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Comparing the Segment Anything Model with Region Growing Algorithms in the detection of irrigated croplands

Comparando o Segment Anything Model com Algoritmos de Crescimento de Regiões na detecção de áreas irrigáveis

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Abstract: The advance of remote sensing and geotechnologies has helped to solve agricultural-related problems, especially those connected to management practices such as irrigation. Image segmentation techniques, for example, bring the possibility of identifying areas and borders of irrigated croplands,a factor that can enhance monitoring and yield estimates. In this research field, a recent innovation is the Segment Anything Model (SAM) algorithm. Thus, this study aimed to compare SAM with two well-known remote sensing image segmentation algorithms, Region Growing and Baatz-Schape, in order to delineate irrigated agricultural lands in the Brazilian semiarid region. The findings indicate that SAM has the potential to generate homogeneous segments when examining such lands. However, it requires refinements in order to distinguish fields with varying crops and to improve the high computational cost of SAM, especially for big data. Additionally, the choice and testing of parameters are crucial for the optimal performance of segmentation algorithms.
Keywords: Remote Sensing Images. Image Segmentation. Irrigated Croplands.

Resumo: O avanço da sensoriamento remoto e das geotecnologias tem ajudado a resolver problemas relacionados à agricultura, especialmente aqueles ligados às práticas de manejo, como a irrigação. Técnicas de segmentação de imagem, por exemplo, trazem a possibilidade de identificar áreas e limites das terras cultivadas irrigadas, um fator que pode aprimorar o monitoramento e as estimativas de área e rendimento. Nesta área de pesquisa, uma inovação recente é o algoritmo Segment Anything Model (SAM). Assim, este estudo teve como objetivo comparar o SAM com dois algoritmos bem conhecidos de segmentação de imagem por sensoriamento remoto, Region Growing e Baatz-Schape, para delinear terras agrícolas irrigadas na região semiárida brasileira. Os resultados indicam que o SAM tem o potencial de gerar segmentos homogêneos ao examinar tais terras. No entanto, ele requer refinamentos para distinguir campos com culturas variadas e aprimorar o alto custo computacional, especialmente para big data. Além disso, a escolha e teste dos parâmetros é crucial para o bom desempenho dos algoritmos de segmentação.
Palavras Chave: Imagens de Sensoriamento Remoto. Segmentação de Imagem. Áreas Irrigadas.

1 INTRODUCTION

Worldwide, agriculture has increased in both area and yield and has intensified land use to meet demands for food, biofuel, and other commodities due to the increasing human population (POTAPOV et al., 2022; VIEIRA et al., 2022). The Green Revolution brought technological innovations that allowed for the intensification of agricultural practices, with irrigation being a successful technology in improving yield (OZDOGAN et al., 2010). Despite this technology reducing the risk of crop failure and favoring overall production, the growth of this technique demands a large volume of clean water (SAVENIJE; VAN DER ZAAG, 2002). In this century, irrigated agriculture came to represent over 70% of all water withdrawn from water resources (CAI; ROSEGRANT, 2002). This percentage is even higher in developing countries like Brazil (BRASIL; MEDEIROS, 2020).

Agriculture is present in all of Brazilian territory, with the Midwest being the most prominent region, where agribusiness occupies large monoculture crop fields. However, the sector has been expanding to other regions in recent decades, mainly expanding to the North and Northeast regions, where the drier climate leads to more pronounced droughts and a greater risk of water scarcity (DIAS et al., 2016; ANGELOTTI et al., 2017). The degradation of water resources due to the accelerated pace of agricultural management growth, associated with inadequate techniques and poorly designed or poorly managed equipment, results in a lack of conservation of these resources by the sector (RODRIGUES; IRIAS, 2004).

Therefore, monitoring these activities is of utmost importance to support decision-makers in creating public policies capable of adapting agricultural production to a more sustainable and responsible model. In this sense, remote sensing images offer tremendous potential for monitoring irrigation due to the agility and practicality of the data, although detecting this target requires other knowledge, such as land use (OZDOGAN et al., 2010). The application of processing techniques to these images can allow targets to be detected, facilitating their monitoring.

Segmentation can be defined as the division of an image into spatially homogeneous regions (segments), to distinguish different land surfaces based on one or more criteria (KOTARIDIS; LAZARIDOU, 2021). There are several applications for segmentation techniques and their use in images obtained through remote sensing is common and enables the identification of heterogeneous land cover in various environments. Although no segmentation method is 100% effective in segmenting all the targets in an image, each methodology should be used according to the desired application and approach in order to achieve better results according to the preferred target to be identified. Therefore, understanding the functioning of each technique allows for a more precise final result.

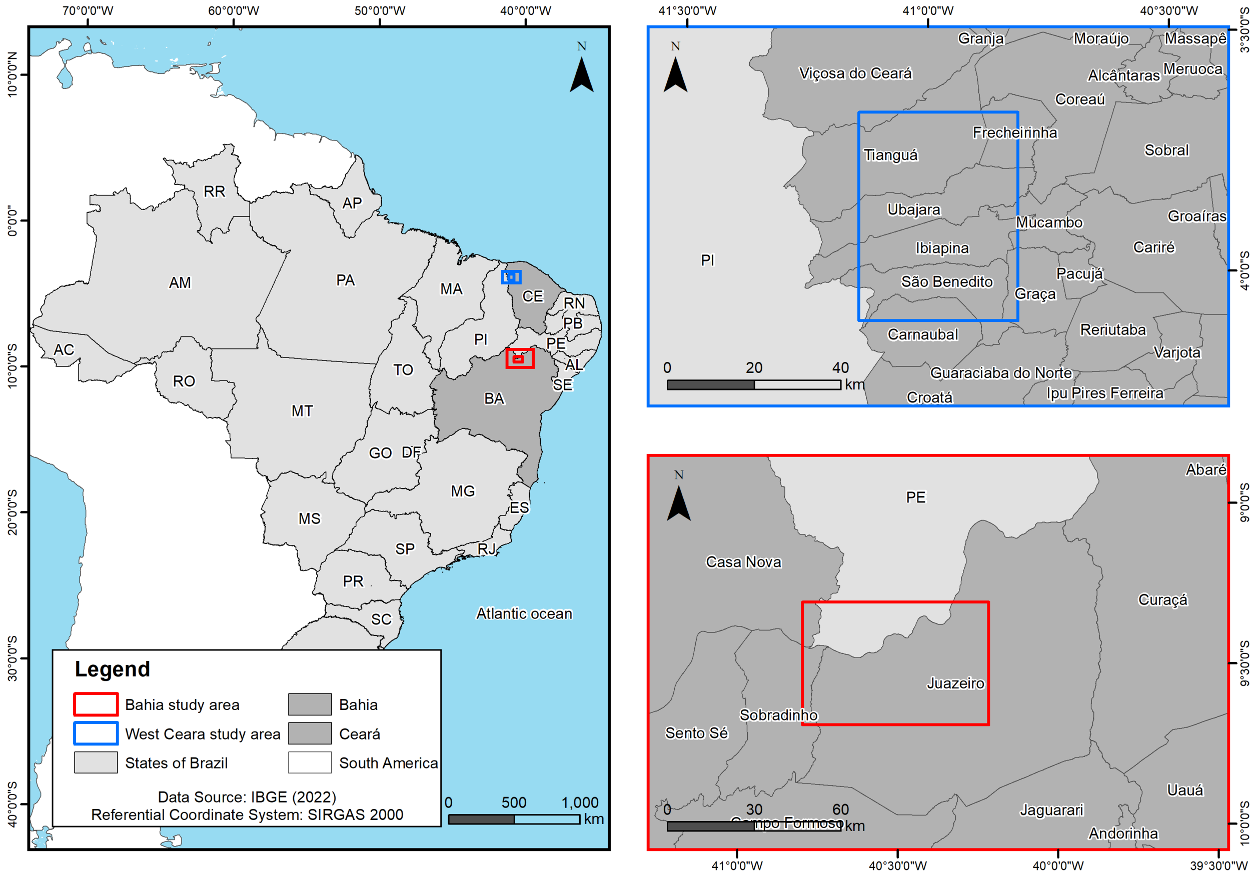
Hence, the objective of this study is to compare three segmentation methods: the Segment Anything Model (SAM) and two Region Growing algorithms (by the traditional method and Baatz & Schape method), in two irrigated agricultural areas in the Northeastern region of Brazil, using optical images from orbital level and remote sensing techniques. Due to the importance of sustainable agriculture and efficient water use, which are related to Sustainable Development Goal (SDG) 2 and SDG 6 respectively (NATIONS, 2024), this study contributes to the implementation of more efficient monitoring methodologies, with the potential to positively impact not only agricultural productivity but also environmental and economic sustainability. This paper is an extended version of (PETRONE et al., 2023), presented in XVII Brazilian Symposium on GeoInformatics (GEOINFO, 2016).

2 MATERIAL AND METHODS

2.1 Study areas

The study areas selected to develop this study were two consolidated crop-producing places of the Brazilian Northeastern region. The first one is located next to the municipality of Juazeiro in Bahia state (BA) and Petrolina, in the state of Pernambuco (PE). The second one is located in the Western region of the state of Ceará (CE) and comprises the municipalities of Tianguá, Frecheirinha, Ubajara, Ibiapina, São Benedito, Mucambo, Graça, and Carnaubal (Figure 1). The main water source for irrigation management in the first study area is the São Francisco River, a natural border between Juazeiro and Petrolina. In the second study area, the main water source is the Jaburu I Dam.

Figure 1 – Study areas.



Source: The authors (2024).

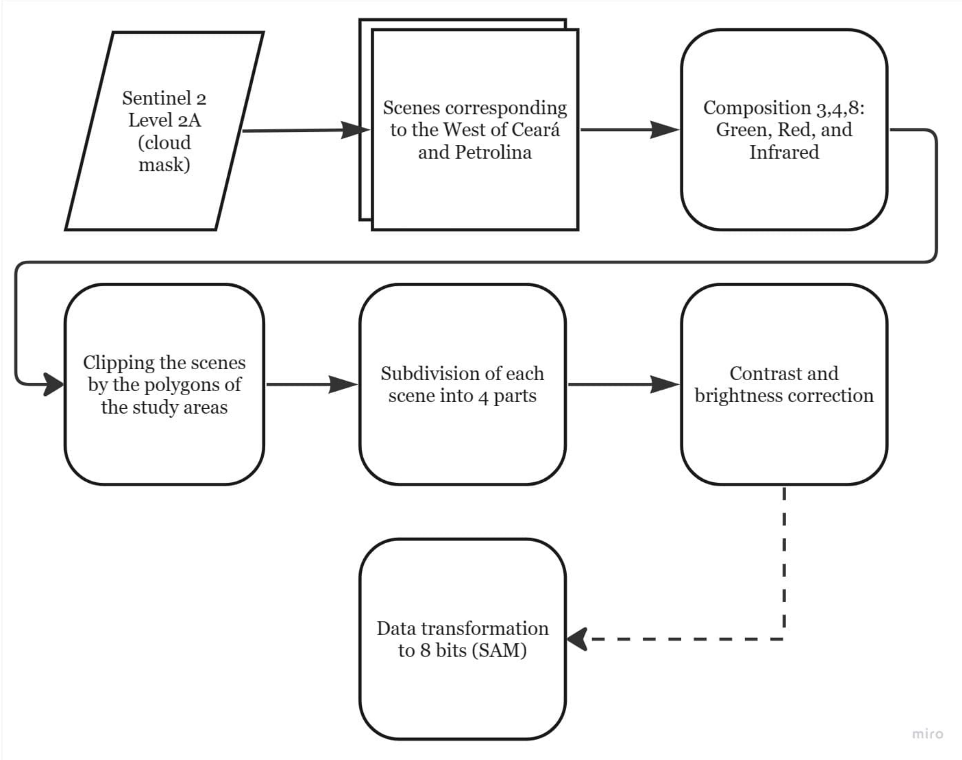
2.2 Remote sensing data

The orbital data used involved images from the MultiSpectral Instrument (MSI) sensor, on board the Sentinel-2 (S2) platform of the Copernicus mission, launched by the European Space Agency (ESA). S2/MSI has 13 bands: four with 10m of spatial resolution, six with 20m, and three with 60m (COPERNICUS, 2023). We used a panchromatic composition also provided by ESA and the green, red, and infrared spectral bands (3, 4, and 8, respectively), all with 10m of spatial resolution. The panchromatic composition consists of the combination of Red, Green, and Blue bands in one band, allowing a more detailed image and a better identification of targets.

We selected one representative image for each study region. They were acquired from the Copernicus spatial data system with processing level 2A (which means that images were atmospherically and geometrically corrected), by considering as a pre-requisite the minimum cloud cover interference for each region from January 2019 to December 2021. For Bahia study area, tile T24MTA, the best image was from February 5, 2021, with 30% of cloud cover interference. For Western Ceará, tile T24LUQ, December 14, 2021, with 10%.

After the selection of images, false-color compositions were made with bands 8 (Near-Infrared), 4 (Red), and 3 (Green) (RGB composition) to enhance vegetation detection (SHIMABUKURO; NOVO; PONZONI, 1998). To reduce computational costs related to the segmentation step, we cropped the images to the limits of each study area and subdivided each crop into 4 parts to speed up the analysis. In addition to these steps, it was necessary to transform the data type into an integer with 8 bits (int8) to use SAM. For the Region Growing and Baatz and Schape segmentation methods, such transformation was not necessary. The complete flowchart of the preprocessing steps can be observed in Figure 2.

Figure 2 – Steps of the preprocessing.



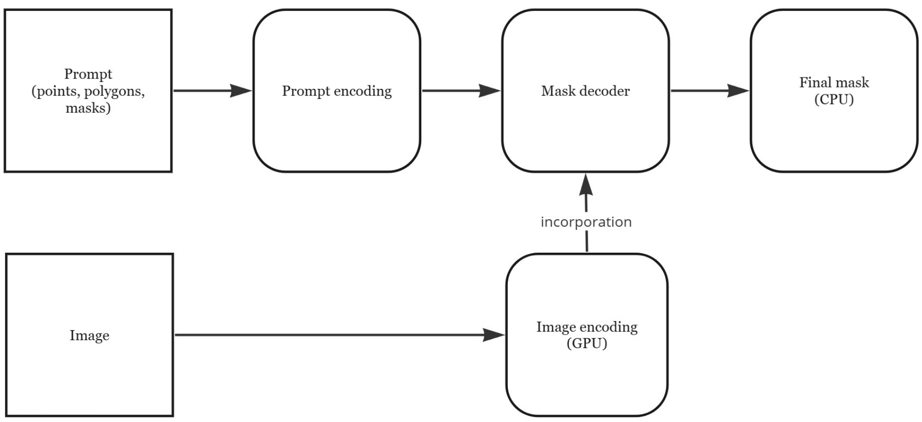
Source: The authors (2024).

2.3 Image segmentation algorithms

2.3.1 SEGMENT ANYTHING MODEL - SAM

The SAM algorithm, developed by Meta AI, is an advanced image segmentation model that aims to identify objects of interest according to user prompts. SAM is composed of three components: (i) Image encoder; (ii) Prompt; and (iii) Fast Mask decoder (OSCO et al., 2023). The Image encoder has 632 million parameters and works specifically with the image of interest, selected by the user from distinct catalogs. The Prompt and Fast Mask decoder have 4 million parameters that work by incorporating the image encoding into the database to produce the final segmentation (which can be interpreted as a mask). Figure 3 shows the segmentation process of SAM.

Figure 3 – Steps of the SAM's processing, adapted from Kirillov2023SegmentA.



Source: The authors (2024).

For the segmentation of images using the SAM method, the Python programming language was employed within the Google Colab environment. The specific script utilized was SAMGeo (OSCO et al., 2023), an adaptation of SAM tailored for the segmentation of geospatial images. Despite this focus, SAMGeo leverages the same training images and masks as the original SAM. The approach adopted was "zero-shot", meaning that the algorithm relies solely on the input image without any prior training samples (SUN et al., 2021). Consequently, the default parameters set were: model_type = “vit_h", erosion_kernel = (3, 3), and mask_multiplier = 255.

The performance of SAM within the SAMGeo script is influenced by the selected model architecture (options include “vit_h", “vit_l", “vit_b"), as highlighted by Osco et al. (2023). This relationship is primarily due to the size and composition of the training database, which directly impacts processing time. For instance, the “vit_tiny"model encompasses approximately 40 MB of images, whereas the “vit_h"model includes 2.56 GB. Generally, larger models such as “vit_h"tend to offer greater accuracy but necessitate more memory and computational resources.

The SAM database (SA-1B) contains around 11 million images, which are publicly accessible, licensed, and of high resolution, alongside over 1.1 billion masks. This extensive dataset enables efficient segmentation of input images by leveraging the comprehensive training data available.

2.3.2 REGION GROWING

The Region Growing algorithm is a well-known segmentation algorithm, made available for remote sensing image by SPRING and TerraView software (CÂMARA et al., 1996; INPE, 2013) that considers the minimum size of the segments and similarity thresholds. Through an iterative process, the regions are segmented until all of the cells have been analyzed. Region growing segmentation has been described by the following four essential steps (BINS et al., 1996): (i) segmentation of the entire image into pattern cells (seeds), (ii) comparison of the pattern cell with its neighboured cells using similarity parameters, (iii) examine all of its neighbors until all cell regions are examined, and (iv) repeating this process to integrate all cells until none remain.

Each image of the study areas was subdivided into 4 parts to accelerate the processing time. Therefore, the segmentation was performed using TerraView software, and the same parameters were used to segment each subdivision: 100 as the minimum size and 0.030 as the similarity threshold, with all bands selected. The results were combined in three verification steps to ensure that no information from the overlaps was lost. Each segmented part was merged with the others, resulting in the integrated segmentation of each study area.

2.3.3 BAATZ & SCHAPE REGION GROWING

The Baatz and Schape algorithm has the same principle as the traditional Region Growing algorithm and the one implemented by (BINS et al., 1996), but considers both morphological and spectral attributes, which are spatial and spectral heterogeneity (Eq. 1).

$$f = W_{color} \cdot H_{color} + (1 - W_{color}) \cdot H_{shape} \tag{1}$$

The function of merging (f) is defined by the weighted sum of the component of the spectral heterogeneity (H_{color}) and the others related to morphological heterogeneity (H_{shape}).

H_{color} (Eq. 2) is the weighted sum of the standard deviation (σ) of the values of the pixels (N) that make up the segment. A weight (ω) is associated with each spectral band given their relative importance in the sum.

$$H_{color} = \sum_{i}^{N} \omega N . \sigma N \tag{2}$$

H_{shape} (Eq. 3) is the weighted sum between compacity (ratio of the edge length to the segment area), represented by $H_{compact}$, and smoothness (ratio of the edge length to the length of the minimum involving rectangle), represented by H_{smooth}.

$$H_{shape} = \omega_{compact} . H_{compact} + (1 - \omega_{compact} . H_{smooth}) \tag{3}$$

To apply the algorithm, we also used the TerraView software, and the parameters were 110 for minimum size, 0.9 for color weight, and 0.130 for similarity threshold. For the compacity weight, the values were 0.55 to band 0 (Near-Infrared), 0.3333 to band 1 (Red), and 0.53333 to band 2 (Green).

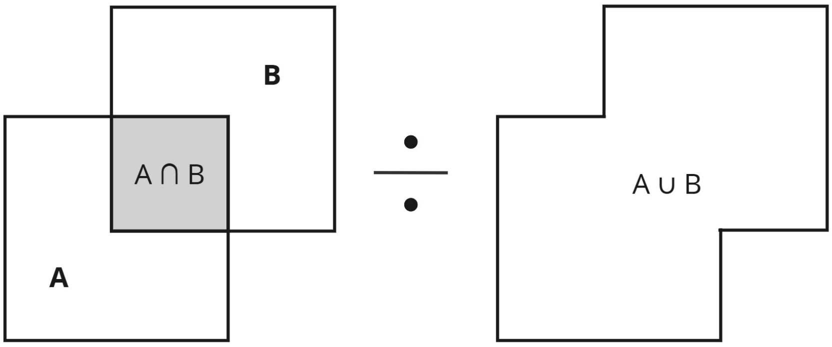
2.4 Segmentation evaluation with Intersection over Union (IoU)

The metrics used to evaluate segmentation can be quite visual and consequently subjective, causing uncertainties. A specific metric to quantify machine learning models' accuracy is the Intersection Over Union (IoU).

Intersection Over Union, also called Jaccard's Index (YU et al., 2021) is used to detect errors by calculating the overlap between a segment used as a reference and a predicted segment. IoU is given by the ratio of the reference segment and the predicted one's intersection for its area of union (Eq. 4 and Figure 4).

$$IoU = \frac{| A \cap B |}{| A \cup B |} \tag{4}$$

Figure 4 – Visualization of how Intersection over Union works.



Source: The authors (2024).

For this study, twenty crop fields with different shapes, colors, and textures were created using the free Quantum GIS software. The selection of samples were arbitrary and aims to ensure that the chosen fields present a variety of characteristics, allowing a more comprehensive evaluation of the algorithms. By applying IoU method, the result is a score ranges from 0 to 1 for the segments, where 1 represents the perfect match between the two segments and 0 represents no match.

3 RESULTS

3.1 SAM's segmentation

The SAM algorithm considered mostly the shape parameters in the image segmentation. Furthermore, SAM's segmentation made a 'square' in the center of each part of the image and interpreted all of the surroundings of the square both as a segment only and as little fragments of segments (Figure 5). The square has no data assigned to it. Inside the squares, SAM segmented well the main stands, considering the frontiers of the segment, although its inner segmentation didn't identify important agricultural patterns. Visual verification can be made by assessing frontiers and borders even if they are soft and continuous. Quality segmentation has more integral areas with higher spatial continuity, which simulates the ground reality. This evaluation shows that SAM has good results in making continuous segments (Figure 6). Another way of verifying the segmentation is through the geographical patterns in the image, which shows that SAM sub-segmented the areas and didn't represent all of the expected objects of the study's phenomena. In some regions of the Bahia study area image, the segmentation afforded all of the crop field segments but didn't identify features inside of them. In Western Ceará, many areas

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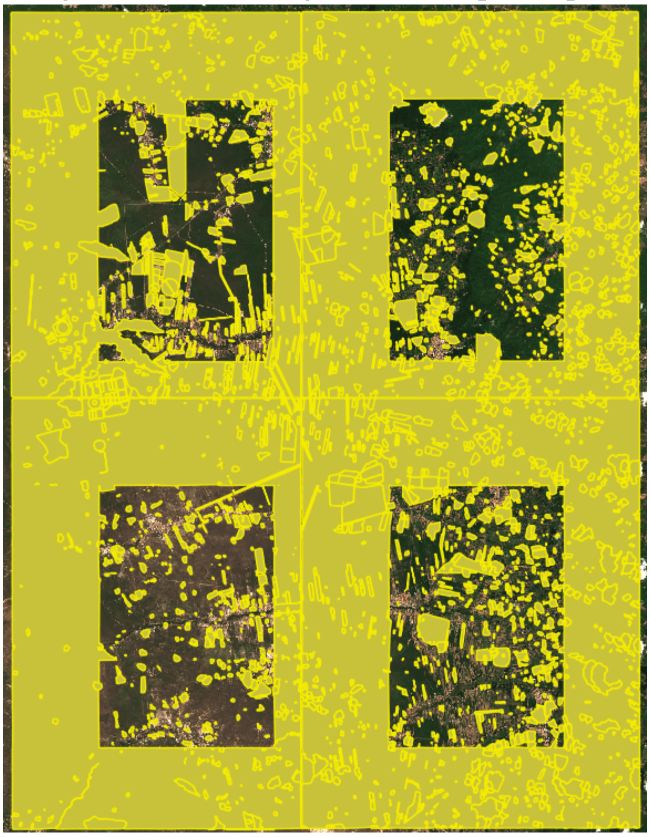
weren't segmented, mainly those surrounded by forests, which shows that SAM confused highly heterogeneous features.

Figure 5 – SAM's Segmentation Square Split.



Source: The authors (2024).

3.2 Region growing and Baatz-Schape segmentation

The traditional Region Growing algorithm (Figure 7 and Figure 8) presented more capability of identifying segments than SAM. Probably, it occurs due to the ease and convenience of testing parameters before performing this segmentation in TerraView - an operation still not possible when using SAM. With the final parameters, most of the agricultural areas could be identified. However, it caused super-segmentation. Related to the traditional Region Growing algorithm, Baatz and Schape (Figure 8) was the one in which the most segments were identified. An explanation is the significant influence of parameters related to spectral responses of targets in this segmentation, causing small heterogeneity to be divided when they belong to the same segment. Also, it was identified as a super-segmentation, too.

For a numerical comparison, in Table 1 are the total numbers of the segments produced by the three algorithms and the percentage of the total of the segments produced by each algorithm.

Table 1 – Number and percentage of segments generated by each algorithm.

Algorithm	Bahia Study Area	West Ceará Study Area	Percentage
SAM	11561	5279	4.6
Region Growing	103125	53042	40.8
Baatz-Schape	137985	72015	54.6

Source: The authors (2024).

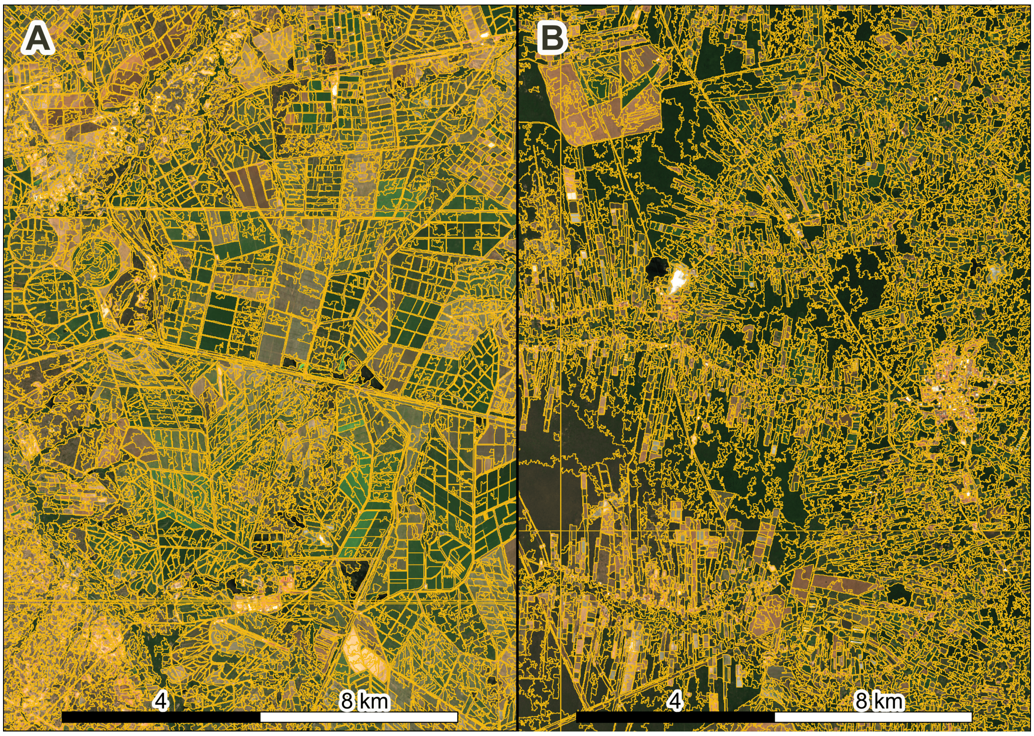
3.3 Intersection over Union segmentation's comparison

The robust comparison between the segments can be done by the IoU method. The analysis of the results revealed variations in the IoU scores, reflecting the effectiveness of the algorithms in identifying and delimiting

Figure 6 – Bahia (A) and Western Ceará (B) study areas segmented via SAM algorithm.

Source: The authors (2024).

Figure 7 – Bahia (A) and Western Ceará (B) segmented via Region Growing.



Source: The authors (2024).

the different agricultural regions. Fields with more distinct shapes, colors, and textures tend to have higher scores, indicating that the algorithms were able to target these areas more accurately. In contrast, regions with more similar or less defined characteristics resulted in lower scores, suggesting challenges in precise segmentation.

Figure 9 shows the area overall for all algorithms. For IoU on Western Ceará, SAM highlighted in samples 6 and 20, having an overall of more than 0,9. Still, in samples 10, 11, and 12, the segmentation process generated imprecise objects. It can be seen a relation between the area of the sample and SAM's segmentation, in which it mostly segmented the larger area samples.

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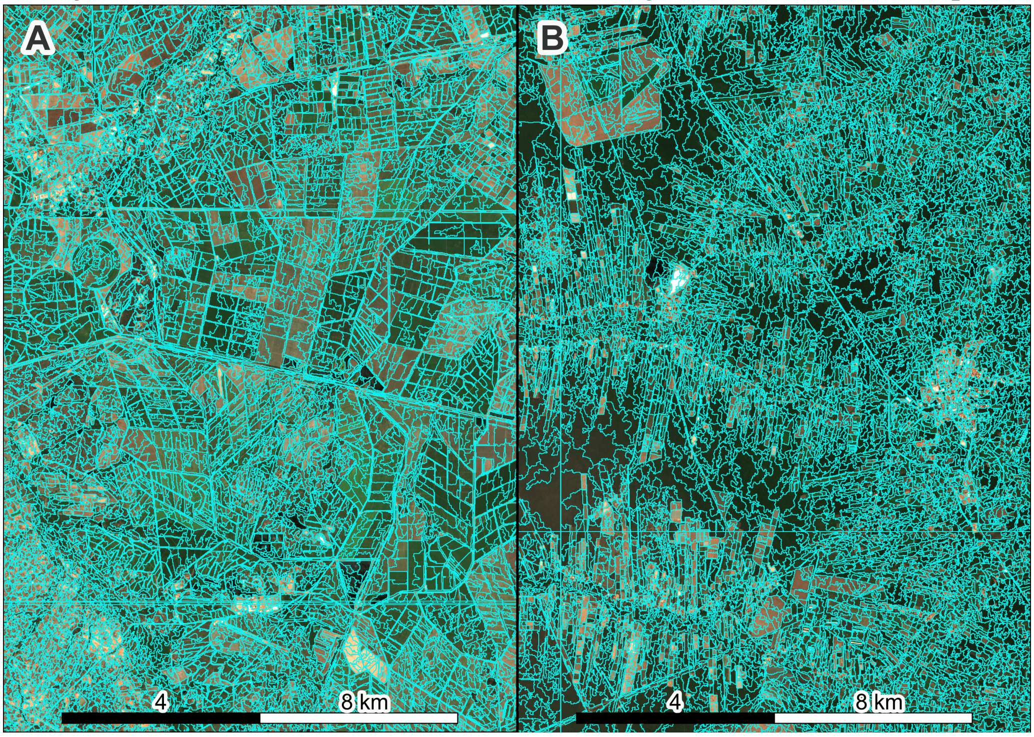
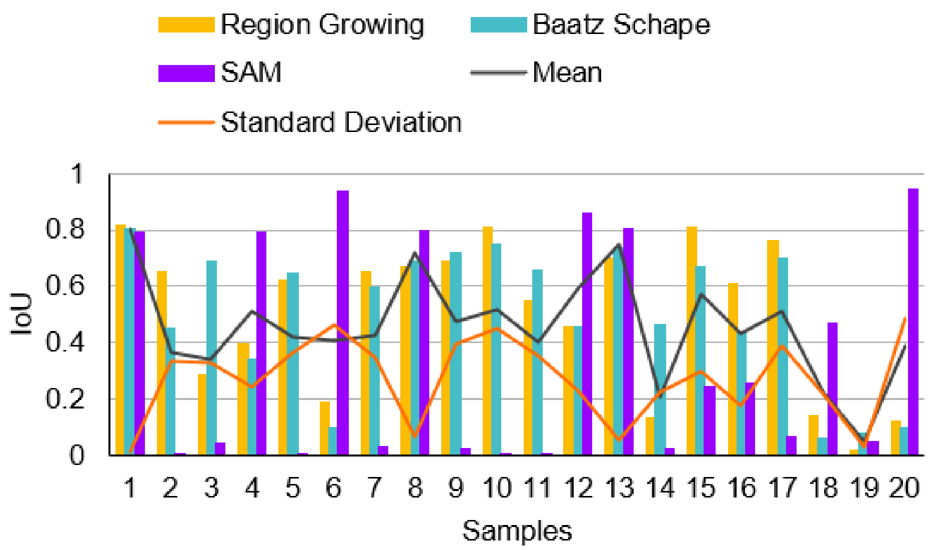
Figure 8 – Bahia (A) and Western Ceará (B) segmented via Baatz-Schape.



Source: The authors (2024).

Figure 9 – Intersection Over Union for Western Ceará.

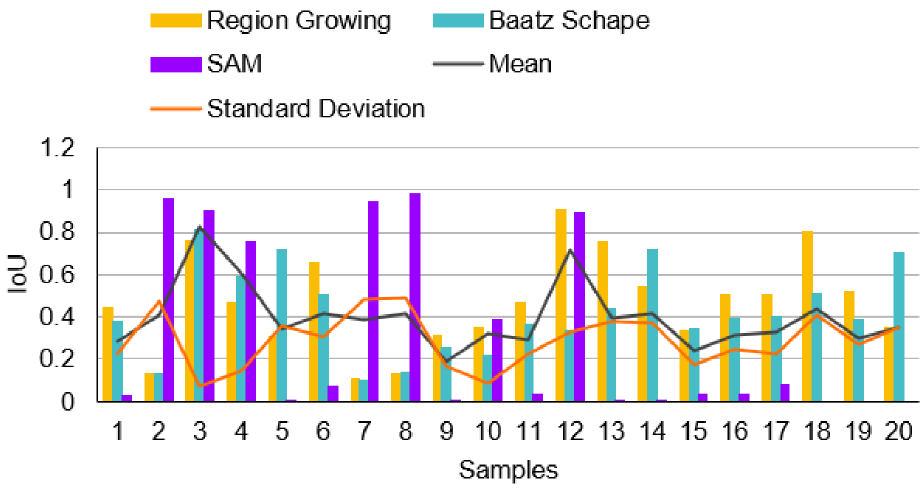


Source: The authors (2024).

The same happens for Bahia study area, where SAM highlighted the bigger areas represented by samples 2, 8, and 13 while not segmenting samples 15, 16, and 17 (Figure 10).

For Bahia study region, sample 3 had the highest mean IoU, as well as the lowest standard deviation, reaching approximately 0.82 and 0.069, respectively. The highest standard deviation value (≈ 0.49) occurred in sample 8, where the IoU for SAM is ≈ 0.98 and the others are close to 0.13. For the data from the West of Ceará, the standard deviation values between the methods used vary between 0.013 and 0.48, with the lowest value corresponding to sample 1, with a mean of ≈ 0.8. For this region, similarly to Bahia, the largest deviation (sample 19) presents the IoU for the SAM greater than 0.9, while for the others, between 0.11 (Growing Region) and 0.09 (Baatz Schape).

Figure 10 – Intersection Over Union for Bahia study area.



Source: The authors (2024).

4 DISCUSSION

4.1 Segmentation

Although large areas were not segmented, SAM generated homogeneous segments in areas corresponding to center pivots, one of the most used ways of land management for irrigation systems. Despite not providing adequate segmentation between crop fields (commonly irrigated), the entire edges of the pivots were well delimited - mitigating border effects derived from the spectral interference of adjacent land uses, such as pasture. Some groups of crop fields were segmented efficiently, as represented in Figure 5 and 6, specifically. In all cases, the segmentation process has generated large polygons. Even when testing different parameters for the region growth methods, both generated over-segmentation (Figure 7 and 8), which can be considered less problematic than over-segmentation given the difficulty of splitting segments of a image in compare to merging them (KOTARIDIS; LAZARIDOU, 2021). This is one of the main challenges in segmenting agricultural targets since these methods can identify variations in spectral response within crop fields due to environment conditions and other factors (BARTH et al., 2018). Hence, the adequate process of identification of the irrigated area would benefit from segmenting the entire crop field.

The number of segments generated via the Region Growing segmentation was much higher than SAM, as represented in Table 1. However, it was inferior to those generated via Baatz-Schape, which has the highest total of segments in both study areas. Looking at Figure 9 and 10, we can infer that the area of the crop field is not directly related to the quality of the segmentation. SAM failed to segment some regions in both study areas, resulting in voids in samples between 9 and 11 in Western Ceará and between 15 and 17 in the Bahia study area, for example. The highest IoU values for the SAM occurred in the analysis of center pivot areas and large homogeneous crop fields.

4.2 Implications on irrigation water policies

Irrigation water policies are essential to guarantee water supply in the Brazilian Semi-arid region. The success of these policies involves, at an initial stage, the accurate identification and monitoring of irrigation projects where central pivots and other models of irrigation activity have increased more significantly over the years. Due to the extension and fragmentation of this activity within the Brazilian Semi-arid region, orbital remote sensing is the only viable way to monitor them all. Remote-sensing-based analysis-ready datasets (ARDs) and segmentation methods, as used in this study, have the potential to fill a gap for decision-makers. In the specific case of the study areas, we can note the existence of irrigation policies contrasting with conflicts for different water-use purposes. In both regions, the constant water supply favored the implementation of irrigation schemes since the 1960s (RESENDE; YURI, 2021). However, increasing water demand due to the expansion of irrigated agriculture reduced the availability of water for irrigation, limiting agricultural production (HAGEL; RINCON; DOLUSCHITZ, 2022). Currently, there are marked periods of limited water supply from droughts occurring in the high and upper part of the São Francisco river catchment, for example (ANGELOTTI et al., 2017). In both cases, reducing uncertainties in the identification of irrigated croplands benefits the expansion of poles for agricultural production and economic development where it was not expected (ARAUJO; TEIXEIRA; BASSOI, 2020). As a fruit farming pole, Bahia study area (especially Juazeiro and Petrolina municipalities), concentrates large irrigated agricultural projects that have been generating and intensifying land use changes throughout the years.

On a macro-level, the accurate identification and monitoring of irrigated croplands can subsidize national policies regarding the combat of desertification in strategic regions and accomplish Sustainable Development Goals (SDGs), which can bring funds for financing upscaled projects on water and food security, as resource-efficient agricultural production is crucial to ensure food and nutrition security for the global population. Also, as the agropastoral activity will expand for the next 21 years, surpassing the pasture cover (SILVA et al., 2023), well-monitored irrigation systems can decrease poverty, rural exodus, and conflicts of interest between several stakeholders that require highly efficient water use.

4.3 Conflicts related to water access

The scarcity of water in the Brazilian Semi-arid region coupled with the lack of public policies that properly regulate and monitor the use of irrigation systems creates a concerning scenario (SILVA et al., 2023). As a common good guaranteed by the constitution, water is appropriated by large farmers for their benefit under the pretext of generating food for the population. Meanwhile, the population, especially the poor ones, suffer most from the effects of water scarcity (VENDRUSCOLO et al., 2021). Many alternatives have already proven to be promising in the responsible use of water. The choice of drought-resistant crops, the use of native species from the ecosystem, and responsible methods such as drip irrigation, among others. The use of water resources, especially in circumstances like these, should be done responsibly and properly distributed to prevent abuses from occurring (ARAUJO; TEIXEIRA; BASSOI, 2020).

By analyzing the yield, economic feasibility, and water use efficiency of three agricultural production systems - extensive smallholder farming, small-scale irrigated agriculture, and middle-scale export-oriented fruit and vegetable production, (HAGEL; RINCON; DOLUSCHITZ, 2022) show the high vulnerability of irrigated agriculture to climate change and market effects. In this line, changes in temperature patterns, for example, driven by climate change, reduce the favorability of grapevines in Bahia study area and other producing regions in the Brazilian Northeast (ANGELOTTI et al., 2017). However, with adequate infrastructure and market access, irrigated agriculture generated adequate farm income. The authors highlighted that education, agricultural extension initiatives, market access, and incentives to economize water consumption are crucial for sustainable water use in Bahia study area. In this line, the adequate management of water resources provides an increase in water productivity for food production (ARAUJO; TEIXEIRA; BASSOI, 2020). In part, this engagement and adequate management of water are provided by the unit of the Brazilian Agricultural Research Corporation (EMBRAPA) for the Semi-arid region (*EMBRAPA Semiárido*, in Portuguese), located in Petrolina, via rural extensionist actions that bring to farmers technical acknowledgment and management techniques.

5 CONCLUSIONS

From the tests carried out in this work, we can infer that the choice of the parameters is crucial for all the algorithms, and the high computational cost of SAM segmentation makes it difficult to adjust it for better results. Often, prioritizing a small target leads to a loss of segmentation of larger targets. In addition, homogeneous targets are segmented more efficiently than heterogeneous ones.

SAM was developed based on several images in the horizontal plane, lacking better references for remote sensing images. Even though there are scripts that incorporate geospatial data libraries that adapt this segmenter for remote sensing application, it is still necessary to reduce the computational cost of SAM, as it is a major obstacle for its application to big data, such as geospatial data. Therefore, further studies evaluating the benefits of SAM in conjunction with a decrease in its computational cost are needed for its effective and practical use in the remote sensing field.

Plugins have been developed to integrate the SAM with GIS, an interesting alternative for reducing operating costs. Future work would contribute to the subject by comparing the computational cost of these plugins with the scripts used here. Others suggestions for future work are: comparing SAM with other segmenters; using satellite images with other compositions of spectral bands; better spatial resolution; applying filters to highlight the edges of objects; and exploring other parameters, such as the erosion window. A larger use of samples for validation would also be a significant contribution for future works, contributing greatly to compare the results of SAM with other segmenters.

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Author Contributions

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Interest Conflicts

The authors declare that there are no conflicts of interest.

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