environmental and earth sciences proceedings

MDPI

Proceeding Paper

Improving ANFIS Classification of Rice Growth Stages Using Airborne Remote Sensing: A Fuzzy C-Means Clustering Approach †

A. Hadi Syafrudin *, Affiani Machmudah and M. Arif Saifudin

Research Center for Satellite Technology, Research Organization for Aeronautics and Space (ORPA), National Research and Innovation Agency (BRIN), Bogor 16310, Indonesia

* Correspondence: ahad001@brin.go.id

† Presented at the 1st International Online Conference on Earth Science (IOCEA 2026), 2–4 September 2026; Available online: https://sciforum.net/event/IOCEA2026.

Abstract

Monitoring rice growth stages in topographically complex and heterogeneous agricultural landscapes is essential for precision agriculture. However, unmasked airborne mapping in such environments is challenged by staggered planting schedules and interspersed tree cover. To address these challenges without heavy pre-masking, this study introduces a joint land-cover and rice growth stages classification framework using airborne multispectral imagery (Red, Green, and Near-Infrared [NIR] bands). An Adaptive Neuro-Fuzzy Inference System (ANFIS) initialized with Fuzzy C-Means (FCM) clustering was developed to simultaneously discriminate six categories: four active rice growth stages (new planting, vegetative, reproductive, and ripening) alongside other land-cover classes (fallow/preparation land and surrounding tree canopy in Agricultural land). A data-driven 10-cluster FCM-ANFIS model was evaluated against a benchmark 27-rule Grid-Partitioning ANFIS (GP-ANFIS) architecture. While GP-ANFIS suffered from rule-explosion and poor generalization—achieving a validation accuracy of only 66.30% (Kappa = 0.57)—the FCM-ANFIS framework achieved an overall validation accuracy of 89.90% (Kappa = 0.86) in just 73.16 s. These findings demonstrate that data-driven FCM initialization significantly enhances ANFIS optimization, offering a robust, computationally efficient solution for joint land-cover and phenological mapping in complex agricultural terrains.

Keywords: rice growth stages classification; ANFIS; fuzzy c-means clustering; airborne multispectral remote sensing

Check for updates

Academic Editor: Eliseo Clementini

Published: 24 November 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Rice growth-stage monitoring is important for precision agriculture because information on crop development can support field management, yield assessment, and timely agricultural decisions. Conventional field observations can provide detailed information but are often labor-intensive and difficult to apply over large areas. Remote sensing provides an alternative approach by enabling repeated observations with high spatial and temporal coverage. Recent reviews have shown that remote sensing has been widely investigated for mapping rice fields and monitoring different stages of crop development.

Machine-learning methods have therefore been increasingly applied to agricultural remote sensing. Among these methods, the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines fuzzy rules with adaptive neural-network learning to model nonlinear

relationships between input features and output responses. The original ANFIS framework proposed by Jang uses a hybrid learning procedure that combines neural-network adaptation with fuzzy inference [1].

However, the initialization of the fuzzy rule base is an important consideration in ANFIS. Conventional Grid Partitioning (GP) assigns membership functions independently to each input variable. As the number of input variables or membership functions increases, the resulting number of fuzzy rules can increase rapidly. This can make the model unnecessarily large and increase the number of parameters that must be trained. Chiu introduced an efficient method for estimating cluster centers and initializing iterative optimization based-fuzzy models, with an emphasis on reducing computational requirements compared with more computationally intensive approaches [2]. Fuzzy C-Means (FCM) provides another clustering-based approach by representing the data through fuzzy cluster memberships and has also been widely used as a basis for fuzzy model initialization. ANFIS is often used in biomedical or health research, for example in Clinical Diagnosis with topic Thyroid Nodules Analysis [3], Cardiology with research title Atrial Fibrillation Detection [4], and Oncology with focus research is Breast Cancer Identification [5]. Although rarely employed, the use of ANFIS with general settings—specifically GP—has been successfully applied in remote sensing for rice growth monitoring [6].

This study investigates joint land-cover and rice growth stages classification in a topographically complex and heterogeneous agricultural landscape using a clustering-based ANFIS framework. Although the paddy rice life cycle is conventionally divided into vegetative, reproductive, and ripening phases (which can be further detailed as in [7]), the unique spatial characteristics of the study area require a broader categorization. To accommodate heterogenous planting schedules and tree cover across topographically complex terrain, this paper establishes a six-class scheme that jointly discriminates active rice growth stages alongside other land-cover categories, specifically fallow (flooded/preparation) areas and tree cover.

2. Materials and Methods

The data acquisition campaign was conducted over Pamijahan district, located in Bogor, West Java, Indonesia. The study area is dominated by agricultural systems. To account for sensor-level radiometric inconsistencies, the raw multispectral imagery captured by the custom-filtered airborne camera (utilizing a KLI-8023 trilinear CCD sensor, onsemi, Scottsdale, AZ, USA, with dedicated Red, Green, and Near-Infrared [NIR] optical filters) mounted on the aircraft underwent dedicated pre-processing prior to atmospheric and geometric correction. Fixed-pattern noise was suppressed using a dual-calibration procedure: Dark Signal Non-Uniformity (DSNU) correction removed sensor dark current signatures, while Photo Response Non-Uniformity (PRNU) calibration normalized pixel-to-pixel responsivity variations across the sensor line scanner. This calibration sequence ensures reliable radiometric consistency across all spectral bands, providing stable input features for the subsequent FCM-ANFIS modeling stages. The flight was executed under clear-sky conditions to minimize cloud-shadow artifacts. The flight profile parameters were maintained as Altitude 2500 m with Ground Speed: 120 knots (61.73 m/s). The primary imaging payload consisted of a push-broom line-scan sensor with a spatial resolution of 0.5 m and a swath width of 4000 m per flight line.

Field observations were conducted across 99 polygon plots to identify the ongoing growth stage of the rice crops. 58 polygons are used for training and 41 polygons for validating models. This field survey took place six days after aerial imagery was acquired; plots were classified according to their specific growth stage at the time of the survey

(e.g., land preparation/flooding, vegetative, generative, or post-harvest/fallow), and local farmers were questioned regarding any changes in the crops during that six-day interval.

Based on field survey results and site characteristics, the dataset was categorized into a six-class joint framework combining non-crop land cover and active rice growth stages:

1. Fallow/Pre-Planting: Flooded, tilled, or uncultivated fields representing the pre-planting land-cover phase.
2. Early Vegetative (New Rice Planting): Newly transplanted or recently emerged rice crops.
3. Vegetative: Rice during peak tillering and stem elongation phases.
4. Reproductive: Rice during panicle initiation, booting, and flowering phases.
5. Ripening: Rice during grain filling, maturation, and pre-harvest phases.
6. Tree Canopy: Interspersed non-crop tree cover and surrounding vegetation.

Under this joint framework, classes 1 (Fallow) and 6 (Trees) account for essential other land-cover categories, while classes 2 through 5 represent the dynamic rice growth stages.

The flowchart outlines an integrated remote sensing framework for automated agricultural mapping utilizing the ANFIS shown in Figure 1. This study develops a robust, data-driven agricultural mapping framework by integrating FCM clustering with the default hybrid ANFIS optimization engine (analytic Least-Squares Estimation and Gradient Descent backpropagation). Utilizing multi-band airborne raster imagery (Red, Green, and NIR bands), we systematically evaluated a 27-rule grid-partitioned baseline against an optimized 10-cluster FCM-ANFIS model to classify six distinct joint land-cover and rice growth stages over an independent validation dataset.

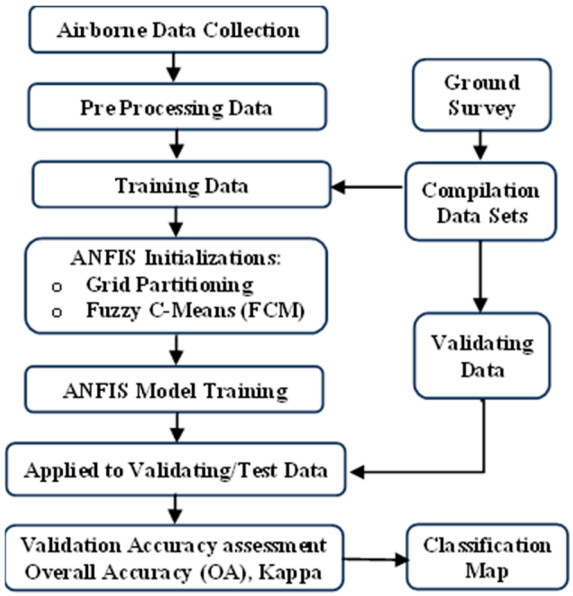


Figure 1. Methodology Schemes Adaptive Neuro-Fuzzy Inference System (ANFIS) Model for Grid Partitioning (GP) and Fuzzy C-Means (FCM).

Pixel-level spatial and spectral features extracted from the 0.5-m airborne imagery were used as network inputs. To optimize the system's structural parameters, a hybrid learning algorithm was deployed, combining a least-squares estimator in the forward pass to establish consequent parameters with gradient descent backpropagation in the backward pass to refine antecedent membership functions.

To initialize the fuzzy inference structure, two distinct input space partitioning methods were implemented and compared: GP- and FCMclustering. The GP method establishes a baseline by dividing the universe of discourse into a symmetric grid of orthogonal mem-

bership functions, though it remains highly vulnerable to computational "rule explosion" as input dimensions increase. Conversely, the FCM algorithm employs a data-driven approach, clustering spectral features based on multi-dimensional similarities to generate a condensed, optimized rule base. Following network training on a training and testing split, the highest-performing ANFIS configuration—validated via Root Mean Square Error (RMSE) and Kappa Coefficient—was deployed to generate the final thematic agricultural classification map.

3. Results and Discussion

The class classification results are presented in Figure 2. The figure shows the confusion matrix resulting from data validation using GP and FCM.

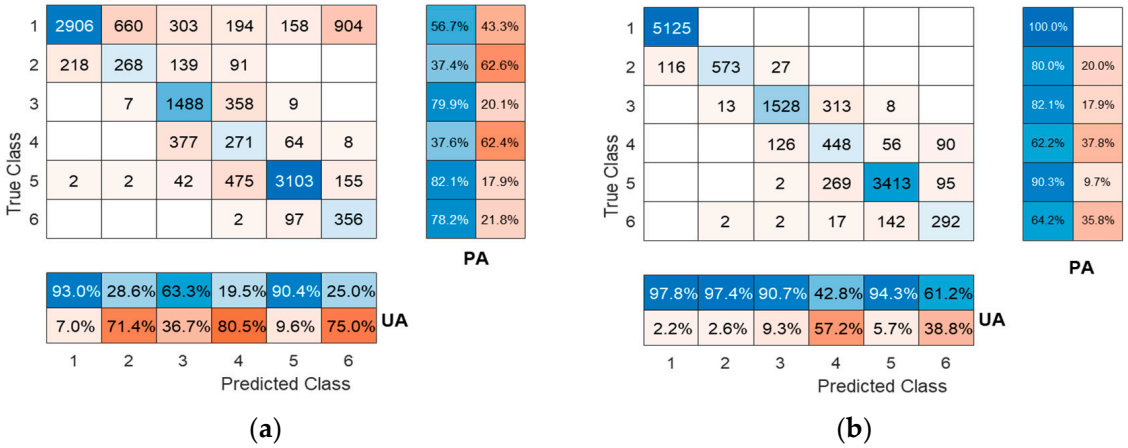


Figure 2. Confusion matrix evaluation on the independent validation data: (**a**) Grid Partition; (**b**) Fuzzy C-Means. PA: Producer Accuracy; UA: User Accuracy.

3.1. Classification Performance and Comparative Analysis

Refer from Table 1, The FCM-ANFIS model demonstrated superior performance over the GP-ANFIS model across both training and validation phases. While GP-ANFIS achieved a training accuracy of 83.52% and a Training Kappa coefficient of 0.80, its capacity to classify independent testing data degraded severely, yielding an overall validation accuracy of only 66.30% and a Validation Kappa coefficient of 0.57. In contrast, the data-driven FCM-ANFIS architecture achieved an overall training accuracy of 85.75% (Kappa = 0.83) and successfully generalized to the testing dataset, producing a validation accuracy of 89.90% and a Validation Kappa coefficient of 0.86.

Table 1. Performance Metric ANFIS Grid Partitioning (GP) and Fuzzy C-Means (FCM).

Performance Metric	Grid Partitioning	Fuzzy C-Means
Overall Training Accuracy	83.52%	85.75%
Overall Validation Accuracy	66.30%	89.90%
Training Kappa Coefficient	0.80	0.83
Validation Kappa Coefficient	0.57	0.86
Computational Elapsed Time	178.86 s	73.16 s
Core Structural Settings	3 Gaussian MFs per input	10 Gaussian Clusters [1]

[1] fuzziness exponent (m) = 2.1.

3.2. Dimensionality, Structural Rule Explosion, and Overfitting

The poor generalization capability exhibited by the GP-ANFIS structure highlights the "curse of dimensionality" inherent to rigid grid-based input space partitions. By assigning

3 Gaussian membership functions uniformly to each input feature axis (comprising the Red, Green, and NIR spectral arrays), GP causes an exponential, combinatorial growth in the generated fuzzy rule base. This structural rigidity forces the model to construct rules for mathematically possible but physically non-existent spectral combinations. Consequently, empty or irrelevant spatial zones of the feature space are incorporated into the system architecture, directly triggering severe overfitting. The model effectively memorizes the noise patterns within the training pixel sample subsets but fails when classifying the complex, heterogenous agricultural matrices of the actual landscape.

Conversely, the clustering approach of FCM overcomes this structural bottleneck through data-driven adaptation. Rather than cutting the feature space into arbitrary, uniform grids, FCM strategically locates 10 tailored clusters based on the actual density and multi-dimensional distribution of the spectral data points. The implementation of a fuzziness exponent (m = 2.1) introduces a soft partitioning gradient that maps the overlapping spectral boundaries common in changing crop stages. By focusing only on valid data clusters, FCM-ANFIS suppresses irrelevant rule generation, avoiding overfitting and maintaining high validation stability (89.90% accuracy) across diverse crop parcels.

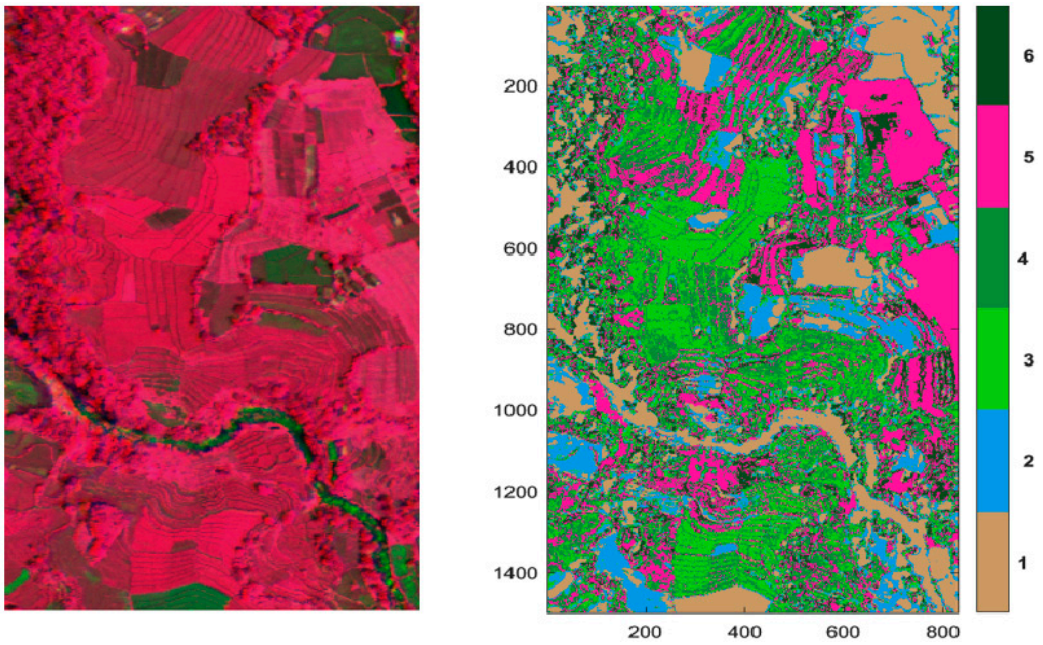
To evaluate the performance of FCM-ANFIS model, 31.18 hectares of the local agricultural area in Pamijahan district is implemented as testing area. Figure 3 illustrates the spatial performance of the proposed FCM-ANFIS classification framework applied to the airborne multispectral dataset. Figure 3a presents the false-color composite image (NIR-Red-Green), highlighting the complex topography and heterogeneous layout of the agricultural land cover, including terraced fields, riparian corridors, and staggered, heterogeneous planting practices that result in multiple rice growth stages being captured simultaneously within a single overpass. Figure 3b depicts the resulting thematic map, effectively segregating the landscape into six distinct classes. The spatial distribution reveals clear boundaries between non-crop background features—such as fallow pre-planting fields (Class 1) and tree canopy (Class 6)—and the active phenological stages of rice, spanning from early new planting (Class 2) and vegetative development (Class 3) to the advanced reproductive (Class 4) and ripening (Class 5) phases.

3.3. Computational Processing Efficiency and Scalability

Beyond thematic mapping accuracy, computational efficiency is an essential metric for processing high-resolution airborne imagery covering large geographic expanses. As illustrated by the processing logs, the GP-ANFIS framework required 178.86 s to complete its execution loop. This prolonged processing time is directly caused by the bloated rule base generated during grid initialization, which increases the matrix inversion and gradient-descent tracking overhead in the ANFIS hybrid learning algorithm.

By comparison, the FCM-ANFIS framework converged in just 73.16 s, operating more than 2.4× faster than Grid Partitioning. using the FCMclustering method, the groups then being further reduced by correlation analysis [8]. Because FCM condenses the input space into a highly optimized rule base matching the true data dimensions, the mathematical complexity of both the forward least-squares step and backward error propagation pass is greatly minimized. FCM-clustered models perform better at lower cluster size [9].

In general, the performance of classifier depends on several factors such as size and quality of training set, the rigor of the training imported and also parameters chosen to feed to ANFIS as inputs can be influencing the classifier performance [10]. This stark reduction in processing time, coupled with high classification accuracy, proves that the FCM-ANFIS framework provides a scalable, practical architecture for large-scale, 0.5-m resolution aerial mapping workflows.



(**a**) (**b**)

Figure 3. (**a**) False-color composite of the airborne multispectral test image (**b**) Corresponding Adaptive Neuro-Fuzzy Inference System- Fuzzy C-Means (ANFIS–FCM) thematic classification map displaying the six distinct classes (1: Fallow, 2: New Rice Planting, 3: Vegetative, 4: Reproductive, 5: Ripening, 6: Trees).

4. Conclusions

This study demonstrates that the choice of input space partitioning directly dictates the viability, accuracy, and efficiency of fuzzy neural networks applied to high-resolution remote sensing data. When mapping complex, heterogeneous landscapes, traditional GP approaches suffer from an exponential explosion of rules, which integrates irrelevant data zones into the system architecture and triggers severe model overfitting. Conversely, utilizing a data-driven FCM clustering strategy mitigates the curse of dimensionality by shaping the network's rule base around the actual distribution and density of the environmental feature space.

Ultimately, shifting from rigid structural division to adaptive, cluster-based space partitioning yields a model that is both highly accurate and computationally streamlined. The optimized clustering approach drastically cuts down algorithmic processing overhead, offering greater than twofold processing speeds alongside superior generalization capabilities on independent validation datasets. These findings establish that integrating data-driven clustering with adaptive inference models provides a highly scalable, precise, and practical framework for large-scale geographic classification and automated land-use monitoring workflows.

Author Contributions: All authors are main contributors and have made equal research contributions. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: I would like to express my gratitude to all fellow researchers at the Research Center for Satellite Technology BRIN for their support of research into remote sensing technology and its applications.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANFIS	Adaptive Neuro-Fuzzy Inference Systems
GP	Grid Partitioning
FCM	Fuzzy C-Means
PA	Producer Accuracy
UA	User Accuracy
MF	Membership Function
RMSE	Root Mean Square Error
PRNU	Photo Response Non-Uniformity
DSNU	Dark Signal Non-Uniformity
NIR	Near-Infrared

References

1. Jang, J.-S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man. Cybern.* **1993**, *23*, 665–685. [CrossRef]
2. Chiu, S.L. Fuzzy Model Identification Based on Cluster Estimation. *J. Intell. Fuzzy Syst. Appl. Eng. Technol.* **1994**, *2*, 267–278. [CrossRef]
3. Gao, L.; Jiang, J.; Li, X.; Wang, H. Differentiation of Benign and Malignant Thyroid Nodules with ANFIS by Using Genetic Algorithm and Proposing a Novel CAD-Based Risk Stratification System of Thyroid Nodules. *Diagnostics* **2023**, *13*, 740. [CrossRef] [PubMed]
4. Kim, J.; Shin, H.; Lee, S. Comparison of ANN and ANFIS Models for AF Diagnosis. *Appl. Sci.* **2023**, *13*, 1712. [CrossRef]
5. Nagalakshmi, K.; Suriya, S. Performance Analysis of Breast Cancer Detection Using the ANFIS Algorithm. *Comput. Syst. Sci. Eng.* **2023**, *44*, 501–517. [CrossRef]
6. Syafrudin, A.H. Mapping of Rice Plant Growth from Airborne Line Scanner Using ANFIS Method. Master's Thesis, IPB University, Bogor, Indonesia, 2012.
7. Sheng, R.T.-C.; Huang, Y.-H.; Chan, P.-C.; Bhat, S.A.; Wu, Y.-C.; Huang, N.-F. Rice Growth Stage Classification via RF-Based Machine Learning and Image Processing. *Agriculture* **2022**, *12*, 2137. [CrossRef]
8. Abdul Shahed, A.M.; Longstaff, A.P.; Fletcher, S. The application of ANFIS prediction models for thermal error compensation on CNC machine tools. *Appl. Soft Comput.* **2015**, *27*, 158–168. [CrossRef]
9. Wiharto, W.; Esti, S. The analysis effect of cluster numbers on fuzzy c-means algorithm for blood vessel segmentation of retinal fundus image. In *Proceedings of the 2nd International Conference on Information and Communications Technology. ICOIACT 2019*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 106–110.
10. Hosseini, M.S.; Zekri, M. Review of Medical Image Classification using the Adaptive Neuro-Fuzzy Inference System. *J. Med. Signals Sens.* **2012**, *2*, 49–60. [CrossRef] [PubMed] [PubMed Central]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.