente redução acentuada no rendimento e na diversidade de espécies forrageiras de alta qualidade, aumento de espécies tóxicas e nocivas e intensificação da erosão do solo, o que restringe seriamente as funções e seus serviços ecossistêmicos (SHENG et al., 2022). A implementação de práticas agrícolas sustentáveis, como a possibilidade de melhorar o manejo de formações campestres para produção agrícola e pecuária, podem aumentar a produtividade ao mesmo tempo em que melhoram a adaptabilidade e a conservação destes ecossistemas (CASTELLANOS et al., 2022).

Em uma tentativa de conter a degradação, a prática da queima da vegetação foi considerada proibida pela Lei Estadual do RS n° 9.519/1992, que institui o Código Florestal do Estado do RS. Desde a sua proibição, a pecuária tradicional tem sido substituída por outras práticas consideradas mais viáveis economicamente, como a agricultura e a silvicultura, que, contudo, são consideradas mais degradantes ao meio ambiente (BUFFON; PRINTES; ANDRADES-FILHO, 2018; CRAVINO; BRAZEIRO, 2021).

Atualmente, o uso do fogo para manejo de formações campestres no Estado do RS é regulamentado pela Lei Estadual 13.931, de 30 de janeiro de 2012, a qual deixa claro que o fogo pode ser utilizado em caráter fitossanitário e para controle de pragas e doenças em áreas não mecanizáveis, desde que com autorização ambiental do órgão municipal, responsável por difundir normas e critérios para este manejo.

Estudos anteriores questionam a eficácia das ferramentas de gestão ambiental regulamentadas pelas legislações municipais acerca do uso do fogo (SANTOS; ANDRADES-FILHO, 2021), em que enfatizam a necessidade de criação de novas grandes áreas protegidas, aplicação de restrições legais de uso da terra e gestão ambiental para ecossistemas não-florestais (OVERBECK et al., 2015).

A exclusão do fogo em ecossistemas como estes pode não ser viável (DURIGAN, 2020; PIVELLO et al., 2021), o que pode favorecer a evolução de uma composição com poucas espécies dominantes, com predomínio de gramíneas de hábito cespitoso e até mesmo arbustos que, com o acúmulo de biomassa inflamável, aumentam o risco de incêndios devastadores (PILLAR; VÉLEZ, 2010). Estabelecer métodos para implantação e monitoramento de queimas prescritas contribui para avanços do ponto de vista social, econômico e ambiental.

2.1.2.1 Satélites e Sensores

Atualmente, existem diversos satélites em órbita que foram projetados para a Observação da Terra. Muitos deles foram utilizados em diferentes épocas para avaliação do comportamento do fogo em formações campestres. A lista de alguns destes satélites/sensores, operador, e suas resoluções temporal e espacial estão descritos na Quadro 01.

Quadro 01 – Satélites e sensores comumente utilizados em estudos em sensoriamento remoto aplicado a monitoramento de fogo.

Satélite (sensor)	**Operador**	**Resolução temporal**	**Resolução espacial**
JPSS (VIIRS)	NOAA	1–2 dias	375-750 m
GOES – 16	NOAA / NASA	Geoestacionário	1 km - 4 km
Landsat 5 (TM)	NASA / USGS	16 dias	30-120 m
Landsat 7 (ETM +)	NASA / USGS	16 dias	15 / 30–60 m
Landsat 8 (OLI/ TIRS)	NASA / USGS	17 dias	OLI: 15/30 m TIRS: 100 m
NOAA-7-19 (AVHRR)	NOAA	1–2 dias	1100 m
Sentinel 2A-B (MSI)	ESA	5 dias	10–20-60 m
SPOT (HRV - XS)	CNES	26 dias	2,5 a 20 m
Terra-Aqua (MODIS)	NASA	1–2 dias	250 m
WorldView 2	DigitalGlobe	1,1 – 3,7 dias	0,3 a 2 m

Em relação às plataformas orbitais, existem diferentes alternativas, tais como as apresentadas pelo programa Landsat, que tem os satélites Landsat 7, 8 e 9 em operação atualmente. Ambos são operados pelo Serviço Geológico dos Estados Unidos (USGS) e cobrem a Terra a cada 16 dias, podendo ser combinados para reduzir o tempo de revisita, coleta dados em várias bandas nas faixas de onda do visível (V), NIR, SWIR, e infravermelho termal (TIR), em uma resolução de 30 m e 100m, respectivamente (USGS, 2022). Um dos pontos fortes de satélites como o Landsat além da sua extensa série histórica, são os ciclos consistentes de revisita, que fornecem os dados necessários para a análise de séries temporais (ALVARADO; SILVA; ARCHIBALD, 2018; GOODWIN; COLLETT, 2014).

Por outro lado, o sensor *Moderate-Resolution Imaging Spectroradiometer* (MODIS), a bordo dos satélites Terra e Aqua, também administrados pela NASA, possui uma resolução espacial mais baixa, porém com uma alta resolução temporal, de cerca de 1-2 dias. Este sensor fornece alta sensibilidade radiométrica de 12 bits, obtendo dados em 36 bandas espectrais que variam de 0,4 a 14,4 µm, com resolução espacial de 250 m a 1 km. O sensor MODIS desempenha um papel vital no desenvolvimento de modelos de sistemas terrestres interativos, globais e validados, capazes de prever mudanças globais com precisão suficiente para ajudar os formuladores de políticas a tomar decisões acertadas sobre a proteção do meio ambiente (NASA, 2022).

Diversos estudos utilizaram tanto a série Landsat para obtenção de dados acerca do fogo e construção de séries temporais (ALVARADO; SILVA; ARCHIBALD, 2018; LIU; POPESCU, 2022; SCHEFFLER; FRANTZ, 2022; VIANA-SOTO et al., 2022), como imagens ópticas de resolução espacial mais baixa, como as obtidas pelo MODIS e AVHRR (CHEN et al., 2017; JIANG et al., 2022; MAFFEI; LINDENBERGH; MENENTI, 2021; MAYR; VANSELOW; SAMIMI, 2018)

A vantagem de uma taxa de revisita mais frequente como a do sensor MODIS é a possibilidade de detectar mais rapidamente não apenas mudanças drásticas na cobertura, mas qualquer desvio do estado saudável esperado do ecossistema (SLINGSBY et al., 2020), e, consequentemente, fornece informações relevantes que servem de apoio para compreensão do uso do fogo (CHEN et al., 2017).

Porém, vale destacar que algumas desvantagens do sensor MODIS estão correlacionadas com a sua baixa resolução espacial, a qual não consegue detectar incêndios de pequeno porte. Uma opção para solucionar este problema seria a utilização de dados do Sentinel-2, satélite lançado mais recentemente, em 2015, que transporta uma carga útil de instrumento óptico que possui 13 bandas espectrais, sendo quatro bandas com 10 m, seis bandas com 20 m e três bandas com 60 m de resolução espacial e, ainda, apresenta um tempo de revisita de cinco dias com os dois satélites Sentinel 2A e 2B (ESA, 2021).

Em razão da borda vermelha e bandas SWIR e da resolução espacial refinada, os dados ópticos do Sentinel podem apresentar melhor desempenho aplicados à vegetação, caso comparado a outros sensores. A combinação de bandas isoladas e índices de vegetação das imagens do satélite Sentinel-2 tem potencial e robustez para estimativas de biomassa de pastagens naturais, pois apresentaram desempenhos superiores na discriminação de espécies de gramíneas em relação aos dados do Landsat e Worldview (GUERINI FILHO; KUPLICH; QUADROS, 2020).

2.1.3 Computação em nuvem e aprendizado de máquina

Em aplicações de SR, os conjuntos de dados a serem processados, analisados e interpretados estão cada vez maiores e cobrem áreas extensas, com abrangência regional ou mesmo global, devido à necessidade de atender às crescentes demandas por informações mais precisas e atualizadas (WANG et al., 2018). Portanto, os grandes volumes de dados, bem como a sua complexidade crescente de interpretação são os principais desafios atuais. A computação em nuvem oferece algumas soluções para resolver esses desafios com o desenvolvimento de plataformas de serviço para pré-processamento, análise e visualização de *Big Data* (GILL et al., 2019).

A *Google* introduziu uma plataforma baseada em nuvem chamada *Google Earth Engine* (GEE) para processamento rápido e eficiente de grandes conjuntos de dados geoespaciais (GORELICK et al., 2017). Essa fornece uma plataforma sistemática para analisar dados com capacidades computacionais robustas em linguagens *JavaScript* ou *Python*, sendo amplamente utilizado para monitoramento e análise ambiental (TAMIMINIA et al., 2020). Estudos começaram a fazer uso de plataformas como essa para examinar incêndios a partir de séries temporais de refletância de superfície espectralmente consistentes (ARRUDA et al., 2021; DALDEGAN; ROBERTS; RIBEIRO, 2019; QUINTERO et al., 2019).

Além disso, o rápido desenvolvimento recente em inteligência artificial levou a um aumento de algoritmos de aprendizado de máquina que foram aplicados com sucesso em vários domínios e, por vezes, superam outras técnicas tradicionais (LECUN; BENGIO; HINTON, 2015). As técnicas de aprendizado podem ser classificadas em supervisionadas e não supervisionadas, sendo a supervisionada dívida em duas categorias, regressão e classificação (MITCHELL, 1997). Técnicas de aprendizagem de máquina, como *Random Forest* (RF) (BREIMAN, 2001) e *Classification and Regression Trees* (CART) (BREIMAN et al., 1984), são exemplos de algoritmos para classificação e regressão.

O algoritmo RF cria várias árvores de decisão aleatórias para chegar ao resultado e fornece uma classificação com a importância de cada variável, o que permite fazer suposições sobre o papel de cada fator (CUTLER et al., 2007; OLIVEIRA et al., 2012). Por exemplo, esses algoritmos são utilizados para identificar áreas queimadas (BAR; PARIDA; PANDEY, 2020) e compreender os fatores que contribuem à ocorrência de fogo (BARROS et al., 2021; YU et al., 2017), devido à robustez no trato com um grande número de variáveis de entrada e problemas não lineares.

2.2 Metodologia

Este estudo foi realizado por meio da elaboração de artigos científicos, que serão apresentados em quatro capítulos conforme apresentados na Figura 01, cada um composto por passos metodológicos descritos respectivamente nos itens 2.3.1, 2.3.2, 2.3.3 e 2.3.4.

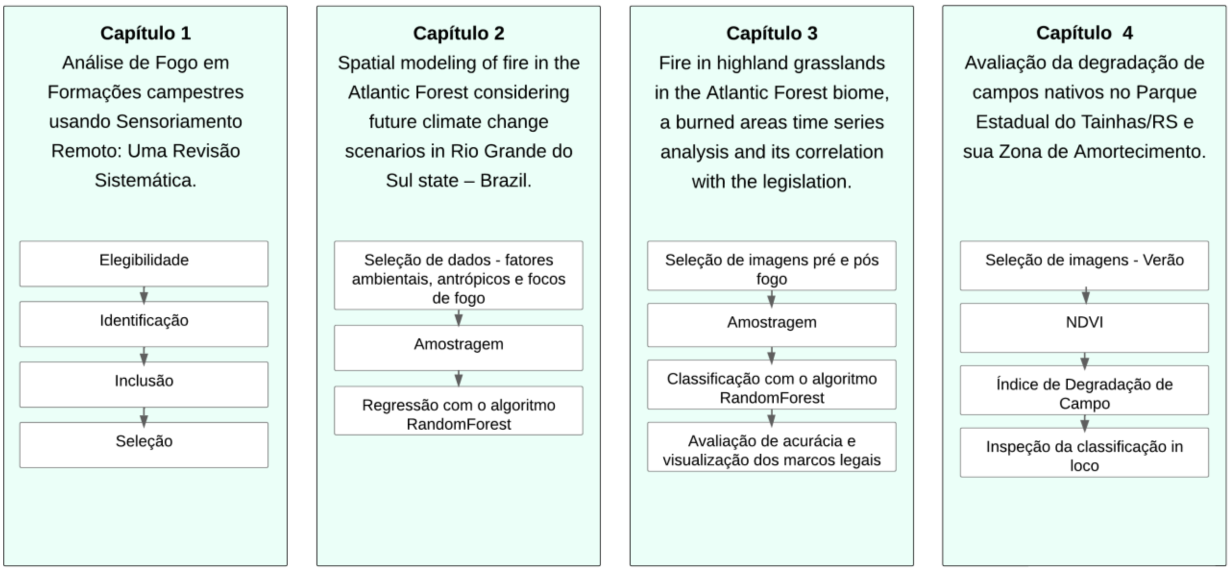

Figura 01: Fluxograma da metodologia de pesquisa e a sua divisão por capítulos.

2.3 Resultados e discussões

2.3.1 Capítulo 1: Sensoriamento Remoto Aplicado à Análise de Fogo em Formações Campestres: Uma Revisão Sistemática

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Fire Analysis in Grasslands using Remote Sensing: A Systematic Review

Sensoriamento Remoto Aplicado à Análise de Fogo em Formações Campestres: Uma Revisão Sistemática

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Abstract: Assessing the fire impact on grasslands requires understanding how the environmental and anthropic relationships affect the landscape dynamics. This study carries out a systematic literature review to understand fire behavior in grasslands through remote sensing techniques. To this end, the Scopus data was used employing the PRISMA method with the cluster mapping aid. Initially, 7,881 articles were found in the literature. The methodological steps applied to them resulted in 67 articles, which were used in the analysis. The results indicated increased interest in research in the area, with Brazil having the second-highest number of studies. Several publicationsutilized orbital images. However, there has been recent growth in the use of images obtained from UAV-mounted sensors. In addition to the NDVI and EVI indices, other indices have been used recently for analyzing burn severity and the vegetation recovery process. These subjects are primarily related to integrated fire management, which must consider conserving biodiversity and human use to reduce the fire's intensity and severity to make them more controllable and reduce their negative impacts. Therefore, remote sensing is essential for understanding the fire spatial-temporal behavior and, consequently, serves as a scientific aid to help decision-making in burn prescription cases, considering the ecosystems maintenance and the better grassland use.
Keywords: Burns. Spectral indices. Grasses. NBR. VOSviewer.

Resumo: Avaliar o impacto do fogo em formações campestres requer uma compreensão das relações ambientais e antrópicas sobre a dinâmica da paisagem. Este estudo faz uma revisão da literatura para entender o comportamento do fogo em formações campestres por meio de técnicas de sensoriamento remoto. Para isso foi utilizada a base de dados da Scopus por meio do método PRISMA com o auxílio de mapeamento de *clusters*. Primeiramente, foram encontrados 7.881 artigos na literatura cientifica, onde foram aplicados os passos metodológicos, resultando em 67 artigos, os quais foram utilizados na análise. Os resultados apontam uma tendência de crescimento de pesquisas coma temática, sendo o Brasil o segundo país com maior contribuição ao resultado. Grande parte das publicações utilizaram imagens orbitais, porém há um crescimento recente da utilização de imagens obtidas por sensores acopladosa VANT's. Além dos índices espectrais NDVI e EVI, observa-se a recente a utilização de outros índices para analisara severidade das queimadas e o processo de recuperação da vegetação. Estes temas são principalmente relacionados com o manejo integrado de fogo, que deve levar em consideração a conservação da biodiversidade e uso antrópico com o objetivo de reduzir a intensidade e severidade do fogo, para torná-lo mais controlável e reduzir seus impactos negativos. Portanto, o sensoriamento é essencial para entender o comportamento espaço-temporal do fogo e consequentemente servir de subsídio científico para auxiliar a tomada de decisão em casos de prescrição de queimadaslevando em consideração a manutenção dos serviços ecossistêmicos e a utilização destas formações campestres.
Palavras-chave: Queimadas. Índices espectrais. Gramíneas. NBR. VOSviewer.

1 INTRODUCTION

Grasslands are an important ecosystem component, covering more than 30% of the globe (SHOKO;MUTANGA; DUBE, 2016) and providing essential ecosystem services, such as vegetal and animal biodiversity maintenance, soil erosion control, and carbon cycle regulation (WANG *et al.*, 2019). Nonetheless,this vegetation formation is highly susceptible to fragmentation, and the remnants are vulnerable to land use, bad management practices, and climate variability (HE; YANG; GUO, 2020).

Beyond the factors mentioned above, it can be said that fire is one of the primary ecological process dynamic disturbances in various ecosystems, including grasslands (HOFFMANN *et al.*, 2012), making them a critical transformation agent for terrestrial system behavior (BOND; WOODWARD; MIDGLEY, 2005).

Although some of these ecosystem changes are desirable from an ecological perspective, the destructive consequences are generally considered undesirable and require greater observation (SZPAKOWSKI; JENSEN, 2019). So, the grassland fire's spatio-temporal incidence patterns need to be assessed to understand better the environmental relationships and the anthropic factors that influence landscapedynamics. Therefore, remote sensing constitutes an essential data source to analyze the burn's effect on multiple spatial, temporal, and spectral scales (ABDOLLAHI et al., 2018; CHUVIECO et al., 2019; GIGLIOet al., 2010).

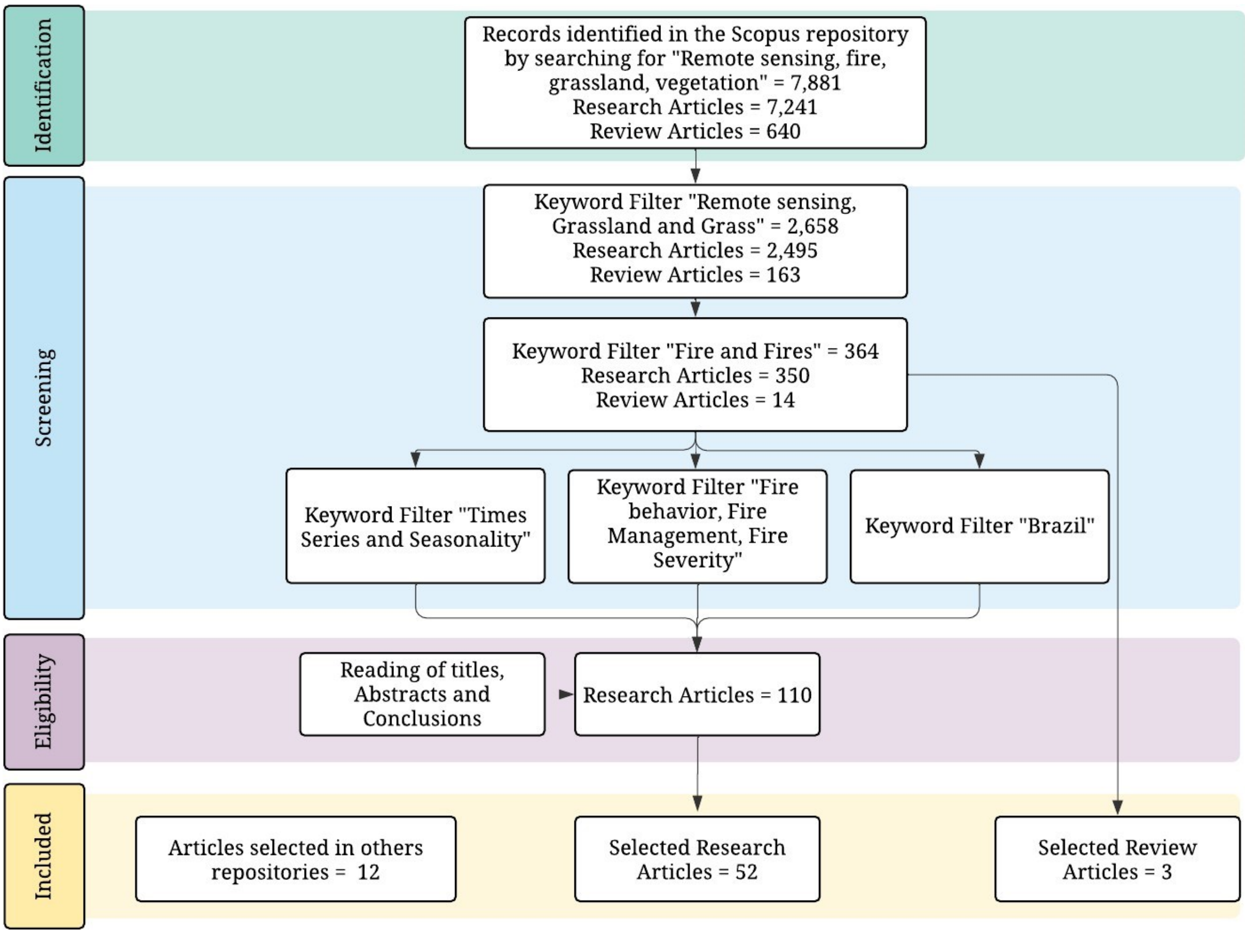
Once several studies apply remote sensing to research fire, a comprehensive review of these investi- gations is needed to understand the investigation standards in the area. Thus, systematic reviews applied to geoscience have been undertaken more often, as remote sensing has become a complementary information source and, in many cases, the only viable (SHEFFIELD *et al.*, 2018). Systematic reviews are helpful becausethey use a method that visualizes quantitative information about a research domain, allowing the researcher togain insights into specific aspects of the subject studied (SU; LEE, 2010).

One of the most used methodologies for this is the Preferred Report Items for Systematic Revision andMeta-analysis (PRISMA) which was elaborated to address various conceptual and practical advances in the systematic review science (MOHER *et al.*, 2009). The PRISMA was previously used for remote sensing re- views, for example, to analyze large-scale data sets and environmental monitoring (TAMIMINIA *et al.*, 2020), in urban scenario simulations in land use and cover change models (WANG; MURAYAMA; MORIMOTO, 2021), in machine-learning methods (SHEYKHMOUSA *et al.*, 2020), and UAV data processing (ESKANDARI; MAHDIANPARI; MOHAMMADIMANESH, 2020). In addition to PRISMA, this study alsoused VOSviewer, a bibliometric mapping application capable of providing a broad scientific literature view. Our main goal is to do a systematic literature review describing the state of the art in fire behavior and use in grasslands via remote sensing techniques.

2 METHODOLOGY

For this study, a systematic review was done, gathering the primary publications, influential authors, journals, countries, and organizations to identify emerging research directions regarding remote sensing tech-niques applied to understand the fire in grasslands published through March 2021. It's important to highlight that no review study about this subject was found before in the literature, thus suggesting a need to synthesizethis knowledge. This research used the PRISMA method, divided into four phases labeled identification, se- lection, eligibility, and inclusion, presented in Figure 1 and described in the items below.

Figure 1 – Flowchart of the PRISMA methodology research phases.



Source: The authors (2021).

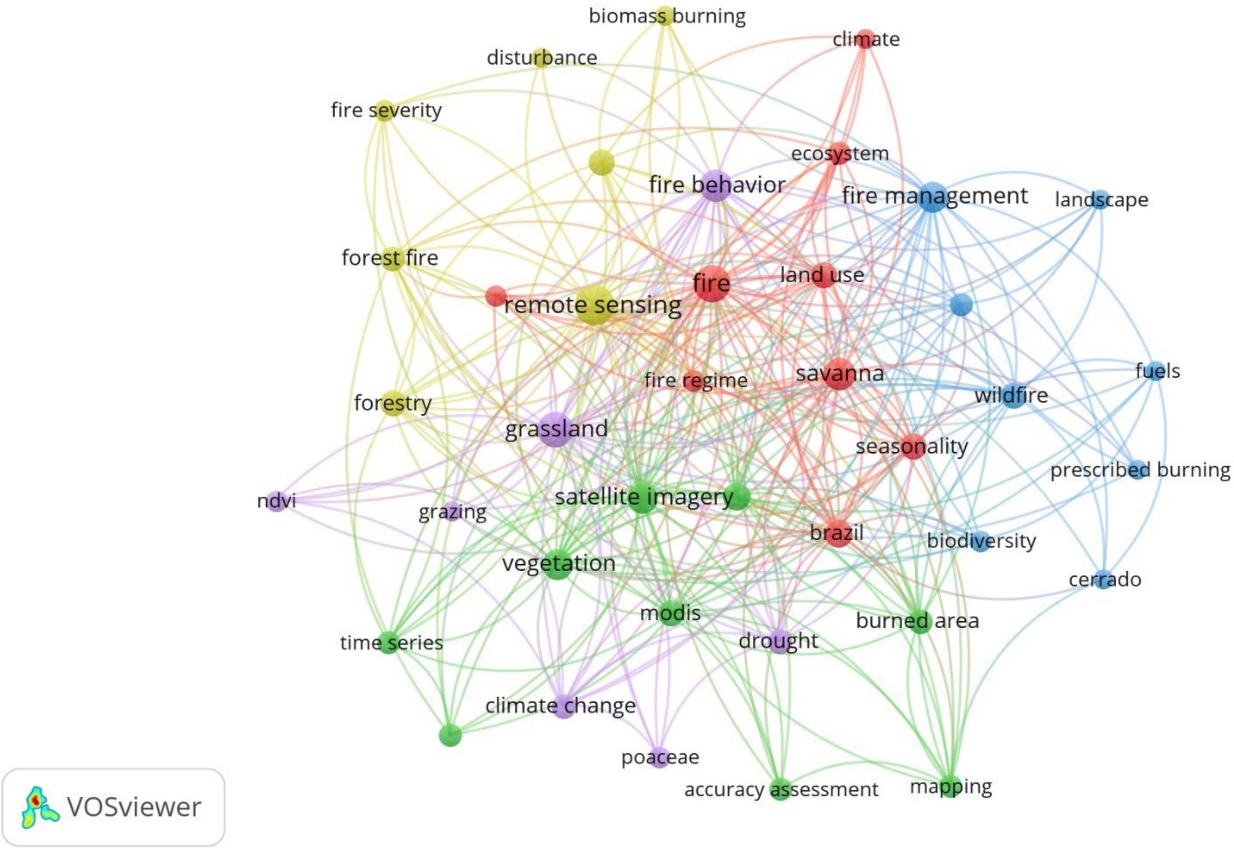
2.1 Step 1: Identification

In the identification phase, the approach adopted for consulting the literature consisted of a search forwords that best represented the subject of interest, namely: ”remote sensing,” “fire,” “vegetation,” and “gras- sland.” The keywords were used to filter the Scopus library (www.scopus.com), one of the most extensive abstracts and citation databases in the world's peer-reviewed research literature, covering over 5,000 interna- tional journals (VIANA et al., 2017). Only documents published as research and review articles in Portuguese,English, or Spanish were chosen. In this first step, 7,881 articles were found.

2.2 Step 2: Selection

The articles identified in the first step were extracted for the selection step and filtered using the keywords “remote sensing,” “grassland,” and “grass” to select studies with an emphasis on remote sensing applied to grasslands resulting in 2,658 articles. Then, they were passed through a new filter, where the keywords “fire” and “fires” were used to understand how the fire occurrence in this vegetation was being addressed, resulting in 364 articles.
Of these, 14 articles were directly chosen for the eligibility step. Next, the other 350 articles were submitted for keyword and thematic axis identification via the VOSviewer software (Figure 2), which createsmaps based on network data, forming clusters. In the figure, the item’s weighting determines the circle size, the group to which the keyword belongs, and the cluster’s color. The lines represent links or associations, whilethe distance indicates the strength of the relationship between the occurring keywords (ECK; WALTMAN, 2020; WALTMAN; VAN ECK, 2013).

Figure 2 –Keywords cluster network analysis of the 364 articles found in the PRISMA method selection step.



Source: The authors (2021).

The following filter choice was based on the connection between words in the cluster map (Figure 2)and their relationship to this article's subject. The words selected were:

a) "time series" and "seasonality" = were chosen to understand the temporal occurrence and inter-annual fire behavior over the years and the intra-annual fire between seasons.
b) "fire behavior," "fire management," and "fire severity" = were selected to gain insight into the leading spectral indices and methodologies utilized to monitor the fire intensity and factors that contribute to its occurrence related to vegetation recovery after burn.
c) "Brazil" = was chosen to limit the studies to ones addressing the fire use in grasslands fields in Brazil to verify how the subject has come to be applied in the country.

The above filters applied in this selection step resulted in 110 articles analyzed in the next stage.

2.3 Step 3: Eligibility

In the eligibility step, the titles, abstracts, and conclusions were read to select only the articles whose content was related to fire use and behavior in grasslands throughout remote sensing.

2.4 Step 4: Inclusion and data analysis

In this last step, inclusion, 52 research and three review articles were chosen. In addition, 12 referencescited by the articles read and found in other databases than Scopus were added to the analysis. Thus, 67 articleswere included in this systematic review and had their information cataloged (Table 1). Additionally, VOSviewer was used to classify the article's relevance and their regional and global contribution in this last step. In addition, several pieces of information, such as the satellites, sensors, and spectral indices most employed in the articles, were cataloged to identify the research trends.

Table 1 – Parameters cataloged during the systematic review.

Parameter	Description
Type	Article type (study or review)
Citations	Number of article citations relative to its publication date
Name	Name of study/review
Author	Author(s) name(s)
Journal	Name of the journal where the study was published
Publication year	Year article was published
Satellites and sensors	Name of satellite(s) and/or sensor(s) used
Spectral indices	Number and name of Indice(s) used

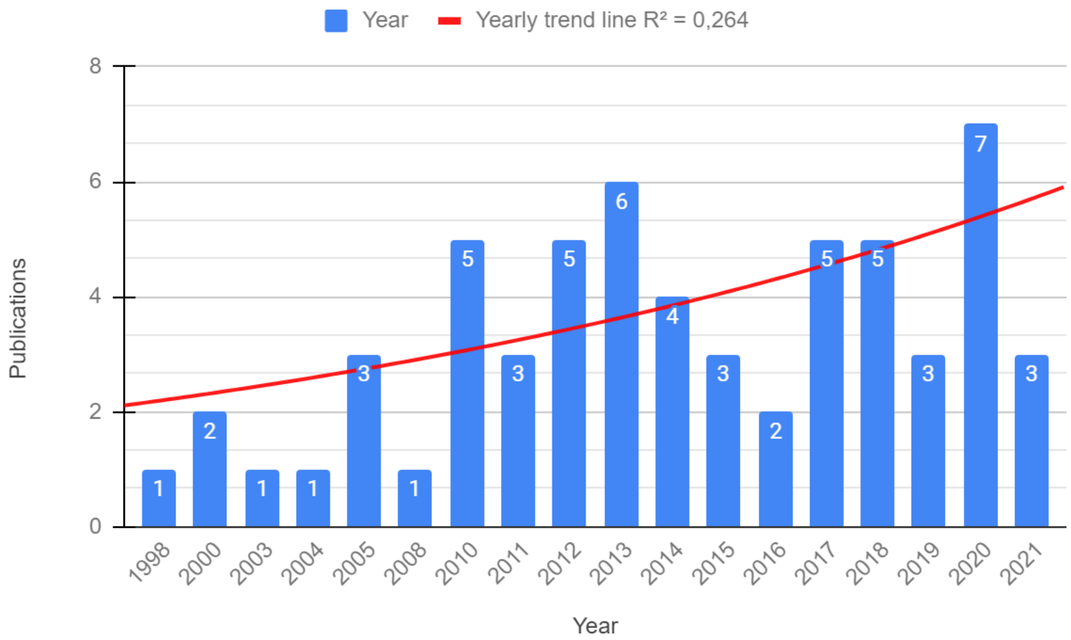
Source: The authors (2021).

3 RESULTS AND DISCUSSION

3.1 Analysis of scientific production and its relevance

Of the 7,893 publications found, after applying the filters presented in Figure 1, 67 articles remained;the complete list is shown in the (supplementary material). These articles were analyzed more deeply in the systematic review. The reviewed articles were published between 1998 and the first trimester of 2021 (Figure3).

Figure 3 – Distribution of publications from January 1998 to March 2021.



Source: The authors (2021).

The publications' growth over the period can be seen, particularly starting in 2010. Most noteworthy are the years 2013 and 2020, with six and seven scientific articles published, respectively, and 2021 which could easily surpass these years since it already presented three articles published in the first trimester.

In addition, each article's citations were counted, which according to GARNER et al. (2018), is the measure commonly adopted to assess the publication's academic influence. However, the following equation was used to normalize the citations number over time and define the reviewed article's influence degree: Influence = Citations / (Base year – publication year). The publications were ranked from most to least influential, and the six highest are presented in (Table 2).

Table 2 – Most influential articles.

Author	Title	Year	Journal	Influence
CHUVIECO *et al.*, 2019	*Historical background and current developments for mapping burned area from satellite Earth observation*	2019	Remote Sensing of Environment	34.0
STAVER; ARCHIBALD; LEVIN, 2011	*Tree cover in sub-Saharan Africa: Rainfall and fire constrain forest and savanna as alternative stable states*	2011	Ecology	29.0
BOWMAN *et al.*, 2020	*Vegetation fires in the Anthropocene*	2020	Nature	24.0
(ROY *et al.*, 2005)	*Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time series data*	2005	Remote Sensing of Environment	22.8
YEBRA *et al.*, 2013	*A global review of remote sensing of live fuel moisture content for fire danger assessment: Moving towards operational products*	2014	Remote Sensing of Environment	16.4
ALVARADO *et al.*, 2017	*Drivers of fire occurrence in a mountainous Brazilian cerrado savanna: Tracking long-term fire regimes using remote sensing*	2017	Ecological Indicators	11.0

Source: The authors (2021).

Many of the most influential articles are reviews and have been available for at least ten years, with only two of them having been published in the last three years. One common characteristic among them is thestudy’s area scale, which was regional or global. As was noted by ROY et al. (2005), one of the satellite remotesensing advantages is to be capable of monitoring the vegetation burn on a broader scale. Moreover, it is worthhighlighting the Chuvieco et al. (2019) study, which reviews remote sensing applied to fires over the last 40 years. In this study, the authors synthesized the physical basis for detecting burned areas, the historical trendsof satellite sensors used to monitor them, and the identification of potential opportunities for improving burn area detection.

3.2 Analysis of satellites and sensors used

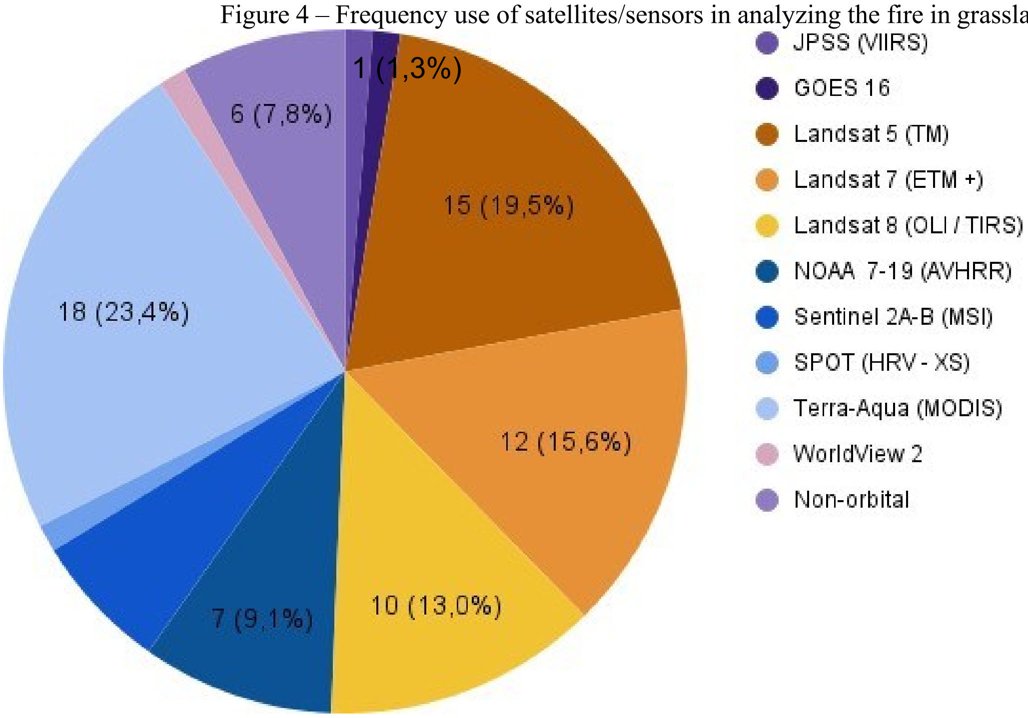
This study found many sensors and platforms used in various stages to assess the grassland fires behavior via remote sensing data. A list of the satellites/sensor's names, operators, and temporal and spatial resolutions is described in (Table 3), while the frequency with which they were utilized is presented in Figure4.

Table 3 – Satellites and sensors found in the systematic review.

Satellite (sensor)	Operator	Temporal resolution	Spatial resolution	Publications
JPSS (VIIRS)	NOAA	1 - 2 days	375-750 m	1
GOES - 16	NOAA / NASA	Geostationary	1 - 4 km	1
Landsat 5 (TM)	NASA / USGS	16 days	30 - 120 m	15
Landsat 7 (ETM +)	NASA / USGS	16 days	15 - 30 - 60 m	12
Landsat 8 (OLI/ TIRS)	NASA / USGS	17 days	OLI: 15/30 m TIRS: 100 m	10
NOAA-7-19 (AVHRR)	NOAA	1 - 2 days	1100 m	7
Sentinel 2A-B (MSI)	ESA	5 days	10 - 20 - 60 m	5
SPOT (HRV - XS)	CNES	26 days	2.5 -20 m	1
Terra-Aqua (MODIS)	NASA	1 - 2 days	250 m	18
WorldView 2	Digitalglobe	1.1 - 3.7 days	0.3 - 2 m	1

Source: The authors (2021).

Figure 4 – Frequency use of satellites/sensors in analyzing the fire in grasslands.



Source: The authors (2021).

Although the majority of studies, around 48%, used the Landsat series (ALVARADO; SILVA; ARCHIBALD, 2018; PEREIRA JR. et al., 2014; WILLIAMSON; MURPHY; BOWMAN, 2014), optical images with lower spatial resolution, such as those obtained by MODIS and AVHRR, represent approximately23% and 9% each. It is also worth noting that only one study used hyperspatial orbital imagery fromWorldView (FERNÁNDEZ-GUISURAGA; CALVO; SUÁREZ-SEOANE, 2020). Meanwhile, satellites with high spatial resolutions, such as Sentinel and SPOT, were used in approximately 8% of the reviewed articles.Regarding orbital platforms, there are several alternatives, such as those offered by the NASA/USGS program. For example, Landsat 7 and 8 are currently in operation, while Landsat 9 was launched in the secondhalf of 2021 to continue obtaining Earth's remote sensing images. All the satellites, operated by the UnitedStates Geological Survey (USGS), cover the Earth every 16 days, collecting data in various frequency bands,such as the visible (V), near-infrared (NIR), short-wavelength infrared (SWIR), and thermal infrared (TI), from30 to 100 meters of special resolution (USGS, 2021). One of the Landsat satellite's strengths is the coveragecycle consistency along the time (ALVARADO; SILVA; ARCHIBALD, 2018; GOODWIN; COLLETT,2014). Currently, with three satellites in operation, it should go down to eight days, providing essential data for temporal series analysis.

On the other hand, the Moderate-Resolution Imaging Spectroradiometer (MODIS) onboard thesatellites Terra and Aqua, also administered by NASA, have a lower spatial resolution but a higher temporal resolution with revisits every 1-2 days. This sensor provides high radiometric sensitivity, gathering data in 36frequency bands from 0.4 to 14.4 µm, with a spatial resolution varying from 250 m to 1 km. It plays a vital role in developing interactive, global, validated Earth system models capable of predicting global changes withenough precision to help policymakers protect the environment and make decisions (NASA, 2021).

MODIS and Landsat images were likely used more often because of their long history and are freely available. With their higher revisits time, Aqua and Terra allow detection of drastic changes in Earth and anydeviation from the expected ecosystem healthy state (SLINGSBY *et al.*, 2020), consequently giving relevant information that serves to bolster fire use understanding (CHEN et al., 2017).

However, it is worth highlighting that some of MODIS's disadvantages are its low spatial resolution,making it impossible to detect small fires. One solution for this problem would be to use Sentinel-2 data, a more-recently-launched satellite in 2015, which carries an optical instrument with 13 frequency bands, a spatialresolution between 10 and 60 meters, and five days revisit time with two satellites, Sentinel 2A, and 2B currently in operation (ESA, 2021).

Due to the visible-near infrared and SWIR bands and their refined spatial resolution, the optical data from Sentinel-2 presents better performance when applied to vegetation than other sensors. The isolated bandsand vegetation indices combined from Sentinel-2's images have the potential and robustness to estimate the grasslands biomass. They have demonstrated superior performance in grass species discrimination compared to Landsat and Worldview (GUERINI FILHO; KUPLICH; QUADROS, 2020).

Non-orbital data sources represent approximately 8% of the remote sensor used in our reviewed articles. Most of these studies were published recently, in the last five years. The data was obtained from UAVspresenting high spatial and temporal resolution images as one of their main advantages. In addition to acquiringnear real-time data, new remote sensing information sources are arising, such as multispectral and hyperspectral sensors (HAKALA et al., 2018; RAMPANT; ZDUNIC; BURROWS, 2019, CRUSIOL et al., 2020).

3.3 Spectral Index Analysis

Analyzing the grassland's spectral reflectances in different phytosociological compositions and climatic variations may help to classify and discriminate them (YANG *et al.*, 1998). Using image analysis techniques, detailed vegetation characteristics can be identified, such as the annual cycle and phenological variations, demonstrating the remote sensing potential.

The interaction process between visible spectrum electromagnetic radiation and a leaf depends on chemical factors such as photosynthesizing pigments and water and structural elements such as leaf tissue organization, which can be analyzed using radiation absorption, transmission, and reflection (FLORENZANO,2011).

Based on the vegetation spectral signature, mathematical models represented by several indices can beobtained. These are developed to evaluate the vegetation cover and associate the spectral signature to quantitative and qualitative parameters in the field (GUERINI FILHO; KUPLICH; QUADROS, 2020).

The indices function as vegetation growth and vigor indicators. They can be used to diagnose variousbiophysical parameters with which they highly correlate, including leaf area, biomass, soil-covered percentage,photosynthetic activity, and vegetation productivity. In this systematic review, the most-used spectral indicesin the reviewed articles were organized and are presented in (Table 4).

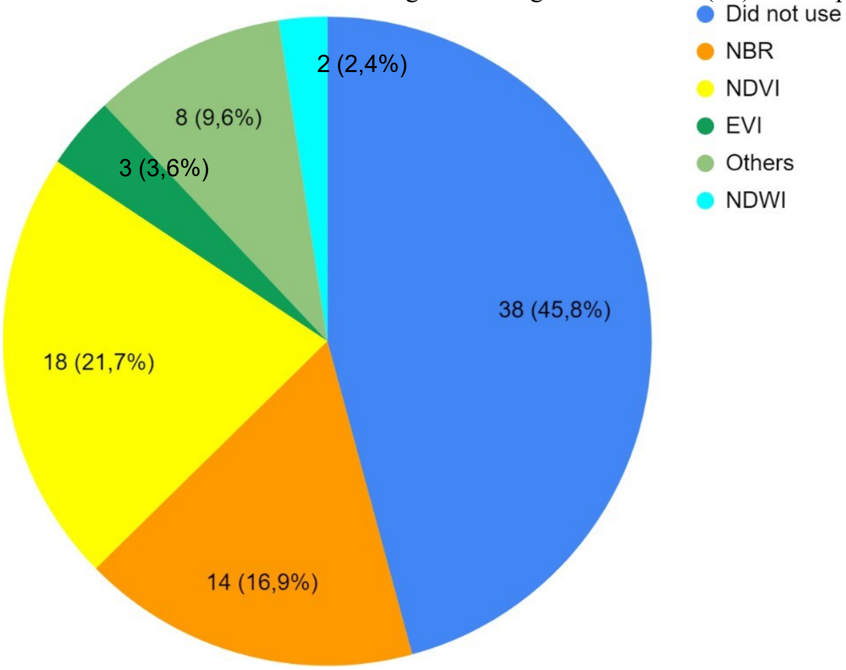
Table 4 – Principal spectral indices used in the remote sensing studies for analyzing fire use in field vegetation.

Index	Equation	Author
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - Red}{NIR + Red}$	ROUSE et al., 1973
Enhanced Vegetation Index (EVI)	$EVI = G * \frac{(NIR - Red)}{(NIR + C1 * Red - C2 * Blue + 1)}$	HUETE et al., 1997
Soil-Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(NIR - Red)}{(NIR + Red + L) * (1 + L)}$	HUETE, 1988
Normalized Difference Water Index (NDWI)	$NDWI = \frac{\rho(0.86\mu m) - \rho(1.24\mu m)}{\rho(0.86\mu m) + \rho(1.24\mu m)}$	GAO, 1996
Normalized Burn Ratio (NBR)	$NBR = \frac{NIR-SWIR}{NIR+SWIR}$ $dNBR = NBR_{pre-fire} - NBR_{pos-fire}$	KEY; BENSON, 2006

Source: The authors (2021).

This study discovered that more than half of the articles used vegetation indices (VI) to investigate thefire and its interactions with vegetation (Figure 5). A general VIs characteristic is the data reduction volume to be analyzed by estimates of structural and physiological biophysical data extractable from vegetation.

Figure 5 – Vegetation indices (VI) use frequency.



Source: The authors (2021).

Among the best-known indices, applied via the equation proposed by Rouse et al. (1973), NDVI is obtained by normalizing the reflectances in the NIR and red (R) bands to values that lie between -1 and +1. However, for vegetation, these values varied from 0 to +1. NDVI was the most prominent VI and was used inapproximately 22% of the articles reviewed and applied in study areas on all continents. For example, YANGet al. (1998) showed that time-series NDVI data could measure grassland performance under seasonal climaticinfluences.

Some remote sensing grassland challenges are soil, atmosphere effects, and variations in vegetation density. Spectral indices that take these interference sources into account, such as SAVI and EVI, are a solutionfor mitigating the NDVI limitations (ALVARADO, S.T. *et al.*, 2017).

Hence, a VI such as SAVI involves only the constant "L" addition to the NDVI denominator equation,where L takes values accordingly to the vegetation density: very low (L = 1), intermediate (L = 0.5), or veryhigh (L = 0.25) (HUETE, 1998). For EVI, in addition to the SAVI soil increment, there are the constants C1and C2, which are functions that use the blue band to correct the aerosol influences on the red band, with themost used values being G = 2.5, C1 = 6.0, and C2 = 7.5 (HUETE et al., 1997). EVI represented around 4% ofVI in the articles reviewed. The index has one "ready to use" version available as a time series fromMOD13Q1, produced from MODIS data. The MODIS EVI index synthesizes vegetation data every 16 daysand first became available in February 2000, with a 250 m spatial resolution (ALVARADO, S.T. *et al.*, 2017).Thus, spectral indices have been applied in several grasslands fire science and management aspects, including fuel estimation, fire risk mapping, burn severity assessment, fire detection, and fire propagation rateestimation (DÍAZ-DELGADO; LLORET; PONS, 2003; WANG, J. *et al.*, 2019; WULDER *et al.*, 2020).

Recently, among the most-used indices is NBR, a ratio of NIR and SWIR regions. It was developed to identifypost-fire burn areas and quantitatively measure their severity (KEY; BENSON, 2006).

NBR is primarily sensitive to chlorophyll and the water content of soil and vegetation. These characteristics associated with land use, fire history, topography, climate, and field data need to be evaluated together to establish effective strategies for managing protected areas and prescribed burns in the case of fire management (FRANKE et al., 2018). NBR represents around 17% of the VIs used. However, it is usually usedwith other indices in many studies and is notoriously applied to model the vegetation response capacity after fire perturbation events (ADAGBASA; ADELABU; OKELLO, 2020a).

Also, using SWIR frequencies, NDWI corresponds to approximately 2% of the VIs in the articles reviewed. Since NDWI uses vegetation water spectral ranges, it can minimize the confusion between burned, wetland, and agricultural bare soil areas and also estimate dry biomass (XU *et al.*, 2014). These effects implya highly variable vegetation response that depends on different post-fire vegetation regeneration strategies, such as massive seed production and regrowth (ADAGBASA; ADELABU; OKELLO, 2020).

Other VIs were used in around 9% of the articles reviewed. They were presented together with NDVIor NBR, or other meteorological and soil indices. Moreover, it is worth stressing that geomorphometric data combined with vegetation response can provide information about burn area severity (EVANGELIDES; NOBAJAS, 2020). In addition, the interactions between fire severity and plant regeneration and topographic,climatic, and vegetation factors are not still well understood.

3.4 Regional and global contribution

Among the review papers' author's peer groups and home countries (Figure 6), around ten countries are noteworthy (Table 5). The largest contributors are the United States, with about 25% of the articles and 34% citations, followed by Brazil with 16% and 7%, respectively. Although Brazil has nearly two-thirds the number of articles that the United States has, its strength is close to half the United States, probably due to theconnections between the American authors. On the other hand, even though Spain has fewer publications thanBrazil, it has an almost equivalent strength, which may be because it has over 300 more citations.

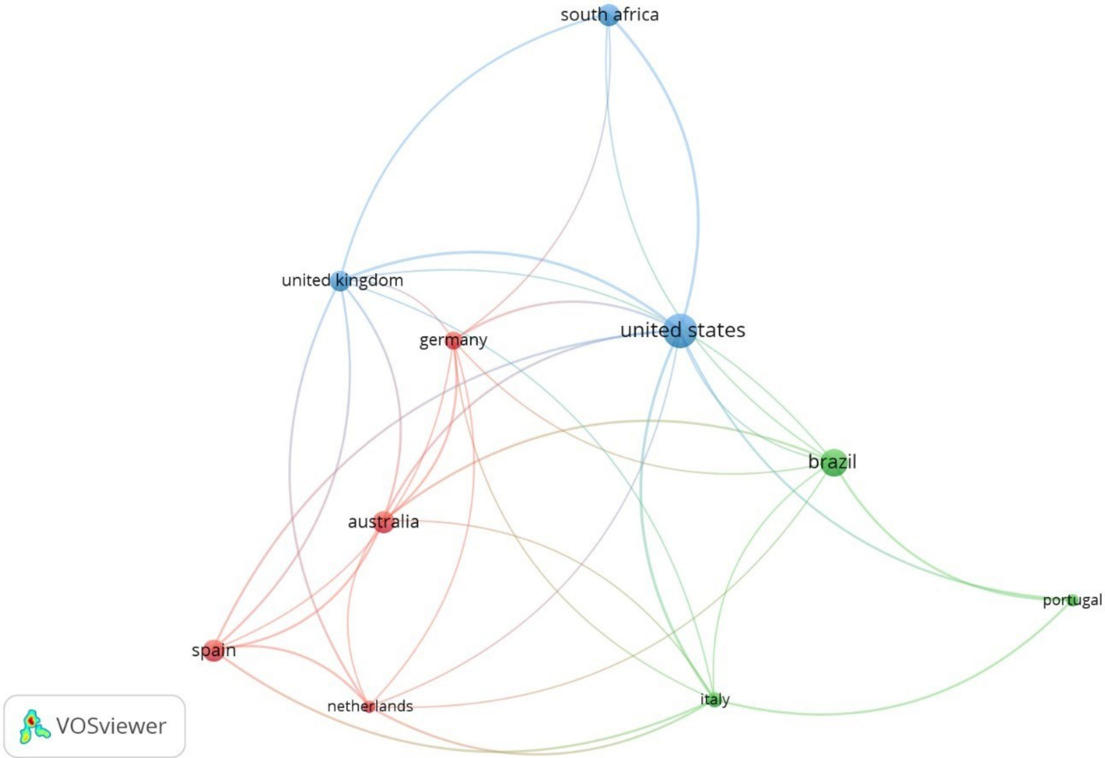
Table 5 – Originating countries of the reviewed articles author's institutions.

Country	Articles	Citations	Strength
United States	22	1567	19
Brazil	14	319	10
Spain	10	620	11
South Africa	9	500	7
Australia	9	358	12
United Kingdom	8	686	14
Germany	6	149	10
Italy	5	246	13
Netherlands	3	139	10
Portugal	3	64	6

Source: The authors (2021).

However, if the European publications are added, they constitute around 35% of the articles and 40%of citations, while publications from the Americas represent 40% and 41%, respectively. Finally, Africa and Oceania are represented by only one country each. South Africa has 10% of the articles and 11% of the citations, and Australia, has 10% and 8%, respectively. In this case, while the two countries have the same number of articles, they present different citations, with Australia's count being almost double that of South Africa's and grouped in other clusters (Figure 6).

Figure 6 – Cluster network analysis of the principal connections between the countries of the articles reviewed.



Source: The authors (2021).

The connection network between authors has ten nodes, three clusters, and 34 links. Each link has a strength, represented by a positive number, where the higher the value, the stronger the connection. The strength may, for example, indicate the references citation's number the two publications have in common, inthe case of shared bibliographic links, the publications number of which the researchers are coauthors, or the publications number in which two terms occur together (ECK; WALTMAN, 2020).

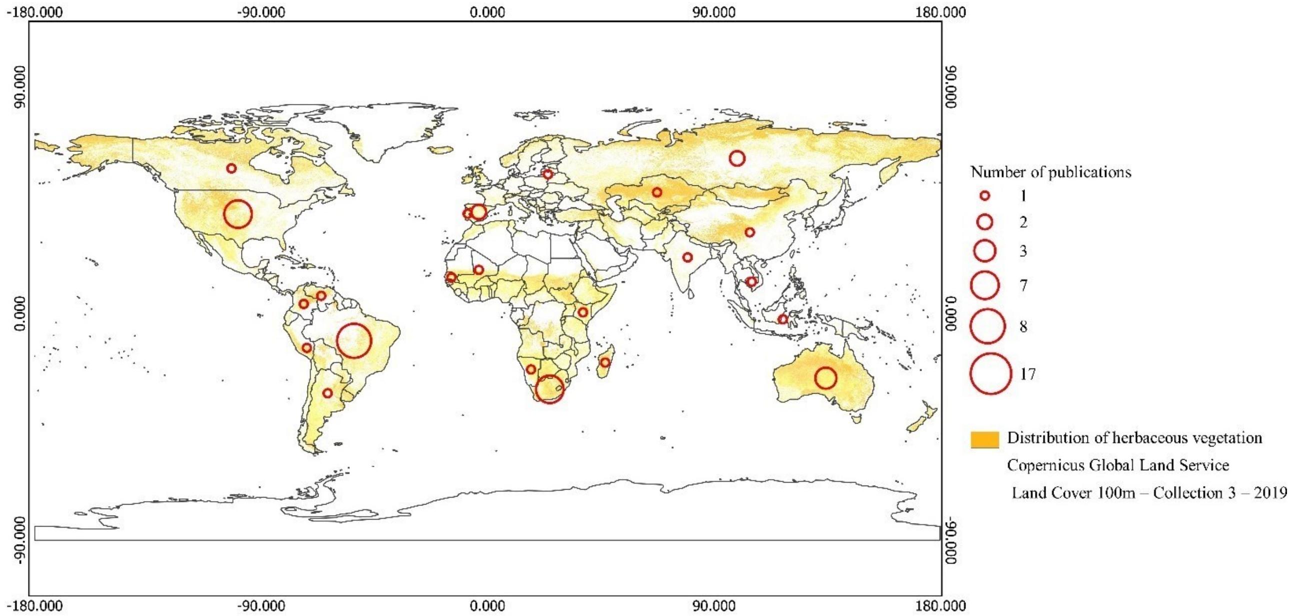
Upon analyzing the publications' originating countries, the study areas often do not correspond to the same countries. Therefore, to spatialize the grassland vegetation and fire distributions worldwide, we used theCopernicus Global Land Service: Land Cover 100m: collection 3 - 2019 (BUCHHORN *et al.*, 2020) and hotspots obtained by MODIS, collection 6.1, also for 2019 (NADA, 2022). The herbaceous vegetation class distribution combined with the reviewed article's study areas is shown in Figure 7 and Table 6.

Table 6 – Locations of study areas and article number by country.

Study area	# of articles
Brazil	17
South Africa	8
United States	8
Australia	7
Spain	3
Russia	3
Argentina	2
Cambodia	2
Canada	2
Colombia	2
India	2
China	1
Indonesia	1
Kazakhstan	1
Lithuania	1
Mali	1
Namibia	1
Peru	1
Kenya	1
Senegal	1
Sub-Saharan Africa	1
Venezuela	1
Madagascar	1
Portugal	1

Source: The authors (2021).

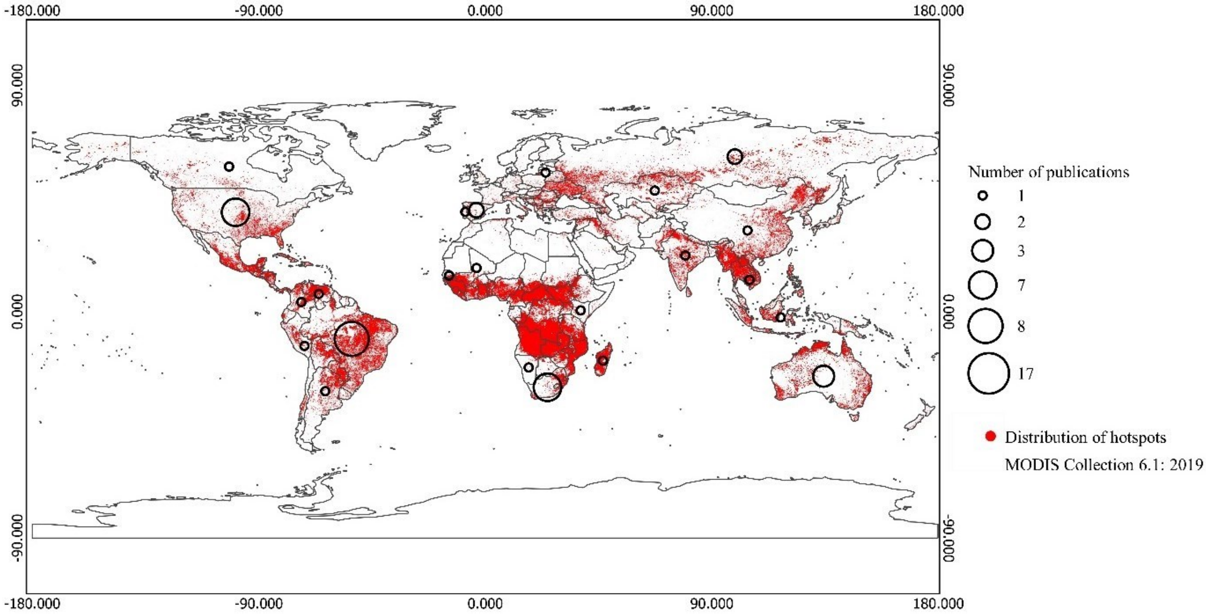
Figure 7 – Geographic distribution of grassland formations worldwide and concentration of reviewed articles by country.



Source: The authors (2021).

Ecosystems such as savanna/Cerrado and steppe/prairies/plains are the most common grassland vegetation type in most reviewed studies' countries. In regions such as the Brazilian Cerrado, fire probabilityestimation studies are recurrent as they help prevent big fires (ALVARADO et al., 2017; FRANKE et al., 2018; PEREIRA et al., 2014; SANTOS et al., 2020). This highlights that regions with intermediate primary productivity levels, such as tropical savannas, burn more often (Figure 8) due primarily to the fuel abundance,consequently raising interest in the issue (BOWMAN *et al.*, 2020).

Figure 8 – Hotspots geographic distribution in 2019 and concentration of reviewed articles by country.



Source: The authors (2021).

There are grassland vegetation remnants in the Amazon region where savanna phytophysiognomies predominate (DIPAOLO, 2020). As a decentralized remnant of the Cerrado biome, monitoring fire activity is essential to understanding the ecological processes, human impacts, and aspects connected to seasonality andpatterns in the fire incidence (ALVES; PÉREZ-CABELLO, 2017).

In southern Brazil, a different situation is found, with mosaic formations of Araucaria (Brazilian pine)forests and Campos (grasslands), where it is hypothesized that grassland maintenance is anthropogenic in origin, since the landscape dynamics show the initial Araucaria expansion into Campos fields after grazing and fire no longer being used (OLIVEIRA; PILLAR, 2004).

3.5 Journals Analysis

The publications journal's co-citation analysis sought to discover which research contexts the remote sensing subject applied to understanding fire use in grassland vegetation was addressed. In this study, scientificarticles published in 32 scientific journals were founded and classified. The journals were ranked in descendingorder by the number of articles published (Table 7).

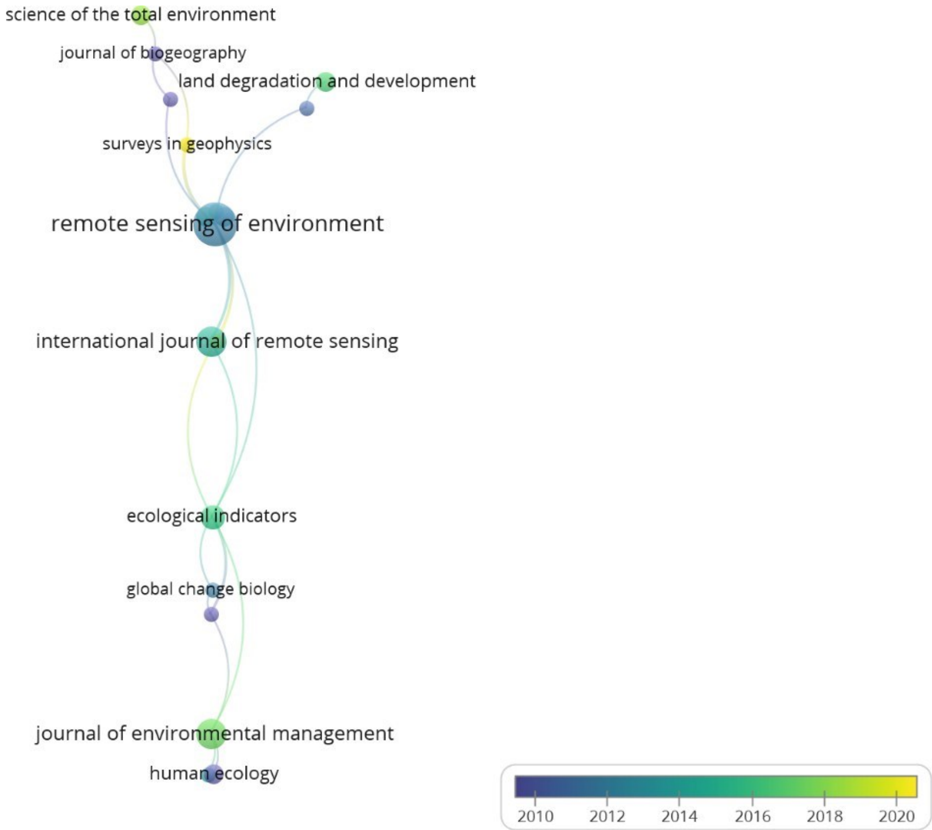
Table 7 – Journal's contribution.

Journal	Articles	Citations	Strength
Remote Sensing of Environment	13	1124	13
Journal of Environment Management	5	65	4
International Journal of Remote Sensing	5	206	3
ISPRS – Journal of Photogrammetry and Remote Sensing	4	40	0
Ecological Indicators	3	70	7
Fire Ecology	2	17	1
Forest Ecology and Management	2	13	1
Human Ecology	2	193	1
Land Degradation & Development	2	55	1
Science of the Total Environment	2	17	1
Ecological Applications	2	112	0
Ecology	2	325	0
Global Ecology and Biogeography	1	82	4
Surveys in Geophysics	1	2	4
Ecosystems	1	8	3
Journal of Biogeography	1	109	3
Agricultural and Forest Meteorology	1	51	2
Environmental Management	1	14	2
Global Change Biology	1	38	2
New Phytologist	1	34	1
PLOS One	1	34	1
Applied Geography	1	29	0
Austral Ecology	1	10	0
Community Ecology	1	98	0
Earth Interactions	1	25	0
Global Biogeochemical Cycles	1	32	0
Holocene	1	19	0
Perspectives in Plant Ecology, Evolution and Systematics	1	27	0
Photogrammetric Engineering & Remote Sensing	1	13	0
Remote Sensing Applications: Society and Environment	1	3	0
Sensors (Switzerland)	1	23	0
Nature Reviews Earth & Environment	1	24	0
Sustainability (Switzerland)	1	0	0
Revista Eletrônica Científica da UERGS	1	0	0
Revista Brasileira de Meio Ambiente	1	0	0

Source: The authors (2021).

The collaborative relationship between journals demonstrated that only 18 had connection (Figure 9).Furthermore, the remote sensing area periodicals have a higher publications frequency about fire use between2010 and 2020. However, others focused on ecology have a higher concentration in more recent years afterward 2020.

Figure 9 – Network cluster analysis of the connections between the journals and their distribution over time.

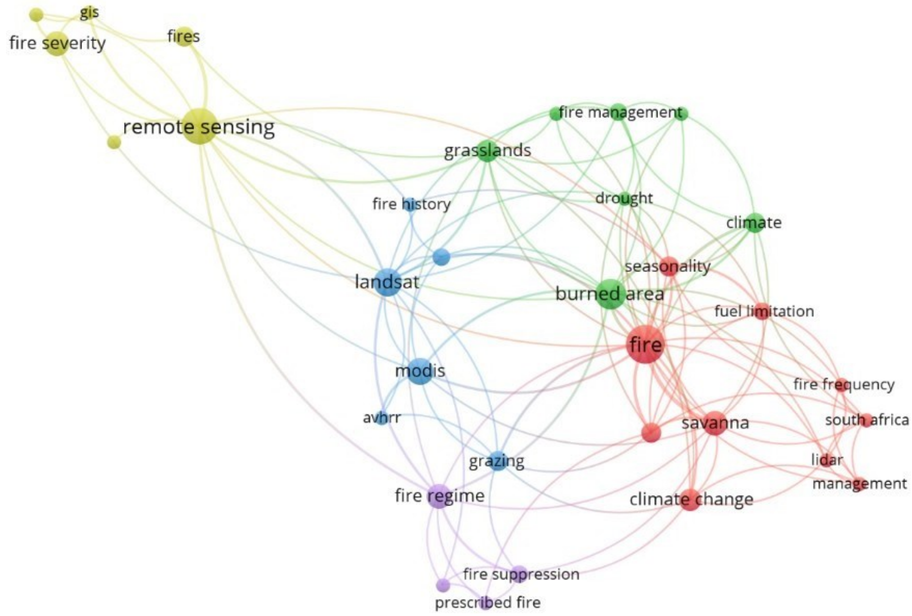


Source: The authors (2021).

3.6 Principal topics and trends

This step created a review of articles' keywords cluster maps to understand their frequency and co- occurrence (Figure 10) and temporal trend (Figure 11). Note that keywords appearing only once were not usedso that the grouping would be more realistic and without noise.

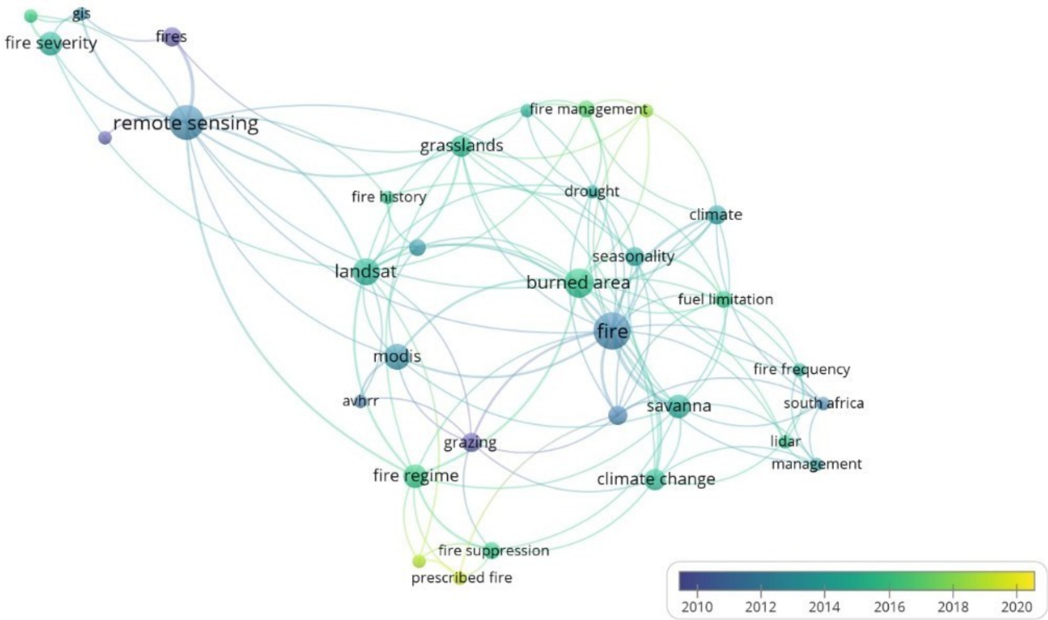
Figure 10 - Keywords' network cluster analysis.



Source: The authors (2021).

The keywords' distribution reveals a certain consolidation of some research topics, specifically thoserelated to the use of time series such as from Landsat and MODIS, as well as the emergence of other topics related to the application of spectral indices for fire severity analysis and vegetation recovery.

Figure 11 - Network cluster analysis of keyword trends over time.



Source: The authors (2021).

When analyzing the keyword clusters and their distribution over time (Figure 11), it was seen that wildfire burns and pasture grazing appeared in higher concentration starting in 2010. This trend may be relatedto the growing use of time series to estimate burned areas for pasture. Another reason might be the need to evaluate how socioeconomic shifts contribute to changes in land use and cover, as well as assessing whether there are specific disturbance agents. In arid areas, the decline of grazing could result in the transition of the ecosystem to different state. However, vegetation changes due to reduced grazing probably led to a switch ofpractices with fire being the new primary disturbance agent (DUBININ *et al.*, 2010).

Therefore, fire propagation requires information about its occurrence, danger, and influence. Fire conditions vary significantly in time and space, for example, fuel requires time to accumulate, and the topography and microclimate influence the fuel conditions. Remote sensing measurements meet these requirements and are particularly useful for investigating the history of burns (ELMORE; ASNER; HUGHES,2005).

Between 2012 and 2016, an increase in publications addressing climate change and drought can be seen. It is known that prolonged seasonal drought linked to the water regime is strongly connected to the fire regime (NELSON *et al.*, 2012). Therefore, climate change may influence these conditions, compromising theaboveground biomass, with adverse effects on the pasture's health, presenting significant challenges not onlyto biodiversity conservation, but also to farmers and the subsistence of communities in general (SHOKO; MUTANGA; DUBE, 2016).

Finally, it is worth highlighting that in more recent years, between 2018 and 2020, the subjects "prescribed burning," "post-fire recovery," and "integrated fire management" point to the current trend in remote sensing studies of fire use in grasslands. Usually, it is correlated with integrated management and conservation to reduce fire's intensity and severity. These trends can make fire events more controllable and reduce their negative impacts. Fire continues to be used around the world by society for various reasons, including agriculture, stimulating plant flowering/fruiting and regrowth, fuel load reduction, species prevention and selection, and pest eradication, among other uses. Remote sensing of burn areas has changed our view of burn patterns and the understanding of the causes and impacts of fires on regional, continental, and global scales (CHUVIECO et al., 2019). Earth observation can meaningfully support prescribed grassland burns, abetting the identificationof crucial factors in these decisions.

4 CONCLUSION

The systematic review using the PRISMA method done in this study initially identified 7,881 articlesin the scientific literature, which the subsequent eligibility step reduced to 67. These were used in the meta- analysis, where their information was cataloged by means of tables and cluster analysis maps.

The primary objective of this systematic review was to assess the state of the art in fire behavior and use in grasslands via remote sensing. The results show the number of publications on the subject has been growing over the years and presents a growing trend, verifying the scientific community's interest. The UnitedStates and Brazil have the most authors working on this subject. Brazil contributed approximately 16% of thearticles and 7% of the citation as well as studies done in various biomes, confirming the subject's importancein the country.

Of total number of publications analyzed, most of them, over 71%, used Landsat series or MODIS sensors. Currently, with the launch of satellites such as Sentinel, there has been an improvement in spatial, spectral, and temporal resolutions of orbital images used to estimate natural pasture biomass and to discriminate between grass species. Moreover, only 8% of publications used non-orbital data, with more thanhalf of them published in the last five years, revealing the growth in obtaining images from UAV-mounted sensors.

It was found that spectral indices are an essential tool in the fire use analysis because they furnish details about their influence on landscape change and vegetation dynamics. Many of these indices, such as NDVI, NDWI, and EVI, have been used for a long time, while NBR has come to be more used in recent yearswhen it started to be applied by connecting the burn severity concepts present in ecology to remote sensing.

Cluster analyses using keywords indicate a recent trend in spectral indices to analyze fire severity andvegetation recovery, considering biodiversity conservation and anthropic use integration, since fire studies seek to reduce its intensity and severity to make it more controllable and reduce its negative impacts.

Climate change has been influencing aboveground biomass in grasslands and, consequently, having environmental and social impacts. At the same time, some issues such as prescribed burns, post-fire vegetationrecovery, and integrated fire management are studied more often through remote sensing.

Finally, it is important to stress that this study has some limitations, including the method of choosingarticles and the source of the database used. For example, the systematic review could have been developed using other quantitative or qualitative methods or even other scientific article databases, such as Web of Science or Google Scholar, which could present different results, particularly citations. However, by adding some articles not found in Scopus, we tried to ameliorate this problem and demonstrate the state of the art in the fire behavior and use in grasslands using remote sensing techniques.

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Authors' Contribution

The first author (Pâmela Boelter Herrmann) was responsible for Conceptualization, Data Curation, Formal Analysis, Research, Methodology, Visualization, Writing - initial draft, and Writing - review and editing. The second author (Victor Fernandez Nascimento) was responsible for Methodology, Supervision, Validation, Writing, Review, and Editing. The third author (Marcos Wellausen Dias de Freitas) was responsible for Supervision and Writing, Proofreading, and Editing.

Conflict of interest

The authors declare no conflict of interest.

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Biography

Pâmela Boelter Herrmann was born in 1994 in the city of Canela/RS. She has a bachelor's degree in environmental management from the State University of Rio Grande do Sul (UERGS), and a Specialization in Georeferenced Spatial Information from the Vale do Rio dos Sinos University (UNISINOS). She is currently a master's student in the Graduate Program in Remote Sensing at the RioGrande do Sul Federal University (UFRGS). She works mainly in environmental analysis of fire behavior in grassland vegetation and the UAVs use.

2.3.2 Capítulo 2 - Avaliação da degradação de Campos de Altitude no Parque Estadual do Tainhas/RS e sua zona de amortecimento.

1. INTRODUÇÃO

A degradação dos ecossistemas é um dos problemas ambientais globais mais prementes e desafiadores (IPCC, 2019). As formações campestres degradadas mostraram principalmente redução acentuada no rendimento e na diversidade de espécies forrageiras de alta qualidade, aumento de espécies tóxicas e nocivas e intensificação da erosão do solo, o que restringe seriamente as funções e seus serviços ecossistêmicos (SHENG et al., 2022). A implementação de práticas agrícolas sustentáveis, como a possibilidade de melhorar o manejo de campos de altitude para produção agrícola e pecuária, podem aumentar a produtividade ao mesmo tempo em que melhoram a adaptabilidade e a conservação destes ecossistemas (CASTELLANOS et al., 2022).

Por muito tempo, a degradação destas formações campestres foi associada a fatores antropogênicos, incluindo práticas de manejo com fogo e pastejo excessivo (ZHOU et al., 2017). No sul do Brasil, encontramos formações campestres nativas denominadas "Campos de Altitude", utilizadas historicamente para pastejo principalmente de bovinos e ovinos e manejados com fogo no período do inverno para retirada de biomassa seca, com o intuito de acelerar o rebrote da vegetação (IBGE, 2004; BOLDRINI, 1997).

Por muito tempo, o uso do fogo foi uma prática considerada prejudicial ao ambiente, e em uma tentativa de conter a degradação, a queima da vegetação foi considerada proibida pela Lei Estadual do RS n° 9.519/1992, que institui o Código Florestal do Estado do Rio Grande do Sul. Desde a sua proibição, a pecuária tradicional tem sido substituída por outras práticas consideradas mais viáveis economicamente, como a agricultura e a silvicultura, que, contudo, são consideradas mais degradantes ao meio ambiente (BUFFON; PRINTES; ANDRADES-FILHO, 2018; CRAVINO; BRAZEIRO, 2021).

Atualmente, o uso do fogo para manejo dos campos de altitude no estado do RS é regulamentado pela Lei Estadual 13.931, de 30 de janeiro de 2012, a qual deixa claro que o fogo pode ser utilizado em caráter fitossanitário e para controle de pragas e doenças em áreas não mecanizáveis, desde que com autorização ambiental do órgão municipal, sendo este o responsável por difundir normas e critérios para este manejo.

Os métodos convencionais para monitorar a produção e o manejo de pastagens incluem medições ou estatísticas de campo, que incluem colheita de biomassa, medições com espectrômetros de campo, entre outros. Além desses métodos, a vegetação verde pode ser monitorada continuamente usando suas propriedades de refletância espectral adquiridas por sensores ópticos remotos (ATZBERGER, 2013; REINERMANN; ASAM; KUENZER, 2020)

Assim, o desenvolvimento e aplicação da tecnologia de sensoriamento remoto pode contribuir no monitoramento de tais mudanças no uso do solo e na degradação das formações campestres em larga escala. Muitos estudos utilizaram a resposta espectral para definir o grau de degradação por meio de índices de vegetação (GAO et al., 2010; LIU et al., 2019; SUN et al., 2017).

O uso do sensoriamento remoto como ferramenta de monitoramento e avaliação da degradação ocasionada pelo fogo é abordada principalmente em sistemas florestais, os quais enfatizam o desmatamento, as mudanças de cobertura da terra e as emissões de gases de efeito estufa (DUTRA et al., 2023; JESUS et al., 2022; SANNIGRAHI et al., 2020).

Entretanto, estudos voltados à degradação de formações não florestais, avaliam o manejo com fogo como uma estratégia que necessita a reintrodução das práticas tradicionais de uso do fogo, para remoção de acúmulo de material combustível e estímulo da rebrota (DURIGAN, 2020; FRANKE et al., 2018; LADWIG; CAMPOS, 2021). Estas praticas podem ser consideradas como necessárias para a manutenção das características ecológicas e a biodiversidade típica destes sistemas (OVERBECK et al., 2005).

Neste contexto, este estudo visa determinar a partir de imagens orbitais e índices de vegetação, o grau de degradação de uma área em campos de altitude e a sua sensibilidade ao uso do fogo.

2. MATERIAIS E MÉTODOS

2.1 ÁREA DE ESTUDO

O Parque Estadual do Tainhas (PET) foi criado com o objetivo de proteger a vegetação no vale do rio Tainhas (Figura 01). O PET possui florestas com araucárias, campos de altitude e áreas alagadas (banhados) com uma variação que se desdobra desde terrenos relativamente planos na parte sul até vales mais profundos na parte norte (SEMA, 2008).

Segundo BOND-BUCKUP (2008), há comunidades na zona de amortecimento (ZA) ao redor do PET que dependem de agricultura, silvicultura e pecuária e frequentemente usam o fogo para gerenciar o Campo. O PET tem poucas áreas adquiridas com regularização fundiária, e muitas dessas são campos que precisam ser avaliados quanto ao nível de conservação e ter uma gestão definida visando a conservação.

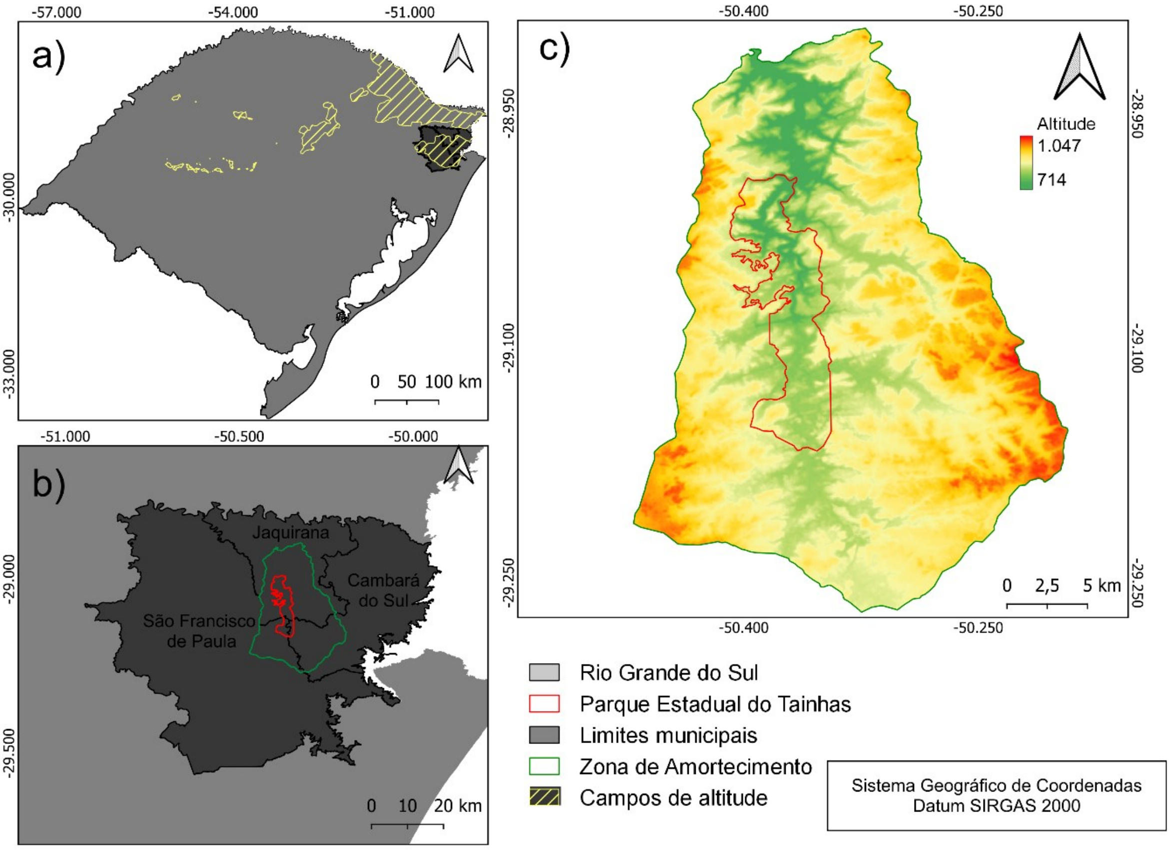


Figura 01: a) Localização das formações campestres no Rio grande do Sul. b) Localização do PET e ZA em relação aos municípios e, c) abrangência das formações campestres no perímetro do PET e ZA.

2.2 PARCELAS AMOSTRAIS

Para subsidiar as análises realizadas, foram implantadas 12 parcelas (Figura 02) de 100m x 100m (1ha) dentro da sede do PET com distribuição aleatória em áreas que correspondessem a vegetação campestre, sem afloramentos rochosos ou áreas alagadas. Ainda, as parcelas foram selecionadas conforme a disposição de pixels de imagens sentinel 2, para que correspondessem a pelo menos 16 pixels de uma imagem Sentinel 2 (Figura 02C).

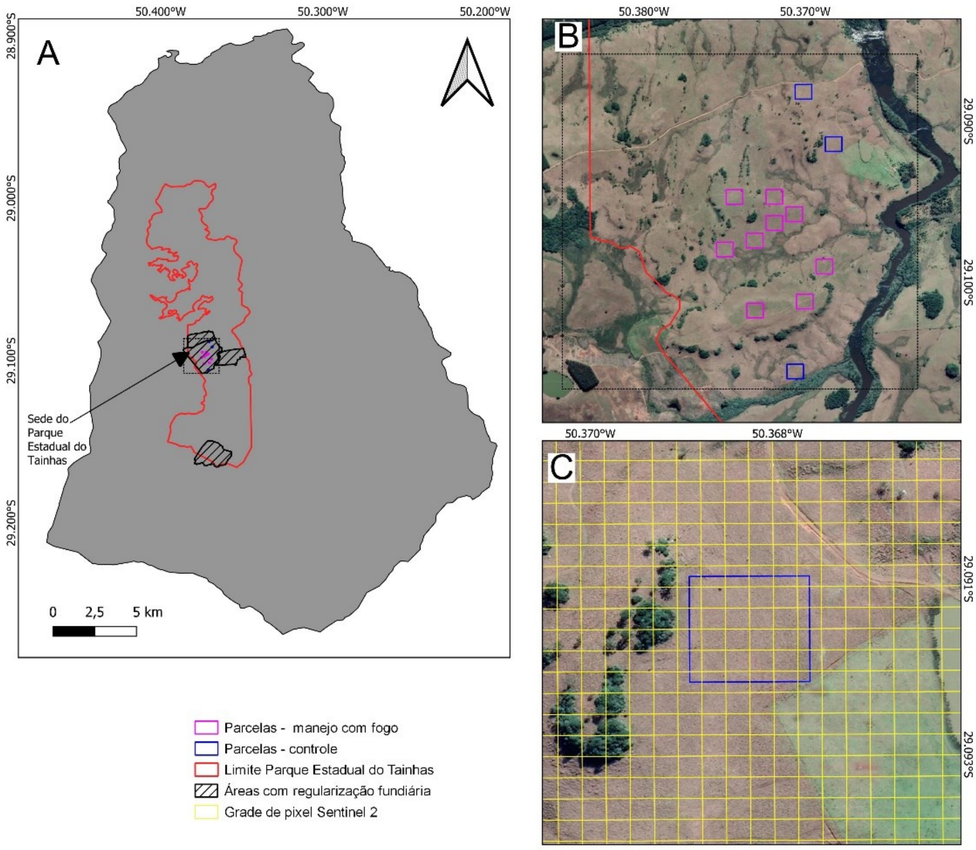


Figura 02: A) Localização das parcelas na área com reguralização fundiária do PET; B) Distribuição das parcelas na área da sede do PET; C) Localização da parcela em relação a grade de pixels Sentinel 2.

As parcelas foram submetidas a um evento de fogo, realizado em agosto de 2020, onde 3 parcelas não sofreram queimada, denominadas de parcelas controle. A metodologia de campo pode ser observada na figura 03.

Figura 03: Metodologia de campo.

2.3 ÍNDICE DE DEGRADAÇÃO DE CAMPO

Para a análise da degradação de campo, foram utilizadas imagens *Sentinel-2 MSI Multispectral Instrument - Level-2A* (Tabela 01). O produto *Level-2A* fornece imagens de refletância de fundo da atmosfera (BOA) derivadas dos produtos do nível 1C. Selecionadas nos anos de 2020 (anterior ao evento de fogo), 2021 (imediatamente após o evento de fogo) e 2022 (um ano após o evento de fogo), período de 01 de fevereiro a 01 de abril de cada ano, período que a vegetação não passa por perturbações com fogo e já passou pelo rebrote do último inverno.

Tabela 01 – Cenas selecionadas.

Ano	Cenas
2020	COPERNICUS/S2_SR_HARMONIZED/20200204T132229_20200204T132226_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20200224T132229_20200224T132410_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20200229T132231_20200229T132228_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20200229T132231_20200229T132228_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20200305T132229_20200305T132856_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20200310T132231_20200310T132229_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20200310T132231_20200310T132229_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20200315T132229_20200315T132231_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20200315T132229_20200315T132231_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20200320T132231_20200320T132229_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20200325T132229_20200325T132335_T22JEN
2021	COPERNICUS/S2_SR_HARMONIZED/20210208T132229_20210208T132522_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20210208T132229_20210208T132522_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20210320T132229_20210320T132511_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20210320T132229_20210320T132511_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20210325T132231_20210325T132528_T22JEP
2022	COPERNICUS/S2_SR_HARMONIZED/20220203T132229_20220203T132227_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20220203T132229_20220203T132227_T22JEP
	COPERNICUS/S2_SR_HARMONIZED/20220305T132229_20220305T132523_T22JEN
	COPERNICUS/S2_SR_HARMONIZED/20220305T132229_20220305T132523_T22JEP

As imagens foram manipuladas no *Google Earth Engine* (GEE), onde se realizou inicialmente o cálculo de *Normalized difference vegetation index* (NDVI), proposto por ROUSE et al., (1973) e representado pela (Equação 01).

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad (1)$$

O NDVI é obtido através da normalização das reflectâncias nas bandas do infravermelho próximo (NIR) e vermelho (R), com valores que variam de -1 a +1, entretanto o que diz respeito a vegetação, está entre os valores que variam de 0 a +1.

Purevdorj et al. (1998) indicou que existe uma relação linear significativa entre a cobertura vegetal e indices de vegetação. Para avalizar o grau de degradação das formações campestres, utilizamos o resultado do NDVI de cada ano, e o cálculo de Cobertura Vegetal de Campo (CVC), com a metodologia proposta por GAO et al., (2006), definida pela (Equação 02).

$$CVC = \frac{NDVI - NDVIs}{NDVIv - NDVIs}\ x\ 100 \qquad (2)$$

Onde NDVI = Índice Vegetal por Diferença Normalizada, NDVIs = é o menor valor de NDVI encontrado entre os pixels representativos de área com solo exposto e NDVIv = é o maior valor de NDVI encontrado entre os pixels de área de campo.

Os níveis de degradação de campo foram classificados conforme os valores descritos na (Tabela 02), assim como as classes do índice de degradação de acordo com a (Tabela 03), também proposta por GAO et al., (2006).

Tabela 02: Classificação dos níveis de degradação do campo.

Classe	Cobertura Vegetal de Campo	Score
Não degradada (ND)	CVC >90%	1
Levemente degradada (LD)	90% ≥ CVC > 75%	2
Moderadamente degradada (MD)	75% ≥ CVC > 60%	3
Severamente degradada (SD)	60% ≥ CVC > 30%	4
Extremamente degradada (ED)	CVC ≤ 30%	5

Essas classes de CVC entraram no cálculo do Índice de Degradação de Campo (IDC), adaptado de Gao et al. (2006), calculado pela (Equação 03).

$$\mathrm{IDC} = \frac{\sum_{i=1}^{5} D_i \times A_i}{A} \qquad (3)$$

Em que, Di é o score da classe de degradação, Ai é a área de distribuição do nível de classificação i, e A é a área total de Campo da área de estudo.

Tabela 03: Classes do Índice de degradação de campo.

Índice de degradação de Campo (IDC)	Classe
IDC≤1	ND
1<IDC≤2	LD
2<IDC≤3	MD
3<IDC≤4	SD
4<IDC	ED

3. RESULTADOS

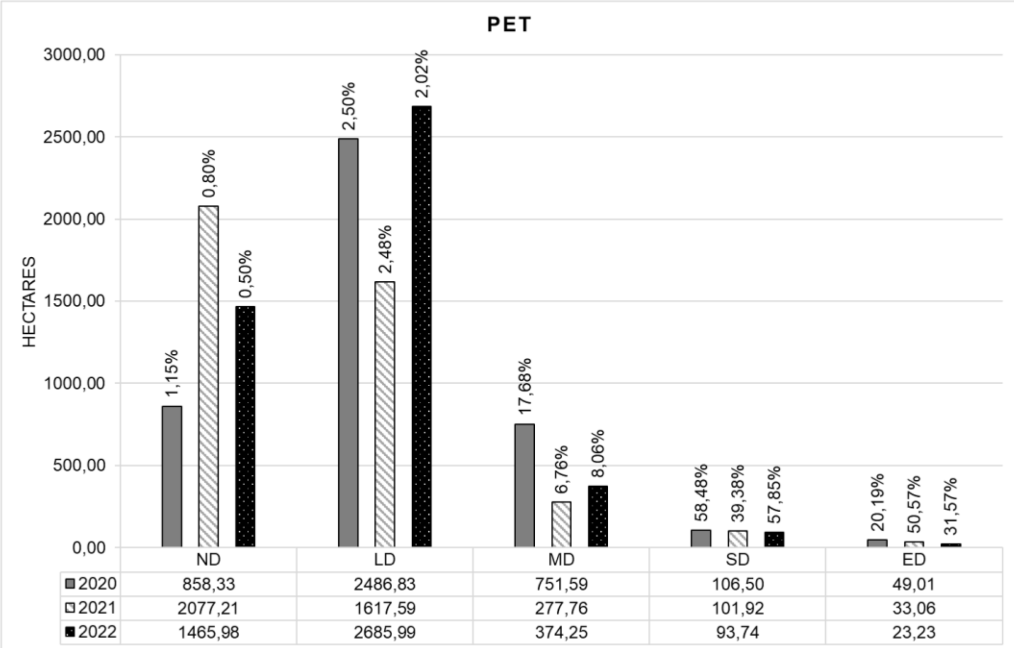
3.1. DEGRADAÇÃO DE CAMPO NO PET E ZA

Os resultados são divididos entre os valores de degradação dentro do PET e fora representado pela sua ZA (Figura 04). Por meio da análise as classes de degradação dentro do PET, podemos notar uma redução significativa na área de ED de 49,01 hectares em 2020 para 23,23 hectares em 2022, uma redução de cerca de 52%. A classe SD também apresentou uma redução de 12% na área, passando de 106,50 hectares em 2020 para 93,74 hectares em 2022.

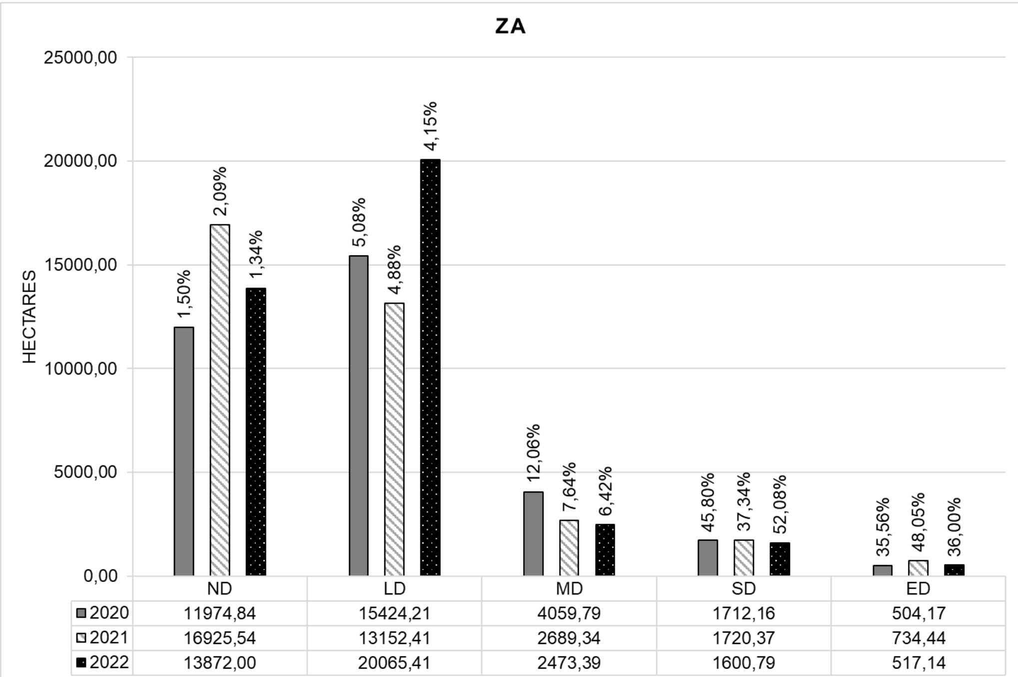
A classe MD teve uma redução significativa de 63% na área em 2021, comparado ao ano anterior, passando de 751,59 hectares para 277,76 hectares. Entretanto, em 2022, a área aumentou para 374,25 hectares, ainda abaixo da área original em 2020.

Já a classe LD apresentou uma redução de 35% em 2021, comparado a 2020, passando de 2486,8 hectares para 1617,6 hectares. Porém, em 2022, houve um aumento significativo na área de LD, chegando a aproximadamente 2686 hectares, superando a área original em 2020.

A classe ND teve um aumento significativo em 2021, passando de 858,3 hectares em 2020 para 2077,2 hectares. Entretanto, em 2022, houve uma redução de 29%, chegando a aproximadamente 1466 hectares.



	ND	LD	MD	SD	ED
2020	858,33	2486,83	751,59	106,50	49,01
2021	2077,21	1617,59	277,76	101,92	33,06
2022	1465,98	2685,99	374,25	93,74	23,23



	ND	LD	MD	SD	ED
2020	11974,84	15424,21	4059,79	1712,16	504,17
2021	16925,54	13152,41	2689,34	1720,37	734,44
2022	13872,00	20065,41	2473,39	1600,79	517,14

Figura 04: Níveis de degradação como Não degradada (ND),Levemente degradada (LD), Moderadamente degradada (MD), Severamente degradada (SD) e Extremamente degradada (ED) do campo por área a cada ano dentro do PET e da ZA.

Mesmo apresentando padrões de distribuição de classes semelhantes ao PET, a área correspondente a ZA, para a classe ED teve um aumento de 45,5% entre 2020 e 2021, mas em 2022 houve uma redução de 29,5% em relação a 2021, voltando a um patamar próximo ao de 2020, não apresentando recuperação no período analisado. No entanto, a classe SD teve uma leve redução de 0,5% entre 2020 e 2021, com uma redução mais expressiva em relação ao ano anterior, de 6,8% em 2022.

A classe MD apresentou uma redução significativa de 33,3% entre 2020 e 2021, e em 2022 houve uma redução adicional de 8,0%. A classe LD teve uma redução de 15,7% em 2021 em relação a 2020, mas em 2022 houve um aumento de 52,8% em relação ao ano anterior, chegando a um patamar superior ao de 2020. A classe ND apresentou um aumento expressivo de 41,1% entre 2020 e 2021, e embora tenha tido uma redução de 18,1% em 2022 em relação a 2021, sua área ainda foi superior a de 2020.

A espacialização anual por nível de degradação dos campos da área de estudo pode ser observada na (Figura 05). É possível identificar que as áreas classificadas como ED e SD correspondem a áreas com presença de solo exposto em preparo para plantio, estradas ou áreas com atividade de silvicultura, no estágio de derrubada (Figura 04d). Entre os anos de estudo, de 2020 a 2022 verifica-se que houve um aumento na classe ND no ano de 2021, seguido de um aumento na classe LD em 2022, demonstrando uma queda de um nível na classe de classificação.

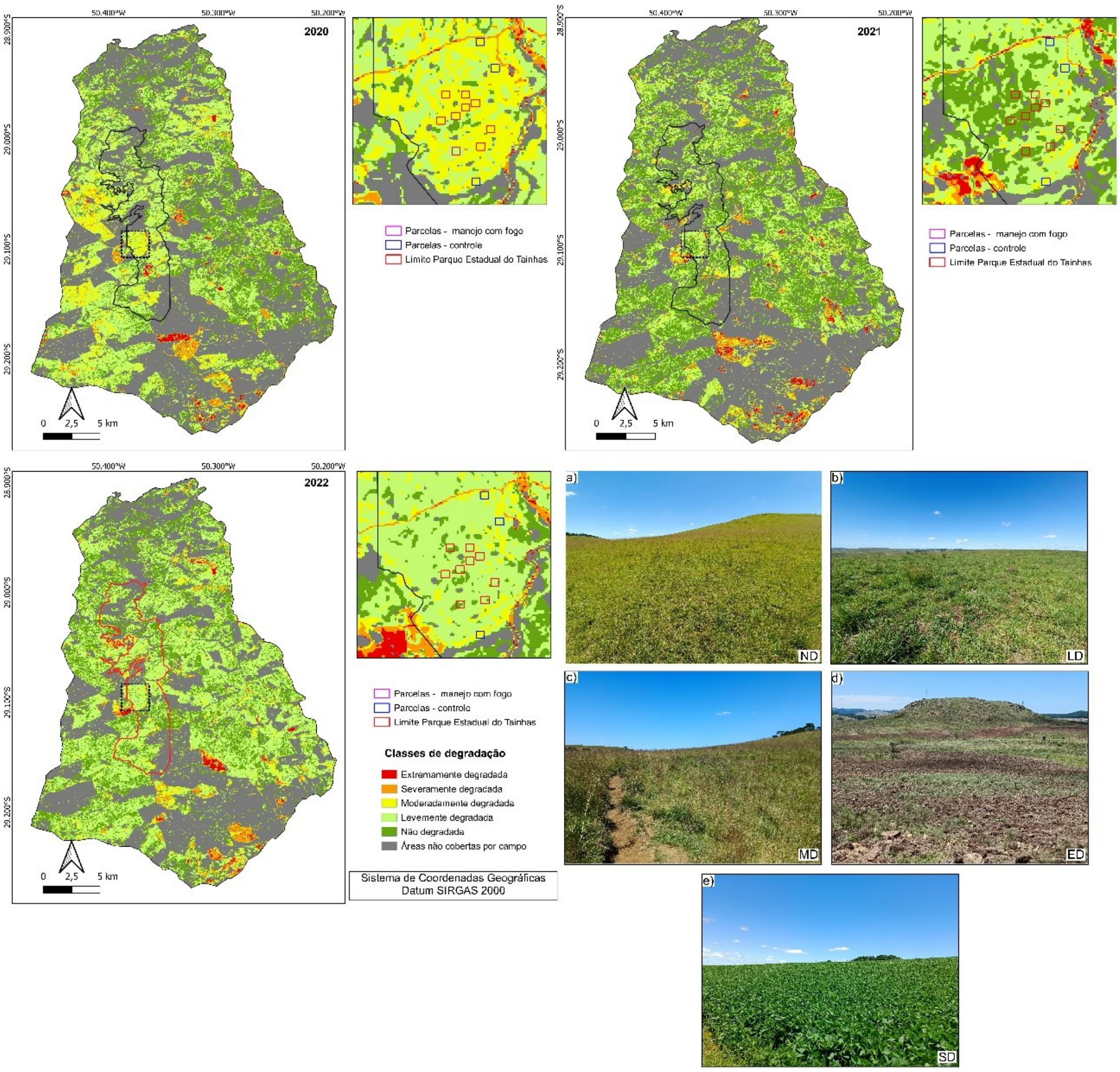


Figura 05: Degradação anual (2020 – 2022) dos campos de altitude. a) Área classificada como não degradada; b) Área classificada como levemente degradada; c) Área classificada como moderadamente degradada; d) Área classificada como extremamente degradada, e e) Área classificada como severamente degradada

Para o cálculo do IDC, também foram analisados de forma individual a área do PET e de sua ZA, tendo em vista que a unidade de conservação se encontra na modalidade de proteção integral, que de acordo com o Sistema Nacional de Unidades de Conservação (SNUC), visa manter a manutenção dos ecossistemas livres de alterações causadas por interferência humana, admitido apenas o uso indireto dos seus atributos naturais (BRASIL, 2000). Assim, prevê a exclusão do manejo com fogo. Em 2020, a classificação do PET se encontrava um nível abaixo da classificação de sua ZA. A partir de 2021, o IDC obteve a mesma classificação para ambos (Tabela 04).

Tabela 04: índice de degradação de campo para o PET e ZA.

	2020	IDC	2021	IDC	2022	IDC
Área total	1,928	LD	1,743	LD	1,827	LD
PET	2,060	MD	1,636	LD	1,820	LD
ZA	1,912	LD	1,756	LD	1,828	LD

Não degradada (ND),Levemente degradada (LD), Moderadamente degradada (MD), Severamente degradada (SD) e Extremamente degradada (ED)

3.2. ÁREA AMOSTRAL

Os resultados obtidos nas parcelas mostram que em 2020, antes do evento de fogo, a classe MD era predominante na área onde as parcelas foram implantadas, podendo ser observado na Figura 05 e na Tabela 05. Entretanto, em 2021, as parcelas submetidas ao manejo com fogo aumentaram dois níveis de classificação, correspondente a classe ND, enquanto as parcelas de controle apresentaram o aumento de um nível, classificado como LD. Após um ano do evento de fogo, em 2022, as parcelas com o manejo de fogo foram classificadas como LD, enquanto as parcelas de controle foram novamente classificadas como MD (Figura 6).

Tabela 05: Média dos valores de CVC encontrados nas parcelas.

	2020	CVC	2021	CVC	2022	CVC
Parcelas - regime de fogo	70,65%	MD	92,06%	ND	86,38%	LD
Parcelas - controle	69,80%	MD	77,09%	LD	74,53%	MD

Não degradada (ND),Levemente degradada (LD), Moderadamente degradada (MD), Severamente degradada (SD) e Extremamente degradada (ED)

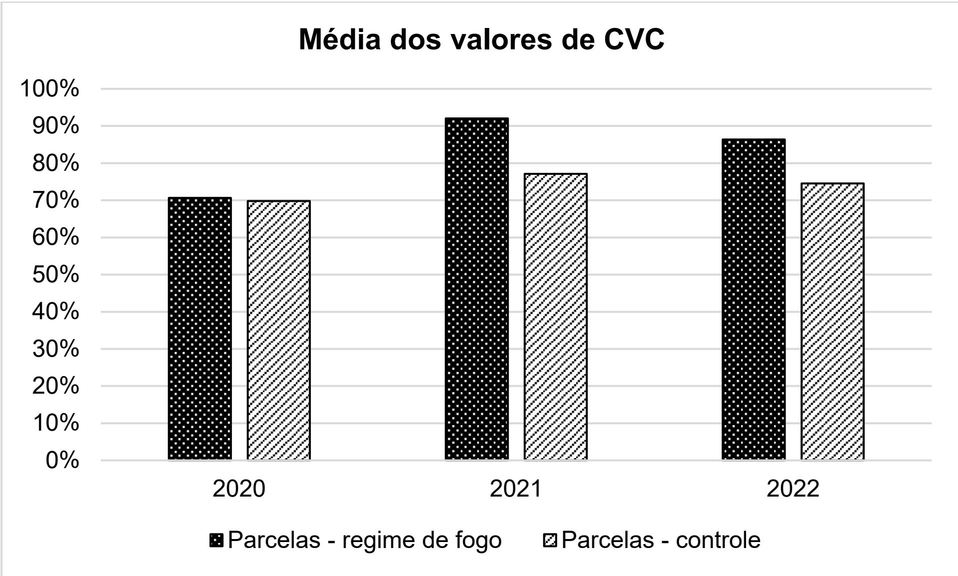


Figura 06: Média dos valores de CVC encontrados nas parcelas.

Na figura 04c, a área em situação MD demonstra a formação de plantas de hábito cespitoso (touceira) que expõem o solo e, consequentemente, favorecem a emergência de ravinas. As figuras 4a e 4b representam as classes ND e LD, respectivamente, em que podemos observar maior cobertura de solo e uma menor formação de touceiras. Assim, as parcelas com manejo com fogo apresentaram uma melhora imediata quanto à classificação em relação às parcelas sem o manejo, tendência também identificada no ano seguinte.

4. DISCUSSÃO

4.1 RELAÇÃO DAS CLASSES DE DEGRADAÇÃO E USO DO FOGO

A dinâmica entre as classes MD, LD, ND observada no estudo pode ser explicada pela prática do manejo bianual com fogo, conforme previsto nas leis municipais e na experiência dos produtores locais. De acordo com essa prática, o manejo com fogo não ocorre continuamente e é utilizado apenas para remover touceiras de palha e quebrar a dormência das sementes a cada dois anos na mesma área (SÃO FRANCISCO DE PAULA, 2013; BUFFON et al., 2018).

Sendo assim, quando uma unidade de conservação (UC) é implementada em área formada por campos de altitude, estes distúrbios antrópicos são suprimidos. Sem distúrbios, comunidades campestres evoluem para uma composição com poucas espécies dominantes, com predomínio de gramíneas de hábito cespitoso e até mesmo arbustos, e com acúmulo de biomassa inflamável, aumentando assim o risco de incêndios devastadores (PILLAR; VÉLEZ, 2010).

Em relação aos valores de IDC, não foram identificadas diferenças significativas entre a área do PET e a ZA. Como o PET ainda possui sua regularização fundiária abaixo de 5% (SEMA, 2008), muitas propriedades de dentro do PET continuam suas atividades econômicas e utilizam do manejo com o fogo em Campo. Portanto, conforme novas áreas são adquiridas, é necessário ter cuidado a se estabelecer a ausência de manejo dos campos de altitude dentro da UC, podendo resultar em perda de biodiversidade.

No Brasil, estudos que utilizam de técnicas de sensoriamento e sensibilidade de índices de vegetação em áreas que correspondem a sistemas não florestais suscetíveis ao fogo, como o Cerrado, são aplicados na avaliação da frequência no fogo em áreas após a criação de UCs (Carvalho et al., 2023), assim como o mapeamento de biomassa inflamável, para contribuir na gestão territorial (FRANKE et al., 2018) e no monitoramento de degradação de pastagens (PEREIRA et al., 2018).

A exclusão do fogo não é uma alternativa viável para manutenção destes ecossistemas (DURIGAN, 2020; PIVELLO et al., 2021). Estabelecer métodos para implantação e monitoramento de queimas prescritas contribuirá para avanços do ponto de vista social, econômico e ambiental.

4.2 DINÂMICA DO FOGO NA ÁREA AMOSTRAL

A área onde as parcelas foram inseridas estão dentro do PET, área com situação fundiária regularizada, sendo assim atendem ao que é estabelecido pelo SNUC. Os valores obtidos nas parcelas-controle apresentaram uma estabilização do valor de CVC em MD, porque com a ausência do fogo, o excesso de biomassa não é removido, tornando a recuperação da vegetação mais lenta.

As parcelas manejadas com fogo apresentaram uma dinâmica de classificação entre ND e LD. A remoção da biomassa acima do solo pelo fogo estimula a regeneração e fornece microssítios para o estabelecimento de novas espécies, remoção de concorrentes dominantes e favorece o surgimento de bancos de semente (FIDELIS et al., 2012).

Anteriormente, Ferreira & Ferreira Neto (2018) utilizaram o IDC para definir o nível de degradação de um assentamento rural em relação ao nível de lotação de gado, identificando uma melhoria geral com sua redução, ao longo do período analisado.

Em pastagens nativas como as encontradas nos campos de altitude o IDC foi utilizado para auxiliar na busca por alternativas de manejo de grandes áreas para conciliar a conservação com o uso sustentável (PEREIRA; KURTZ, 2020).

A área queimada na unidade amostral excedeu significativamente o planejado, sugerindo que é importante iniciar a queima em condições ambientais adequadas e seguras. Para isso, recomenda-se que a queima seja iniciada nas primeiras horas da manhã, quando a temperatura e umidade são mais favoráveis para controlar o fogo e minimizar o risco de propagação violenta e altas emissões de calor.

Resultados como este são apresentados pela primeira vez na área de estudo, sendo necessário explorar dados medidos a campo e dar seguimento no monitoramento a longo prazo, para obter dados mais precisos e aprimorar a metodologia.

5. CONSIDERAÇÕES FINAIS

Este estudo utilizou imagens orbitais e índices de vegetação para determinar o grau de degradação de uma área de Campo e a sua sensibilidade ao uso do fogo. Foi possível observar que áreas classificadas como moderadamente degradada são sensíveis com a exclusão de manejo com fogo, pois favorece o surgimento de espécies de hábitos cespitosos, aumentando a exposição do solo e o acúmulo de biomassa inflamável.

Houve diferenças no nível de degradação entre parcelas com regime de fogo das parcelas com exclusão de fogo (controle), pois as parcelas passaram de moderadamente degradadas em 2020 a não degradadas em 2021, e levemente degradadas em 2022.

Conforme novas áreas forem adquiridas durante a regularização fundiária do PET, será necessário assegurar a manutenção dos campos de altitude e todo seu espectro de fisionomias e espécies associadas, bem como estabelecer planos para recuperação de áreas já degradadas.

Essas variações nas áreas das diferentes classes podem ser causadas por diversos fatores, tais como eventos climáticos, mudanças na dinâmica da paisagem, alteração do regime de fogo, atividades humanas, entre outros. É importante monitorar essas mudanças ao longo do tempo e compará-los com os dados obtidos quanto a degradação.

A pressão antrópica nas áreas com remanescentes de campos de altitude é evidente. A busca do uso sustentável e da conservação destas áreas deve ser levado como prioridade pelos gestores públicos. A metodologia proposta por este estudo se mostrou eficaz para identificação da degradação de formações campestres e pode auxiliar na tomada de decisão na gestão territorial de grandes áreas.

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2.3.3 Capítulo 3 - Fire in highland grasslands in Atlantic Forest biome, a burned areas time series analysis and its correlation with the legislation.

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Abstract

Fire has been an intrinsic ecological component of the ecosystems, affecting the public, economic, and socio-cultural policies of human-nature interactions. The use of fire over grassland vegetation is a traditional practice for livestock in the highland grasslands and has economic and environmental consequences that have not yet been understood. A better description of the spatio-temporal biomass burning patterns is needed to analyze the effects of creation and application in these areas. This study used remote sensing techniques based on Sentinel-2 data and machine learning algorithms to identify burning scars and compare them with a national fire collection database for the highland grasslands in the Atlantic Forest Biome in Brazil. The aim is to evaluate public management tools and legislation evolution during the 35 years of the time series analyzed. The results indicated that 12,285 ha of grasslands were converted to other uses, losing about 24% of their original formation, with 10% occurring after banned this practice in 2008. The burned areas classification using the Random Forest algorithm obtained an overall accuracy of 99% and 95% Kappa index. Divergences in the burned area's extent and frequency were found between the municipality's authorized license and those classified as burned. On average, only 43% of the burned area in the Parque Estadual do Tainhas and its buffer zone had an environmental permit in the last five years. This research's results provide subsidies for revising and creating public policies and consequently help territorial management.

1. INTRODUCTION

Fire activity in Brazil is influenced by several factors, the result of complex and dynamic processes generated by interactions between climatic conditions, vegetation attributes, land use and land cover, and ignition patterns (Andrade et al., 2015; Pivello et al., 2021). Brazilian biomes have a long history of fire conflicts, as in the Atlantic

Forest Biome (AFB), one of the most critical biodiversity hotspots in the world (Myers et al., 2000).

Currently, the AFB remnants are highly fragmented and restricted to highland grasslands areas in southern Brazil, where there are mosaics of Araucaria (Brazilian pine) forests and grasslands linked to a fire events history (Pillar et al., 2009; Meireles and Shepherd, 2015). In these areas, fire has been an intrinsic ecological component of the ecosystems, affecting the public, economic, social, and even cultural policies of human interactions with nature (Overbeck et al., 2007).

In recent years, conflicts related to fire use have presented economic and environmental consequences that have not yet been clearly understood. The fire use on grassland vegetation in the northeastern Rio Grande do Sul (RS) state is a traditional practice for livestock (Boldrini, 1997). However, it was prohibited by Law 9,519/1992 (Rio Grande do Sul, 1992). This has led to natural grassland area changes to simplified land uses, such as agriculture and forestry, leading to biodiversity loss and difficulties recuperating degraded areas (Buisson et al., 2019). Subsequently, Law 13,931/2012, which amended Law 9,519/1992 (Rio Grande do Sul, 2012), attributes to the municipal government the power to authorize and supervise the use of fire as a grasslands management practice in areas that cannot be mechanized or as a form of phytosanitary treatment.

Therefore, a better description of biomass burning spatio-temporal pattern is needed to analyze the effects of fire legislation. So, the use of remote sensing derived products such as (i) the Modis product MCD64A1 – Collection 6, with 500 m resolution at a global scale (Giglio et al., 2018); (ii) the MapBiomas Fire – Collection 1, based on Landsat time series, with 30 m resolution for the Brazil territory (Alencar et al., 2022), and (iii) the global forest loss by fire product, also at a spatial resolution of 30m (Tyukavina et al., 2022) are consolidated as an essential data source by covering vast areas with a multitemporal and multispectral information.

In this study, to minimize these products limitations, such as the spatial resolution, we used Sentinel-2 data developed by the European Space Agency (ESA), which has four bands with 10 m, six with 20 m, and three bands with 60 m (ESA, 2022). Therefore, this study's objective is to improve the spatial resolution of burned areas and compare them with the national MapBiomas Fire product to evaluate the fire use legislation over time in the highland grasslands in Atlantic Forest Biome in Brazil.

2. MATERIAL AND METHODS

2. 1. STUDY AREA

This study was conducted in the conservation area denominate Parque Estadual do Tainhas (PET) and its buffer zone (BZ) located at latitude 29°5'15" S and longitude 50°22'4" W (Figure 01). The PET was established in 1975 to protect the grasslands and forests in the Tainhas river valley, inserted in the AFB.

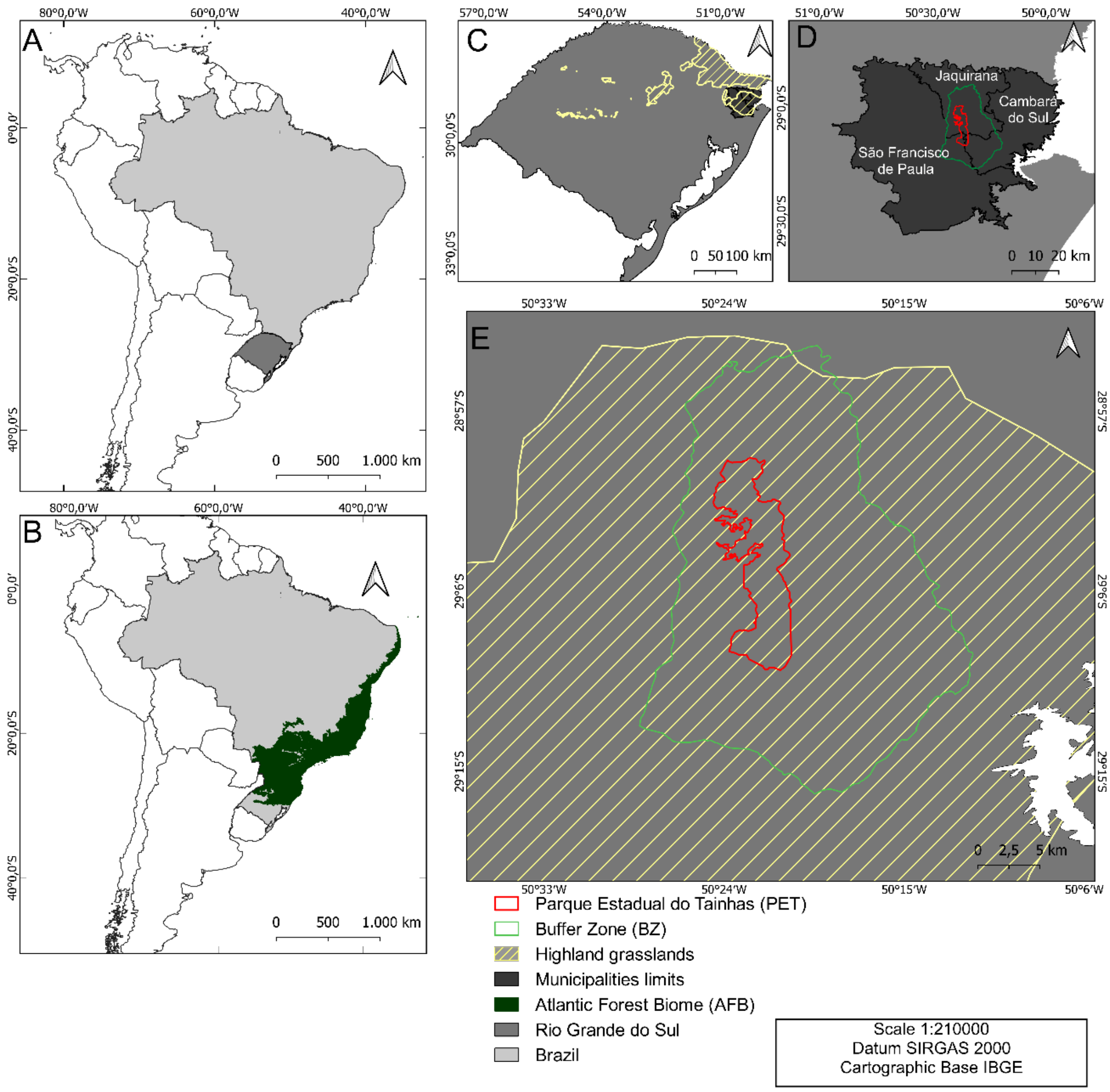

Figure 01. (A) Rio Grande do Sul location, (B) AFB location, (C) Highland grasslands distribution, (D) Location of the municipalities that make up PET, (E) Location of the PET and its BZ in relation to the highland grasslands.

The Park is formed by mosaics of forests with Araucaria pine, grasslands, and flooded areas (wetlands) with flatter terrain in the southern portion to valleys in the northern part (SEMA, 2008). It has an area of 6,654 hectares with a BZ of approximately 60,000 ha, covering the municipalities of Jaquirana (69.8%), São Francisco de Paula (20.6%), and Cambará do Sul (9.6%) of the Park's area. Around the PET, communities in its BZ depend on agriculture, forestry, and livestock and regularly use fire as a management tool (Bond-Buckup, 2008).

The PET is close to other protected areas, which favors the emergence of the biogeographic conditions that can contribute to the interconnection of these units through ecological corridors, helping preserve fauna and flora populations and maintain the ecosystem services balance in the region.

2.2 BURNED AREAS CLASSIFICATION IN HIGHLAND GRASSLANDS

The methodological approach for burned area detection used in this study is shown in the flowchart (Figure 02). We use Sentinel-2 MSI Multispectral Instrument, Level-2A data. The Level-2A product provides Bottom Of Atmosphere (BOA) imagery derived from the associated Level-1C products. The imagery used is available from the Google Earth Engine (GEE), a platform that brings together three tools (code editor, explorer, and client libraries) for users to perform geospatial analysis in the cloud (Adagbasa, Adelabu and Okello, 2020). We select images from 2018 to 2022, before the start of the fire season, from January 1 to April 1, denominating as "pre-fire" images, while the post-fire images were selected from July 15 to September 15 of each year, when the "burning window" allowed by municipal legislation was established. A cloud mask was applied. First, the function defines two bitmask values for clouds and cirrus (bit 10 and bit 11, respectively) and selects the pixel quality band (QA) of the image. Then, the function creates a mask that filters out all the pixels where the cloud and cirrus bits are equal to zero, indicating clear conditions.

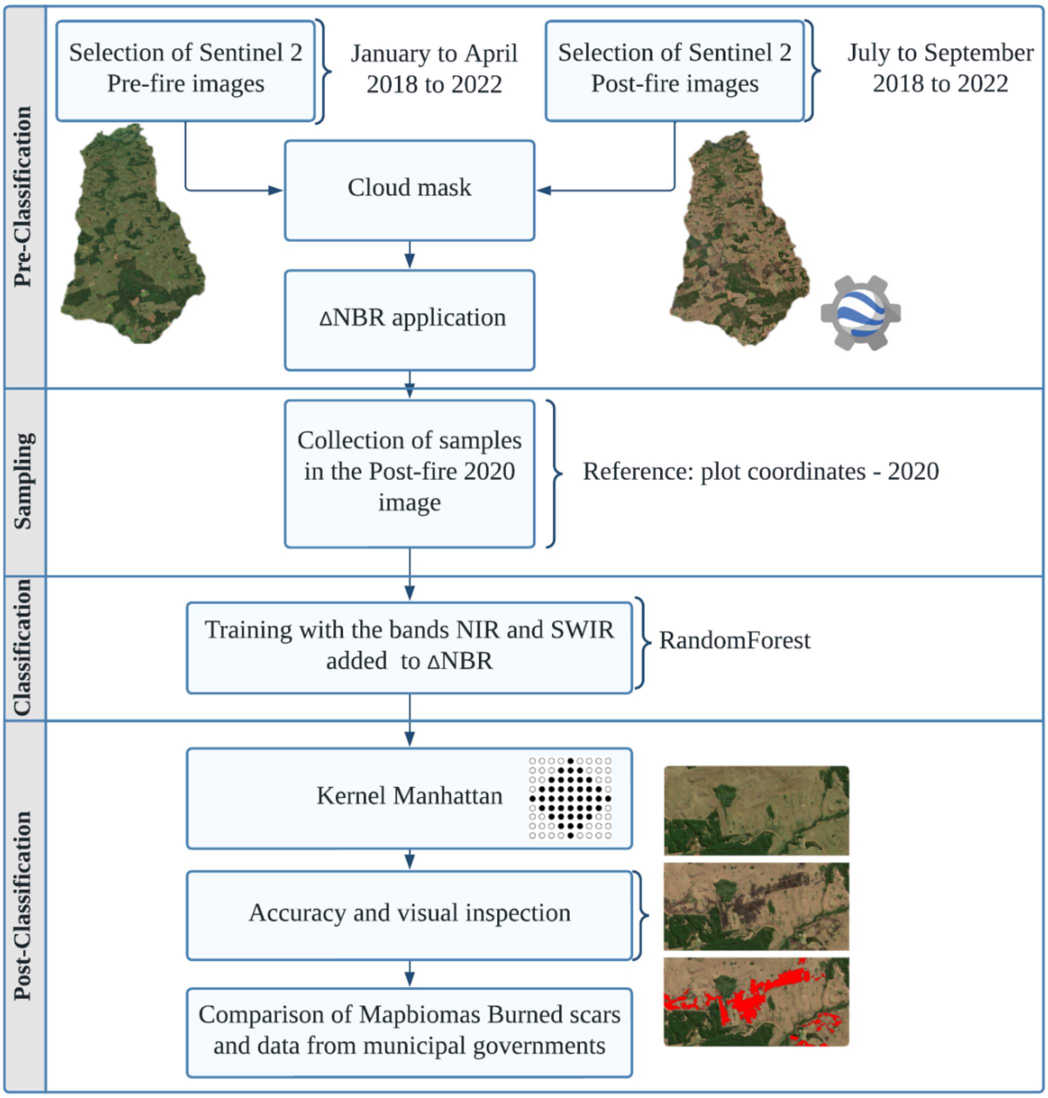

Figure 02: Overview of the burned area classification method.

We used the GEE to collect spectral signatures of the burned and unburned areas, which served as samples for the model classification. In addition, we used data collected from the field in the year 2020 as a reference for sampling in this year's post-fire images. This effort resulted in 7133 sampled pixels, manually collected as small polygons from burned areas (2295 sampled pixels) and unburned areas (4838 sampled pixels).

For training, we used the shortwave infrared (SWIR) and near-infrared (NIR) bands and the result of the Normalized Burn Ratio spectral index (ΔNBR) calculation. The NBR is a ratio of the NIR to the SWIR region, developed to identify post-fire burned areas and provide a quantitative measure of burn severity (Key and Benson, 2006).

The NBR is calculated by the pre- and post-fire difference (denoted as ΔNBR) using Eqs. (1) and (2).

$$\boldsymbol{NBR} = \frac{\boldsymbol{NIR-SWIR}}{\boldsymbol{NIR+SWIR}} \quad \textbf{(1)}$$

$$\boldsymbol{\Delta NBR} = \boldsymbol{NBR_{pre-fire}} - \boldsymbol{NBR_{pos-fire}} \quad \textbf{(2)}$$

The algorithm used for our classification was the Random Forest (RF) (Breiman, 2001; Goehry et al., 2021), which is an ensemble algorithm operated by building multiple decision trees in a training session and assigning the target class by majority vote (PAL, 2005).

In this study, we used the ee.Classifier.smileRandomForest in the GEE library. The parameters used were: number0fTrees (20), variablesPerSplit (null), minLeafPopulation (1), bagFraction (0.5), maxNodes (null), and seed (0). After classification, we applied a spatial filter to remove noise and fill in gaps, where burned areas smaller than or equal to 1 ha (5x5 pixels) were removed, and, in the same way, internal spaces were filled as burned. The spatial filter selected was the Manhattan Kernel, which generates a distance kernel based on rectilinear distance (city-block). Reduction is performed by calculating the mode (most common value) of the pixel values in a neighborhood defined by the specified kernel (or window). The filter size was defined considering the difference in the spatial resolution of the Landsat 8 satellite, which was used for the MAPBIOMAS product methodology proposed for exclusion. Finally, we used the error matrices for the accuracy evaluation, performing the statistical analysis by the global map and Kappa index accuracy.

2.3. TEMPORAL ANALYSIS OF BURNED AREAS

To evaluate the management tools available in conjunction with the classification data generated, we used data on the annual area burned by MapBiomas Fire – Collection 1.0 (Alencar et al., 2022) and the land use and land cover areas classified as grassland from 1985 to 2020 available in MapBiomas Collection 7.0 (Souza et al., 2020). In addition, we also used the extent area authorized for burning by Jaquirana, São Francisco de Paula, and Cambará do Sul municipalities located within PET and its BZ.

The annual burned areas stationarity trend covered by grassland was checked using the Augmented Dickey-Fuller (ADF) test. The ADF test is an "augmented" version of the Dicker-Fuller test. The ADF test expands the test equation to include high-order regression processes in the model. Afterward, the trend was verified through time series decomposition to verify the seasonality and the residuals. Results are obtained by first estimating the trend by applying a convolution filter to the data. Therefore, the trend is removed from the series, and the average of this unbiased series for each period is the seasonal component returned (McKinney, Perktold and Seabold, 2011).

3. RESULTS

3.1 RECONSTRUCTING THE HISTORY OF FIRE USE

The burnt areas and the grasslands from 1985 to 2020 in the PET and its BZ is shown in (Figure 03). In this figure is highlighted in vertical dotted lines, the primary legislation, which is also presented in (Table 01) together with the grasslands and the total burned area values. This analysis reveals an increasing trend for the burned area, while there is a decreasing trend for grassland in the PET.

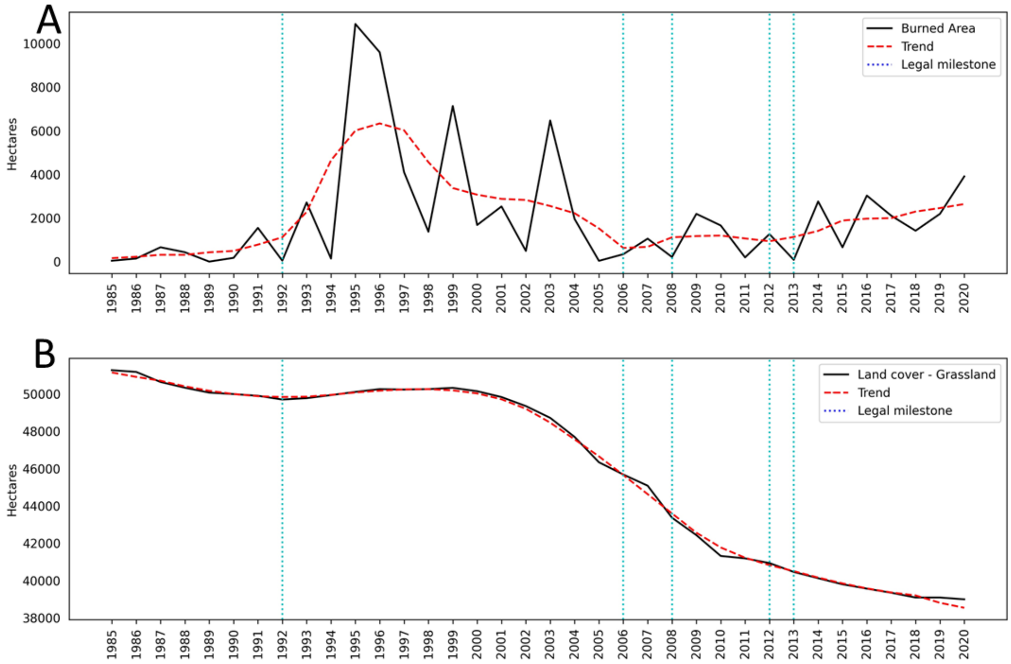

Figure 03: (A) Burned area accordingly MapBiomas Fire – Collection 1.0, and (B) Grassland accordingly MapBiomas – Collection 7.0, both in the PET and its BZ from 1985 – 2020.

Table 01. Relationship of burned areas (hectares per year) mapped and permissions of environmental permits.

Legislation	Event	Burned area (ha)	Grasslands (ha)
Law nº 9.519/92	Fire use Prohibition in the Rio Grande do Sul state	44	49709
Law nº11.428/2006	Atlantic Forest Biome Law - Prohibits the conversion of grassland to other land uses	339	45689
Decree nº 6.660/2008	Regulates the provisions of the Atlantic Forest law and defines the legal framework for the conversion of areas.	210	43378
Law nº13.931/ 2012	Conditional fire use permission	1262	40943
Municipal Law nº. 2.954/2013 (Cambará do Sul) Municipal Law nº 1.083/2013 (Jaquirana) Municipal Law nº2.924/2013 (São Francisco de Paula)	Regulation of fire use licensing by municipal agencies	80	40464

We can observe that the burned areas remained low after the fire use prohibition in 1992. However, this pattern was not established for a long time and the highest values for the time series analyzed occurred in 1995 and 1996, with about ten thousand hectares burnt each year.

The most significant burned areas reduction occurred in 2002, reaching the lowest value in 2005, with only 35 ha. By observing the trend curves of burnt area and area occupied by grassland formation, the curve's decline in the same years is noticed.

In 2002, the area corresponding to grassland was 49,359 ha, while in 2005, it was 46,345 ha. Therefore, the PET and its BZ lost more than 3,000 ha in only three years. These years precede the AFB Law creation (Brasil, 2006) and its regulation decree (Brasil, 2008), prohibiting new conversions of areas with native vegetation in the biome.

During the 35 years of the analyzed time series, 12.285 ha of grassland areas were converted to other uses, losing about 24% of their original formation, with 10% occurring after the AFB decree banned this practice in 2008 (Brasil, 2008).

Finally, concerning the burnt areas only when municipalities begin to legislate about the use of fire, in 2013, a trend definition and a biannual frequency can be observed, as provided by several municipal legislation (Municipio de Jaquirana, 2013; Municipio de São Francisco de Paula, 2013; Municipio de Cambará do Sul, 2013).

3.2. Burned area and frequency of occurrence

The burned areas classification with the RF algorithm obtained an overall accuracy of 99% and a 95% Kappa index. With a visual inspection, the scar's demarcation can be identified when comparing the pre-fire and post-fire images (Figure 04).

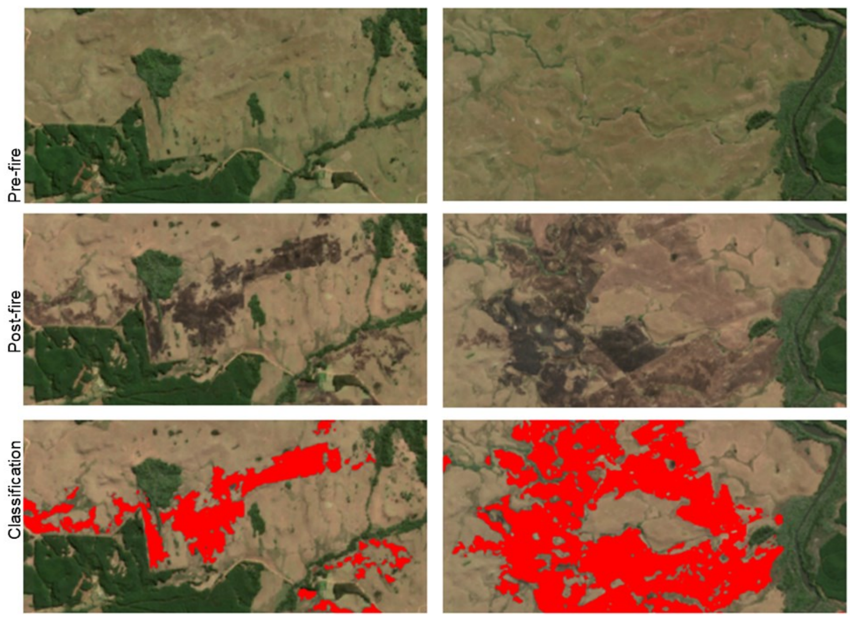

Figure 04: Examples of burnt area classification using RF.

The results show that larger areas were burned for all years than those allowed by the municipalities' environmental permits. In addition, larger burned areas were found in our classification than those presented by the MapBiomas Fire collection, as can be seen in Table 02.

Table 02 – Comparison of burned areas authorized by the municipality between mapped by mapbiomas and Burned Areas Classification in Highland Grasslands (BACHG).

	2018	**2019**	**2020**	**2021**	**2022**
Mapbiomas	1417	2189	3909	-	-
BACHG	5380	7373	7859	2813	4681
Match pixels BACHG and Mapbiomas	772	1132	2616	-	-
Municipalities	2587	2479	1851	1953	2038

The licenses issued correspond to only 48.09% (2018), 33.62% (2019), 23.55% (2020), 69.43% (2021), and 43.54% (2022) of the area identified as burned in our classification. For the three available years of the analyzed period from the MapBiomas collection, they represent only 26.34% (2018), 29.69% (2019), and 49.74% (2020) of the burned areas.

The Mapbiomas burned areas that coincide with our classification represent only 21% of the total classified area on average (Figure 05). The MapBiomas burned omission areas are formed by scars smaller than 10 ha or with sites that present a non-continuous formation with gaps of 1 ha.

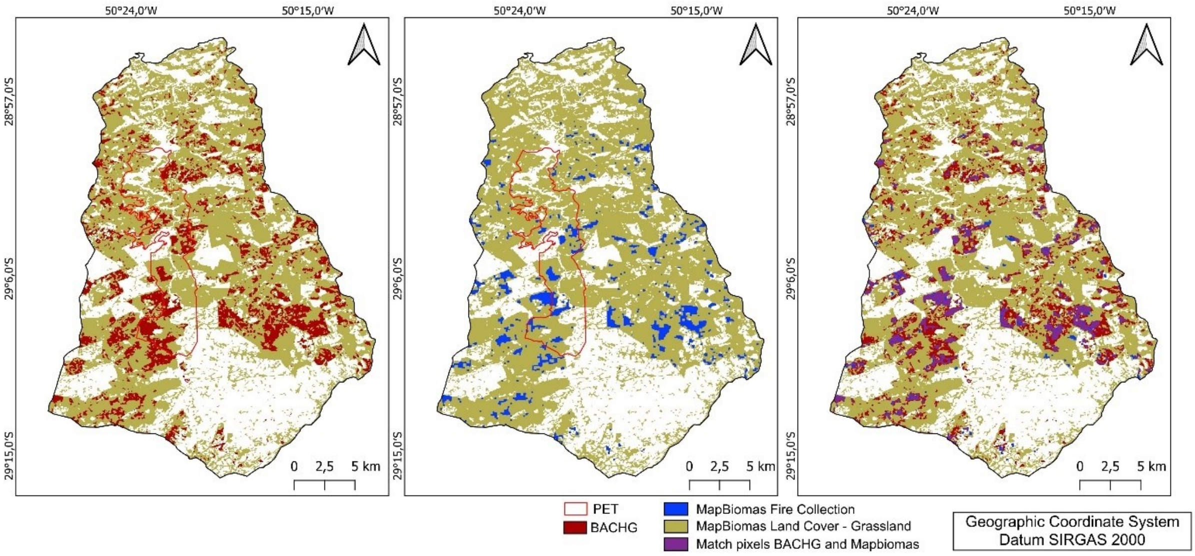

Figure 05. Representation of the comparison of classified areas in both methods for 2020.

The Table 3 presents the data in hectares (ha) of the disagreements and agreements of the classifications. The first presents the area detected only by MAPBiomas, it has a total area of 507 ha that was not identified by BACHG. The second, which is the area detected only by BACHG, has a much larger area of 5,243 ha. Finally, the third is detected by both, resulting in a total classified area of 2,616 ha.

Table 03 – Differences between the classifications of each method in 2020.

	ha
Area classified only by MAPBiomas	507
Area classified only by BACHG	5243
Classified area in both	2616

In addition to the burning extent, the frequency of areas affected by the fire was verified, and about 28% of the PET and its BZ were burned at least once, as shown in (Figure 06). It is noteworthy that according to the legislation, the areas could present a burning frequency of 2 to 3 times for five years. However, the results showed that 353 ha were burned 4 to 5 times, exceeding the legal requirements for this period. These areas are within the Jaquirana municipality territory inside the PET or near its boundaries.

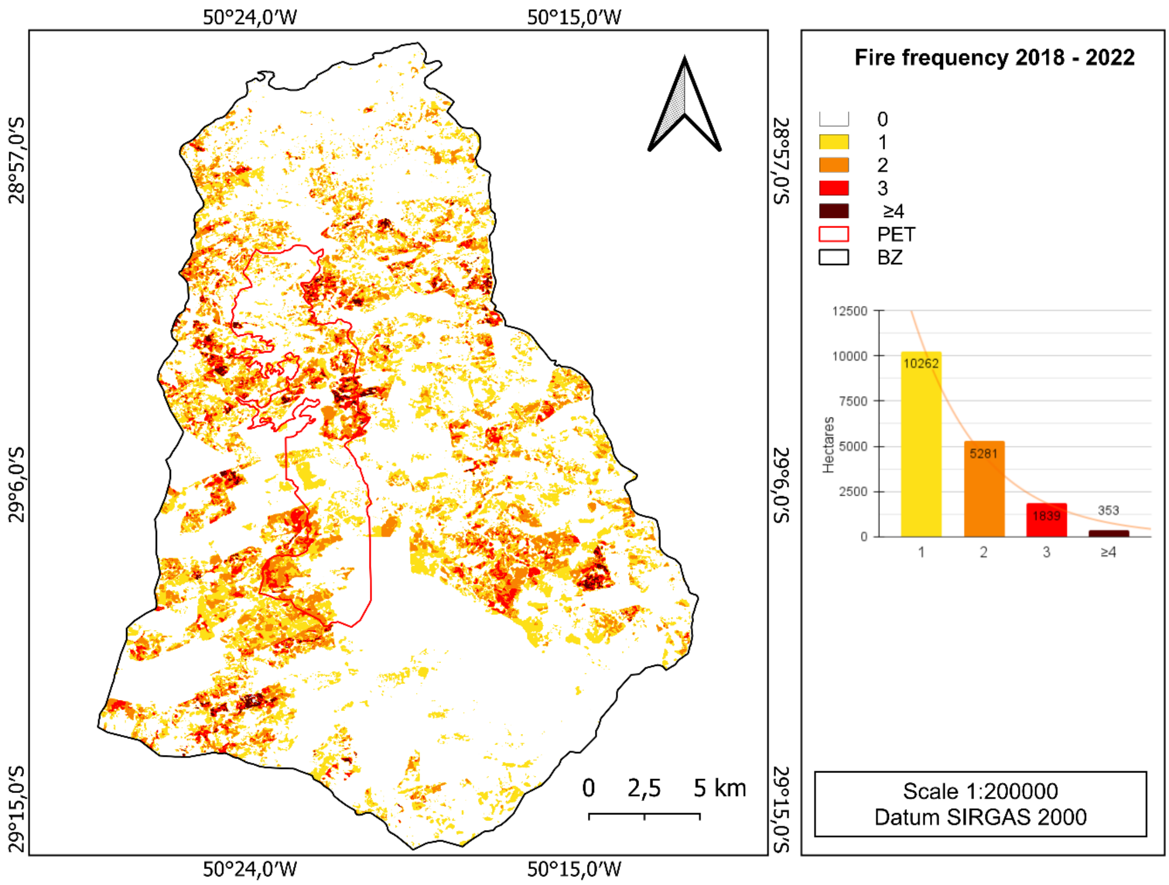

Figure 06: Fire frequency in the PET and its BZ.

4. DISCUSSION

4.1. LEGISLATION ANALYSIS AND REMOTE SENSING

No stationary trends were found in the time series, even though there is a long history of legislation to regulate fire use and vegetation protection practices.

The Program for Monitoring Deforestation in the Brazilian Legal Amazon (PRODES) has observed similar trends to those depicted in Figure 3A at a national level, presenting annual deforestation rates for the region (INPE, 2023). The historical records show that deforestation reached its peak in 1995, with a total of 29,059 km². This surge in deforestation coincided with the implementation of the Real Plan, which introduced reforms that increased the availability of capital and credit for agriculture (MESSIAS, 2021; FEARNSIDE, 2005). As a result, there was a significant incentive to expand the production of agricultural commodities, leading to an increase in the area dedicated to crop cultivation, as illustrated in Figure 3B, and resulting in the loss of grassland.

During the 20 years (1992-2012) of fire use practice prohibition, producers changed their economic profile, and extensive native grassland areas conversion to monocultures in the region occurred (Boziki; Beroldt; Printes, 2011; Buffon; Printes; Andrades-Filho, 2018). Grasslands are important for livestock, especially where other agricultural practices are not viable. In this study, we noticed that legislation changes over the time series are related to changes in land use.

The fire management practice in the winter period is expected in the region, and it is used to remove dry biomass to provide the vegetation regrowth that will be used to feed the cattle herd in spring and summer (Pillar et al., 2009).

Once forbidden, it can be replaced by other activities much more environmentally damaging than the old fire management grasslands practice, such as forestry and monocultures, which have been advancing into the grasslands (Buffon, Printes and Andrades-Filho, 2018).

It was observed during the study that municipalities lack data and tools to manage and enforce current environmental legislation. So it is necessary to evaluate the effectiveness of existing environmental management tools regulated by municipal laws related to the use of fire (Santos and Andrades-Filho, 2021).

In addition to the environmental laws presented, it was verified the irregularity in the data availability by the municipalities, which do not meet the legal provisions of free access to information in Brazil, especially regarding publicity, accessibility, and transparency, making technological advancement impossible (Brasil, 2011).

4.2. NEW BURNED AREA CLASSIFICATION APPROACH

The brief characteristics of the fire marks left on satellite imagery complicate the burned area's detection. There are few fire products available globally, and only one at the national level (Alencar et al., 2022). So, evaluating its applicability to different regions and vegetation formations in Brazil is extremely important.

Our study found significant differences in areas mapped as burned, increasing by more than 50% in our study using a better spatial resolution. The improvement of available products is substantial and progresses with the recent technologies emergence. In previous studies of Russian grassland, the difference in the area mapped between satellites with lower spatial resolutions also increased dramatically from no burning to as much as 19% of the total study area (Dubinin et al., 2010). The strategy of using ΔNBR in conjunction with the NIR and SWIR bands for burned areas classification reduced noise and class confusion, especially with wetlands. The areas with the highest commission error were exposed soil from recently cleared forestry areas.

Due to the rugged relief and mosaics of forest and mountainous grassland vegetation that form the landscape of the area, remote sensing data with higher spatial resolution can be explored as they become available. Therefore, Earth observation can significantly support public fire prescription policies and added to other factors that take into account CO_2 emissions. (Herrmann, Nascimento and Freitas, 2022).

The study was conducted to compare the national product of burned areas from MAPBIOMAS with our methodology to analyze the divergences that can be generated, considering that public authorities use this information as a means of monitoring these areas, often imposing significant fines based on MAPBIOMAS data or failing to create monitoring actions due to lack of data.

5. CONCLUSIONS

In this study, remote sensing techniques were employed to examine the behavior of burned areas in highland grasslands in Brazil with respect to legislation regarding the use of fire. To identify the key impacts of human-induced changes, it is essential to utilize long-term time series and explore new methodologies for improvement.

Divergences in extent and frequency were found between the burned areas authorized by the municipalities and the areas classified as burned. On average, only 43% of the burned area in the PET and its BZ was licensed in the last five years. The municipal databases had recorded only from the year 2018, and it is possible to improve the time series from the continuity of data collection.

Our new burned area methodological classification developed in this article presented results that provide subsidies for reviewing and creating public policies and territorial management. The next step is to evaluate the exclusion and excess effects of fire use in these areas to verify their degradation degree.

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2.3.4 *Capítulo 4 - Spatial modeling of fire in the Atlantic Forest considering future climate change scenarios in Rio Grande do Sul state – Brazil.*

ABSTRACT

Several biomes worldwide have a long history of conflict over fire use and management. The Atlantic Forest Biome (AFB) is a Brazilian biome that suffers the most from land use and cover changes that cause environmental degradation. The impact of climate change is expected to exacerbate this situation, with extreme weather events potentially leading to a higher frequency and intensity of fire. The main goal of this study is to understand the spatiotemporal distribution of fires for future climate scenarios obtained from CMIP6 climate simulations in the AFB in Rio Grande do Sul state, Brazil, using machine learning algorithms. This study selected several environmental and anthropogenic variables as factors associated with the cause, occurrence, and spread of fire. The results showed an uneven fire density distribution in the study area. An extensive fire cluster was found in pasture areas located northeast of Rio Grande do Sul, reaching more than 1,500 fire foci per km² on an average per year. The final model had a training R^2 value of 0.99, and a test R^2 value of 0.931. The most significant variable identified by the model was the average maximum temperature during the warm period, with livestock economic activity being the most influential variable. Regarding the simulated fire densities, the period between 2021 and 2040 in the SSP 5.8-5 scenario displayed maximum values that were equivalent to those observed in 2018, with an expansion in the occurrence region observed for the same scenario. However, unexpectedly, between 2081 and 2100, fire density decreased across all areas under the SSP 5.8-5 scenario.

1. INTRODUCTION

The effects of fire on vegetation and soil can be disturbances of natural and anthropogenic origin, although both can influence ecosystem changes. To better understand and manage the relationship between fire, climate, land use, vegetation, and economic and social relationships, it is critical to recognize and comprehend the history of fire use (DENNIS et al., 2005; GOODWIN; COLLETT, 2014).

Brazilian biomes have a long history of conflicts regarding fire use and management. For example, in the Amazon, fire dynamics occur primarily in areas affected by severe droughts, resulting in forest fires that are frequently related to deforestation and agriculture (SILVA et al., 2021). Recent studies in the Cerrado have aimed to use fire to manage savanna vegetation and reduce the impact of large fires (DURIGAN, 2020; FRANKE et al., 2018).

The Atlantic Forest Biome (AFB) is considered one of the world's most important biodiversity hotspots (MYERS et al., 2000), and it is the Brazilian biome that suffers the most from changes in land use and land cover, causing environmental degradation, including the use of fire (BUSTAMANTE, 2019). According to INPE (2021), over 250,000 fire foci were registered only in 2020 in the AFB.

Additionally, climate change is expected to increase the occurrence of extreme weather events, which can increase the frequency and intensity of fires (IPCC, 2022). Therefore, future climate change projections, such as those provided by the Coupled Model Intercomparison Project Phase 6 (CMIP6) (O'Neill et al., 2016; EYRING et al., 2016), were used in this study to improve our understanding of how fire behavior will respond to anthropogenic activities.

Fire dynamics are a hot topic in the scientific literature and should be further investigated through spatial models, allowing us to understand the main factors associated with fire events (MCLAUCHLAN et al., 2020). Machine learning techniques, such as Random Forest (RF), have been used in several studies (BARROS et al., 2021; PANG et al., 2022; YU et al., 2017) because of their robustness in dealing with a large number of input variables and nonlinear problems, such as fire mapping. RF also provides an ordination of each variable’s importance, allowing us to make assumptions about the relevance of each environmental and anthropogenic factor. (CUTLER et al., 2007; OLIVEIRA et al., 2012). In addition, these results may support the elaboration of public policies, territorial planning, and monitoring in these areas (FRANKE et al., 2018).

The potential impact of climate change on fire behavior is still subject to debate in the scientific community and lacks conclusive answers (CASTELLANOS et al., 2022). It is unknown how fire behavior changes in response to external forcing (HANAN et al., 2021). For instance, an increase in atmospheric concentrations of greenhouse gases depends on many complex interactions between biophysical and sociocultural spheres, making the investigation even more complicated.

The primary aim of this study was to examine the occurrence of fire and its predictive capabilities in the Atlantic Forest Biome in the Rio Grande do Sul state using machine learning algorithms. The proposed spatial model considers both environmental and anthropogenic variables. Environmental variables reflect intrinsic natural conditions, whereas anthropogenic influences are associated with economic, cultural, and social factors. This study aimed to analyze the fire response to radiative forcing changes derived from future climate scenarios.

2. MATERIALS AND METHODS

2.1. STUDY AREA

Over 70% of the Brazilian population, approximately 150 million inhabitants, lives in the AFB region. Despite its tremendous economic and ecological importance, it is the most degraded biome in Brazil, remaining only approximately 12.4% of the original coverage (FUNDAÇÃO SOS MATA ATLÂNTICA, 2018).

The Rio Grande do Sul State occupies 282,480 km², corresponding to approximately 3.3% of the total area of Brazil. The northern half of the State is within the AFB territory, with vegetation cover consisting of grasslands and Araucaria forests (OLIVEIRA; PILLAR, 2004).

The southern Brazil grasslands part of the AFB (Fig. 01) are threatened by habitat loss associated to the landscape fragmentation caused by severe and long-term human disturbances, often related to excessive use of fire, cattle grazing overloading, agriculture dissemination and the introduction of exotic species (SCHLICK, 2004).

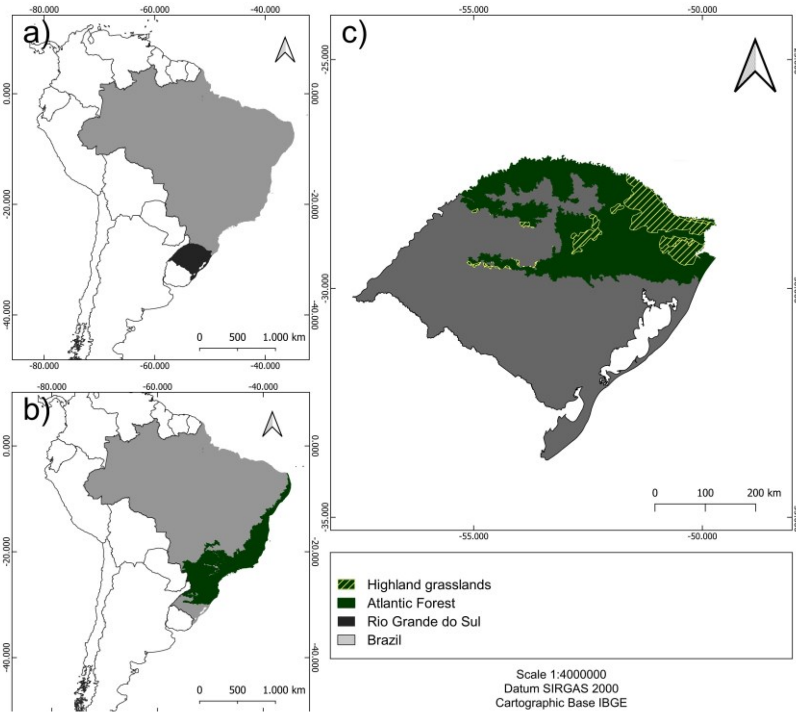


Figure 01: Location of the study area: a) Rio Grande do Sul State; b) AFB; and c) Distribution of grasslands (IBGE, 2004) .

2.2. DATABASE

2.2.1. Fire foci

The occurrence data for fire foci were downloaded from the National Institute for Space Research (INPE) base (INPE, 2022). To avoid redundancy, only signals from active satellites during the entire period under analysis or from successors of the same satellite family (AQUA, TERRA, NOAA) were included. We also applied a mask based on the urban infrastructure developed by MAPBIOMAS (SOUZA et al., 2020).

We used the kernel density algorithm to spatialize the fire foci and assess their concentration per unit area (SILVERMAN, 1981). The generated raster maps presented a spatial resolution of 1 km, and we calculated the density in each output pixel by adding the values of all kernel surfaces that overlapped the center of the pixel.

2.2.2. Variables: selection and preprocessing

Thirteen variables were examined as factors associated with the cause, occurrence, and propagation of fire and were classified into environmental and anthropogenic factors (Table 01) and (Fig. 02).

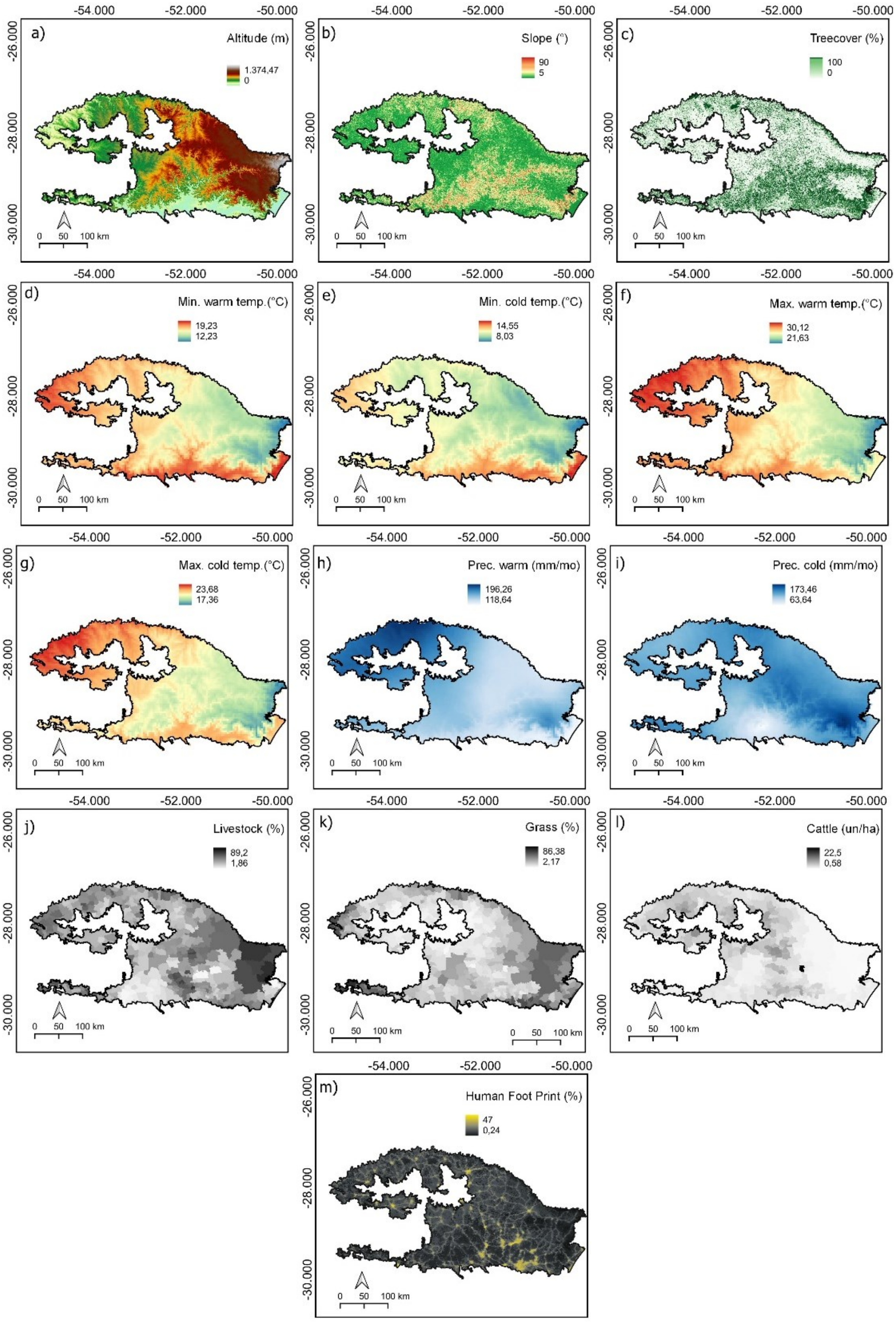


Figure 02: Environmental variables a) Altitude, b) Slope, c) Tree cover, d) Minimum warm average temperature period, e) Minimum cold average temperature period, f) Maximum warm average temperature period, g) Maximum cold average temperature period, h) warm precipitation average, i) cold precipitation average and anthropic variables j) Economic activity linked to livestock k) Economic activity linked to pastures, l) Livestock occupation per hectare and m) Human Foot Print.

Table 01 – Variables analyzed as a factor associated with fire occurrence.

Factor	Variable	Source	Code	Spatial Resolution	Year
Environmental	Elevation and slope	Brazilian Geomorphometric Database http://www.webmapit.com.br/inpe/topodata/	Alt Slope	30 m	2011
	Precipitation, Maximum and Minimum Temperature	http://worldclim.org/.	p_hot p_cold tmax_hot tmax_cold tmin_hot tmin_cold	1000m	2002 - 2018
	Tree cover % (>5m)	Global Land Cover Facility at the University of Maryland, Hansen, et al. (2013). https://earthenginepartners.appspot.com/science-2013-global-forest.	Treecover	30 m	2000
Anthropic	Pastures % livestock cattle/HA	IBGE Agricultural Census https://mapasinterativos.ibge.gov.br/agrocompara/	Grass Livestock Cattle	Vector	2017
	Human Footprint	Global Human Footprint, Venter, et al. (2016). https://wcshumanfootprint.org/.	HFP	1000m	2009

2.3. ENVIRONMENTAL FACTORS

Among the selected environmental variables, the topographic variables of altitude and slope were based on the Digital Elevation Model (DEM) obtained by the Shuttle Radar Topography Mission (SRTM) and refined by the Topodata project (VALERIANO & ROSSETI, 2012). Díaz et al. (2003) suggested the significance of the relationship between topo-climatic parameters and fire severity and that the slope can affect the origin of anthropogenic fire ignition by limiting accessibility (CONEDERA et al., 2011).

Grasslands, woody savannas, and savannas account for over 60% of the global burned area (DUBININ et al., 2010). Therefore, to characterize the vegetation with the highest fire foci occurrence, we used the vegetation cover data obtained through Landsat image time series analysis by the University of Maryland (HANSEN et al., 2013).

The climate data used in this study were the monthly, maximum, and minimum air temperatures and monthly precipitation accumulation, calculated as the averages of the warm months (austral summer and spring) and cold months (austral autumn and winter). Data were obtained from the WorldClim high-spatial-resolution global climate and meteorological database (WORLDCLIM, 2021). This dataset was used to model the historical, present, and future conditions. To evaluate the model, 2018 was used for validation and replaced by the predicted data of the average periods over the 20 years for 2021 – 2040 (short-term) and 2081 – 2100 (long-term).

Future climate projections for the mean maximum temperature, mean minimum temperature, and precipitation from the Canadian Earth System Model version 5 (CanESM5) were obtained from WorldClim (SWART et al., 2019). WorldClim v2.1 was used as the baseline climate for downscaling and calibration (WORDCLIM, 2021).

The analyzed SSPs adopted in this study were SSP2-4.5, representing an intermediate social vulnerability scenario with an intermediate forcing level of 4.5Wm -2 of radiative forcing with 600 ppm of CO2 concentration, and SSP5-8.5, expressing the future paths in the upper limit with the ability to produce a radiative forcing of 8.5Wm -2, with 1200 ppm of CO2 concentration up to 2100 (O'NEILL et al., 2018).

2.4. ANTHROPIC FACTORS

To select anthropic variables, grazing and burning were considered management practices that generated conflicts regarding economic and environmental interests (OVERBECK et al., 2015). In addition, extensive livestock farming on native pastures has been widely recognized as an economical alternative to conservation (PILLAR et al., 2009).

The most recent data from the agricultural census of the Brazilian Institute of Statistics and Geography (IBGE, 2017) were used to spatialize the information about the areas declared as natural and planted pastures, the main municipal economic activity as livestock (all presented in percentage), and the distribution of cattle heads by area (measured in hectares). Fire management practices in winter were widespread in the study area. It is used for dry biomass removal to provide vegetation regrowth that can be used to feed cattle herds in the spring and summer (PILLAR et al., 2009).

Human Footprint data were added to complement the anthropic factors. This is a quantitative analysis of human influence worldwide (SCOTT, 2003). The human impact was rated on a scale from 0 (minimum) to 100 (maximum) for each terrestrial biome, using human activities such as1) the extent of built environments, 2) population density, 3) electric infrastructure, 4) crop lands, 5) pasture lands, 6) roads, 7) railways, and 8) navigable waterways, based on the methodology developed by Sanderson (2002) and adapted by Venter et. al (2016).

2.5. METHODOLOGY

The thirteen variables and the data corresponding to fire occurrence were submitted to a series of methodological steps and separated into two groups (Fig.03). First, we extracted data from environmental and anthropogenic factors and generated fire density maps in ArcGIS 10.5 software. Second, a historical fire exploratory data analysis and fire scenario predictions for the future were performed using Python. In addition, exploratory data analysis was performed on the sampled set to visualize its distribution, run statistical tests, and identify any anomalies or unusual events. Finally, Pearson's correlation coefficient between the observed values was calculated to assess the correlation between variables.

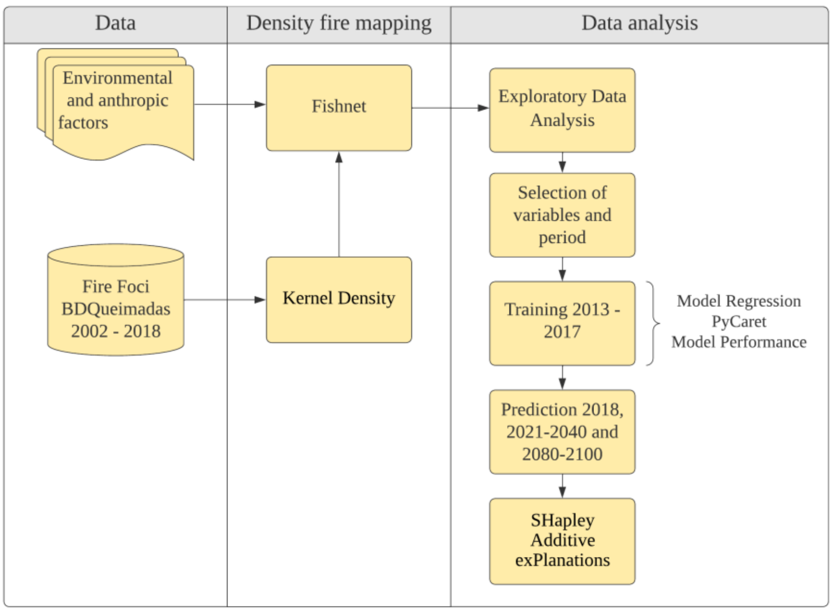


Figure 03: Flowchart of the applied methodology.

2.5.1. Sampling

The samples were gathered by utilizing a fishnet file with a 1km distance for point, covering the entire extent of the AFB in the Rio Grande do Sul state. The mesh of points allowed the extraction of variable values and heat maps generated between 2002 and 2018.

2.5.2. Machine learning algorithms

This study applied several machine learning algorithms to find the most suitable method for estimating fire density in the study area, including the CatBoost Regressor (CBR), Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (EGB), Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), Decision Tree Regressor (DTR), and Extra Trees Regressor (ETR). The algorithms were evaluated using the PyCaret package in Python language (ALI 2020).

ETR was considered the best performing algorithm, is a set learning method based on decision trees and bagging algorithms (GEURTS ERNST; WEHENKEL, 2006). It was developed as an extension of the RF algorithm (Breiman, 2001), and is less likely to overfit the dataset. The main difference between the ETR and RFR algorithms is that the ETR algorithm employs the entire training dataset to train each regression tree. In contrast, the RFR uses a bootstrap replica (Wang et al., 2021).

In this study, the performance of machine learning methods was measured using the mean square error (RMSE), mean absolute percent error (MAPE), coefficient of determination (R^2), and mean absolute error (MAE) scores. When analyzing the distributions of the data obtained, we selected the data collected from 2013 to 2017 for training and testing, whereas 2018 was separated for validation. We introduced a cross-validation ten times to avoid model overfitting, and the random seed was set to 42. The Yellowbrick visualization program was used to illustrate the performance, stability, and predictive power of the model (BENGFORT; BILBRO, 2019).

Given the model's complexity, such as the RF in explaining the predicted value concerning the input variables data (PRASAD; IVERSON; LIAW, 2006), and to assist the interpretation, the SHapley Additive exPlanations (SHAP) package was used (LUNDBERG; LEE, 2017). It aims to explain the estimate of instance x by calculating the contribution of each variable to prediction. This method calculates SHAP values using coalition game theory, in which the values of variables in a data instance function as players in a coalition. The SHAP values provide a method to equally distribute the "payment," which is the forecast among the variables.

3. RESULTS AND DISCUSSION

3.1. SPATIO-TEMPORAL DISTRIBUTION OF FIRE AND ITS CORRELATE VARIABLES

The fire density distribution in the study area was irregular (Fig. 04). An extensive fire density cluster, reaching more than 1,500 fire foci per km² on average per year, was formed in the northeast of Rio Grande do Sul. This area corresponds to grassland within the AFB, mainly in the municipalities of São Francisco de Paula, Bom Jesus, Jaquirana, Cambará do Sul, and São José dos Ausentes.

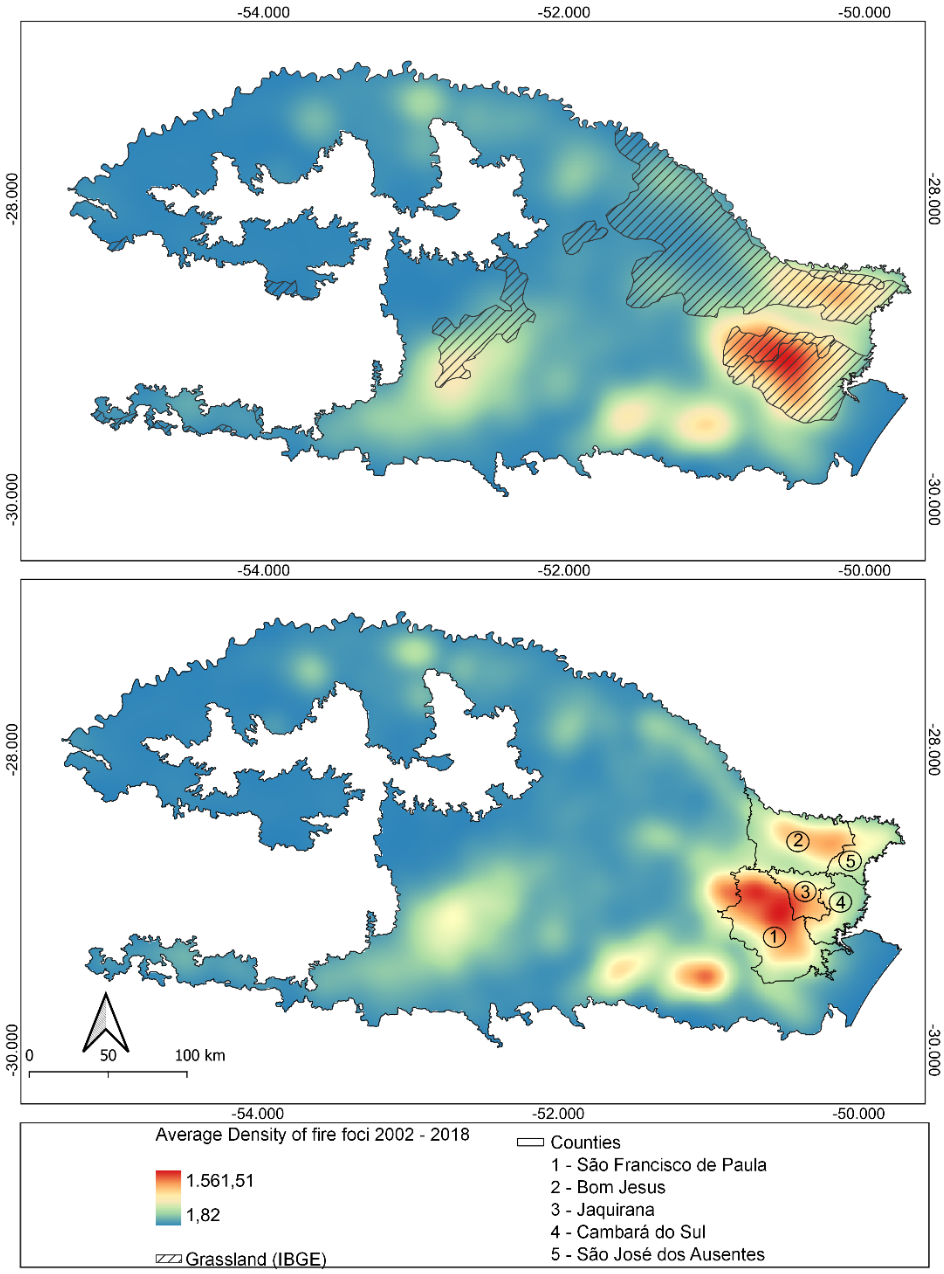


Figure 04 – Average density of fires between 2002 and 2018 in the AFB in Rio Grande do Sul.

The years with the highest values were 2012, 2014, 2016, and 2017 (Fig. 05), coinciding with the release of field burning through municipal licensing (JAQUIRANA, 2013; SÃO FRANCISCO DE PAULA, 2013; CAMBARÁ DO SUL, 2013).

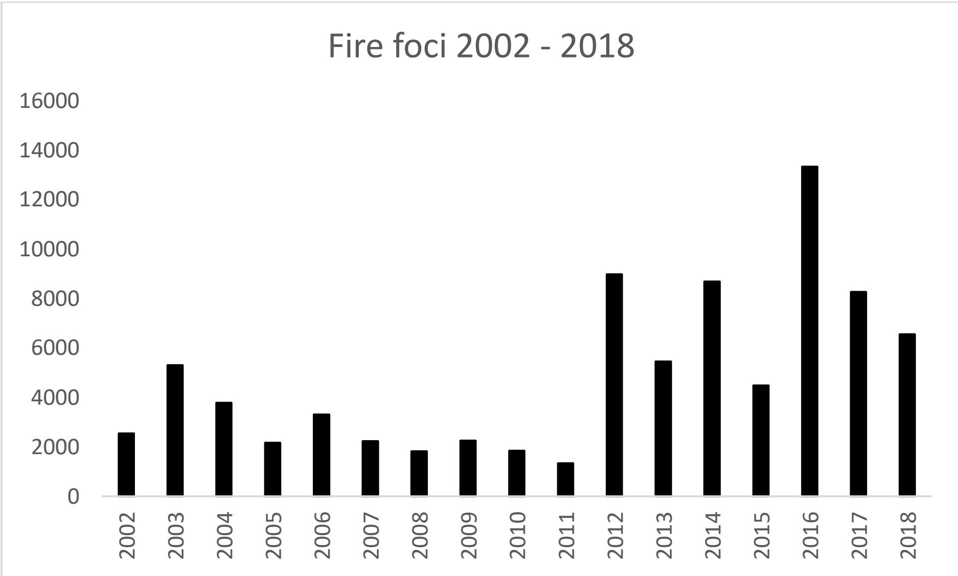


Figure 05 – Distribution of fire foci from 2002 to 2018 in the study area.

To avoid degradation, the field burning practice was restricted by the RS State Law No. 9.519/1992, which established the Forest Code of the RS state. Since the ban on using fire to manage grasslands, traditional livestock farming has been replaced by other practices that are considered more profitable (BUFFON; PRINTES; ANDRADES-FILHO, 2018).

Currently, the use of fire for field management in the RS state is regulated by Law No. 13,931 on January 30, 2012, where fire can only be used for phytosanitary purposes and for pest and disease control in areas that cannot be mechanized. In addition, it requires authorization from the municipal agency, which is responsible for disseminating the norms and criteria for this management. Therefore, municipalities began to regulate fire management practices and create procedures for their licenses in 2012, and the first licenses were issued only between 2014 and 2016.

Figure 6 shows the values for each correlation from -1 (perfect negative correlation) to +1 (perfect positive correlation). Pearson's correlation coefficients showed a linear relationship between variables. The most significant positive correlations with fire were altitude (alt) and pastures (grass), and livestock economic activity (livestock) was positively correlated with them. The ones with the most significant negative correlation were the maximum warm average temperature period (tmax_hot) and minimum warm average temperature period (tmin_hot), which had the strongest negative correlation with altitude (alt).

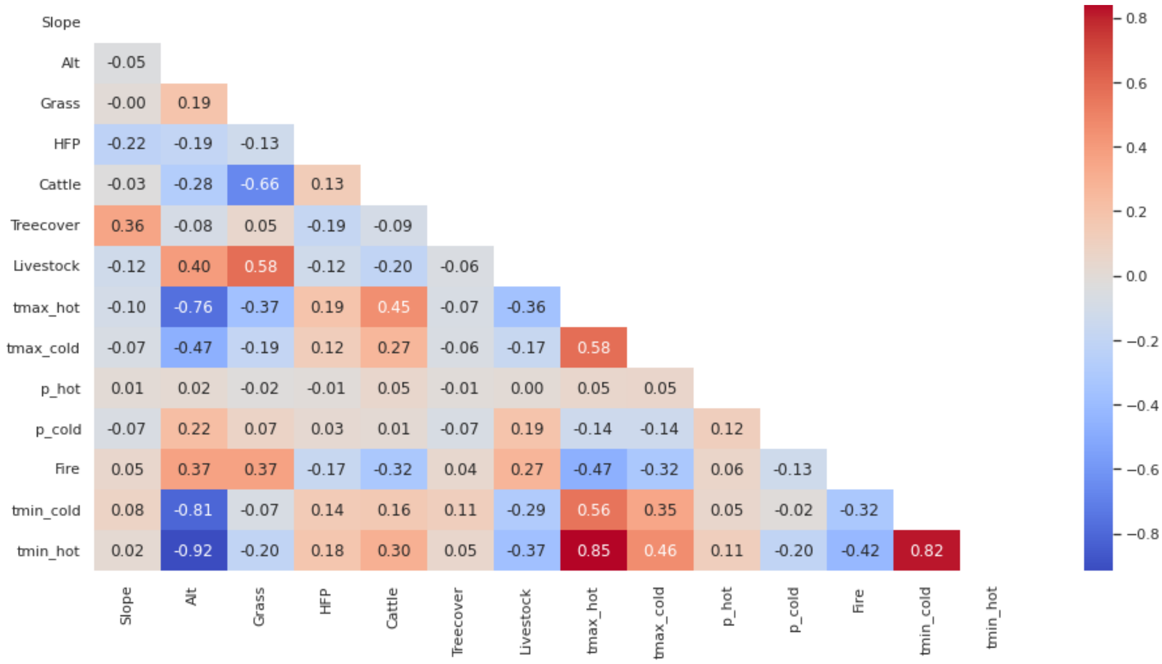


Figure 06 – Pearson correlation between model variables.

Treecover and p_hot showed the lowest correlations among variables. Therefore, it was chosen to eliminate the Treecover variable from the dataset to reduce noise after evaluating the data's distribution, deviations, and variance (Fig. 07).

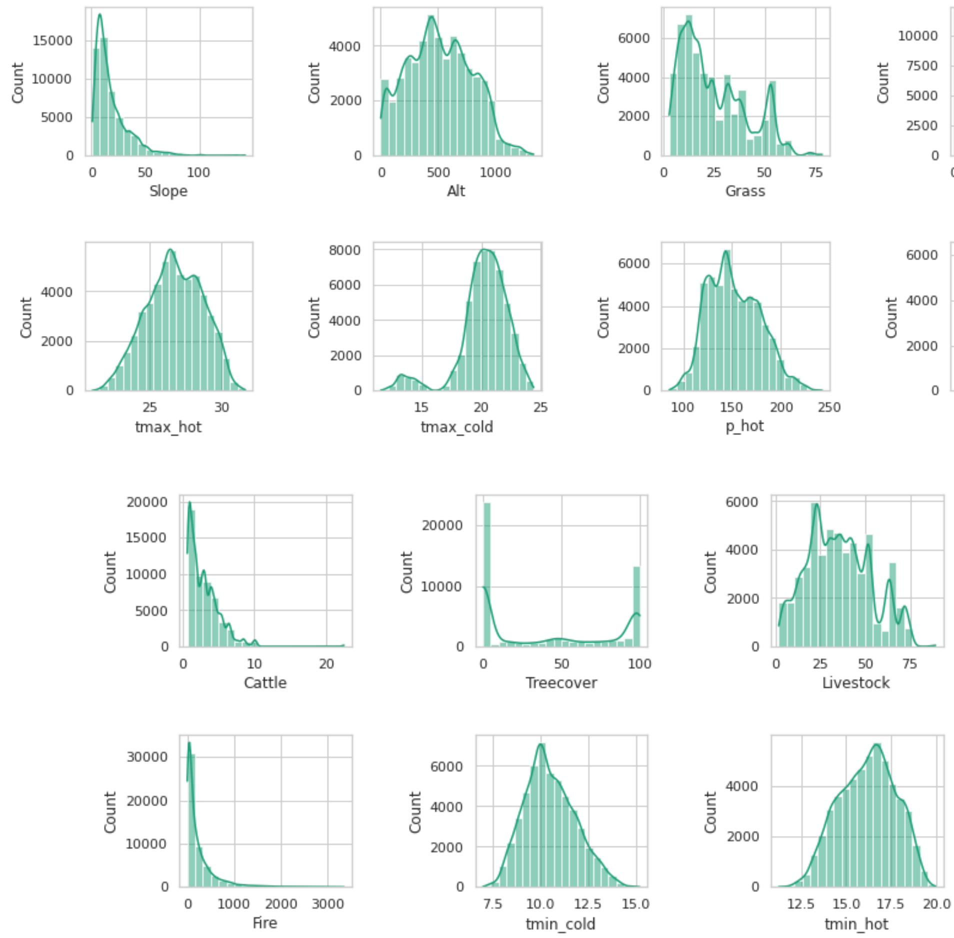


Figure 07 – Distribution of variable values.

3.2. MODELING FIRE

Table 02 shows the results of the model analysis. The values shown are the averages obtained in the cross-validation of the ten test datasets.

Table 02 – Scores obtained for MAE, RMSE and R².

Model	MAE	RMSE	R²
Extra Trees Regressor	43.9591	89.6454	0.9266
CatBoost Returner	53.8822	97.9260	0.9124
Extreme Gradient Boosting	53.6528	99.7324	0.9094
Random Forest Regressor	49.5128	102.1474	0.9048
Light Gradient Boosting Machine	58.2542	105.3286	0.8988
Decision Tree Regressor	63.9392	140.8941	0.8181
Gradient Boosting Regressor	82.3171	147.0536	0.8027
K Neighbors Returning	82.6236	167.3327	0.7443

The ETR algorithm showed the highest R² and lowest RMSE and MAE values, indicating greater prediction accuracy. Finally, the model was built from the twelve variables previously described and presented a training R² of 0.99, whereas the test R² for round 01 was 0.93 (Fig. 08).

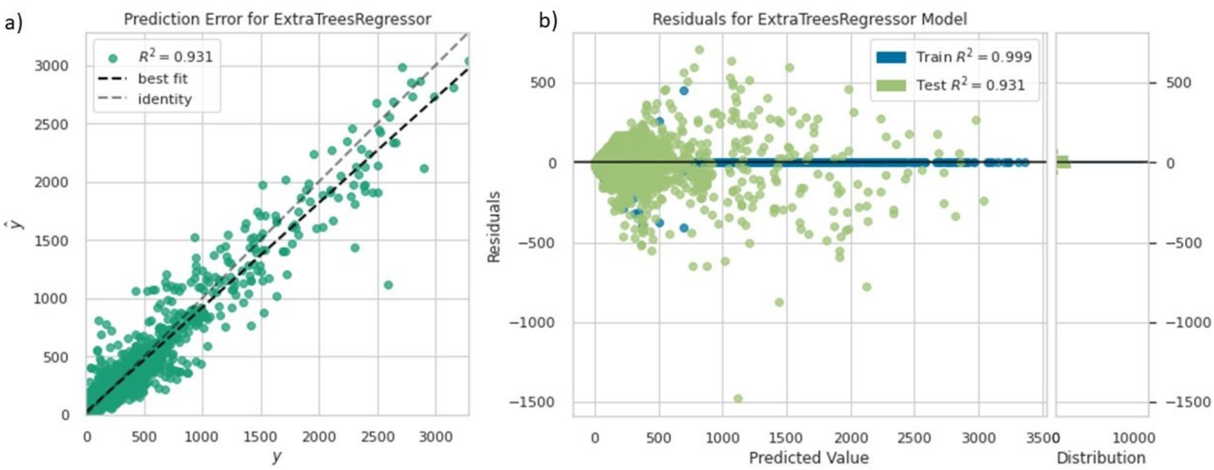


Figure 08 – a) prediction error for the plot model of round 01; b) analysis of the residual plot of round 01.

The importance of the characteristics was calculated as the mean and the standard deviation of the accumulation of impurity decrease within each tree (Fig. 09).

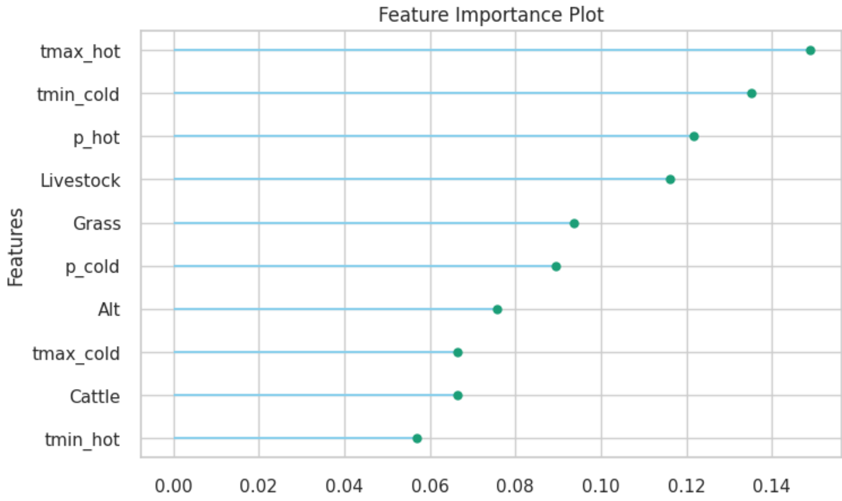


Figure 09 – Importance of variables used in the model.

The essential variable identified by the model was the average maximum temperature in summer and spring (tmax_hot), followed by the average minimum temperature in autumn and winter (tmin_cold) and average precipitation in summer and spring (p_hot). We believe that this is related to the positive influence of spring rain and heat on vegetation growth and the increase in biomass, which serves as fuel throughout the dry season (KEYSER; WESTERLING, 2017). Previous research has demonstrated a significant impact of precipitation on fire foci occurrence (MORENO; ZUAZUA, 2011; OLIVEIRA et al., 2012). According to the authors, precipitation outside the fire foci season was positively correlated with fire frequency.

The anthropic variable with the most significant impact on the model was the economic activity linked to livestock (livestock) and pastures (grass). One explanation for the result is that livestock farming has traditionally been practiced extensively on grassland and using their native vegetation (JAURENA et al., 2021)

Cattle graze most fields in the region, and fire is frequently used as a management tool, particularly in highland areas (ANDRADE et al., 2015). Under moderate intensity or frequency, they are considered vital for maintaining the characteristics of natural systems, as in other production systems of pastures worldwide (LEZAMA et al., 2014).

However, excessive animal load and excessive use of pastures reduce forage and animal performance. Production is based on the forage grace period to fill the fields; therefore, the applied animal load is low, causing underutilization of the produced forage in the growing season. The excessive accumulation of biomass is affected by cold, resulting in the deposition of dry material with a low nutritional value, which is burned at the end of winter (BOLDRINI, 1997).

Their importance in the complete test dataset was computed to compare variables in the ETR. Although the superior characteristic is the same in both methods (the maximum number of concave points in a collection of cells), the second most crucial characteristic analyzed is the maximum value in symmetry instead of the standard deviation in the concave points (Fig. 07).

For the maximum value and concave point number, the standard deviation is correlated, suggesting that the permutation variable importance is less likely to select two main correlated variables. It more accurately reflects the aggregate value of a variable, given the presence of all other possibly correlated variables in the model (LUNDBERG; LEE, 2017).

To visualize the relationship between the variables and the forecast, and the positive or negative impact globally, we assessed the SHAP distribution between the variables (Fig. 10).

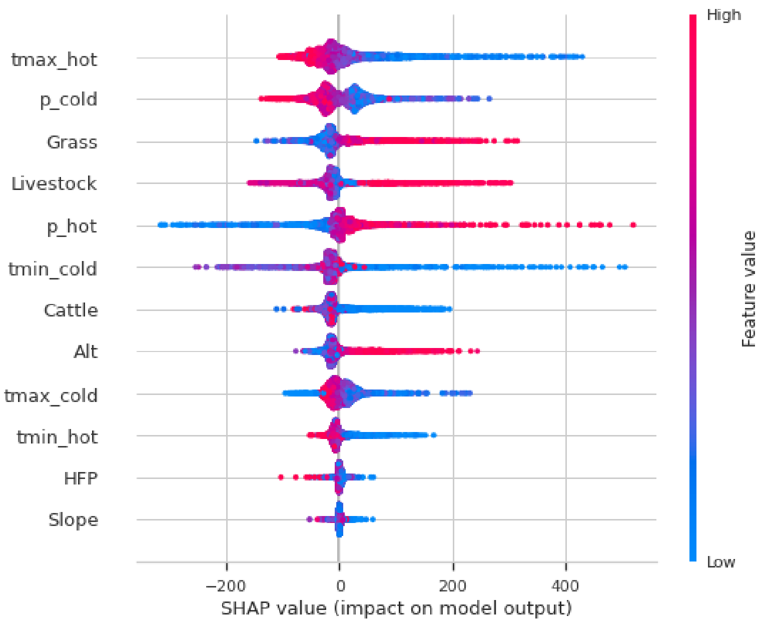
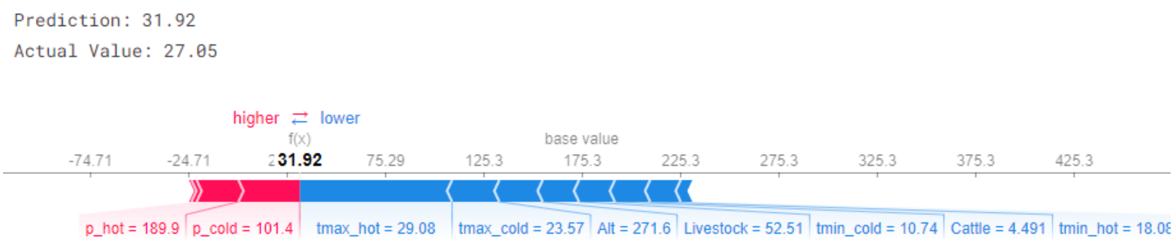


Figure 10 – Impact of variables used in the model.

All the variables used in the model can be found on the y-axis, while their respective SHAP values are shown on the x-axis, and the color scale represents the variable's value from low to high. The overlapping points are skewed in the y-axis direction; therefore, we understand the SHAP value distribution per variable, where the horizontal distribution of points indicates that a given feature contributed to higher or lower predictions along the x-axis. The variables were ordered according to importance (BENGFORT; BILBRO, 2019). Thus, the graph immediately reveals that the lower values (blue) of the variables tmax_hot, tmin_cold, p_cold, and cattle increase the prediction over the mean, whereas the high values (pink) for p_hot, Livestock, Grass, and Alt increase the forecast.

To visualize and understand the contributions of the SHAP value predictor, we produced force graphs with 300 randomly selected samples, as shown in (Fig. 11).

a)



b)

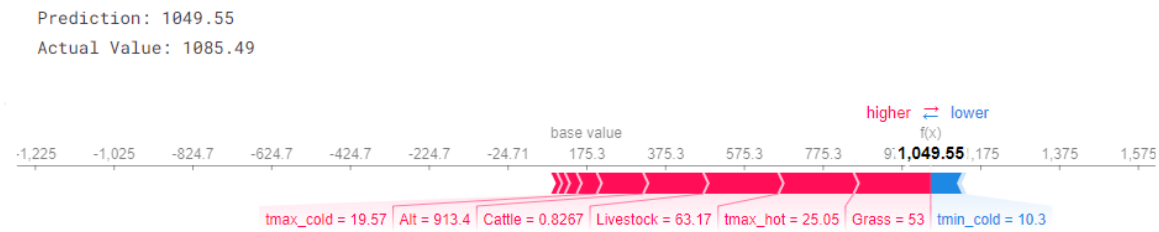


Figure 11 – Plots of individual SHAP values used in the model a) representation of predicted value: 31.92 and actual value: 27.05. b)) representation of predicted value: 1049.55 and actual value: 1085.49.

The output value for sample (a) was 31.92, which was the prediction for this observation. The base value was 175.3, representing the predicted value without considering any variables for the output. The variables that push the forecast to the right, shown in pink, are positive, indicating a higher density of fires. Those that left the forecast, shown in blue, were negative, representing a lower fire density. Tmax_hot has a negative effect on the output. Tmax_hot of this sample is 29.08, which is higher than the mean of 26.75 boosting the prediction to low values, as well as p_cold with positive strength in the sample, with a value of 101.4, which is less than the mean of 132.62 boosting the high value prediction (Table 03).

Therefore, the combination of forces pushes the forecast to the left or right, as in the case of sample (a), indicating a lower probability of fire foci density. In sample (b), the output value is 1049.55. Grass presented positive strength. For values higher than the average, the value is 53 (>24.81), as well as tmax_hot =25.05 (<16 .17), Livestock= 63.17 (<35.56), Cattle = 0.8267 (<2.98), Alt = 913.4 (<517.16), tmax_cold = 19.57 (<20.23) pushed the forecast to the right, which means that these factors contribute to a higher foci density forecast.

Table 03 – Sample means of the variables used in the model.

Variable	**Average**
Treecover	40.68%
Grass	24.81%
tmin_cold	10.49 °C
tmin_hot	16.17°C
tmax_hot	26.75°C
tmax_cold	20.23°C
p_hot	152.13 mm
p_cold	132.62 mm
Alt	517.16 m
Slope	18.02°
HFP	11.17%
Cattle	2.98 one
Livestock	35.56%

3.3. PROBABILITY OF FIRE OCCURRENCE IN FUTURE CLIMATE CHANGE SCENARIOS

Probability maps of fire occurrence density were generated output values for 2018 and two future scenarios: SSP245 and SSP585, considering both the 2021-2040 and 2081-2100 periods (Fig. 12).

A new model was generated for future data considering the annual average provided by the climate data source WorldClim. Thus, the climate variables were average annual maximum temperature, average minimum annual temperature, and average annual precipitation.

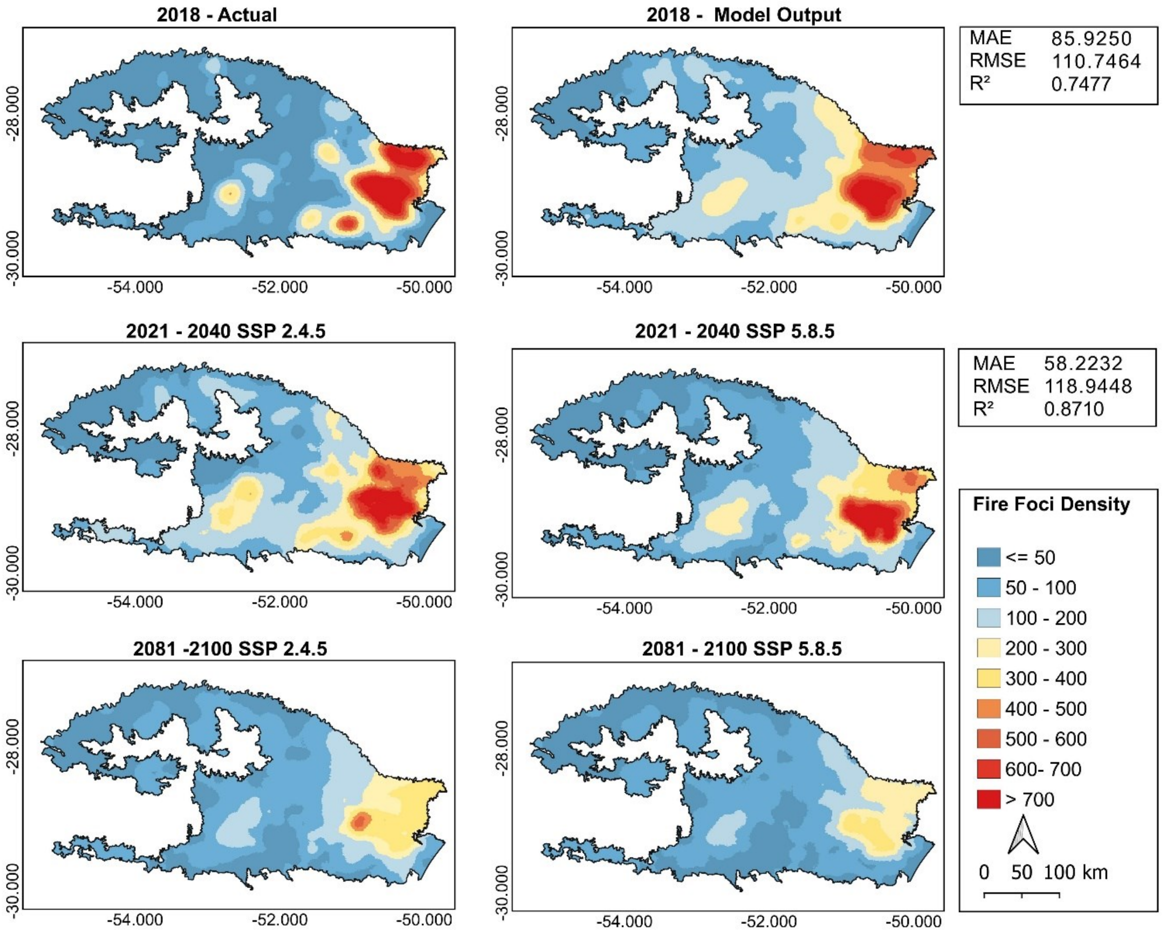


Figure 12 – Probability of fire occurrence in the present and future.

In 2018, the model predicted the region with the highest concentration of fire foci, which corresponded to the municipalities of São Francisco de Paula, Jaquirana, and Bom Jesus, clearly indicating the area with the most conditions of occurrence throughout the year. In 2018, São Francisco de Paula was the municipality with the highest fire foci number, representing 18.7 % of the occurrence within the study area, followed by Bom Jesus with 12.7 % (INPE, 2021). Those municipalities are located where grasslands occur, and the region's cold climate is combined with high rainfall and high altitude (IBGE, 2004). These variables were important in the model's predictions because temperatures lower than average or low rain in the year's coldest months boosted the foci density to high values.

These environmental conditions are related to anthropogenic factors, considering that the economic activity of livestock is related to this type of vegetation, which is regarded as the essential rural activity in the region (BOLDRINI, 1997). The municipalities of São Francisco de Paula, Bom Jesus, Jaquirana, Cambará do Sul, and São José dos Ausentes have livestock as the main agricultural activity of the municipality, representing between 63% and 74% (IBGE, 2017).

Regarding the prediction for the years 2021 to 2040, changes in densities were observed in regions like 2018, with equivalent maximum values but with changes in the areas of occurrence, especially for the SSP 5.8-5 scenario. This result agrees with studies that focused on analyzing the future evolution of average temperatures and precipitation, where issues related to radioactive forcing in different CMIP6 scenarios start to present more distant trajectories in the mid-2040s.(TEBALDI et al., 2021; ZHANG et al., 2022)

However, for the years 2081-2100, we found a decrease in density in all regions under the SSP 5.8-5 scenario. From these results, we can identify at least two paths. First, it is possible to observe that the fires are related to human activities, and as the burning period in the region with the highest density of fires is established in winter, the increase in temperature can cause changes in the dynamics of the biomass (fuel material) that ages, suffers, and dries up owing to the effects of the cold (BOLDRINI, 1997). Analyzing the climate variables introduced in the model, regions with fewer fires have higher average temperatures, which leads the model to predict a reduction in density as the temperature increases. Therefore, future studies should consider both biomass data and the separation of the five most frequent municipalities (fig. 04) for model generation.

Second, with increasing temperatures, another possibility arises: focus densities may be reduced given that the model's input data are based on data obtained by the AQUA, TERRA, and NOAA satellites with a temporal resolution of 1 to 2 days and 1 km spatial resolution (NASA, 2022; NASA, 2022b; NOAA, 2022). With a drier combustible material and favorable climatic conditions, the ignition source can cause a fire of greater magnitude, which will consume a much larger area in a shorter time. The temporal resolution of the data used would not be able to verify new sources of heat because the fire would have already ended, leaving only the fire scar. Therefore, future studies should consider the burned area associated with fire outbreaks for model prediction.

One of the leading global concerns is that climate change will increase the frequency and size of fires because drought periods will become more severe and frequent (CASTELLANOS et al., 2022). A change in fire regimes is expected in highland ecosystems, such as the grassland occurrence in AFB. Although it is difficult to determine the influence of human activities and climate change on fire patterns, fire prevention strategies need to be established (IPCC,2022).

As the degradation of grassland ecosystems in recent decades has been associated with anthropogenic factors and the excessive use of fire and livestock overload in grazing areas (ZHOU et al., 2017), environmental and anthropogenic factors should be further explored. The introduction of integrated management of the use of fire for planning and management that associates ecological, technical, cultural, and socioeconomic aspects and their interactions in the use of fire can be a solution in the search for conservation.

Fire management can be used as an alternative to containing uncontrolled fires, annually burning enough areas to maintain landscape conditions where fire behavior will remain controllable during extreme weather conditions (COCHRANE; BOWMAN, 2021).

Our findings suggest that environmental and anthropic factors influence this distribution, and that there are nonlinear trends; thus, a non-parametric method is considered adequate to model the fire foci occurrence. Previous studies in California also found nonlinear relationships between fire ignition and the independent variables (SYPHARD et al., 2007). In Chile, a study was conducted that used data derived from land cover maps, proving effective in predicting fire occurrence and highlighting the enormous potential to be used to manage the landscape (PAIS et al., 2021).

Considering the large size of the study area, it is reasonable to expect that the same variables operate differently, depending on their geographic characteristics (PRASAD, IVERSON, & LIAW, 2006); thus, traditional parametric methods may not provide satisfactory results.

4. CONCLUSIONS

The results showed that climatic variations altered AFB's predicted fire density values of the AFB. The essential variable identified by the model was the average maximum temperature during the warm period, and the anthropic variable with the most significant impact was the livestock economic activity.

This study evaluated the influence of environmental and anthropic variables on fire occurrence in the AFB in Rio Grande do Sul state, Brazil. In addition, it assessed fire sensitivity with respect to the variation in radiative forcing for past/present and future climate change scenarios. Therefore, the findings help understand the leading spatial distribution of potential causes of fire events across the study area so that decision-makers can adopt management strategies.

Fire management strategies must consider a combination of these variables because there is a tendency to increase the fire density area in the future, which may cause fires of greater magnitude. For future climatic conditions, fire may be altered by rainfall irregularities and an increased dry season; therefore, shorter periods throughout the year can be evaluated in future studies.

Studies that consider environmental and anthropogenic variables should be enhanced for decision making and public policy development because the efficiency of management methods adopted by municipal legislation regarding the use of fire is considered a hot topic and lacks conclusive answers.

Future studies could focus on the variations in predictors at different spatial and temporal scales to assess the variable's explanatory power consistency across the study area. The same method can be applied to other regions with the same types of variables. Once the occurrence and factors are established, the next step is to model the fire severity and recovery of the natural ecosystems.

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3 CONSIDERAÇÕES FINAIS

Esta dissertação teve como enfoque analisar espacial e temporalmente o efeito do uso do fogo em formações campestres do Bioma Mata Atlântica no estado do Rio Grande do Sul, por meio do uso de técnicas de sensoriamento remoto. No **capítulo 1**, foi possível observar o aumento no número de publicações sobre o tema ao longo dos anos, e a tendência no uso de índices espectrais para a análise da severidade de incêndios e da recuperação da vegetação.

Para lidar com o grande conjunto de dados ambientais e antrópicos associados aos 15 anos de densidade de focos de fogo analisados no **capítulo 2**, foram utilizados algoritmos de aprendizado de máquina de regressão para definir a contrição das variáveis como fatores de ocorrência de fogo. Os resultados indicam que as variações climáticas, principalmente a temperatura média nos meses correspondentes ao verão e primavera, e a pecuária são fatores críticos para a distribuição espacial de fogo. A baixa lotação de gado, precipitação média nos meses correspondentes ao verão e primavera, também contribuíram na previsão de altas densidades de focos de fogo.

Com a possibilidade eminente de aumento da temperatura global nos próximos anos, a dinâmica de manejo de formações campestres com o fogo para pecuária e aumento das temperaturas médias precisam ser constantemente avaliados em conjunto, no intuito de conciliar atividades econômicas mais sustentáveis com a busca do equilíbrio climático. Sendo assim, o uso de técnicas de sensoriamento remoto e aprendizado de máquina utilizados neste estudo, podem contribuir para adotar estratégias de manejo de formações campestres e gerenciamento do fogo.

A metodologia proposta para detecção de cicatrizes no **capítulo 3** possibilita a manutenção de um banco de informações auxiliando não apenas a gestão da Unidade de conservação como também o comparativo para dados futuros e análise para criação e aprimoramento de políticas públicas. Foram encontradas divergências na extensão e frequência das áreas queimadas entre o licenciamento municipal autorizado e as áreas classificadas como queimadas. Portanto, o uso da plataforma *Google Earth Engine*, e a combinação de bandas espectrais e cálculo do ΔNBR para diferenciar áreas queimadas e não queimadas, para identificar a dinâmica de cicatrizes de fogo ao longo do tempo pode contribuir com o processo de fiscalização e gerenciamento de grandes áreas, além de auxiliar na priorização de áreas para conservação e redução de impactos negativos.

O Índice de Degradação de Campo aplicado no **capítulo 4**, para campos de altitude dentro do Parque Estadual do Tainhas e sua Zona de Amortecimento apresentam diferença entre áreas manejadas com fogo e áreas de exclusão de manejo. Os resultados apresentados podem embasar novas exigências dos órgãos públicos responsáveis pelo processo de licenciamento ambiental para a região, uma vez que, foram identificados potenciais padrões nas paisagens em relação a sucessibilidade a degradação. Portanto, é importante avaliar os efeitos de exclusão e excesso do uso do fogo nessas áreas para verificar o grau de degradação e promover a conservação desses ecossistemas.

É importante ressaltar que as queimadas em formações campestres podem ter um impacto significativo na qualidade do ar, devido às emissões atmosféricas liberadas durante o processo de queima. Quando a vegetação é queimada, são liberados gases como dióxido de carbono, monóxido de carbono, metano e óxidos de nitrogênio, que são prejudiciais para a saúde humana e contribuem para o aquecimento global. É importante, portanto, que as queimadas sejam conduzidas de maneira controlada e sob condições ambientais favoráveis, estudos futuros podem avaliar as queimadas a fim de minimizar as emissões atmosféricas e proteger a qualidade do ar e da saúde humana.

Por último, é importante ressaltar que é necessário continuar aprimorando os métodos de coleta de dados e explorando novas metodologias para identificar os principais impactos das mudanças induzidas pelo homem, além de garantir a preservação dos campos de altitude e recuperar seus remanescentes. Os resultados e métodos apresentados em cada um dos capítulos desta dissertação estão sendo utilizados pela primeira vez na área de estudo, portanto, é necessário expandir a utilização dessas análises para outros remanescentes de campos de altitude. Para isso, as coletas de dados devem ser continuadas para comparar os resultados relatados neste estudo. Recomenda-se também a realização de experimentos futuros com base em dados adquiridos em outros remanescentes e Unidades de Conservação para aprimorar os métodos e enriquecer os dados existentes sobre este ecossistema.

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