Impacts of the 2024 floods in Rio Grande do Sul, Brazil

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Abstract

Between late April and mid-May 2024, the state of Rio Grande do Sul in southern Brazil experienced catastrophic flooding caused by intense and prolonged rainfall. This event affected nearly 90% of the state's territory and directly impacted millions of residents, resulting in widespread damage to infrastructure, agricultural lands, and urban areas. To support disaster response and environmental management, this project applied remote sensing techniques to assess the spatial extent and environmental impacts of the floods. Multispectral Sentinel-2 Level-2A satellite images acquired before and after the flood event were processed using ArcGIS Pro to generate a detailed Land Cover Land Use (LCLU) map distinguishing water bodies, vegetation, urban zones, and bare soil. The analysis incorporated exploratory assessments of spectral bands and band transformations, specifically the Normalised Difference Water Index (NDWI) and Normalised Difference Vegetation Index (NDVI), which enhanced the detection of floodwater presence and vegetation stress. Information extraction employed both supervised classification via the Maximum Likelihood Classifier and unsupervised classification using the Iterative Self-Organising (ISO) Cluster method. A thematic accuracy assessment validated the classification results, ensuring reliable flood impact mapping. The outcomes provide a comprehensive spatial understanding of flood dynamics and their effects on land cover in Rio Grande do Sul, demonstrating the effectiveness of satellite remote sensing as a cost-effective and timely tool for disaster monitoring. This study offers critical insights that can aid emergency response, recovery planning, and future risk mitigation efforts in flood-prone regions.

Keywords: flood mapping, remote sensing, Sentinel-2, land cover classification, Rio Grande do Sul

1 Introduction

Between late April and mid-May 2024, the southern Brazilian state of Rio Grande do Sul experienced one of the most severe natural disasters in its history due to unprecedented torrential rains. The resulting floods affected approximately 90% of the state's territory and directly impacted nearly 2.3 million residents. These floods caused extensive damage to critical infrastructure, residential areas, agricultural lands, and the local economy, highlighting the urgent need for comprehensive spatial analysis to support recovery efforts and inform future disaster readiness.

Given the vast scale and complexity of the flooding event, traditional ground-based assessments proved insufficient to capture the full extent of environmental and land cover changes. Satellite-based remote sensing technologies emerged as essential tools, offering rapid, cost-effective, and large-scale observation capabilities. These technologies enable detailed monitoring of flood dynamics and their environmental impacts across both urban and rural landscapes, including areas that are difficult to access.

This project uses multispectral Sentinel-2 Level-2A satellite imagery combined with GIS processing in ArcGIS Pro to evaluate the spatial impacts of the 2024 floods. The focus is on producing a Land Cover Land Use (LCLU) map that distinguishes water bodies, vegetation, urban zones, and other relevant surface types before and after the flood event. By leveraging band transformations such as the Normalised Difference Vegetation Index (NDVI) and Normalised Difference Water Index (NDWI), alongside supervised and unsupervised classification methods, the study provides a robust analysis of flood-affected regions.

Through this approach, the project aims not only to quantify the immediate impacts of the disaster but also to demonstrate the practical value of remote sensing in flood monitoring, emergency response, and regional planning. The insights gained contribute to a better understanding of the flood's environmental consequences and support efforts to mitigate risks associated with extreme climatic events in the future.

2 Study Area

The focus of this study is the state of Rio Grande do Sul, located in the southernmost region of Brazil, which experienced significant flooding in 2024. The floods affected both urban and rural areas, with municipalities such as Canoas and Eldorado do Sul among the most impacted. To provide a comprehensive understanding of the event, the analysis includes these municipalities as well as their surrounding regions, capturing the broader hydrological and environmental context.

This expanded study area is important to assess the spatial extent and varied impacts of the floods, as satellite imagery and related data frequently encompass not only the directly affected urban centres but also adjacent rural landscapes, river basins, and floodplains. Including these surrounding areas enables a thorough evaluation of flood dynamics, land cover changes, and recovery potential across the region.

3 Technical Specifications

This project aims to produce a land cover land use (LCLU) map of the Rio Grande do Sul study area to assess the impacts of the 2024 floods. The map classifies the land into categories relevant for flood analysis, such as water bodies, urban areas, vegetation, and bare soil.

The Minimum Mapping Unit (MMU) corresponds to the spatial resolution of the satellite imagery. Sentinel-2 Level-2A images offer a highest resolution of 10 meters for certain bands and 20 meters for others, so the MMU is defined as one pixel, approximately 10 meters.

This resolution enables detailed identification of flood-affected features while keeping data processing manageable. The classes reflect key land cover types relevant to flood impact, defined by the spectral characteristics of Sentinel-2 data and ancillary sources.

These technical specifications ensure the map accurately detects and quantifies flood effects across urban and rural landscapes in the study area.

4 Selection and Acquisition of Satellite Images

After defining the study area to include the most affected municipalities in Rio Grande do Sul, the next step was to select and acquire relevant satellite images to assess the flood impacts. The chosen satellite mission was Sentinel-2, part of the European Union's Copernicus Programme, which provides multispectral images with high spatial resolution and frequent revisit times.

Sentinel-2 Level-2A (L2A) images were selected due to their availability as atmospherically corrected products, which facilitate reliable analysis of land surface changes by minimising atmospheric distortions such as haze and clouds. The images were acquired from the Copernicus Open Access Hub, covering dates before and after the flooding event: April 21st, 2024 (pre-flood) and May 6th, 2024 (post-flood). These dates were chosen to capture the landscape conditions immediately before the floods and the extent of changes caused by the flooding.

The satellite images provide spectral bands in the visible, near-infrared, and shortwave infrared ranges, with spatial resolutions of 10, 20, and 60 meters. This spectral and spatial detail enables effective identification and classification of flood-affected areas, water bodies, and land cover changes. The data acquisition approach aligns with the project's objectives to perform a comparative analysis of the flood's spatial impact using multi-temporal remote sensing imagery.

5 Methodologies

5.1 Ancillary Database

In this project, no ancillary database was used as the Sentinel-2 L2A imagery provided high-quality, atmospherically corrected data sufficient for accurate flood impact and land cover classification. Given the project's focus and the effectiveness of the applied classification methods, additional ancillary data were not necessary. This choice is supported by the clear and reliable results obtained, making the use of supplementary databases optional for this study.

5.2 Exploratory Analysis

Once the satellite images were collected, an exploratory analysis was conducted to understand the data. The analysis began with a visual inspection of individual Sentinel-2 L2A spectral bands for both dates, including water vapour, short-wave infrared (SWIR), aerosol, green, red, blue, vegetation red edge, near-infrared (NIR), and normalised near-infrared (NNIR).

A noticeable feature of the images was the presence of a black strip or "no data" area along the right edges of the scenes, classified as null values. This artefact appeared consistently but did not impact the study area. In indices such as NDVI and NDWI, which are calculated using formulas involving division, these null values cause the calculation to be undefined, resulting in no output for those pixels along the strip. Although the exact cause of this black strip remains unclear, it did not affect the overall analysis since the flood-affected region was outside the affected areas of these anomalies.

True colour composites were generated using the red, green, and blue spectral bands to visualise land cover before and after flooding, providing an initial view of spatial extent and landscape changes. Additionally, four-band composites incorporating red, green, blue, and near-infrared (RGBN) bands were created for both dates, enhancing the differentiation of vegetation and water features.

Figures 1 and 2 display the false colour composites, including the RGBN bands, before and after the flood event, respectively. These images reveal the spatial extent of flooding, with marked increases in water coverage and changes in vegetation reflectance following the flood. The RGBN composites proved valuable for visual interpretation and informed the subsequent selection of indices and classification strategies.

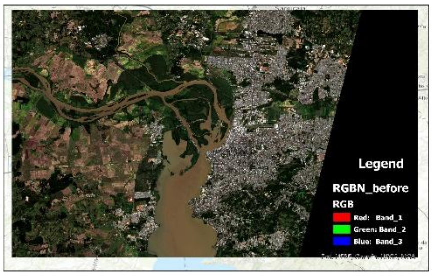

Figure 1. Image before the flood using RGBN bands

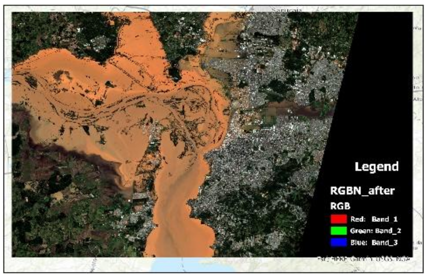

Figure 2. Image after the flood using RGBN bands

Following this, multiple false colour composites and vegetation indices were evaluated to improve flood detection and land cover differentiation. These exploratory steps were essential for understanding spectral responses and guiding the workflow for flood impact mapping.

Overall, this phase in ArcGIS Pro was crucial for refining the analysis approach, confirming data quality, and guiding the choice of key spectral features for further steps.

5.3 Information Extraction Strategy

To effectively assess the impacts of the 2024 floods in Rio Grande do Sul, a systematic information extraction strategy was applied to categorise satellite images and identify flood-affected areas while minimising noise.

Using Sentinel-2 L2A multispectral images in raster format, the minimum mapping unit corresponds to the pixel size (approximately 10 meters). The process was structured into key phases to ensure accuracy and reliability:

- **Feature Selection**: All spectral bands were initially considered, but only the most relevant were selected: Blue, Green, Red, Near-Infrared (NIR), Short-Wave Infrared (SWIR 2), NDVI, and NDWI. These bands effectively distinguish water, vegetation, crops, urban areas, and bare soil, essential for flood impact analysis.
- **Image Classification**: Both unsupervised classification using the ISO Cluster Classifier and supervised classification with the Maximum Likelihood Classifier (MLC) were applied. The MLC assigned pixels to land cover classes based on training samples, while the ISO method grouped pixels by spectral similarity without prior training. The classification included water bodies, urban zones, flooded areas, vegetation, crops, and bare soil.
- **Post-classification Processing**: Filtering and smoothing were applied to reduce noise and improve spatial coherence, refining class boundaries and reducing misclassification.
- **Accuracy Assessment**: Reference data from high-resolution images were used to create confusion matrices measuring overall, user’s, and producer’s accuracy, validating the classification reliability for flood impact interpretation.

This structured approach enabled robust extraction of flood-related information, supporting an informed analysis of spatial and temporal changes caused by the 2024 floods.

5.4 Geographical Stratification

In this project, the study area was carefully defined to include the most affected municipalities in Rio Grande do Sul and their surrounding regions, including the whole geographical area of the 2024 floods. This initial delimitation provides a form of geographical stratification at the macro level, ensuring that the study focuses on key urban and rural zones affected by the flood event.

However, no further subdivision or stratification was applied within this study area for differential processing or classification. The flood impact assessment and land cover classification were conducted over the entire region as a single unified zone. This approach was considered suitable given the objective of producing a comprehensive flood impact map covering the full area without separate treatment of sub-regions.

While stratified analyses, such as separate classifications for urban versus rural areas or hydrologically distinct zones, can sometimes improve accuracy and insight, the unified approach adopted here provided consistent results aligned with project goals. Future work could consider more detailed geographical stratification to refine classification or target specific landscape components.

5.5 Pre-processing

In this study, no additional pre-processing was applied to the Sentinel-2 Level-2A images before analysis. These images are provided as atmospherically corrected surface reflectance products, which effectively reduce atmospheric distortions like haze and aerosol. Given this high-quality correction, other pre-processing techniques like radiometric calibration or atmospheric correction were considered unnecessary. Consequently, the imagery was used directly for classification and mapping.

5.6 Band Transformations

Band transformations were applied in this study to enhance the identification of flooded areas and vegetation stress caused by the 2024 Rio Grande do Sul floods. Two normalised difference indices were calculated and analysed: the Normalised Difference Water Index (NDWI) and the Normalised Difference Vegetation Index (NDVI).

These indices convert original spectral bands into thematic layers that highlight water presence and vegetation health, respectively. NDWI is especially effective in distinguishing water bodies from land surfaces, which is essential for accurate flood mapping. NDVI, on the other hand, indicates vegetation vigour and stress, allowing the detection of areas where flooding has negatively impacted plant cover.

Figures 3 and 4 illustrate the NDWI maps before and after the flood event, showing a clear increase in water coverage in the post-flood image, confirming the flood extent.

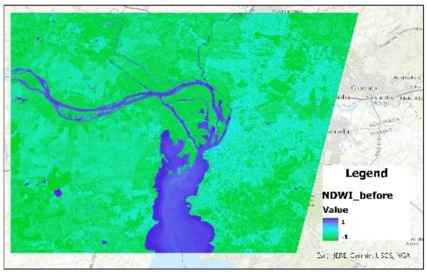

Figure 3. Image before the flood using NDWI

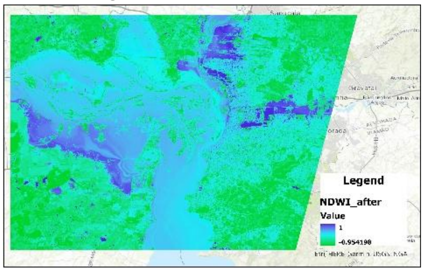

Figure 4. Image after the flood using NDWI

Figures 5 and 6 display the NDVI maps before and after flooding, highlighting decreased vegetation health in inundated regions.

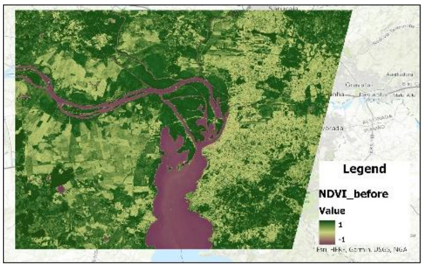

Figure 5. Image before the flood using NDVI

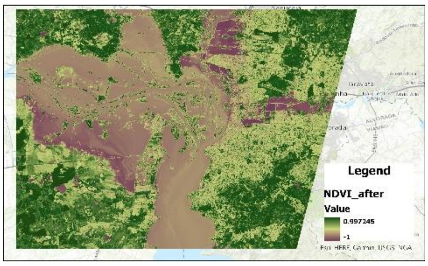

Figure 6. Image after the flood using NDVI

The application of these band transformations was crucial for creating thematic layers that supported the subsequent classification and mapping of flood impacts. The noticeable differences between the pre- and post-flood indices confirm the effectiveness of NDWI and NDVI in monitoring flood dynamics and their environmental effects.

5.7 Feature Selection and Classification

Feature selection is a critical step in remote sensing classification that improves accuracy and efficiency by focusing on the most informative spectral bands. From the Sentinel-2 L2A imagery, the bands with the highest spatial resolution and sensitivity to flood-related features were selected: Blue, Green, Red, NIR, and SWIR 2. These bands effectively distinguish water, vegetation, urban areas, crops and bare soil.

Classification was performed using both unsupervised and supervised methods. The unsupervised ISO (Iterative Self-Organising) Cluster Classifier groups pixels into statistically distinct clusters based on spectral similarity without prior training data, requiring interpretation to assign meaningful thematic classes. The supervised Maximum Likelihood Classifier (MLC) assigns each pixel to the most probable class based on statistical distributions derived from training samples. This combined approach enhanced the robustness of flood impact mapping.

5.7.1 Unsupervised Classification

For remote sensing applications, unsupervised classification is when a classification algorithm generates clusters or classes based on the essential spectral characteristics of each pixel, meaning that it does not require having a training sample to achieve the results. Initiating the phase of classification with the unsupervised classification approach has proven to be particularly useful for initial explorations of spectral groupings within an image.

Isodata clustering, a robust clustering algorithm that decomposes the spectral space into a set of spectrally similar clusters, was performed to initiate this approach. Autonomously grouping pixels with similar spectral responses into a predefined number of initial clusters, a post-classification step was then performed to allocate these initial clusters to meaningful thematic land cover classes. Figures 7 and 8 present the results obtained from the Isodata Cluster Classifier with an accompanying legend. Multiple maps with several classes were made after running the ISO Cluster Classifier, which were then combined into five final land cover categories, namely **Crops, Water, Vegetation, Bare Soil** and **Urban areas**, after manually checking the maps. The spatial distribution of these land cover types can be observed, highlighting key features and patterns across the study area.

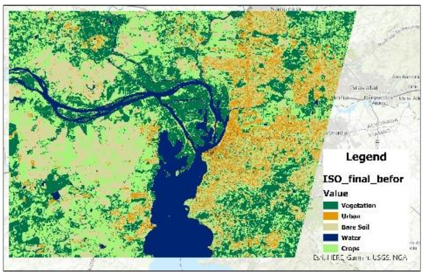

Figure 7. Image before the flood using ISO

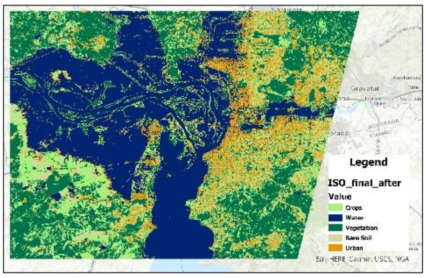

Figure 8. Image after the flood using ISO

5.7.2 Supervised Classification

As opposed to unsupervised classification, supervised classification needs to have a training sample established in order for the classification algorithm, in this case the Maximum Likelihood Classifier (MLC), to learn how to classify the rest of the map. To accomplish this, specific training areas were identified for each desired land cover class. From these areas, the spectral information (digital numbers) for each of the input bands, including Blue, Green, Red, NIR, SWIR 2, NDVI and NDWI, was extracted. This training data provides the basis for the classifier to understand the spectral characteristics of each class, ensuring an accurate categorisation of the landscape.

Numerous combinations of different bands, such as Red, Green, Blue, NIR and NDVI, NDWI, SWIR 2, were performed upon applying the MLC to produce different maps. After manually checking all the resultant maps, the results obtained are presented in Figures 9 and 10. The classified map clearly outlines various land cover types identified from the Sentinel-2 L2A imagery. As indicated by the accompanying legend, the classified map includes distinct class categories such as **Water**, **Urban areas**, **Bare Soil**, **Vegetation** and **Crops**. The distribution of these classes across the study area provides valuable insights into the land cover patterns. Although some similarities might be found when comparing this result to other classification approaches, specific differences in class boundaries or spatial extent may be observed, which will be further analysed in subsequent sections.

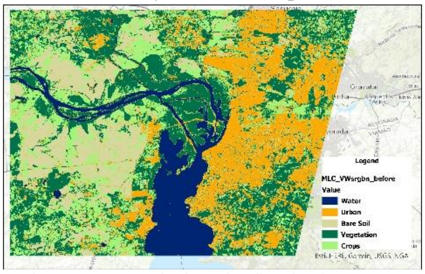

Figure 9. Image before the flood using MLC

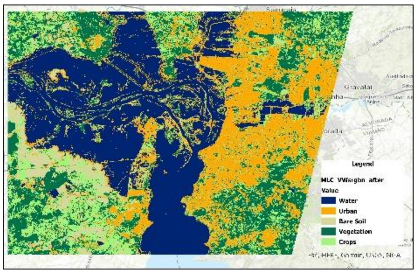

Figure 10. Image after the flood using MLC

5.8 Post-classification Processing

Following the initial land cover classification, post-classification processing techniques such as filtering and smoothing were considered to minimise noise while improving spatial coherence of the classified map. However, during testing, it was discovered that using smoothing filters significantly blurred essential spatial information, especially in urban areas. For example, the smoothing process caused the loss of meaningful features such as flooded streets within cities, which are critical for accurately representing the flood impact.

Given this trade-off, the decision was made to avoid over-smoothing the classification results to preserve essential details in complex urban environments. Instead, the classification outputs were used with minimal post-processing, ensuring that key flood-affected features remain clearly distinguishable. This approach maintains the integrity and interpretability of the map, supporting a more precise analysis of flood dynamics in both urban and rural areas.

5.9 Thematic Accuracy Assessment

Performing an accuracy assessment is crucial to evaluate the reliability of the produced land cover maps for both the supervised (Maximum Likelihood Cluster) and unsupervised (ISO Cluster Classifier) classification methods. This assessment quantifies the degree of correspondence between the classified map and the actual land cover on the ground, as determined by a set of independent reference data points. To implement it, a simple random sample of 100 points was gathered manually, for each classification product, and each point was assigned to one of the predefined land cover classes based on visual interpretation of high-resolution reference imagery.

Multiple confusion matrices, which compare the classified land cover types with the reference land cover types, were created: two for the unsupervised classification (ISO) for both dates and the remaining, due to the multiple combinations of different bands, for the supervised classification (MLC) for both dates. From these matrices, overall accuracy (OA), producer's accuracy (PA) and user's accuracy (UA) were computed.

Table 1 presents the results of the unsupervised classification, using the ISO Cluster Classifier, and Table 2 presents the results of the supervised classification, using the Maximum Likelihood Classifier.

Month & Year	Class	Reference	Map	PA	UA
April 2024	Vegetation	33	29	76%	86%
	Urban	23	10	39%	90%
	Bare Soil	15	22	80%	55%
	Water	6	5	83%	100%
	Crops	23	34	87%	59%
May 2024	Crops	14	11	21%	27%
	Water	35	31	86%	97%
	Vegetation	24	36	83%	56%
	Bare Soil	8	11	38%	27%
	Urban	19	11	37%	64%

Table 1. Unsupervised classification (ISO) accuracy assessment matrix

Month & Year	Class	Reference	Map	PA	UA
April 2024	Water	6	5	83%	100%
	Urban	23	22	87%	91%
	Bare Soil	15	14	80%	86%
	Vegetation	33	33	88%	88%
	Crops	23	26	83%	73%
May 2024	Water	35	28	77%	96%
	Urban	19	23	68%	57%
	Bare Soil	8	8	75%	75%
	Vegetation	24	24	79%	79%
	Crops	14	17	79%	65%

Table 2. Supervised classification (MLC) accuracy assessment matrix

Despite the unexpected decrease in overall accuracy for both classification methods after refinement, the Supervised Classification (MLC) consistently demonstrated superior performance throughout the assessment. With an initial accuracy of 85%, compared to ISO's 71%, and a refined accuracy of 76%, still outperforming ISO's 63%, MLC consistently provided a more accurate thematic representation. Consequently, due to its consistently higher overall accuracy and better class discrimination capabilities, the Supervised Classification was chosen as the final land cover map for subsequent analysis and reporting.

5.10 Map Comparison

Comparing the land cover maps before and after the flood offers valuable insights into the spatial flood dynamics in the study area. The supervised Maximum Likelihood Classifier, using selected spectral bands (Blue, Green, Red, NIR, SWIR 2, NDVI, and NDWI), produced detailed maps distinguishing water bodies, urban areas, vegetation, crops, and bare soil. The post-flood map (Figure 11) highlights flooded areas mainly through expanded water bodies and land cover changes, indicating inundation.

To quantify these changes and assess classification performance, the Tabulate Area tool in ArcGIS Pro generated a confusion matrix comparing land cover before and after the flood (Figure 12). This matrix shows the area (in km²) of pixels classified under each category before (rows) and after (columns) flooding.

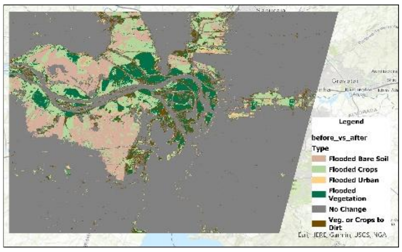

Figure 11. Map Comparison

	After1 (km²)	After2 (km²)	After3 (km²)	After4 (km²)	After5 (km²)
Before 1	166.19	0.00386	0.000089	0.000061	0.000040
Before 2	21.16	303.88	13.04	03.03	24.63
Before 3	139.19	34.91	75.90	0.000323	31.08
Before 4	82.90	41.33	24.96	303.35	44.02
Before 5	130.63	27.91	16.08	30.34	148.60

Figure 12. Classification Comparison Matrix

The total flooded area detected corresponds to the sum of the first column, approximately 540.07 km², reflecting both new floodwaters and persistent water bodies. The matrix also reveals land cover transitions: notably, about 139.19 km² shifted from vegetation to flooded, indicating inundated vegetation. Areas classified as flooded before the event that change class afterwards suggest flood recession or land recovery.

Additionally, the matrix helps identify classification errors. Ideally, diagonal elements, where classes remain the same, dominate if no change occurred. Off-diagonal values, such as urban areas misclassified as flooded or vice versa, may indicate noise or confusion, particularly in complex urban flood zones with overlapping spectral signatures.

6 Limitations & Conclusion

This study faced some limitations, including the 10-meter spatial resolution of Sentinel-2 images, which may miss small-scale flood details. Residual atmospheric effects and sensor noise could also affect classification accuracy. The minimal post-classification smoothing preserved important spatial features but left some noise in the results. Additionally, the absence of ground-truth data meant accuracy assessment relied on visual interpretation, introducing some uncertainty.

In conclusion, the project effectively used Sentinel-2 imagery and GIS methods to map the 2024 floods in Rio Grande do Sul, with supervised classification providing reliable results. The use of NDWI and NDVI indices enhanced flood detection and vegetation analysis. These findings highlight the usefulness of satellite remote sensing for timely flood monitoring and support future disaster management and planning. Future studies could benefit from higher-resolution data and additional ancillary information to improve accuracy.

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