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Multi-attribute decision-making model based on Remote Sensing to enhance the environmental auditing of Sustainable Forest Management in the Brazilian Amazon forest

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Abstract

Sustainable Forest Management (SFM) plans are distributed across 2% of the Brazilian Legal Amazon (BLA) territory. Although these enterprises are authorized through the national system (Sinaflor), there is a lack of a computational platform capable of processing, analyzing, and correlating monitoring data from remote sensing techniques with the production data declared in the system. By combining multi-attribute decision-making (MADM) methods with geographic information system (GIS) data and DETEX satellite image Linear Spectral Mixture Model (LSMM) processing on Google Earth Engine (GEE), we developed a semi-automatic system that calculates an Environmental Pressure Index (EPI). This index, composed of categories of cost and benefit indicators, measures the environmental impacts of SFM operations and the surrounding land use and land cover (LULC) dynamics that can externally stress these enterprises. To test this framework, we evaluated 15 SFMs in operation between 2022 and 2023 in the highly environmentally stressed AMACRO region of the BLA. The evaluation was performed in three tiers, proving that cost indicators developed to measure environmental impacts caused by SFMs are more consistent for the selection of enterprises to be audited than LULC dynamics indicators, as they combine planned and declared production data with the classification of intervention shown by DETEX images. The developed semi-automatic system have the potential to be used by environmental agencies as a decision-making tool for selecting SFMs to be audited, as it provides a quantitative approach based on index calculations and can be easily adapted for specific auditing purposes.

1. Introduction

The Amazon biome occupies approximately 49% of Brazilian territory and is home to a significant portion of the largest tropical forest in the world. With a forested area estimated at 3.35 million km² (SFB, 2020), land change and occupation in the Brazilian Legal Amazon (BLA) territory have shown a significant and consistent trend for at least half a century.

For about 40 years, Sustainable Forest Management (SFM) has been an economic alternative in the BLA. Due to the presence of at least 25 species with wood characteristics suitable for engineering applications, as well as the reduced environmental impact when appropriate forestry engineering techniques are applied, this type of enterprise is encouraged in the biome and is legally recognized. Since at least 2018, authorized full-cycle SFM projects have occupied approximately 2% of the BLA's area, producing 9 million m³ of native timber per year (Macêdo et al., 2022; Ibama, 2019).

In response to that economic alternative, specific legislation, environmental resolutions, and technical norms were developed and recently revised after years of practical knowledge and studies (ABNT, 2013; BRASIL, 2006; BRASIL, 2012; CONAMA, 2009; Ibama, 2006). These regulations have standardized and established mechanisms for proper project and land use characterization; governmental administrative authorization and auditing; and informational systems used for data input and information management, monitoring, and control of the native timber production sector.

In the field of remote sensing (RS), researchers have developed many approaches and techniques to evaluate changes in Land Use and Land Cover (LULC), deforestation, and burned areas time series rates in the BLA, as well as the detection of selective logging areas, among others. The use of fraction images derived from the linear spectral mixing model (LSMM) has long been established in projects conducted by the Brazilian National Institute for Space Research (INPE), such as PRODES (Monitoring of the Brazilian Amazon rainforest by satellite) and DETER (Detection of deforestation in near-real-time). These techniques are still used by authorities for the environmental monitoring of the Amazon forests and other biomes (Shimabukuro et al., 2020; Vieira et al., 2022). Therefore, it is widely understood that the techniques and projects developed by INPE should be prioritized by environmental agencies for monitoring authorized SFM plans. For that purpose, the DETEX methodology (Detection of Selective Exploitation) (Sato et al., 2011; Shimabukuro et al., 1997) has been in use.

Although SFM plans are authorized and controlled by environmental agencies, and it is mandatory to input project and production data into the National System for Controlling the Origin of Forest Products (Sinaflor), there is a lack of a computational platform capable of automatically analyzing this data (Brancalion et al., 2018; Oliveira, 2021). Such a platform, based on multi-attribute decision-making methods (MADM) (Feng et al., 2022; Pena et al., 2022; Seppälä and Hämäläinen, 2001) and the decision maker's objectives and preferences (Tahri et al., 2021), could guide and indicate the best management approaches for conducting environmental audits and monitoring logging licenses. The combined use of these methods with Geographic Information System (GIS) and remote sensing (RS) is desirable (Praticò et al., 2021), as it allows for comparing production data with on-site interventions and assessing LULC dynamics that may externally stress SFM operations.

In the present work, we have implemented MADM methods that calculate an Environmental Pressure Index (EPI) to measure the total environmental impact caused by an SFM intervention or the LULC-buffered stressors that could compromise the SFM operation. The model compares different categories of environmental impact and features (indicators) by using weighting factors (wF) in the aggregation rule, which is normalized (N) using reference values calculated based on Brazilian standards and ad hoc decisions for each category, among other developed criteria for environmental auditing. GIS and DETEX techniques were used to assess these categories between the planning (authorization) phase and the interventions (audit) within the SFM and its buffer zone.

This paper presents the methodological framework for the acquisition, management, and processing of the public data needed, as well as the architecture of the semi-automatic system developed for this proposal. It details the routine implementation for pre- and post-processing of satellite data, including the calculation of the LSMM, generation of fraction images, and DETEX images used to classify interventions and forest cover in the SFM. The paper also describes the developed mathematical model and ad hoc decisions to establish appropriate equations for calculating each indicator that will compose the EPI. Additionally, it discusses the application of this approach in the BLA, specifically in the division of the Amazonia, Acre and Rondônia states (AMACRO), and evaluates the output results in terms of their suitability for different environmental auditing approaches needed due to regional and production characteristics or monitoring and enforcement purposes.

2. Materials and Methods

2.1 Data Acquisition

The conceptual model of the semi-automatic system requires different data characteristics from various sources, such as: tabular data from SFM forest inventories and production declarations; geospatial data of SFM sites and other environmental features; and satellite image data of the Region of Interest (ROI). Below, we describe these data types, presenting the acquisition sources and discussing the stages of processing and data accuracy evaluation where applicable.

2.1.1 Sinaflor SFM data: As established by Brazilian legislation, any enterprise in rural areas that requires the suppression of native vegetation or is dedicated to timber production in native forests must specify its projects in Sinaflor. The information system is managed by the Brazilian Institute of Environment and Renewable Natural Resources (Ibama), the federal environmental agency, and is used by businesses, as well as federal, state, and municipal environmental agencies, for the management, monitoring, and control of land interventions and timber production, industrialization, commercialization, and transport (Macêdo et al., 2022).

For SFM projects in the BLA, a geolocated 100% Forest Inventory (IF) is required to categorize the "intensity of cutting" (IC) of available commercial species for each Annual Production Unit (APU). IC is defined as the volume per area, with a maximum allowable value of 30.0 m³/ha for SFMs with a 35-year cycle. Other criteria’s are also considered during the authorization process, such as the distribution of species, characteristics and number of trees of each species allowed for exploitation, and the inventory of remnant trees for ecological purposes.

Alongside the Forestry Engineering project for the SFM, geospatial data is provided for the demarcation of the entire production site (SFM plan projected over its 35-year cycle) and each year's APU site, including the projected principal and secondary roads and storage yards.

The authorization phase establishes the IC limit for each commercial species at the UPA site and approves the Forestry Engineering project in accordance with Brazilian standards. When the proper intervention occurs, the enterprise must present a "declaration of cutting" (DC) for each commercial tree, including its log characteristics—such as diameters and length—to compute the volume exploited. In Sinaflor, there is an automated control system that compares the DC with the authorized IC.

As inputs required by the developed framework, we utilized 2022 and 2023 IFs, DCs and geospatial data of the selected SFMs to be evaluated. The data were acquired through public requests, Ibama’s Open Data Portal, and PAMGIA Web Feature Service (WFS) (1, 2). Those data were transformed and standardized for further processing and statistical analysis.

2.1.2 Environmental features data: The Brazilian federal government has established the National Geospatial Data Infrastructure (INDE) portal (3), where several geospatial datasets are available through WFS. The data were acquired to delineate features in the ROI and SFMs buffer zones, including: federation units (Brazilian Institute of Geography - IBGE), conservation units (National Registry of Conservation Units - CNUC), indigenous territories (National Foundation of Indigenous People - FUNAI), and hydrography (National Agency of Water and Basic Sanitation - ANA).

To better evaluate the buffer zone of each SFM, data for two additional features were acquired. The first dataset included the boundaries of rural properties where the projects are located. This data is available from the National System of Environmental Rural Registry (SICAR) portal (4). The CAR (Environmental Rural Registry) is a mandatory registry for each rural property, aggregating information about ownership and environmental features. The second dataset consisted of historical mapped deforestation increments (2008-2023), available from the TerraBrasilis portal, developed by INPE (5). The data were provided by the PRODES project, maintained by INPE to produce information on annual deforestation rates in Brazilian biomes. Those data were transformed and standardized for further processing and statistical analysis and also reprojected due to incompatibility of geodetic coordinates.

2.1.3 Satellite data: The study utilized Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-2A Image Collection available in the Google Earth Engine Data Catalog.

[1] Ibama. Open Data Portal. https://dadosabertos.ibama.gov.br/
[2] Ibama. PAMGIA. https://pamgia.ibama.gov.br/home/
[3] INDE. https://inde.gov.br/
[4] SICAR. https://www.car.gov.br/publico/imoveis/index
[5] SICAR. https://www.car.gov.br/publico/imoveis/index

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Images from bands B3, B4, and B8 were used for 2022 and 2023, specifically for the dry season in the BLA—typically from May to November—when SFMs are operational. The images were then processed for clouds using an auxiliary layer (COPERNICUS/S2_CLOUD_PROBABILITY). We chose to retain all available scenes and remove only the pixels classified as clouds, as the decision was to use a monthly composition of images.

Each monthly composition was processed for LSMM calculations and the generation of fraction images, as described by the DETEX method. The same endmembers, equations, and band algebra described in the references were maintained, assuming that the accuracy of these methods was consistent with the reports from those sources.

Since the LSMM estimates the proportion of soil, vegetation, and shadow in each pixel, generating three fraction images, and considering that selective exploitation areas exhibit a strong spectral response in the soil fraction image and a low response in the vegetation fraction image, the DETEX resulting image is obtained by calculating the ratio between these two fractions. This approach enhances areas with selective exploitation.

The DETEX resulting image was classified using a grid overlay on the area of each SFM, with grid cells defined as 200 x 200 meters.

The classification method for intervention levels is based on descriptive statistics, where the population of pixels in each grid cell and for each month is calculated. In the first stage, if a pixel response is equal to -1, the pixel is classified as 'no data' (cloud-covered region). If the pixel response is equal to 0, it is classified as 'Forest'; and if equal to 1, it is classified as 'intervention'. In the second stage, the number of pixels classified within each grid cell is summed and divided by the total number of pixels within the grid cell, thus classifying the grid cell as:

- No Data: Higher proportion of 'no data' pixels compared to others.
- Forest: Absence or lower proportion of 'no data' pixels compared to others, and pixels classified as intervention < 1.5%.
- Initial Stage of Intervention: Absence or lower proportion of 'no data' pixels compared to others, and pixels classified as intervention between 1.5% and 5.0%.
- Medium Stage of Intervention: Absence or lower proportion of 'no data' pixels compared to others, and pixels classified as intervention between 5.0% and 30.0%.
- Advanced Stage of Intervention: Absence or lower proportion of 'no data' pixels compared to others, and pixels classified as intervention > 30.0%.

No field surveys were conducted to collect data for evaluating whether the defined percentage distribution accurately corresponds to the class of intervention. However, empirical tests were performed in areas with DETER alerts classified as 'selective logging,' showing good correlation between the classification of stages and the area's progression toward being classified as 'deforestation' by DETER alerts.

2.2 Region of Interest

In 2022 and 2023, environmental agencies in the BLA authorized 1,218 SFM annual production sites (UPAs) across an area of 7,253 km², distributed throughout all states. Some of these sites are in remote areas with low environmental pressure from the surroundings, others are in well-established areas with constant environmental pressure from nearby activities, and a few are in new areas experiencing increased environmental pressure from the vicinity.

To test the protocol developed in this study, we selected 14 SFMs that operated during 2022 and 2023, all located in the AMACRO region, as shown in Figure 01.

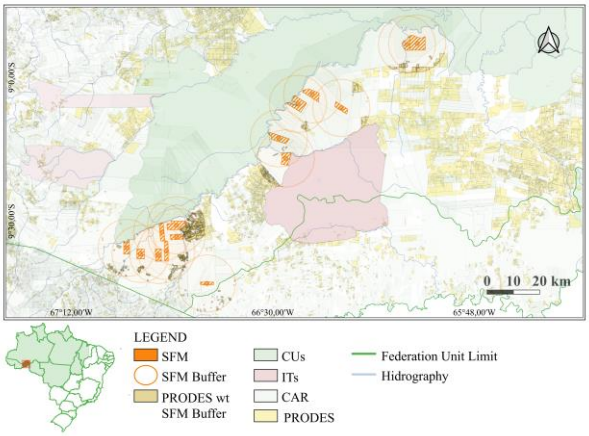

Figure 1. Above: Region of Interest (SFM, Buffer zones, Conservation Units, Indigenous Territories, Environmental Features). Below: ROI and Legends

Another authorized SFM, which did not operate and is near the ROI, was selected for analysis to serve as a comparison.

In addition to the presence of SFMs, the region contains Conservation Units (environmentally protected areas) and Indigenous Territories and has been highly subjected to increasing external stressors, such as deforestation. Due to these factors, it presents a complex environmental dynamic suitable for testing this study's protocol. For this purpose, a circular buffer zone of 350 km² (~10.5 km radius) was established around each SFM site.

2.3 Architecture of the semi-automatic system

The semi-automatic system developed for this study was a crucial component, as it facilitated the storage and processing of large volumes of data from diverse sources and with varying characteristics. Figure 02 presents the conceptual model.

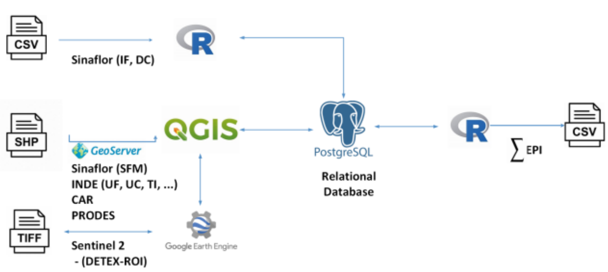

Figure 2. Conceptual model of the semi-automatic system

To access tabular data from Sinaflor (IF and DC) available on Ibama's portal, we used the Tidyverse package in RStudio

2024.04.2. The data was then preprocessed and merged into a single dataframe.

Geospatial data were acquired using QGIS 3.28.12 through connections to available WFS GeoServices. The software served as the GIS platform of the system, with some geoprocessing operations also being applied.

Raster data were processed in Google Earth Engine (GEE) for the selection of available time series, cloud treatment, monthly image composition, LSMM, generation of fraction images in the gridded scene, and generation of the DETEX image with classified grid, as discussed in Section 2.1.3. The DETEX images were then downloaded and uploaded into the GIS. Figure 3 presents the DETEX resulting image and gridded cells classified as Forest or Interventions.

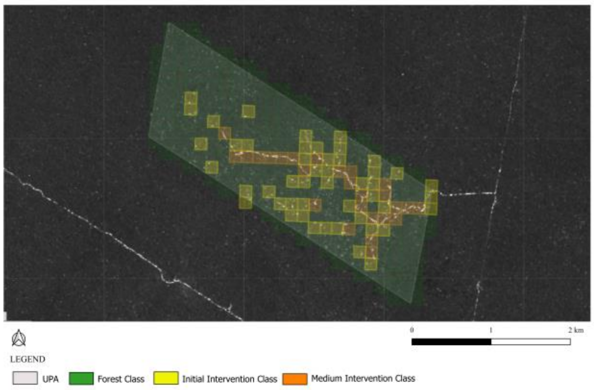

Figure 3. DETEX image with classified grid

The relational database was implemented using PostgreSQL 14.5.1, allowing connections to QGIS 3.28.12 or uploading from a common storage directory. The software was also used to create new dataframes by joining the necessary variables for the calculation of indicators and the final index. This final dataframe was then utilized in RStudio 2024.04.2 with the Tidyverse and DataExplorer packages.

2.4 Multi-attribute Decision Making method

A MADM method is frequently used to solve problems where the decision variables are discrete and the alternatives for decision-making are limited (Feng et al., 2022). A derived MADM applied to evaluate the environmental impacts of a production system can be fundamentally expressed by Equation 01 (Seppälä and Hämäläinen, 2001):

$$I(a) = \sum_{i=1}^{n} w_i^F \cdot \frac{I_i(a)}{N_i(F)} \tag{1}$$

where $I(a)$ = total environmental impact caused by production system ‘a’;
$I_i\ (a)$ = indicator result of impact category ‘i’ caused by production system ‘a’
$w_i^{\ F}$ = weighting factor of impact or category ‘i’ (i = 1, …, n) related to adverse or beneficial effects.
$N_i\ (F)$ = reference value (or normalization factor) of impact or category ‘i’.

In the present study, *I(a)* represents the EPI (environmental pressure index). To calculate *I(a)* indicators, we established two categories:

- *s* : refers to the dimensionality of predicted, absence or confirmed impact due to SFM operation;
- *l* : refers to the dimensionality of absence or confirmed LULC buffered impact that can stress the SFM operation.

These indicators were normalized (Pena et al., 2022) as cost (c) attribute indicators (i.e., impacts considered negative) and benefit (b) attribute indicators (i.e., impacts considered positive). For some indicators, we adopted value ranges to rank them, facilitating understanding, as some impacts were overestimated when comparing production data with the interventions mapped by the DETEX resulting image. Additionally, due to the characteristics and responses of some cost indicators, the corresponding benefit indicators will receive null values.

Since the definition of whether indicators represent cost or benefit attributes and the value of weighting factors are commonly arbitrarily established by decision-makers, we adopted a three-tier approach in the current study, where:

- Tier 1 (T1): as weighting factor values are closer, the results of the indicators are smoothed, bringing the statistical population closer to the mean result.
- Tier 2 (T2): as weighting factor values are much higher for more important impacts, the results of the indicators become uneven, causing the statistical population to deviate further from the mean result.
- Tier 3 (T3): The same weighting factors from Tier 1 were adopted for some indicators, with adjustments made between cost and benefit attributes for certain buffer indicators.

The developed indicators are presented in Tables 1 and 2.

I_c	Description	T1 w^F	T2 w^F	T3 w^F
$I_{c,s,1}$	~ 1.0 indicates strong correlation between DC and DETEX image intervention classification * then *I* ranked as 0.5 > 1.5 indicates excessive DC in correlation of DETEX intervention classification * then *I* ranked as 1.0 ** indicator $I_{b,s,1}$ = 0.0 < 0.75 indicates strong correlation between DC and DETEX image Forest classification * then *I* ranked as 0.25	0.4	0.5	0.4
$I_{c,s,2}$	~ 1.0 indicates high rate of explored volume in DC compared to 30m^3/ha IC	0.25	0.3	0.3
$I_{c,s,3}$	~ 1.0 indicates high rate of volume to be explored in IF compared to 30m^3/ha IC	0.15	0.1	0.15
$I_{c,s,4}$	~ 1.0 indicates high rate of volume to be explored in IF compared to	0.1	0.05	0.1

	ecological volume			
$I_{c,s,5}$	~ 1.0 indicates more available area in CAR for other purposes	0.05	0.0175	0.1
$I_{c,l,1}$	If CU within SFM buffer, then *I* ranked as 1.0	0.025	0.01625	NA*
$I_{c,l,2}$	If IT within SFM buffer, then *I* ranked as 1.0	0.025	0.01625	NA*

Table 1. Description and parameters for each cost indicator
* NA: Not Applicable

I_b	Description	T1 w^F	T2 w^F	T3 w^F
$I_{b,s,1}$	~ 1.0 indicates high presence of Forest in DETEX image classification * *I* ranked as 0.0, if $I_{c,s,1} > 1.5$	0.4	0.5	0.4
$I_{b,s,2}$	~ 1.0 indicates high rate of additional ecological volume to be left, as explored volume in DC was lower than predicted IC.	0.25	0.3	0.3
$I_{b,s,3}$	~ 1.0 indicates high rate of volume to be left as ecological than the volume predicted to be explored in IF	0.15	0.1	0.15
$I_{b,s,4}$	~ 1.0 indicates high proportion of ecological volume within 100 ha	0.1	0.05	0.1
$I_{b,l,1}$	~ 1.0 indicates low rate of PRODES stressors within the buffer	0.05	0.0175	0.1
$I_{b,l,2}$	If CU within SFM buffer, then *I* ranked as 1.0	NA*	0.01625	0.025
$I_{b,l,3}$	If IT within SFM buffer, then *I* ranked as 1.0	NA*	0.01625	0.025

Table 2. Description and parameters for each benefit indicator
* NA: Not Applicable

For better understanding of the results, the EPI for cost attributes was kept separate from the EPI for benefit attributes.

3. Results

All 14 SFMs within the AOI and the non-operational SFM used for comparison purposes (n = 4) were analyzed in the system. The final results of the EPIs for cost and benefit, as well as for each Tier approach, are presented in Table 3 and Figure 4.

There is a strong correlation between EPIc and EPIb, as the indicators developed maintain relationships between them. Therefore, if the model shows high levels of EPIc—close to 1.0—it will also show low levels of EPIb—close to 0.0. However, this is not a direct sum relationship, as some SFMs may have different characteristics compared to others, particularly regarding the characteristics of the rural property and the environmental features within the buffer zone.

For example, if ‘*Ic,s,2’* is close to 1.0—indicating that the volume in the Declaration of Cutting (DC) is near the maximum allowable value (30 m³/ha), as limited by the Intensity of Cutting (IC) granted in the authorization—then ‘*Ib,s,2*’ will tend to be close to 0.0. This suggests that less additional ecological volume remains in the SFM site compared to what was inventoried in the Forest Inventory (IF). Similarly, if ‘*Ic,s,1*’ shows a strong correlation between the DC and the DETEX resulting image classified as intervention, then ‘*Ib,s,1’* will decrease, as fewer forest grid cells will be present in that image.

SFM	T1c	T2c	T3c	T1b	T2b	T3b
04	-0,16776003	-0,08256307	-0,12793734	0,69778856	0,67288982	0,64798153
76	-0,36896426	-0,28917323	-0,30606983	0,63369925	0,67381442	0,58563563
49	-0,36120128	-0,30523885	-0,32948811	0,46594257	0,44667348	0,4166772
16	-0,47523519	-0,4399334	-0,43105525	0,558793	0,58848504	0,51673018
29	-0,50090095	-0,45086779	-0,43909035	0,56509375	0,57877432	0,51651776
32	-0,50413657	-0,45347445	-0,44005959	0,5678995	0,59568015	0,52345713
90	-0,55897589	-0,52510968	-0,50038413	0,36937735	0,33588035	0,31939332
77	-0,64808132	-0,65410181	-0,61207768	0,26990026	0,18358356	0,22069611
70	-0,75312777	-0,76341903	-0,69013798	0,23250951	0,16679585	0,18440996
49	-0,79706998	-0,81169499	-0,71782872	0,2080483	0,15602464	0,16058756
54	-0,78588497	-0,83837191	-0,74095164	0,06969349	0,01736333	0,0271316
87	-0,78716974	-0,84570609	-0,7631792	0,15383566	0,07308475	0,1062059
08	-0,82422652	-0,8490651	-0,76130485	0,17415357	0,09852941	0,12502394
10	-0,81553282	-0,85867617	-0,75723131	0,14826132	0,07882587	0,09864727
82	-0,84131259	-0,86964862	-0,77819242	0,14443007	0,06797763	0,0972528

Table 3. Results of EPI cost and benefit attributes

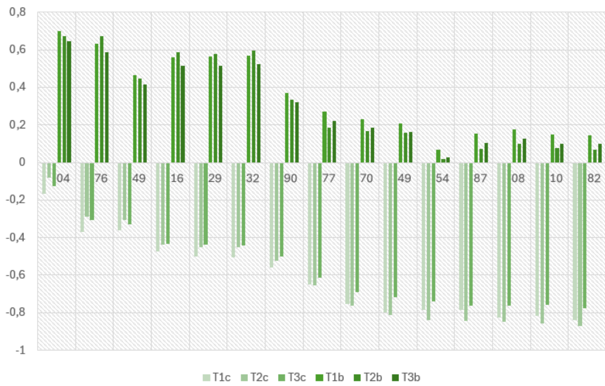

Figure 4. EPI Results for cost and benefit for each Tier

Regarding the weighting factors (w^F) values, we downgraded them to reflect the significance of confirmed impacts rather than predicted ones. For example, levels 2 and 3 for each attribute indicator are derived from the Declaration of Cutting (DC)—which pertains to the intervention phase—while the Forest Inventory (IF)—associated with the planning phase—is used for comparison.

Moreover, level 1 for each attribute indicator receives the highest weighting value, as it combines both the monitoring value provided by remote sensing techniques and the volume of timber/area declared in the DC. In other words, if a higher volume is declared in the DC but the DETEX image shows low intervention classification, it may indicate a problem requiring further evaluation in an environmental audit. Specifically, if ‘*Ic,s,1*’ is high, ‘*Ib,s,1*’ should be null, as high forest classification values in the DETEX image would be questionable. These conclusions can be reinforced by subsidiary indicators.

As an example of the model's practical response, SFM 90 showed a Declaration of Cutting (DC) with 60% of the volume extracted compared to what was predicted by the Forest Inventory (IF). The indicators ‘*Ic,s,1*’ and ‘*Ib,s,1*’ demonstrated a strong correlation with the intervention patterns as classified by the DETEX resulting images (Figure 5).

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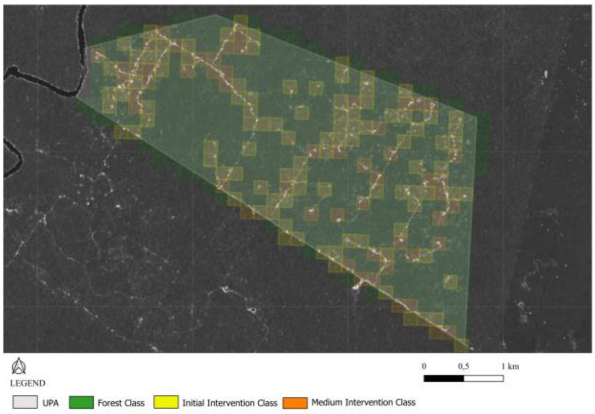

Figure 5. SFM 90 DETEX image with classified grid

On the other hand, SFM 70 showed a Declaration of Cutting (DC) with 54% of the volume extracted compared to what was predicted by the Forest Inventory (IF). However, since the ‘*Ic,s,1*’ indicator exhibited poor correlation with the intervention patterns as classified by the DETEX resulting image, a null value for ‘*Ib,s,1*’ was assigned, indicating questionable forest classification (Figure 5). Notably, the intervention patterns of other nearby SFMs are clearly depicted by DETEX.

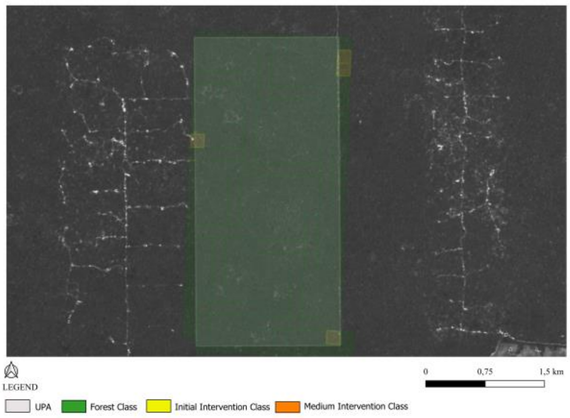

Figure 6 - SFM 90 DETEX image with classified grid

As the Tier approaches prioritize the impact of SFM cost operations over LULC dynamics stressors, when EPIc exceeds -0.5, EPIb notably decreases. This trend aids in decision-making by prioritizing SFMs for auditing based on their cost-related impacts. For instance, SFM 04, which reported no volume extracted and had no intervention classified by the DETEX resulting image, exhibited an EPIb of -0.69 in Tier 1. Conversely, SFM 54, with the lowest EPIb and a high EPIc of -0.83 in Tier 2, faced significant impact due to high volume extraction compared to its authorized IC and was heavily affected by LULC dynamics stressors.

4. Conclusions

This paper analyzes 15 SFMs located in the highly environmentally stressed AMACRO region of the Brazilian Legal Amazon (BLA). It employs a combination of GIS, remote sensing (RS), and a multi-attribute decision-making (MADM) model with the primary objective of ranking projects for auditing.

The indicators developed to measure environmental impacts from SFM operational interventions proved effective for selecting projects for auditing when applied to calculate the Environmental Pressure Index (EPI), as most **\(N_i(F)\)** values are legally standardized. However, indicators measuring external environmental stressors can significantly affect the final EPI and ranking, as the normalization of these parameters relies on expert judgment. In both cases, weighting factors also influence the final EPI, though slight variations in these factors for impact categories did not result in significant differences in the final EPI outcomes.

The satellite time series and spatial resolution were adequate for our purposes, and the DETEX resulting image proved effective for classification. However, it is worth noting that while the DETEX image enhances the representation of forestry engineering interventions such as roads and storage yards, it does not effectively capture the level of tree cover, which is crucial for many indicators in our model. Despite this limitation, when considering the volume of extracted trees distributed across the area (m³/ha), there is an opportunity to use this parameter as a tool to assess reduced-impact forestry engineering practices.

It is important to note that the DETEX image classification approach using grid cells was developed by a team of specialists at Ibama for research purposes. Similarly, this study is research-oriented and should not be interpreted as a tool for official auditing processes.

The developed semi-automatic system has the potential to enhance decision-making processes for selecting SFMs to be audited, given its quantitative approach based on index calculations. The mathematical model can also be adapted for specific operational contexts; however, consultation with an expert panel is recommended for the proper definition of weighting factors and non-regulatory standardized indicators.

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