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Machine learning application to assess deforestation and wildfire levels in protected areas with tourism management

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A R T I C L E I N F O

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A B S T R A C T

This study aims to identify the influence of management plans, management boards and tourism management on the relationship between performance indicators in the management of protected areas and degradation processes. To understand these relationships, 283 protected areas (PAs) in Brazil were analyzed. The first stage of the research used classification models based on machine learning algorithms, which revealed that predictive variables were a promising way to assess PAs vulnerability to deforestation and wildfire, giving decision-makers an 87.5% and 72.8% chance, respectively, of correctly identifying the PAs more susceptible to these threats. The predictive variables more relevant to deforestation were biome, area, and tourism management, while for wildfire, governance and PA type were the most relevant. Predictive variables were also a promising way to assess PAs management, giving decision-makers a 79.7% and 78.1% chance, respectively, to correctly identify the PAs with higher levels of effectiveness and governance. In addition, in the second stage, to empirically reinforce the models, multivariate analyses were performed, through which it was possible to confirm that deforestation levels are significantly higher in areas of sustainable use than in fully protected areas and determine how the positive interaction with tourism management contributes to the reduction in deforestation records and improves effectiveness. Therefore, it is understood that tourism management can strongly influence the sustainability of natural resources, and it is of utmost importance to generate tourism management policies with potential value generation for natural spaces.

1. Introduction

Protected areas (PAs) were created with the aim of diminishing anthropogenic impacts on biodiversity and natural resources around the world (Fritz et al., 2022; Mandić, 2021). However, the capacity to conserve original ecosystems and limit the exploitation of natural resources depends on multiple factors, especially in developing countries such as Brazil. The management of different Brazilian PAs commonly shares some similarities, such as inefficient enforcement against wildfires and deforestation, low maturity in public governance, and weak data control regarding possible threats (Naughton-Treves et al., 2005; Chen & Lopez-Carr, 2015; Macedo & Medeiros, 2018; Oliveira Jr., 2021).

According to the International Union for Conservation of Nature (IUCN) classification for PAs, seven categories of PAs are identified in Brazil, divided into two groups: fully protected areas – biological reserves (Ia), ecological stations (Ia), national parks (II), natural monuments (III) and wildlife refuge areas (III) – which can be identified as units that allow only the indirect exploitation of natural resources, having a great limitation regarding the management of economic

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activities; and those of sustainable use – areas of relevant ecological interest (IV), environmental protection areas (V), sustainable development reserves (VI) and extractive reserves (VII) – in which there is less restriction on the use of the land and more flexibility in the exploitation of natural resources for economic activities (Oliveira Jr., 2021; IUCN, 2019). In this context, due to their potential natural and/or cultural value, these spaces have become tourist attractions, which can generate significant positive or negative impacts on their effective management and governance (Kim et al., 2019). Terrestrial PAs, for example, have suffered from degradation processes, either through deforestation or though wildfires (Fritz et al., 2022; Gazoni & Brasileiro, 2021). Knowing this, sustainable tourism, understood as a type of tourism that respects the basic principles of sustainability, has been investigated as a measure of protection against these degradation processes (Acquah et al., 2017; Banerjee, 2012; Imran et al., 2014; Angelevska-Najdeska & Rakicevik, 2012).

It is noteworthy that in recent years, an increase in deforestation and wildfires has been noted in green areas, as well as ecosystem degradation, especially in tropical forests, where there is a significant and complex biodiversity, which requires a greater effort for reforestation (Baccini et al., 2017; Bera, Saha, & Bhattacharjee, 2020; Bera et al., 2022a,b; Câmara et al., 2022; Silva Jr. et al., 2021). In PAs across Brazil, for example, the increase in wildfires was 24.5% between 2019 and 2020 (Brazil, 2020). These data raise national and international concern, as the country has made commitments at global-level environmental agendas in terms of biodiversity and carbon emissions (Loyola, 2014; Mackey et al., 2020; Silva et al., 2023), the non-compliance to which causes damage to climate regimes in other regions and countries (Arraut et al., 2012). In this context, despite being established with the aim of improving the performance of countries in combating these threats, PAs carry natural wealth, generating strong economic interest, meaning they are not exempt from facing these threats (Gazoni & Brasileiro, 2021).

As a way to protect these PAs, management plans consist of a document that compiles a series of strategies and tools for conservation, monitoring, adequate use, spatial organization, and integration of these areas into the social life of the communities that interact with these spaces. The plan brings together a diagnosis of the space, whether in terms of physical, biological, geological, economic or social issues (Brazil, 2000; Pivčević et al., 2021; Mandić, 2021). Thus, the management board, formed based on the criteria established in the plan, is intended to operationalize this document, promoting shared management of PAs, to establish a collaborative, transparent and participatory governance within society (Brazil, 2000; Gazoni & Brasileiro, 2021). Therefore, the effectiveness and governance of these spaces depend on the effective execution of this plan and, centrally, on the disposition of the managing board (Macedo & Medeiros, 2018; Pfaff et al., 2014; Mandić, 2021).

However, on all continents, PAs have a history of implementing top-down processes, which prioritize environmental protection and conservation over the socioeconomic aspirations of local communities (Oliveira Jr., 2021). Such a scenario opens gaps for anthropogenic threats, such as the disorderly installation of economic activities, without an environmental planning, and unsustainable tourism such as mass tourism, without attention to the adequacies of use (Silva et al., 2022; Gazoni & Brasileiro, 2021). However, it is understood that tourist activity brings humans closer to nature, making them understand their role and position in the environment. This approximation through public visitation in a managed way can be reflected in environmental awareness, leading to a significant impact on the management and governance of PAs (Kim et al., 2019). Therefore, it is understood that public visitation to PAs can strongly influence the sustainability of the natural resources present there (Kim et al., 2019).

Moreover, it must be noted that PAs are complex to manage as they may face internal threats (e.g. urbanization and pollution) (Giraldi-Costa et al., 2020) or be affected by external situations (e.g. climate change) (Naughton-Treves et al., 2005). In this context, the multiple uses of these areas and their social, economic, environmental and cultural roles are understood (Kim et al., 2019; Pivčević et al., 2021; Mandić, 2021). Knowing this, Oliveira et al. (2016) highlight the existing differences between these areass that, even though they have a similar final purpose, are categorized differently depending on their object and purpose and follow different policies for their proper use and spatial organization. Along this same path, Silva et al. (2022) construct a socioeconomic indicator of vulnerability and take advantage of this discussion on types to reinforce how influential these categories can be on the level of susceptibility.

Finally, it is stressed that a range of studies (e.g. Pivčević et al., 2021; Mandić, 2021; Roux et al., 2021; Gazoni & Brasileiro, 2021) have worked on the challenges of planning and managing PAs, assessing the role of the management plan and governance in mitigating human threats and improving effectiveness of these spaces. However, there is a lack of studies that evaluate the strong pressures exerted in these spaces due to economic exploitation in the face of the risk of degradation processes such as wildfire and deforestation. Along this path, the study by Gazoni and Brasileiro (2021) evaluates deforestation in the context of Amazon PAs. However, it is also necessary to consider the influence of some control policies to mitigate this process (e.g. management performance indicators), as well as to take into account the different characteristics of these areas, such as tourism use in fully protected and sustainable use units, which have varying levels of vulnerability (Silva et al., 2022). To fill this gap, this study aims to identify the influence of management plans, management boards and tourism management in the relationship between performance indicators in the management of Brazilian protected areas and degradation processes.

As a theoretical contribution, our study shows that socioeconomic factors related to the management of PAs are not dissociated from environmental goods, such as the exploitation of natural resources (Acquah et al., 2017; Kim et al., 2019; Silva et al., 2022, 2023). In other words, manageable tourism can be an ally in the effective management, monitoring, and governance of protected areas (Gazoni & Brasileiro, 2021). Thus, these types of recreational activities can positively contribute to the conservation of PAs. However, management must be flexible depending on the type of protected area, as these PAs have unique specificities (e.g., protected areas with fully limited use and those with a more relaxed regime regarding economic exploitation).

2. Methods

2.1. Study area

In an effort to ensure the preservation of regions with fundamental values for biodiversity, ecosystem services and sustainable development, the numbers of protected areas around the world was increased (IUCN, 2019). Brazil, for example, already has>2,500 PAs (WWF, 2019; ICMBIO, 2021) but still has several limitations regarding the legalization and environmental zoning of these spaces (Macedo & Medeiros, 2018; Oliveira Jr., 2021). In addition, essential data for monitoring these areas are missing, such as a survey of socioeconomic indicators, visits made, management plans and management boards. Currently, of this total of PAs, 334 were instituted and are governed by the federal government. Therefore, this study is restricted to PAs at the federal level since there is more information available about the variables used in this analysis.

Of this total, 51 PAs were excluded, which were, concomitantly, omitted from the records of wildfire areas, deforestation and managed visits (16.2%), totalling 283 PAs (Fig. 1) in the sample analyzed – this being a high, representative number at continental scale. Regarding the group and categories of these areas, 47% are fully protected (FP), while the rest (53%) are of sustainable use (SUS). The most representative categories were parks (25%), national forests (22.3%) and extractive reserves (19.4%). In addition, the main biomes found were the Amazon (43.5%), Atlantic Forest (26.1%) and Cerrado (15.9%).

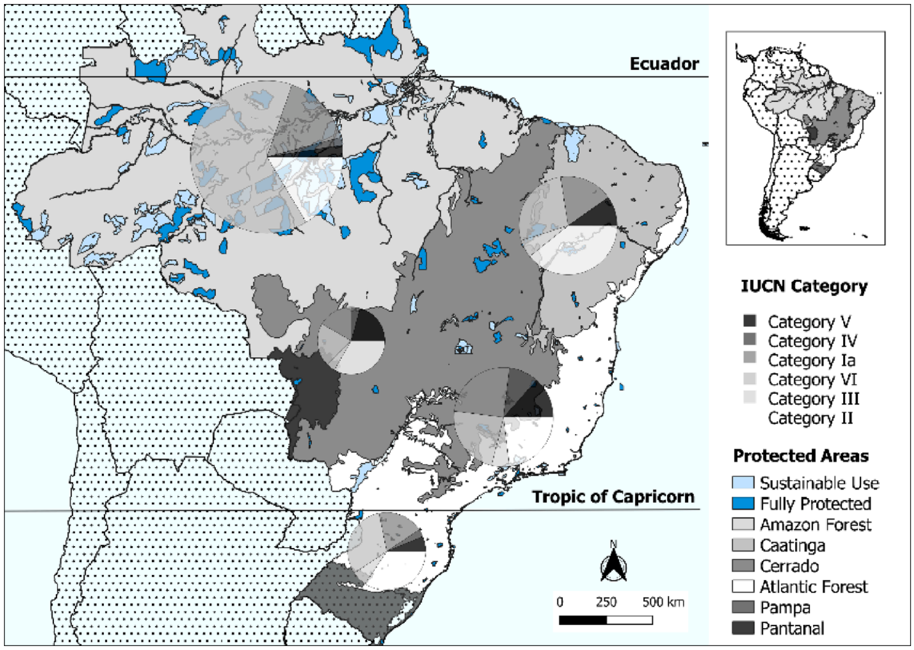

Fig. 1. Analyzed federal protected areas of Brazil, biomes and IUCN categories.

2.2. Data organization

Consistent with the objective of this article, this research has a quantitative nature and is characterized as an exploratory study. Furthermore, regarding research strategies, this is a survey based on secondary data, in which the secondary information was compiled from the public institutions listed below: 1) Chico Mendes Institute for Biodiversity Conservation (ICMBIO, 2020), a database gathers the PAs' basic information; 2) General Coordination of Land Observation (PRODES, 2020), which brings a survey of the deforestation picture in the PAs; and 3) the Brazilian Government Portal (Brazil, 2020), in which it is possible to access the PAs' other information, such as visits, indicators and general characteristics of these spaces.

To compile the database, the 283 PAs were selected based on the existence of at least one of the following pieces of information (Table 1): deforestation levels in the 10-year interval (2011 to 2020); monitoring of wildfire areas from 2011 to 2020; total public visits (free or managed) between the years 2018 and 2020; indicator of effectiveness in the management of PAs, for the years 2017 to 2020, and indicator of governance of processes in the PAs (2017–2020).

Table 1
Analysis variables in the research.

Variables	Description
Management plan	Binary variable considering the existence or absence of a management plan
Management board	Binary variable considering the existence or absence of a management board
Tourism management	Mixed variable composed of a quantitative and a qualitative variable. Quantitative variable: Number of visitors in the PAs; qualitative variable: presence or absence of visitation control
Effectiveness index	Continuous variable gathering data from indicators of context, outcomes and services, outputs, planning, inputs and processes
Governance index	Quantitative discrete variable formed by the average grade given to the priority processes and management actions
Area	Estimated area of PAs measured in km^2
Biome	The biomes considered here are Amazonia, Caatinga, Cerrado, Marine-coastal, Atlantic Forest, Pampas and Pantanal
Type of PA	Group of PA: sustainable use or fully protected.
Deforestation	Deforestation level in a 10-year interval
Wildfire areas	Estimation of the wildfire areas registered in a 10-year interval

2.3. Data analysis

The data analysis was divided into two stages. The first stage (Fig. 2A) aimed to measure the possibility of predicting the variables management plan, management board, tourism management and management performance indicators on the levels of deforestation and wildfires, as well as the first three variable (Fig. 2B) predictors cited on the effectiveness and governance indices. To this end, experiments were conducted with machine learning models using RStudio, selecting the following algorithms, which had the best performance in the analysis of relationships: model based on decision trees and support vector machine analysis (SVM).

In this context, the use of machine learning adopts a new approach in which, from the automation of algorithms, it is possible to learn from the input data and make predictions in a cognitive way (Guégan & Hassani, 2018; Jordan & Mitchell, 2015). Unlike traditional mathematical

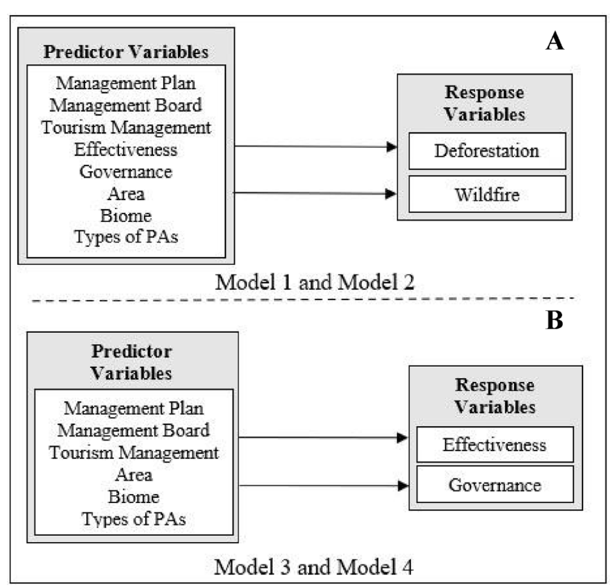

Fig. 2. Proposed classification models. A. model 1 and 2; B. model 3 and 4.

models, this new approach can contribute to advances in this field, since it does not necessarily need to know the relationships between input and output variables (Aniceto, 2016). Therefore, it is essential for the adoption of public policies, since, having only predictor information in hand, it is possible to spatially identify the PAs most threatened by degradation processes and mobilize efforts to improve performance indicators.

Machine learning-based approaches have become increasingly common in research to map and measure likelihood in environmental studies (Saha et a., 2022; 2023; Doyle et al., 2021). This type of approach has some advantages over traditional parametric models, as it has a higher accuracy regarding data representation, one can work with a huge volume and complexity of data, mainly non-linear, high dimensionality and with complicated interaction with missing values (Manoj et al., 2013; Dlamini, 2016). In this regard, the use of machine learning has been recurrent in hazard prediction and risk assessment studies, such as forest fire incidence and deforestation, since its higher accuracy can avoid the cases of false negatives more reliably (Doyle et al., 2021; Saha et a., 2022; 2023).

To categorize the response variables, deforestation and wildfires, the data were divided based on median into two groups, one with low and one with high frequency in these indices. In governance, we considered the score given (1 to 5) for each of the priority processes and then took the final average, dividing the sample into two groups: high and low governance. Similarly, the grades attributed to effectiveness were divided into two groups: high and low effectiveness. The categorization aimed to achieve homogeneity among groups in an attempt to reduce the large difference between them and improve model accuracy, as there were examples of a single group that encompassed 20% of the sample and a smaller group that only accumulated 0.3% of the data.

As there were missing data related to the management plan and management board in two areas, and effectiveness and governance in six, the final sample for the machine learning analyses totalled 278 PAs. In the analysis, the data were segmented into training and testing stages, in a proportion of 83 PAs (30%) for testing and 195 PAs (70%) for training. Finally, to evaluate the performance of the machine learning methods analyzed in this study, the following measures of classifier evaluation were used: accuracy, specificity, sensitivity and area under the receiver operating characteristic (ROC) Curve (AUC). In this context, the proposed models were as follows (Fig. 2):

In the construction of models 1 and 2, the following equation was adopted for the response variables:

$$V = \beta_0 + \beta_1.MP + \beta_2.MB + \beta_3.T + \beta_4.E + \beta_5.G + \beta_6.A + \beta_7.B + \beta_8.TP$$

where:
V = Deforestation or wildfire areas;
MP = Management plan;
MB = Management board;
T = Tourism management;
E = Effectiveness index;
G = Governance index;
A = Area;
B = Biome;
TP = Type of PA.

The following equation was used for models 3 and 4:

$$V = \beta_0 + \beta_1.MP + \beta_2.MB + \beta_3.T + \beta_4.A + \beta_5.B + \beta_6.TP$$

In the second stage of the research, the idea was to empirically reinforce the results of the machine learning models. Thus, the contrast between PA types in relation to levels of deforestation and wildfire and the interaction of these variables with tourism management were examined. Thus, a series of two-way analyses of variance (ANOVAs) were employed. In addition, post-hoc tests were performed to analyze the differences in variance between the proposed groups. Finally, homoscedasticity, correlation and outlier tests were performed. Furthermore, the data were analyzed using the SPSS® software, and the models analyzed were as follows (Fig. 3):

3. Results

3.1. Modelling

From the results, one can see that the different classification models (Fig. 4) generate varied performances. In this study, for each response variable (Table 2), the model with the best performance was chosen between the two samples, training and test, and then the importance analysis was performed for each predictor. As measured, the best-performing model in terms of accuracy was the SVM, which had a prediction ability of 88.4% in the deforestation sample observations and 73.6% in governance, while in the prediction of wildfire areas and effectiveness, the best model was the decision tree, which was able to correctly classify 81.9% and 74.4% of the samples studied, respectively. Regarding the sensitivity measures, it can be seen that all the selected classification models had values>70%, indicating that the models are successful in detecting the true positive values (Luo et al., 2018). For example, based on this measure, the decision-maker can identify the effectiveness of the test to detect PAs with high levels of wildfire and deforestation. Regarding specificity, which allows estimating the probability of less vulnerable PAs being correctly discarded from emergency actions to prevent of these threats (Luo et al., 2018), satisfactory results were obtained again, all above 65%. The AUC results were also significant, showing model adequacy, since the model evaluates the relationship between the specificity and sensitivity indices (Fig. 4), that is, confronting false positives (e.g., incorrectly indicating high levels of wildfire or deforestation) with true positives (Rodrigues et al., 2021).

Thus, from this index, one can establish comparisons between the best models (Fig. 4), arranged in the graph of the ROC curve, which serves as a measure of accuracy, indicating that those models above the diagonal line are valid for overcoming randomness in the classification, having good predictive ability. Finally, in Table 3, the degree of participation of each predictor variable in the model is shown, where it can be seen that the area had a primary role in predicting wildfire areas and effectiveness, while deforestation and governance were significant in the biome and in tourism management, respectively. It is noteworthy that tourism has a degree of importance in all models.

Below is also a vulnerability map (Fig. 5) of the PAs analysed in this study regarding the four proposed models: deforestation, wildfire areas, effectiveness and governance.

3.2. Types of PAs and two-way ANOVAs

The results of the Student's *t*-test for comparison of means for independent samples showed a disparity between the groups analyzed, since the PAs of the sustainable use type (SUS) (n = 150) significantly exceeded the average of the fully protected type (FP) (n = 133) regarding the level of deforestation ($PA_{SUS} = 2.50$, $PA_{FP} = 1.44$; t(281)

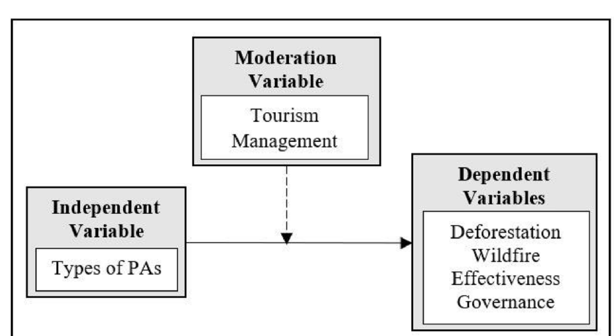

Fig. 3. Proposed conceptual model.

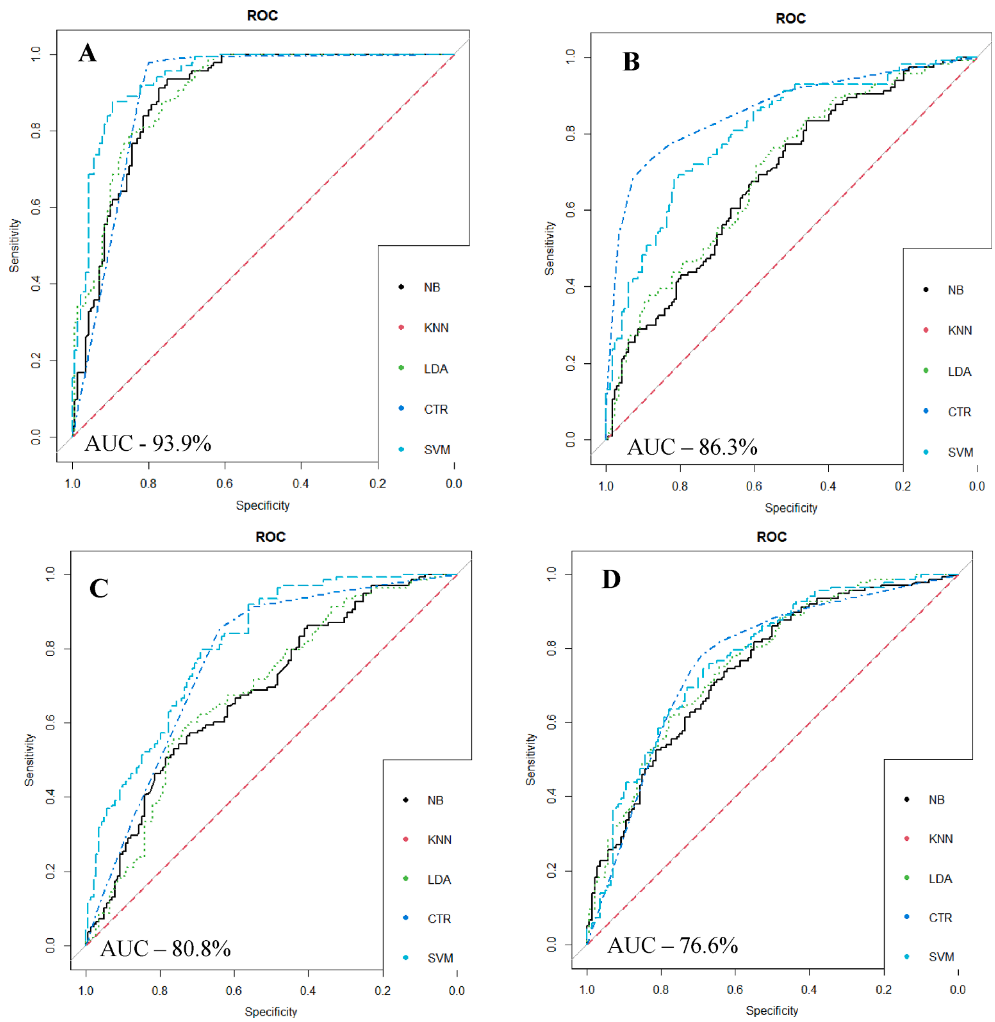

Fig. 4. ROC curve with the analyzed classification models. A. Deforestation; B. Wildfire; C. Effectiveness; D. Governance. Classification models: NB = naïve Bayes; KNN = k-nearest neighbour; LDA = linear discriminant analysis; CTR = classification tree model; SVM = support vector analysis.

Table 2
Adopted classification models and indices of the evaluation measures.

Evaluation measures	Response Variables			
	Deforestation	Wildfire	Effectiveness	Governance
	SVM (%)	tree (%)	SVM (%)	tree (%)
AUC	93.9	86.3	80.8	76.6
Accuracy	88.4	81.9	74.4	73.6
Sensitivity	87.5	72.8	79.7	78.1
Specificity	89.3	88.3	69.1	69.3

= –5.281, $p < 0.05$) and effectiveness indicator ($PA_{SUS} = 4.15$, $PA_{FP} = 2.73$; $t(269) = –24.403$, $p < 0.05$). However, the first group had a significantly lower mean regarding the wildfire areas ($PA_{SUS} = 1$, $PA_{FP} = 2.03$; $t(243) = 4.507$, $p < 0.05$) and level of governance ($PA_{SUS} = 3.24$, PAFP = 3.48; $t(269) = 2.356$, $p < 0.05$).

Further tests were performed with the purpose of identifying new comparison and differentiation relationships between the SUS and FP groups, this time adding the tourism management variable in order to identify whether local tourist attractions, evidenced by the numbers of public visits in a managed way, bring any interaction effect with deforestation, wildfire areas, effectiveness and governance. For this, the results of the two-way ANOVA were used, identifying a significant effect of the SUS group (M = 2.50, SD = 1.69) to the detriment of the FP group (M = 1.44, SD = 1.67) on the levels of deforestation. Additionally, the main effect of tourism management ($F(1, 279) = 54.241$, $p < 0.05$), as well as the interaction of both ($F(1, 279) = 5.303$, $p < 0.05$), was recorded. However, in wildfire areas, the role was reversed. That is, although there was a significant effect on PAs_{FP} (M = 2.03, SD = 2.14) compared to PA_{SUS} (M = 1, SD = 1.61) regarding wildfire outbreak rates ($F(1, 279) = 20.809$, $p < 0.05$), regarding the main effect of tourism management, there was no significance ($F(1,279) = 1.681$, $p > 0.05$), as there was also no interaction between the two categorical variables (F(1,

Table 3
Indication of the degree of importance of the predictor variables over the predicted one in the four proposed classification models.

Predictor variables	Degree of importance			
	Deforestation	Wildfire areas	Effectiveness	Governance
Area	67.6	39.9	26.6	11.1
Biome	76.3	12.9	9.8	8.1
Effectiveness	2.2	15.8	–	–
Governance	9.8	21.1	–	–
Management board	0.9	14.2	8.6	14.4
Management plan	1.0	1.4	8.8	19.7
Tourism management	42.1	10.6	24.1	23.2
Types of PAs	15.3	17.3	6.0	5.2

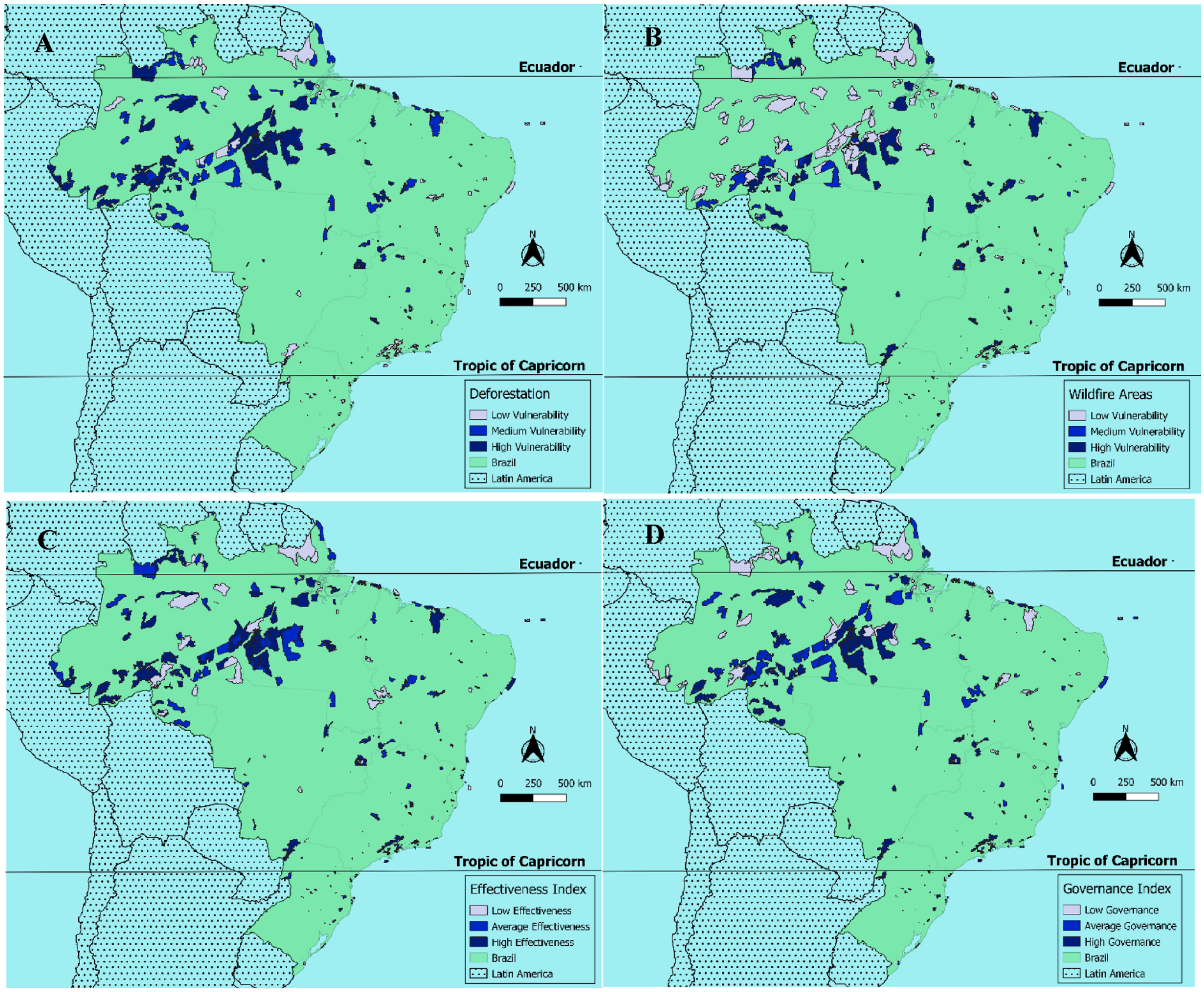

Fig. 5. Vulnerability maps of classification models. A. Deforestation; B. Wildfire Areas; C. Effectiveness Index; D. Governance Index.

279) = 0.324, $p > 0.05$).

Regarding the interaction between tourism management and the other dependent variables, the SUS PAs group was significantly ahead in terms of effectiveness ($PA_{FP} = 2.71$, $PA_{SUS} = 3.96$; $F(1, 279) = 4.895$, $p < 0.05$), while the opposite occurred with governance ($PA_{FP} = 3.47$, $PA_{SUS} = 3.15$; $F(1, 279) = 15.215$, $p > 0.05$). In the interaction of both categories, significance was registered in effectiveness ($F(1, 279) = 6.224$, $p < 0.05$), while there was no significance in governance (F(1, 279) = 0.3, $p > 0.05$).

Overall, the results of the ANOVA (Fig. 6) revealed that the different types of PAs have significantly different levels of deforestation, with the SUS types usually being more vulnerable. Along those same lines, effectiveness was also significant for these types of PAs, with the SUS having the best average performance in the indicator. Furthermore, it is also noted that tourism management acts in a moderate way in both relations, contributing to the reduction in deforestation records in

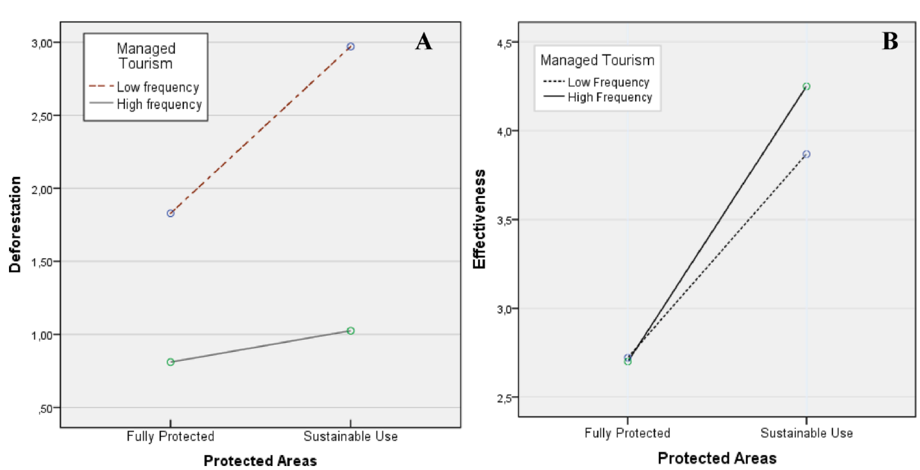

Fig. 6. Types of PAs by management tourism: A. Deforestation; B. Effectiveness.

protected areas and improving the performance in the effectiveness indices.

Continuing the analyses, after confirming the interaction of tourism management with the types of PAs, levels of deforestation and effectiveness, the post-hoc test was performed to verify in which groups the differences in variance were significant. Therefore, a Šidák test revealed that when there is a lower frequency of visits (tourism management), the levels of deforestation are significantly higher in the PAs of the sustainable use type (PA_{SUS} – M = 2.97, SD = 0.144; PA_{FP} – M = 1.83, SD = 0.169), whereas, when there is a high frequency of visits, the difference between the types of PAs is not significant. Based on these data, one can interpret that the management of tourism in these spaces tends to contribute to the reduction in the indices of this degradation process but does not reveal the same association with wildfires.

In this sense, regarding effectiveness, it is understood that when there is a high frequency of tourist flow in a managed way, this indicator is significantly higher in the PAs of the SUS type (PA_{SUS} – M = 4.25, SD = 0.103; PA_{FP} – M = 2.7, SD = 0.88). In the low seasons of tourism management, there was no significant difference between the PAs.

3.3. Summary of the results

In this study, the data were analyzed empirically and explored through two techniques, a more contemporary one using machine learning which aimed to analyze the relationship of all predictor variables on the response variable, and another which focused on traditional statistics, using ANOVA, to verify the differences between the types of PAs. Thus, the classification models revealed (Table 4) that the management plan, management board, high frequency of managed visits, performance indicators, area and classification differences of the PAs had a positive influence on the levels of deforestation and wildfire areas. Additionally, these same variables play a significant role in predicting governance and effectiveness. Thus, with a good measure of prediction fraction and a high chance of true positive hits, the models prove to be promising for evaluating PAs, regarding their vulnerability in facing these threats, once the model's predictor variables achieve a high chance of classification success.

Furthermore, in order to reinforce the results of the machine learning models, as well as accentuate the differences between the types of PAs and verify the interaction of tourism management, it was noticed (Table 3) that the levels of deforestation are significantly higher in areas of sustainable use to the detriment of those of fully protected. However, the moderation of tourism management contributes to the reduction in deforestation. Similarly, it was perceived that this also acts in moderating effectiveness, improving such indices when the tourist flow in the region is greater.

4. Discussion

This study shows that threats such as deforestation and wildfires can compromise productive capacity and sustainable policies in the long term (Câmara et al., 2022; Gazoni & Brasileiro, 2021; Pfaff et al., 2014; Pivčević, Mikulić, & Krešić, 2021). The patterns of answers found in the constructs confirm other studies regarding the management of PAs (Gazoni & Brasileiro, 2021; Banerjee, 2012; Imran et al., 2014), which highlights how tourism management is important in the fight against these degradation processes. However, our study advances by demonstrating how some control policies to mitigate this process (indicators of governability and effectiveness in the management of PAs) are necessary tools, especially in predicting the model of wildfires (see Table 4). Furthermore, unlike other studies, we also highlight the contrast between different types of PAs, such as tourist use in fully protected and sustainably used areas, which present varying levels of vulnerability (Silva et al., 2022).

In Fully Protected PAs, there are a series of restrictions or prohibitions regarding economic exploitation, often limiting the livelihood and culture of local populations, whose economy is usually linked to subsistence and focused on sustainability (Oliveira Jr., 2021; IUNC, 2019), and in these cases, there are more permissive policies regarding resource extraction or human settlements (Jusys, 2018). Therefore, since human presence tied to the exploitation of natural resources

Table 4
Summary of the main findings of the research.

N°	Propositions	Results	Conclusions
1	The existence of a management plan associated with a management board, tourism, management performance indicators, area, biome and PA type influences the reduction in deforestation registers.	AUC = 93.9% Accuracy = 88.4% Sensitivity = 87.5% Specificity = 89.3%	The predictive variables showed a promising way to assess PAs' vulnerability to deforestation and wildfire, giving the decision-maker an 87.5% and 72.8% chance, respectively, to correctly identify the PAs more susceptible to these threats. The predictive variables more relevant to deforestation were biome, area and tourism management, while for wildfire areas, governance and PA type were the most relevant.
2	The existence of a management plan associated with a management board, tourism, management performance indicators, area, biome and PA type influences the reduction in wildfire areas registers.	AUC = 86.3% Accuracy = 81.9% Sensitivity = 72.8% Specificity = 88.3%	
3	The existence of a management plan associated with a management board, tourism, area, biome and PA type influences the improvement of effectiveness indicators.	AUC = 80.8% Accuracy = 74.4% Sensitivity = 79.7% Specificity = 69.1%	The predictive variables showed a promising way to assess PAs' management, giving the decision-maker a 79.7% and 78.1% chance to correctly identify the PAs with higher levels of effectiveness and governance. The predictive variables more relevant to effectiveness were area, tourism management and biome, while for governance tourism management, management plan and management board were the most relevant.
4	The existence of a management plan associated with a management board, tourism, area, biome and PA type influences the improvement of governance indicators.	AUC = 76.6% Accuracy = 73.6% Sensitivity = 78.1% Specificity = 69.3%	
5	Deforestation level is influenced by the type of PA, which also depends on tourism management in these PAs.	Effect of tourism ($p < 0.05$) Interaction of both ($p < 0.05$)	Different types of PA have significantly different levels of deforestation, with SUS type being the most vulnerable. It is worth noting that SUS type relies on tourism management, which contributes to deforestation reduction.
6	Wildfire areas levels are influenced by the type of PA and also by tourism management in these PAs.	Effect of tourism ($p > 0.05$) Interaction of both ($p > 0.05$)	Wildfire areas levels are not influenced by the type of PA nor by tourism level.
7	Effectiveness level is influenced by the type of PA, which also depends on tourism management in these PAs.	Effect of tourism ($p < 0.05$) Interaction of both ($p < 0.05$)	Different types of PA have significantly different levels of management performance, with SUS type being the most effective. It is worth noting that SUS type relies on tourism management, which contributes to improvement of the performance indicator.
8	Governance level is influenced by the type of PA and also by tourism management in these PAs.	Effect of tourism ($p > 0.05$) Interaction of both ($p > 0.05$)	Governance is not influenced by the type of PA nor by visiting level.

generates risks to the conservation of these spaces, several studies (e.g. Gamarra et al., 2019; Lambi et al., 2012; Pfaff et al., 2014) have related the occupation of these PAs to economic activities as sources that undervalue their natural potential.

The central idea is that production in these spaces is economically viable, meeting the strictest sustainability and licensing standards (Schiavetti et al., 2013). However, knowing that there is less restriction on the types of developments licensed in these types of PAs (e.g., hotels, roads, urbanization), there is a potentially greater concern in developing countries. This is because these countries are limited to viewing the management objectives codified in documents such as the management plan, as well as because political instability and weaknesses in enforcement create facilitating mechanisms for corruption in environmental permitting procedures (Gamarra et al., 2019; Naughton-Treves et al., 2005; Chen & Lopez-Carr, 2015; Macedo & Medeiros, 2018).

It is understood that degradation processes such as deforestation and wildfires have significant negative impacts on PAs in Brazil and around the world. These impacts affect both biodiversity and local communities and can have long-term consequences for the integrity of these protected areas. Deforestation, for example, can lead to habitat fragmentation, increasing the vulnerability of species to external factors such as predatory hunting and animal trafficking (Escobar, 2019; Fritz et al., 2022). Additionally, deforestation can also affect the hydrological regime, compromising water availability for local communities and affecting soil quality (Mulligan et al., 2020; Springgay et al., 2019). Wildfires are also a significant problem in Brazilian PAs. In addition to causing animal deaths and habitat loss, wildfires contribute to greenhouse gas emissions, exacerbating climate change (Bera et al., 2022a; Escobar, 2019; Mega, 2020; Saha et al., 2023; Silva et al., 2023). Furthermore, wildfires can endanger local communities, affecting respiratory health and food security (Escobar, 2019; Mega, 2020; Silva et al., 2021; Weilnhammer et al., 2021). Another problem resulting from degradation processes is the loss of ecosystem services. PAs provide various ecosystem services, such as climate regulation, protection against natural disasters, and pollination, among others (Banerjee, 2012; Chen & Lopez-Carr, 2015; Oliveira Jr. et al., 2016). Deforestation and wildfires can negatively affect the ability of PAs to provide these services, compromising the quality of life of local communities and affecting regional economies.

Therefore, it is essential to take measures to mitigate the effects of deforestation and wildfires in Brazilian PAs. This can be done through the adoption of effective public policies for control and surveillance, as well as investments in environmental education and awareness of the importance of biodiversity conservation (Oliveira Jr. et al., 2016, 2021). Sustainable tourism management can also be an important tool to help preserve PAs and promote sustainable development of local communities (Acquah et al., 2017; Banerjee, 2012).

There are real examples of how the creation and strengthening of these PAs have redefined tourism management in the region, resulting in a reduction in forest fires and deforestation. In Brazil, for instance, the ICMBIO (2023) collects data and management effectiveness indicators for PAs in the country, and through the data, one can observe the progress in units such as the Chapada dos Veadeiros National Park, located in the state of Goiás, is considered one of the most important conservation areas in Brazil. Similarly, the Uatumã Biological Reserve, located in the state of Amazonas, and the Serra da Canastra National Park, located in the state of Minas Gerais, are all examples of PAs where deforestation and wildfires have significantly decreased since their creation and visiting activities.

Given these considerations and the fact that deforestation levels are significantly higher in SUS-type areas, it is of paramount importance to generate policies with potential value generation for these spaces. For example, one can highlight the role of managed visits, since PAs are attractive both for their tangible (vegetation and nature) and intangible (natural beauty, climate and cultural values) values. In addition, sustainably managed tourism has proved to be significant in interacting with deforestation in PAs, registering lower levels, especially when there is a high frequency of visits. Tourism management is attractive since the tourism potential of these areas is tied to their conservation and the maintenance of a quality environment (Angelevska-Najdeska & Rakicevik, 2012).

In this sense, tourism management can help reduce this degradation process, as sustainable tourism can be a source of income for local communities and encourage biodiversity conservation (Acquah et al., 2017; Banerjee, 2012). Additionally, tourism can be a tool for raising public awareness about the importance of conserving protected areas (Gazoni & Brasileiro, 2021).

For tourism to be an effective conservation tool, it is necessary for tourism activities to be planned and managed responsibly, taking into account the socio-environmental impacts. It is important to establish visitation limits and promote environmental education activities for visitors (Gazoni & Brasileiro, 2021). Moreover, tourism should be viewed as a complementary activity to conservation efforts, and not as an activity that could compromise the integrity of protected areas.

The inverse situation was revealed for wildfires, in which the PAs of the FP type had the worst performance regarding the recorded outbreaks of heat in the 10-year interval (2011 to 2020). This is an intriguing finding: on one hand, wildfires depend on the existence of vegetation, and additionally, it is understood that a priori, FPs have a wider extension of green areas since they bring together the types of biological reserve (Ia), ecological station (Ia), national park (II), natural monument (III) and wildlife refuge areas (III). On the other hand, PAs of the FP type tend to experience more land conflicts when they are poorly planned, which leads to more unmanaged land use, lack of compliance, and retaliation by local populations, when the local population's land use aspirations are poorly met in the aims of the FP type. Furthermore, it should be noted that one of the problems in the territorial planning of these spaces is regarding the natural isolation of this region, due to its management, application of laws, and management plan. These terms and management proposals are often limited to the interior of the PAs, with no control over the surrounding environment, which can consequently support the inspections of economic activities closer to these areas (Radeloff et al., 2010; Foley et al., 2005). This demobilization and these uncontrolled scenarios encourage the spread of wildfires, which can generate direct consequences for the closest integral protection system with the highest level of vegetation.

Finally, it is worth noting that the effectiveness indicator interacts with tourism management data, showing that the increase in the flow of visits can contribute to the effective management of these areas. In this context, Imran et al. (2014) reinforce that this widespread pro-environmental perception in tourism management is pertinent to factors such as understanding and sharing of knowledge, understanding of adaptive legislation and regulations, as well as forms of collaborative planning and management. Thus, this ecological understanding of visitors and local residents helps in the mobilization of institutions and in the development of policies to protect these areas, crucial objects for the composition of the effectiveness indicator.

Furthermore, it should be noted that the different types of governance in PAs are correlated with the geographical area of the territory, the levels of deforestation and the local economic impact of such interventions (Pfaff et al., 2014), and these changes may even be reflected in the effectiveness of management (Macedo & Medeiros, 2018). In this context, once it is understood that the vulnerability threshold is situational and diverse (Silva et al., 2022; Câmara et al., 2021), the governance of these areas should focus on the specificities of each territory, ratifying this dynamic in the management plan and other suitable documents that will govern the PA.

5. Conclusions and final recommendations

The present paper achieved its objective since it had the purpose of identifying the influence of the management plan, management board and tourism management on the relationships between performance indicators in the management of protected areas and degradation processes. This influence was noted through classification models and analysis of significant differences of variance between the groups. Understanding that planning (management plan) and social mobilization (management board) generate a direct impact on the effectiveness and governance of these spaces is of utmost importance. This is due the fact that threats such as deforestation and wildfires become increasingly common and generate direct damage not only to the physical environment but also to the social and economic environment. In addition, it is also vital to understand that tourism management has a positive effect on mitigating these threats, highlighting the need for public policies aimed at its promotion. Unlike predatory and mass tourism, this activity maintains cultural integrity, preserves the environment and encourages biological diversity and ecosystem services. This activity can also act to generate socioeconomic and environmental values, either by raising the environmental awareness of visitors or by generating income through the diversification of the economic matrix.

Moreover, the analysis of these data is elementary, especially in developing countries and countries on the equator. This is due to the fact that these territories are where tropical forests are concentrated, and they also have in common several social problems, such as inequality, political instability and inefficient environmental enforcement systems. In addition, as already explored, these areas of the tropical zone have suffered from high peaks of deforestation and wildfires, requiring urgent measures to combat these threats. Finally, it is stressed that this research is innovative in that it established machine learning models associated with the data of wildfires and deforestation, not yet used to predict the level of vulnerability of PAs to these threats. This evaluation is fundamental because it allows public managers to project, using data from these PAs, the chances of risk to the levels of deforestation and wildfires in these areas, based on these predictor variables. It is also possible to identify how the planning and mobilization of the PAs are going. In addition, we inserted into the model questions related to the effectiveness and governance of these spaces, for the purpose of comparing the performance of these spaces.

It is worth noting that the variables used in our study to measure the level of vulnerability of these PAs do not take into account their socioeconomic conditions, such as local agricultural performance, prices set for agricultural products, and level of regional development. These variables were excluded from the model as they are cross-sectional data, meaning they do not have variance in spatial series. The inclusion of these new variables would require panel data analysis, covering the period from 2011 to 2020 (reference data for deforestation and wildfires). In addition, our study does not use meteorological factors as predictors of the model; the focus here is on demonstrating the correlation between wildfires, deforestation and human impacts, which is the main factor in carbon emissions in Brazil, as seen in previous studies (Escobar, 2019; Mega, 2020). Therefore, our model focuses on these tourism management, effectiveness and governance variables, and these meteorological factors could be better explored in further research. Finally, when working with this kind of data, our research goal is not to indicate a causal effect but only to show levels of statistical correlations between these variables. Thus, (1) we suggest qualitative studies that involve big data and focus more individually on specific PAs to demonstrate whether tourism management actually impacts these conservation areas; (2) studies monitoring the fulfilment of effectiveness indicators such as the Sustainable Development Goals, relating these indices to the PAs' data on wildfires and deforestation; (3) evaluation of other public policies adopted in PAs that mitigate threats such as wildfires and deforestation; and (4) comparative analysis between countries in the tropical zone and others.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

This article uses secondary data available on the internet.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jnc.2023.126435.

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