Stability Analysis and Case Study for Fire Smoke Removal of Sentilel-2 Satellite Images Using Fuzzy Classification

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Abstract: *Satellite imagery allows for the identification of wildfire locations and potential spread. However, smoke generated by fires often blocks the penetration of visible and near-infrared (VNIR) radiance, making it difficult to recognize surface features by satellite images. In contrast, shortwave infrared (SWIR) radiance can penetrate smoke particles, thereby improving the visibility of surface information and providing the possibility of wildfire monitoring for the smoke affected areas. A previous study, "Using Sentinel-2 SWIR to Remove Forest Fire Smoke" (ACRS), a fuzzy classification-based method offers a soft classifier approach to combine multiple linear functions and provide SWIR to VNIR mapping for improving the results obtained in previous study using only a single linear mapping. This method provides better correspondence between the SWIR and VNIR bands in smoke removal applications. However, in the fuzzy classification process, the number of classes must be defined prior to processing, and this parameter significantly affects both computational efficiency and the quality of results. Using fewer classes (e.g., 3 to 5) may have better efficiency in performance, but it often leads to poor outcomes due to an inability to resolve complex land cover types within the image. Conversely, using too many classes (e.g., more than 30) requires a high number of iterations and substantial processing time to achieve convergence, while yielding only limited improvements in classification accuracy. This study investigates how the number of fuzzy classification classes affects the accuracies across different wildfire case images. Based on the results, the study will offer practical recommendations for optimal class settings in future wildfire monitoring applications using Sentinel-2 satellite images.*

Keywords: Sentinel-2, Forest Fire Smoke, SWIR, VNIR, fuzzy classification

Introduction

Wildfires are frequent natural disasters that cause severe impacts on ecosystems, property, and human lives. Remote sensing plays a key role in wildfire monitoring because satellites provide wide-area, frequent, and timely observations (Roy et al., 2019; Giglio et al., 2018). Satellite images are commonly used to detect fire locations, map burned areas, and track fire spread, offering valuable information for emergency response and recovery.

A major challenge in wildfire monitoring is the presence of smoke. Wildfire smoke contains particles that scatter and absorb radiation, especially in the visible and near-infrared (VNIR) bands. This effect reduces the ability to observe ground features clearly (Lavreau, 1991). As a result, widely used indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio (NBR) become unreliable in smoke-affected regions (Chen & Chang, 2014).

Shortwave infrared (SWIR) bands, however, are less affected by smoke due to their longer wavelength and stronger penetration capability. Previous studies have shown that SWIR and VNIR are strongly correlated, and that SWIR can be used to simulate VNIR information in smoky conditions (Li et al., 2025). This makes it possible to restore hidden ground information and improve post-fire assessment and vegetation monitoring.

Literature Review

Most existing studies apply a global linear regression model (GLRM) to describe the relationship between SWIR and VNIR bands. This method uses one regression equation for the whole image. While simple, it does not perform well for heterogeneous landscapes. Different land cover types such as forests, croplands, water bodies, and urban areas have very different spectral properties. A single regression cannot represent all of them accurately, which often leads to reconstruction errors, especially in the near-infrared (NIR) band (Roy et al., 2019).

Another difficulty is that smoke is not evenly distributed. Differences in smoke density and thickness cause varying levels of interference on VNIR signals (Lavreau, 1991). This makes reconstruction even more complex and limits the usefulness of global regression models.

To address these challenges, fuzzy c-means (FCM) clustering has been introduced (Bezdek et al., 1984; Pal & Bezdek, 1995). FCM groups pixels into different land cover classes and builds separate SWIR–VNIR regression models for each class. In the case of the 2023 Greece wildfire, this method improved the NIR correlation coefficient from 0.49 to 0.71, showing that class-based modeling performs better than a single global model (Li et al., 2025, SG43).

However, the FCM method also has challenges. The number of clusters must be set in advance, and this has a strong influence on both accuracy and efficiency. Too few clusters (e.g., 3–5) improve efficiency but fail to capture land cover diversity, resulting in poor accuracy. Too many clusters (e.g., more than 30) increase computation time and require many iterations, while improvements in accuracy are often small (Pal & Bezdek, 1995).

Therefore, this study applies the FCM method with different cluster numbers to Sentinel-2 wildfire images. The goal is to evaluate the effects of cluster settings on reconstruction accuracy and efficiency, and to provide practical guidelines for smoke removal in remote sensing applications.

Methodology

This study applies the FCM clustering method to reconstruct VNIR information in Sentinel-2 images affected by wildfire smoke. The workflow consists of four steps: data preparation, fuzzy clustering, regression modeling, and accuracy evaluation:

a. Data Preparation:

The data are Sentinel-2 images from the European Space Agency (ESA) (Drusch et al., 2012). Two wildfire cases were selected: the United States in 2025 (Figure 1). Six spectral bands were used for analysis, and the scene classification layer (SCL) was applied to mask clouds and cloud shadows.

To identify smoke regions, the haze vector method was applied (Figure 2). This approach, derived from the Landsat tasseled cap transformation (Crist & Cicone, 1984), has been used to detect haze and smoke in satellite imagery. It creates a smoke mask that separates smoke-affected areas from clear regions (Lavreau, 1991).

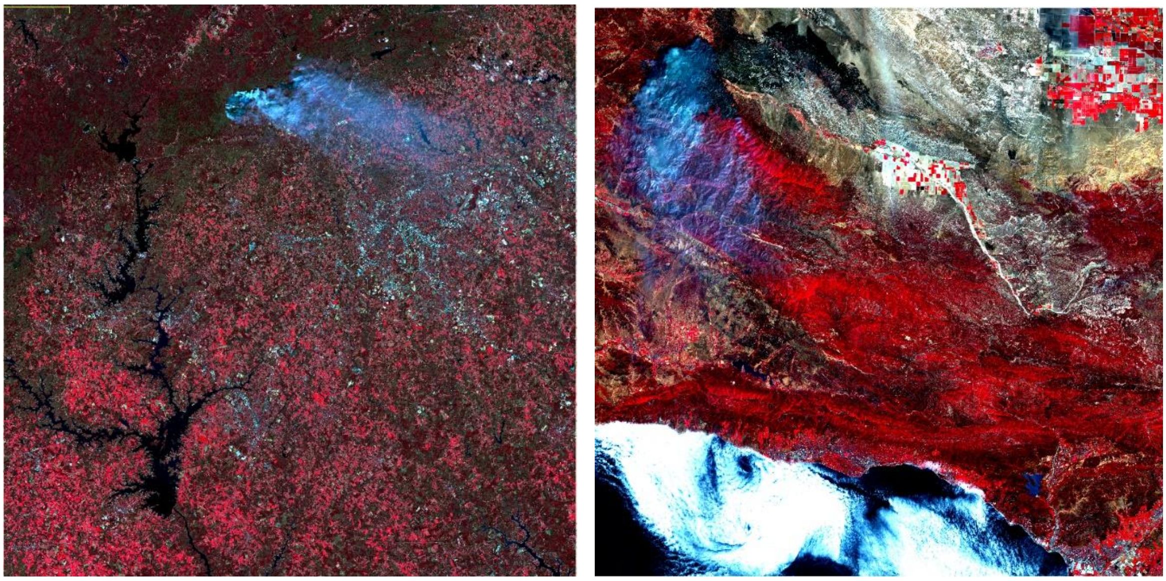


Figure 1: False-color composite images of wildfires: (left) Table Rock State, USA, March 2025; (right) California, USA, August 2025. Image source: Sentinel-2.

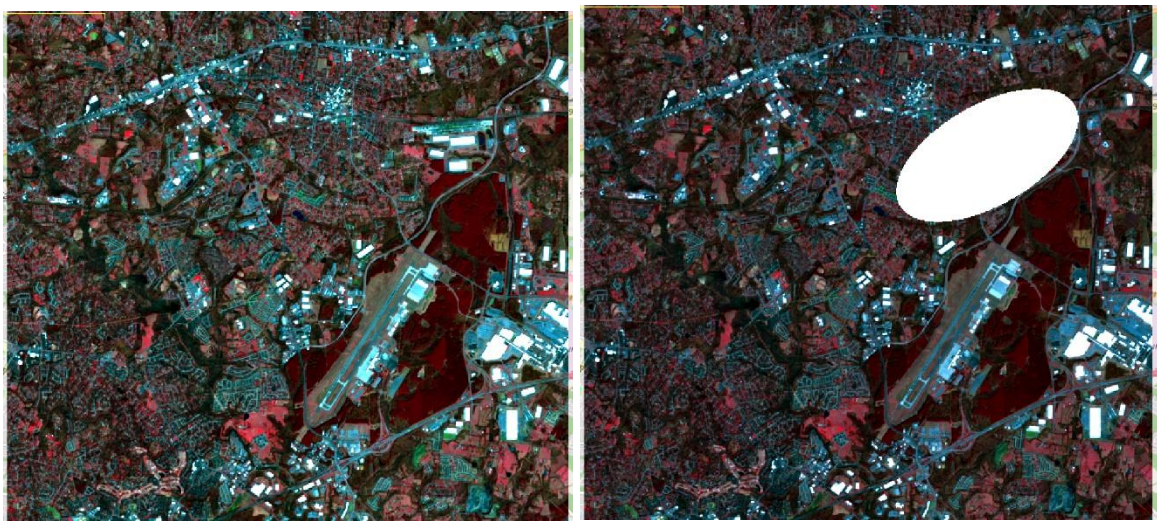


Figure 2: (Left) Original image; (Right) image with applied smoke mask.

b. Fuzzy C-Means Clustering:

The FCM algorithm (Bezdek et al., 1984) was used to classify pixels in smoke-affected areas. Unlike hard clustering, FCM allows each pixel to belong to multiple classes with different membership values between 0 and 1. This flexibility helps to capture mixed land cover conditions.

The objective function is:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \, ||X_i - C_j||^2$$

where

N = number of pixels,

C = number of clusters,

x_i = pixel vector,

c_j = cluster center,

u_{ij}= membership value of pixel i in cluster j,

m = fuzzifier, usually set to 2 (Pal & Bezdek, 1995).

Membership values and cluster centers are updated iteratively until convergence.

c. Regression Modeling and VNIR Reconstruction:

For each class, the least squares method (LSM) was used to calculate the linear relationship between SWIR and VNIR bands. Unlike the global model, which uses one equation for the whole image, this approach uses class-specific models. Previous studies confirmed that

SWIR data can be used to simulate VNIR information under smoke conditions (Li et al., 2025).

The SWIR values in smoke regions were used to simulate VNIR bands. The reconstructed smoke areas were then merged with the unaffected VNIR regions. A buffer mosaic technique (Chen & Chang, 2014) was applied to smooth boundaries and reduce visual discontinuities.

d. Accuracy Evaluation:

Two experiments were performed:

- ✓ Test Case: Artificial smoke was added to a clear image, and the reconstruction was compared with the original to check effectiveness.
- ✓ Real Case: The method was applied to wildfire images (United States and Greece), and results were compared with unaffected areas.

Three accuracy metrics were used:

- Root Mean Square Error (RMSE) – measures absolute differences.
- Correlation Coefficient (R) – measures linear correlation.

These metrics were used to compare different cluster numbers and to evaluate the practical performance of the FCM method for smoke removal.

Results and Discussion

This study included eight test cases and one real case to evaluate the performance of the fuzzy c-means (FCM) method under different numbers of clusters. In the test cases, the number of clusters was varied from 3 to 42, and three key factors were compared: the required iterations, processing time, and the correlation coefficient (R). These comparisons were used to assess the effect of cluster settings on image reconstruction.

The results show that as the number of clusters increases, the correlation coefficient of the reconstructed VNIR images generally improves. However, when the number of clusters exceeds 35, the improvement becomes very limited, while the number of iterations and processing time increase significantly. This indicates that too few clusters cannot represent the spectral diversity of the land surface, while too many clusters result in high computational cost without proportional accuracy gains.

Based on further analysis of different land cover conditions, the optimal number of clusters can be summarized as follows:

a. Forest and agricultural areas: because of similar spectral features, about 20–25 clusters are sufficient.

b. Water bodies: due to simple spectral properties, only 5–10 clusters are needed.

c. Urban and complex land cover areas: because of high diversity, at least 25–30 clusters are required to balance accuracy and efficiency.

Overall, the results suggest that the most practical choice is to select a cluster number that provides a higher correlation coefficient with a reasonable computation cost. This balance can improve the usability of the FCM method for smoke removal and image reconstruction in real-world wildfire applications.

The detailed results are shown in Tables 1–3 and Figure 3, which present the images and statistics of the eight test cases, demonstrating the relationship between cluster number settings and reconstruction performance.

Table 1: Case simulation result (1).

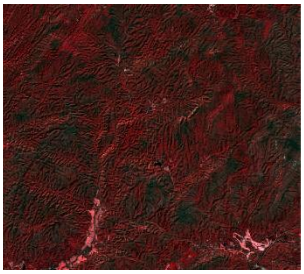
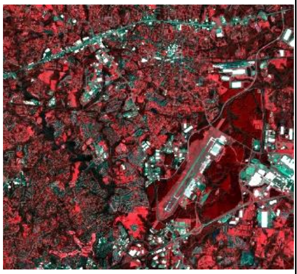
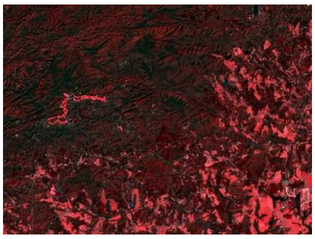
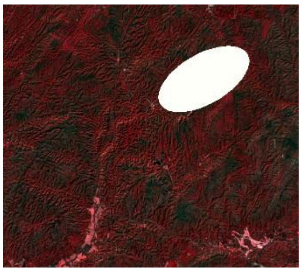
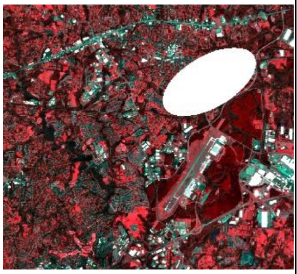
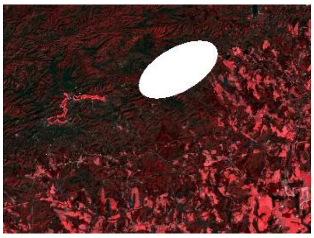
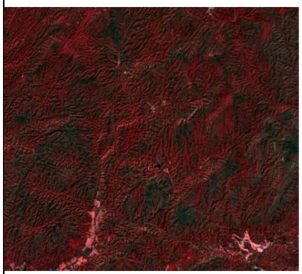
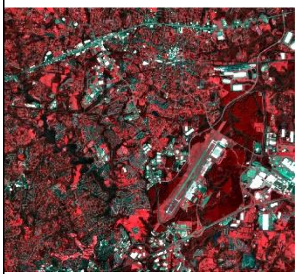
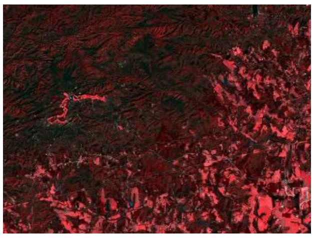
Cases Image / Input/ Output	T1	T2	T3
Original image			
Image with simulated smoke			
Result of smoke removed			

Table 2: Case simulation result (2).

Cases Image / Input/ Output	T4	T5	T6

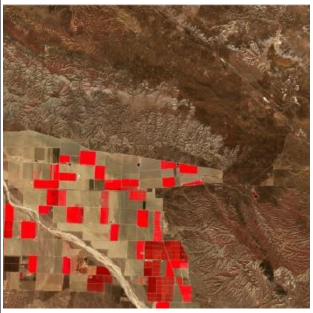
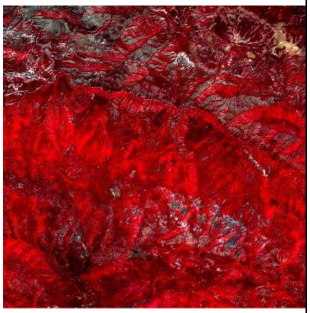
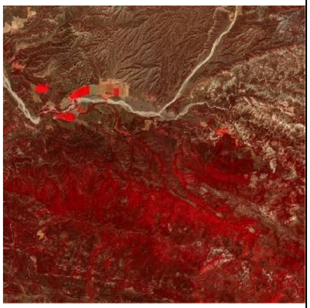
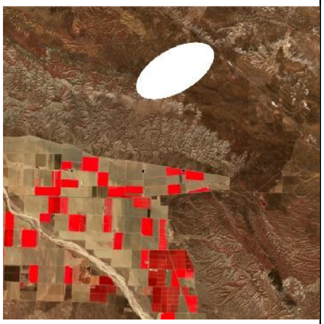
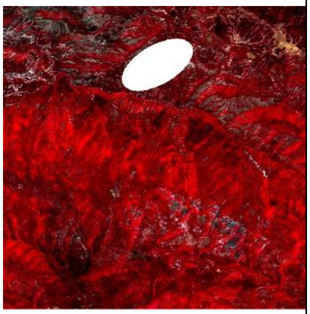
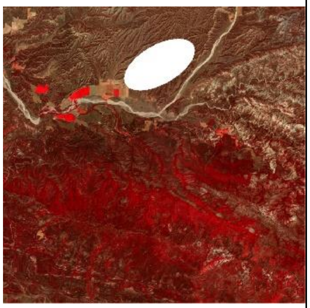
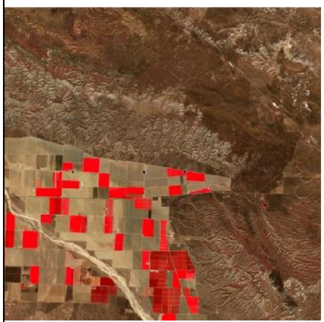
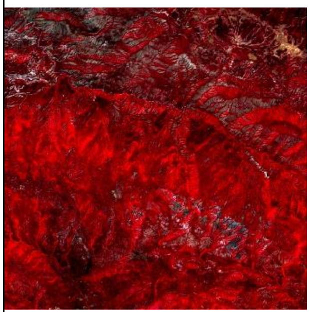
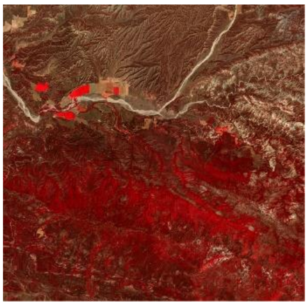
Original image			
Image with simulated smoke			
Result of smoke removed			

Table 3: Case simulation result (3).

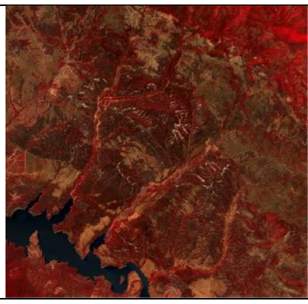
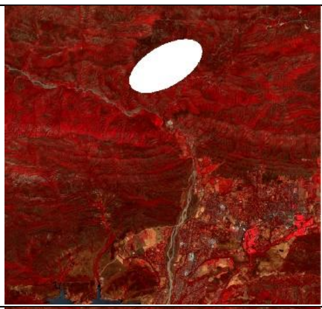
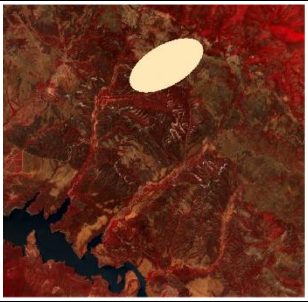
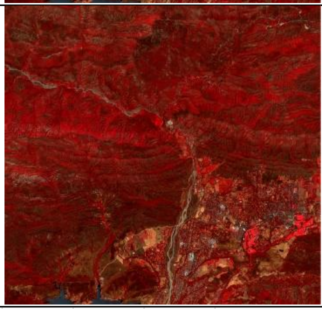
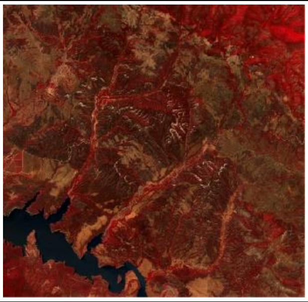
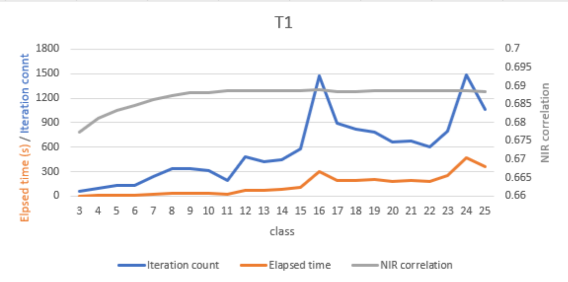
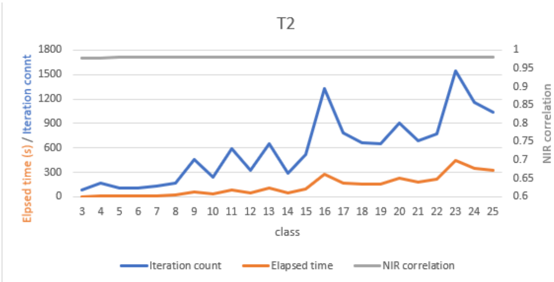
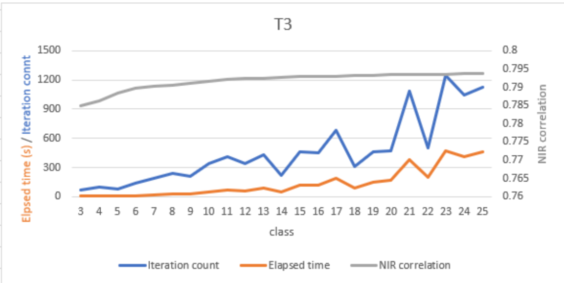
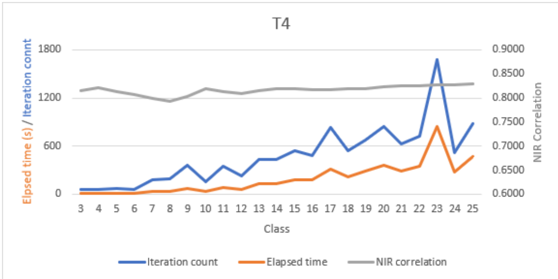
Cases Image / **Input/ Output**	**T7**	**T8**
Original image		

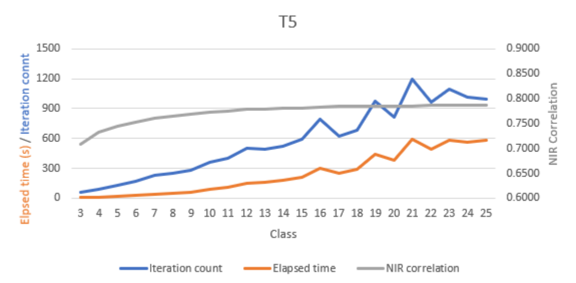
Image with simulated smoke		
Result of smoke removed		

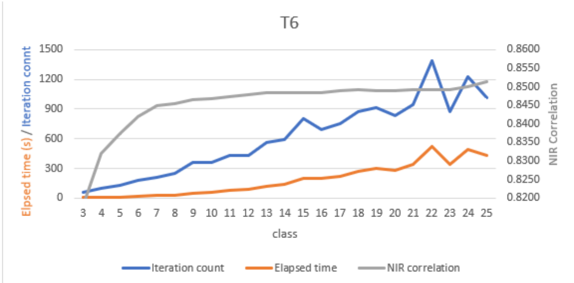


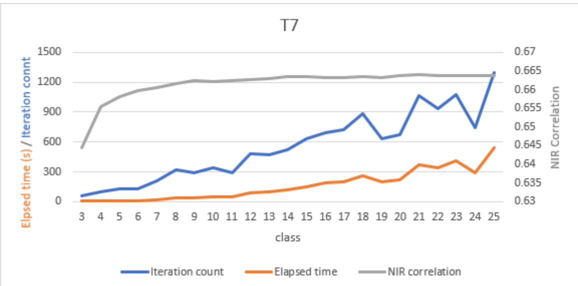












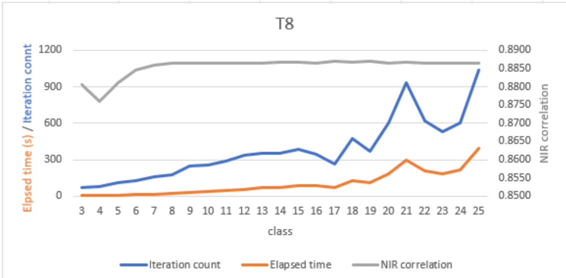


Figure 3: Time consumption and correlation coefficients under different land-cover image class numbers.

Table 3: Classification numbers and NIR correlation coefficients for classes.

Case no.	Land TYPE	Optimal number	Iteration count	Elapsed time (s)	NIR correlation
T1	Forest	9	336	37.27	0.68
T2	Urban and complex land cover areas	3	79	2.90	0.97
T3	Forest and agricultural areas	6	134	11.43	0.78
T4	agricultural areas	15	539	183.62	0.81
T5	Forest	11	403	110.46	0.77
T6	Forest and agricultural areas	10	356	57.01	0.84
T7	Forest and Urban	8	316	38.21	0.66
T8	Water bodies	9	247	31.44	0.88

Real Case: Canadian Wildfire

In addition to the test cases, the proposed method was applied to a real wildfire case in Canada. The selected region had relatively homogeneous land cover, which reduced the complexity of classification. For this case, the number of clusters was set to 10, which was sufficient to represent the spectral characteristics of the area.

The reconstruction process was completed in 172 seconds, showing a good balance between efficiency and accuracy. The results demonstrate that the smoke-affected VNIR information was successfully reconstructed, and the ground features were restored with realistic spectral properties.

As shown in Figure 4 and Figure 5, the reconstructed image provided clearer boundaries and more natural colors compared to the original smoke-affected image, confirming that the FCM-based approach can be effectively applied to real wildfire scenarios.

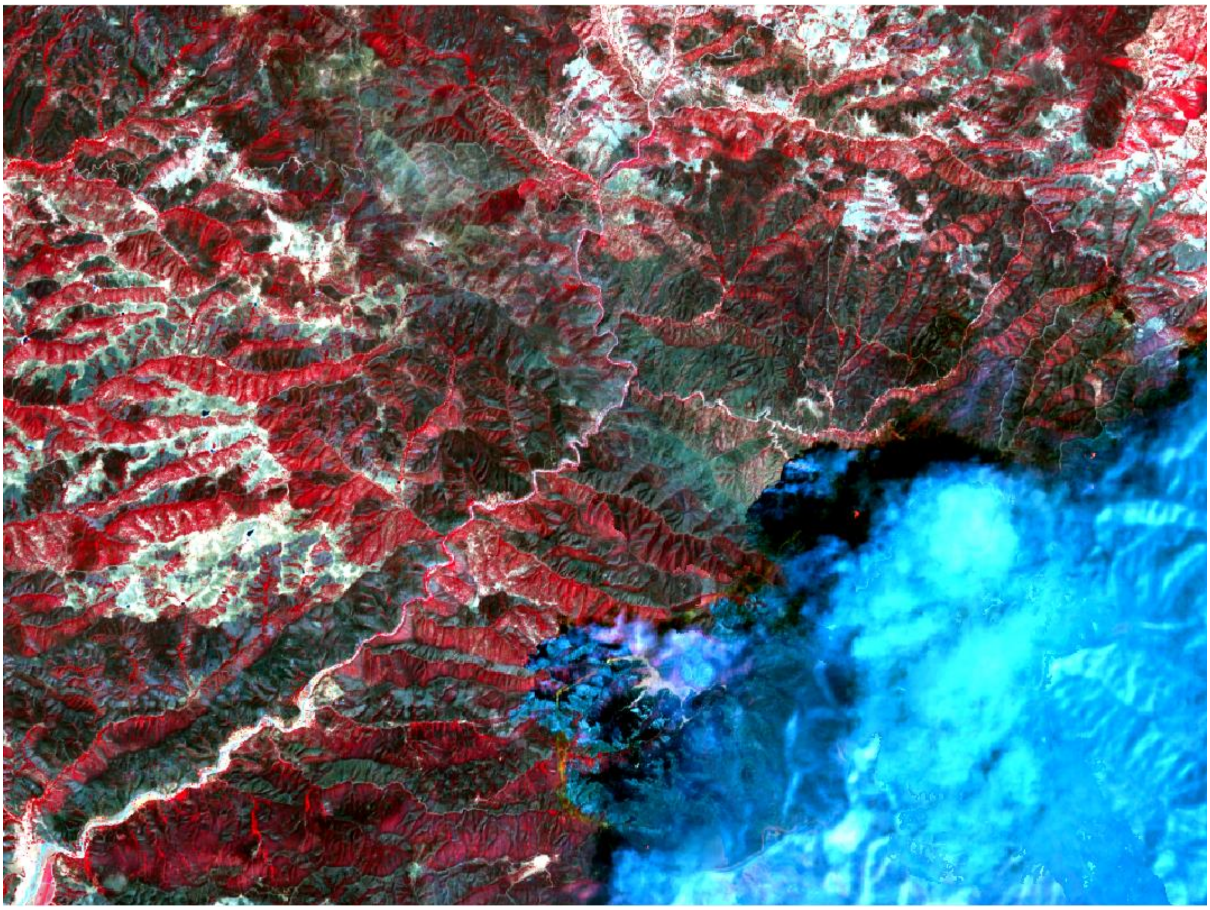


Figure 4: Original smoke-affected image

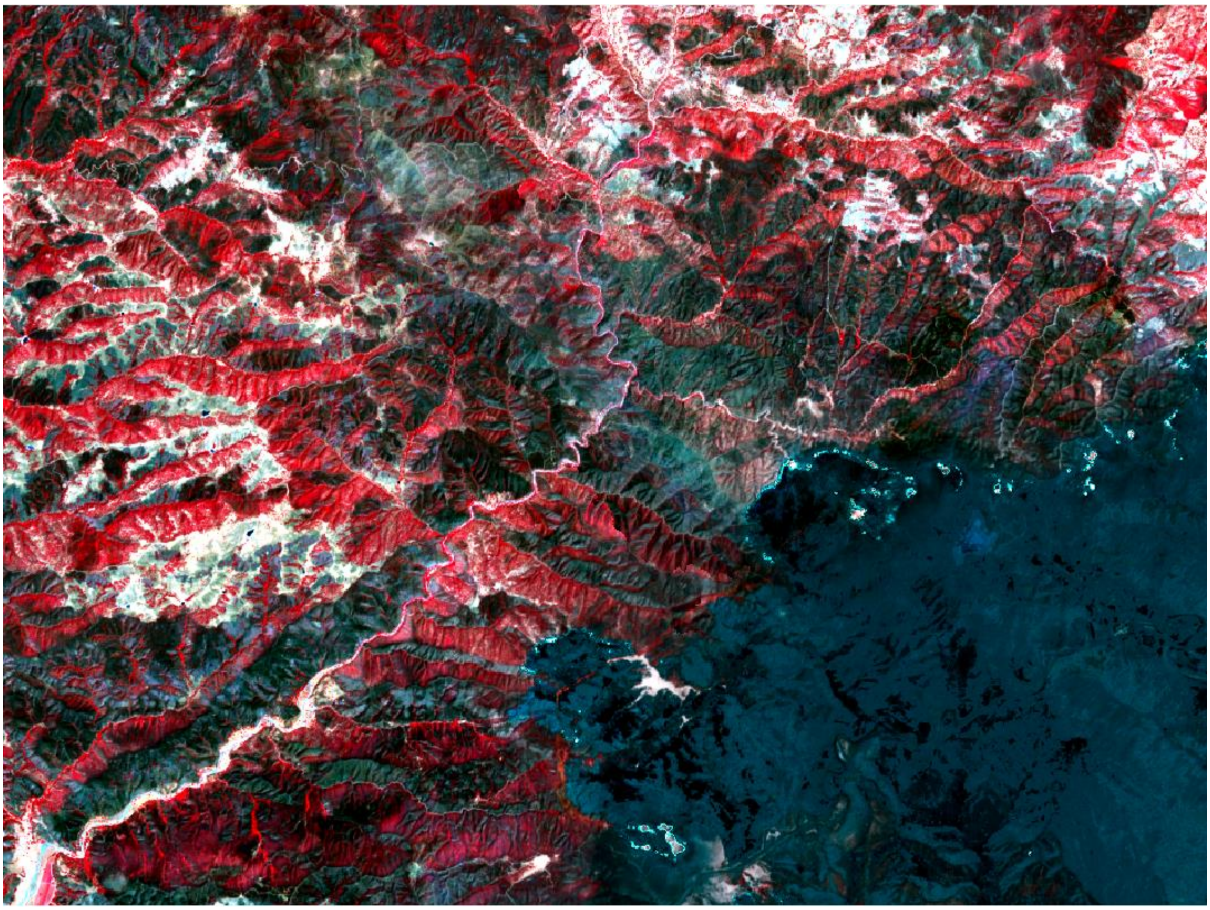


Figure 5: Wildfire burning image derived using 10-class fuzzy classification

Conclusion and Recommendation

This study applied the fuzzy c-means (FCM) clustering method to Sentinel-2 imagery for smoke removal and VNIR reconstruction, validated through both test cases and a real wildfire case in Canada. The results confirm that the FCM method improves reconstruction accuracy while maintaining computational efficiency.

In the test cases, the number of clusters was found to be a critical factor. Too few clusters failed to capture land cover diversity, leading to poor reconstruction, while too many clusters resulted in excessive iterations and computation time with limited accuracy gains. The analysis identified optimal ranges depending on land cover: 6-10 for forests/agriculture, 5–10 for water bodies, and 10-15 for urban or complex regions. This demonstrates that cluster settings should be adapted to surface heterogeneity.

In the Canadian wildfire case, the study area was relatively homogeneous, and 10 clusters were sufficient to represent spectral features. Reconstruction was completed in 172 seconds, effectively removing smoke and restoring surface details. This result highlights that in less heterogeneous regions, good performance can be achieved with moderate cluster numbers, confirming the practical feasibility of the FCM approach.

Overall, the main findings are summarized as follows:

a. FCM outperforms the global regression model (GLRM), achieving better quantitative metrics (e.g., correlation coefficient, RMSE) and more natural visual results.

b. Optimal cluster numbers vary by land cover: setting too few or too many clusters reduces overall performance.

c. Real case validation confirms practicality: in the Canadian wildfire, 10 clusters were sufficient for effective reconstruction within 172 seconds.

d. Broader application potential: beyond smoke removal, the method can be extended to vegetation monitoring, fire impact assessment, and post-disaster recovery analysis, enhancing the value of remote sensing in disaster management.

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