

# ICFLIPA 2024

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## **Selection of Segmentation Algorithm for Satellite Images**

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# Introduction

## Selection of Segmentation Algorithm for Satellite Images

The combination of MCDM and fuzzy sets offers new potential ways to solve the challenges posed by complex image contents, such as selecting the optimal segmentation algorithm or evaluating the segmentation quality based on various parameters. Since no single segmentation algorithm can achieve the best results on satellite image datasets, it is essential to determine the most appropriate segmentation algorithm for each satellite image, the content of which can be characterized by relevant visual features. In this research, we proposed a set of visual criteria representing the fundamental aspects of satellite image segmentation.

# Main Contributions

- We developed a methodology for selecting the most appropriate segmentation algorithm for satellite images using the PROMETHEE multi-criteria decision-making (MCDM) method extended with intuitionistic fuzzy sets (IFSs). In connection with this, we also applied the SWARA weight selection method and proposed a set of visual criteria representing the fundamental aspects of satellite image segmentation.
- In the suggested methodology, we proposed an extension of the classical PROMETHEE MCDM method by incorporating intuitionistic fuzzy sets (IFSs). Since traditional fuzzy sets do not define negative numerical values, two arrays have been used to separately contain positive and negative outranking flow differences of the proposed PROMETHEE-IFS method.
- An innovative approach to constructing a decision-making matrix is introduced. In this methodology, the fuzzy fusion of the image content vector and segmentation algorithm matrix allows for assessing and comparing different segmentation algorithms based on their performance against each visual criterion of image content.

# Selection of the dataset

The Aerial Image Dataset (AID) is a large-scale aerial scene classification dataset that was selected for this experiment. The AID dataset is larger than the popular UC Merced Land Use dataset. It contains 220–420 images per class (10,000 images in total) in RGB color space, a size of  $600 \times 600$  px, 24-bit JPG image format with a multi-pixel resolution that varies from approximately eight meters to half a meter. Files are named using the following format: .jpg, where ID is a numeric value that varies depending on the class of aerial scene



**Figure 8.** Images from the AID bridge class. (a) “bridge\_7.png”, (b) “bridge\_6.png”, (c) “bare-land\_218.png”, (d) “desert\_41.png”.

# Methodology

Selection of optimal segmentation algorithm for satellite images

## 1. Selection

**Segmentation  
algorithms\***

A1 A2 A3 A4 A5

**Visual image  
characteristics\***

C1 C2 C3 C4 C5

\* **Visual image characteristics:** C1-Contrast, C2-Roughness, C3- Regions of very small size, C4 - Distortions of regions (holes, shadows etc.), C5 - Smoothness (continuity) of region edges; **Alternatives:** A1 - FCM, A2 - GMM, A3 - SFFCM, A4 - FRFCM, A5 - RSSFCA

# Creation of decision matrix

## *Segmentation Algorithm Selection. (Alternatives)*

The process of selecting an image segmentation algorithm involves considering various factors and criteria like dataset characteristics and application area. To demonstrate the practical realization of methodology, we selected five soft clustering alternatives: fuzzy Cmeans (FCM), superpixel-based fast fuzzy C-means (SFFCM), significantly fast and robust fuzzy C-means (FRFCM), robust self-sparse fuzzy clustering (RSSFCA), and the Gaussian mixture model (GMM). Except for the GMM, all segmentation algorithms are modified versions of the FCM segmentation method.

## *Visual Characteristics (Features) of the Satellite Image Content (Criteria)*

For this research, we selected five distinct visual features to construct the initial image vector: contrast, roughness, regions of very small size, distortions of regions, and smoothness (continuity) of region edges.

# Methodology

Selection of optimal segmentation algorithm for satellite images

## 2. Evaluation

[1-9] rating scale

river\_237.jpg

|    | A1 | A2 | A3 | A4 | A5 |
|----|----|----|----|----|----|
| C1 | 9  | 9  | 2  | 8  | 1  |
| C2 | 4  | 2  | 6  | 5  | 7  |
| C3 | 4  | 3  | 6  | 5  | 7  |
| C4 | 4  | 3  | 7  | 5  | 6  |
| C5 | 6  | 5  | 9  | 7  | 8  |

Evaluation of algorithm sensitivity  
according to visual image characteristics



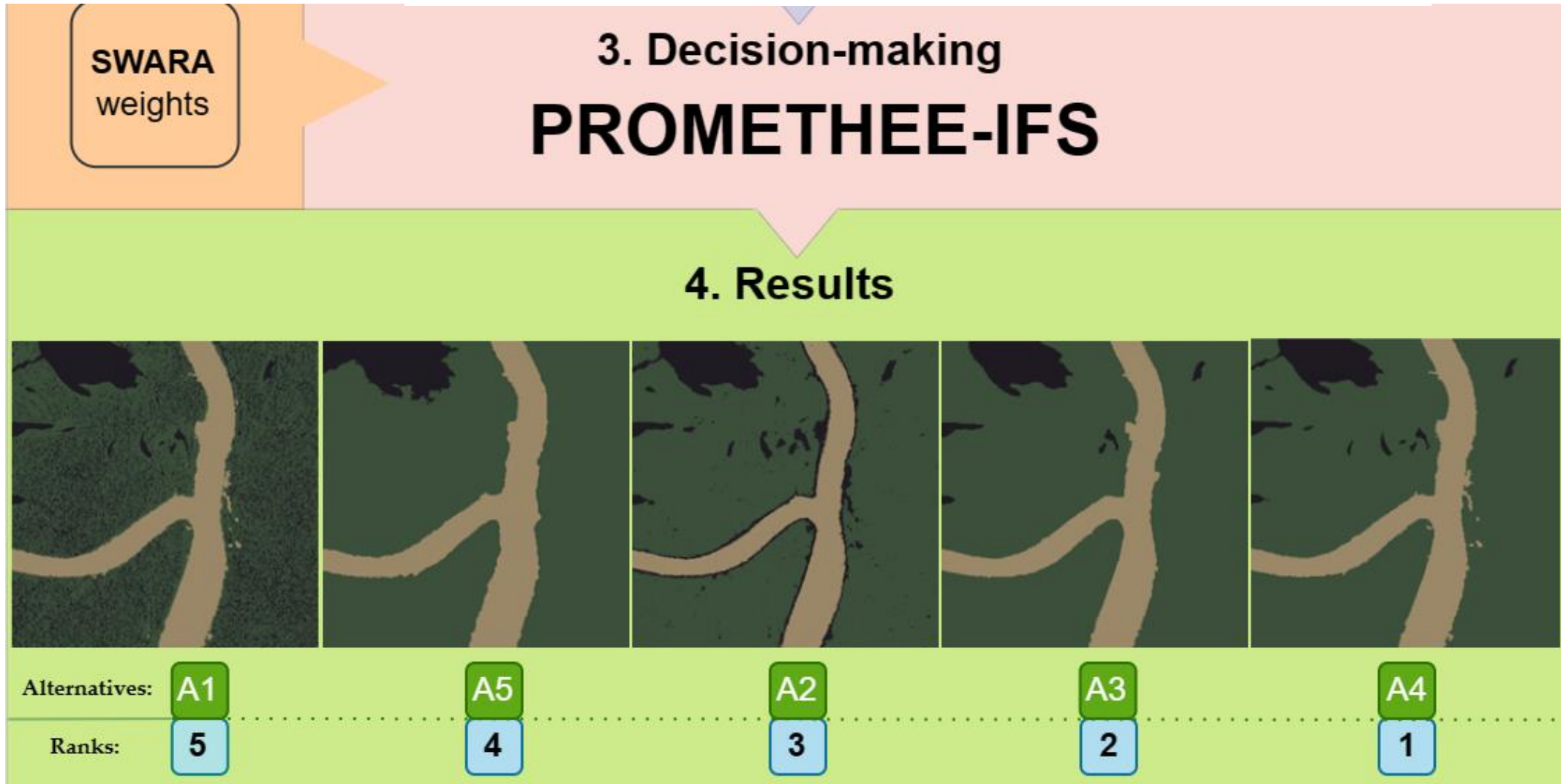
|    |   |
|----|---|
| C1 | 6 |
| C2 | 4 |
| C3 | 5 |
| C4 | 5 |
| C5 | 6 |

Image content evaluation according to  
the set of visual image characteristics

# Methodology

to obtain the final decision matrix  $\widetilde{XI}$  by fuzzy column-wise addition (Equation (13)) of the fuzzy image assessment vector  $\widetilde{I}_i$  and the fuzzy algorithm evaluation matrix  $\widetilde{X}_{ij}$ :

$$\widetilde{XI}_{ij} = \widetilde{X}_{ij} \oplus \widetilde{I}_i$$



# Results

4. *Definition.* In the defuzzification stage (converting the fuzzy number back to its original crisp form), the score value of IFN can be calculated by the score function  $S(IFN)$  proposed by Szmidt and Kacprzyk [55]:

$$S(IFN) = \frac{1}{2} \cdot (1 + \pi_{ifs}) \cdot (1 - t)$$

**Table 6.** Intuitionistic fuzzy PROMETHEE method ranking. The best values (first places are in bold).

| Image Segmentation Algorithms (Alternatives) | Satellite Images          |                           |                           |                           |                           |                           |
|----------------------------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
|                                              | square_1,                 | desert_23,                | beach_19,                 | port_19,                  | farmland_159,             | river_237,                |
|                                              | PROMETHEE-IFSScore   Rank | PROMETHEE-IFSScore   Rank | PROMETHEE-IFSScore   Rank | PROMETHEE-IFSScore   Rank | PROMETHEE-IFSScore   Rank | PROMETHEE-IFSScore   Rank |
| FCM                                          | <b>0.0334</b> 1           | −0.0054 3                 | −0.0156 5                 | −0.0634 5                 | −0.0098 4                 | −0.0306 5                 |
| GMM                                          | 0.0046 4                  | 0.0052 2                  | −0.0112 4                 | <b>0.0779</b> 1           | <b>0.0092</b> 1           | −0.0135 3                 |
| SFFCM                                        | 0.0059 3                  | −0.0122 4                 | <b>0.0298</b> 1           | 0.0732 3                  | −0.0092 3                 | 0.0226 2                  |
| FRFCM                                        | 0.0063 2                  | <b>0.0393</b> 1           | −0.0129 3                 | 0.0741 2                  | 0.0007 2                  | <b>0.0231</b> 1           |
| RSSFCA                                       | 0.0040 5                  | −0.0174 5                 | 0.0015 2                  | −0.0545 4                 | −0.0118 5                 | −0.0145 4                 |

*FCM* Fuzzy C-Means

[]

*GMM* Gaussian Mixture Model

[]

*SFFCM* Super pixel based Fast Fuzzy C-Means

[]

*FRFCM* Superpixel-based Fast Fuzzy C-Means Clustering

[]

*RSSFCA* Robust self-sparse fuzzy clustering algorithm

[]

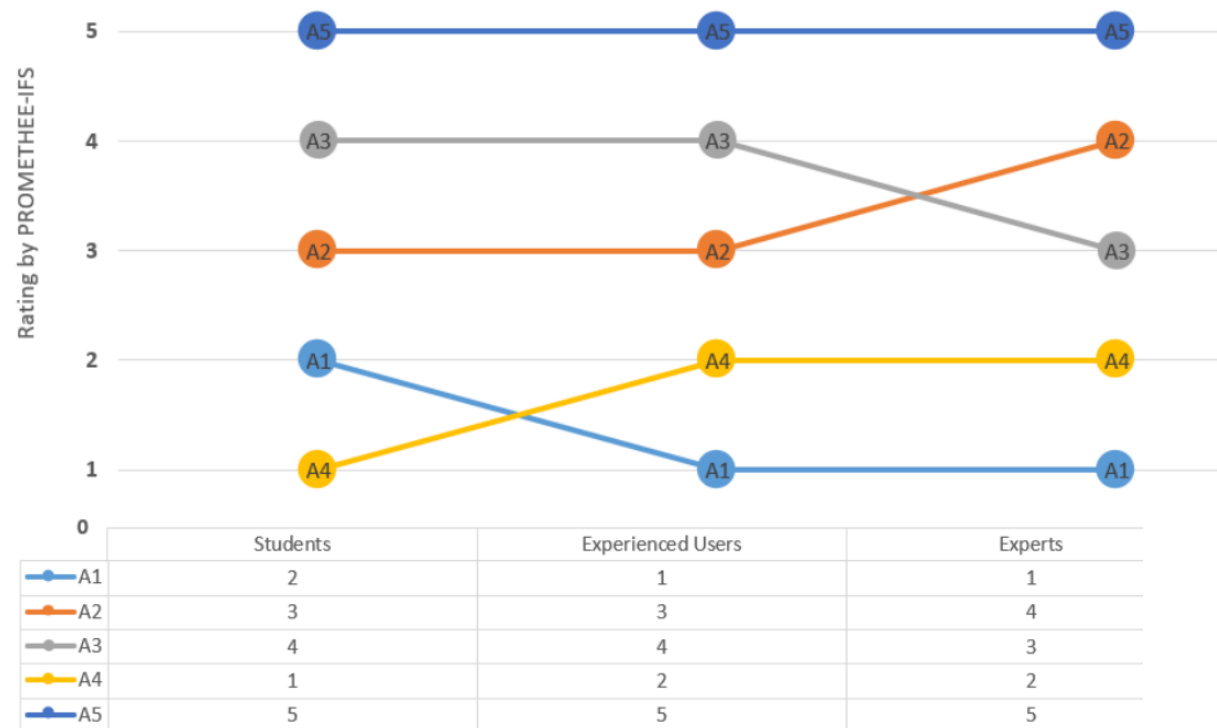
# Verification

## Sensitivity analysis

$$FA = \frac{1}{n} \cdot \sum_{i=1}^n \left( \frac{1}{m_i} \cdot \sum_{j=1}^{m_i} x_{ij} \right)$$

$$\text{Percentage difference} = \frac{|A - B|}{\frac{(A+B)}{2}} \cdot 100$$

| Method | Expert Rank | PROMETHEE-IFS | Rank Difference | Percentage Difference |
|--------|-------------|---------------|-----------------|-----------------------|
| FCM    | 3.35        | 3.8(3)        | −0.48(3)        | 13.4571               |
| GMM    | 2.9(6)      | 2.50          | 0.4(6)          | 17.0731               |
| SFFCM  | 2.8         | 2.(6)         | 0.1(3)          | 4.8780                |
| FRFCM  | 2.05        | 1.8(3)        | 0.21(6)         | 11.1588               |
| RSSFCA | 3.88(3)     | 4.1(6)        | −0.28(3)        | 7.0393                |



# Conclusions

1. In terms of content, classical segmentation methods can achieve better results than modern methods.
2. The characteristics of visual content are often interconnected. Changing one visual attribute affects other visual features (increased contrast can create more distinction between adjacent colors).
3. Different segmentation algorithms have varying sensitivity and interpretation of visual content features, so there is no single algorithm suitable for all content. The results and verification of this experiment confirm this hypothesis.
4. The methodology can be applied to other subjective visual attributes; however, these attributes must have a clearly defined direction for optimization."

# Future Work

Further research perspectives:

- Assessing the impact of optimal segmentation method selection under different score functions or other normalization methods of the decision-making matrix;
- Although we have chosen criteria that reflect the main aspects of segmentation, it is worth exploring other specific criteria/metrics when developing the methodology.

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**Thank you.**

*End of the presentation*

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