Spatial Classification of Fertilizer Requirements Using Fuzzy C-Means on Shallot Agricultural Land

Roghib Muhammad Hujja, Ahmad Ashari, Danang Lelono, Agus Prasekti
Dept. Computer Science and Electronics, Universitas Gadjah Mada, Yogyakarta, Indonesia

***Abstract*—Spatial variability in soil fertility constrains productivity in intensive shallot farming, yet fertilizer is frequently applied uniformly across fields. This practice results in nutrient inefficiencies, increased costs, and heightened environmental risks. This study introduces a fertilizer requirement mapping framework utilizing Fuzzy C-Means (FCM) clustering, a machine learning technique for data grouping, applied to in-situ measurements of soil Nitrogen (N), Phosphorus (P), and Potassium (K). The framework was evaluated in a 500 × 500 m shallot field in Srikayangan, Kulon Progo, Indonesia, subdivided into 10 × 10 m management blocks suitable for smallholder operations. Soil NPK levels were measured using IoT sensor nodes and georeferenced with GNSS, while high-resolution RGB imagery from a UAV provided spatial context. Normalized NPK data were clustered with FCM to delineate fertility zones exhibiting nutrient differences. To operationalize clustering results, a nutrient-priority decision logic identified the most limiting nutrient (N, P, or K) for each block. Fertilizer recommendation points were visualized on a UAV-derived orthomosaic map to facilitate interpretation and field application. The results indicate that this approach effectively captures gradual fertility transitions and produces actionable fertilizer zones for site-specific nutrient management (SSNM) in smallholder systems. The study demonstrates the practical integration of fuzzy clustering, IoT-based soil sensing, and UAV mapping to inform precision agriculture decisions.**

Keywords—Fuzzy C-Means (FCM); soil fertility zoning; NPK (Nitrogen, Phosphorus, Potassium); fertilizer recommendation; precision agriculture; Site-Specific Nutrient Management (SSNM); IoT (Internet of Things); UAV (Unmanned Aerial Vehicle)

I. INTRODUCTION

Soil fertility variability represents a significant constraint to productivity and sustainability in intensive vegetable farming. In many fields, soil properties such as nutrient availability, texture, and organic matter content exhibit substantial variation over short distances. Despite this, fertilizer is typically applied uniformly. This disconnect between spatial variability and uniform management leads to inefficient nutrient use, increased costs, and elevated risks of environmental impacts, including nutrient leaching and accumulation [1], [2].

Shallot (Allium cepa var. aggregatum) cultivation, prevalent in Indonesia and Southeast Asia, depends on effective fertilizer management to achieve optimal yield and bulb quality. Grown in narrow beds with intensive inputs, shallots are particularly sensitive to nutrient imbalances. Nitrogen (N), Phosphorus (P), and Potassium (K) are the primary drivers of growth, root development, bulb formation, and stress resistance. The distribution of these nutrients varies according to soil conditions, irrigation practices, and fertilization history, resulting in significant variability even within smallholder plots [1].

Precision agriculture and site-specific nutrient management (SSNM) address this challenge by tailoring fertilizer inputs to spatially variable soil and crop conditions. A central aspect of SSNM involves delineating relatively homogeneous management zones to enable differentiated fertilizer application [1], [3]. Early research employed dense grid-based soil sampling and geostatistical interpolation to generate continuous fertility maps. Although effective, these methods often demand considerable sampling effort and may not readily translate into fertilizer decision rules that are easily adopted by farmers [3].

Clustering-based methods group spatial units—defined areas within a field—into management zones based on similar soil or crop attributes. Fuzzy C-Means (FCM) clustering, a technique that allows data points to partially belong to multiple groups, is widely used in soil fertility assessment, as it captures gradual transitions and inherent uncertainty in soil properties. Unlike hard clustering (which assigns each spatial unit to only one group), FCM gives each spatial unit a degree of membership in multiple clusters, reflecting spatial continuity. Studies have used FCM to delineate management zones based on soil chemical properties (e.g., nutrient levels), electrical conductivity, yield data, and remote sensing (data collected from satellite or aerial images) across cropping systems [3], [8], [9].

Recent research extends FCM zoning by adding multi-nutrient data, principal component analysis, and geospatial techniques. These support variable-rate fertilization and site-specific management. For example, fuzzy clustering has generated nutrient-based zones that capture macro- and micronutrient variability, thereby improving fertilizer targeting [4]-[7]. These studies confirm FCM's suitability for capturing soil heterogeneity and supporting differentiated management. However, most prior work focuses on general fertility zones or composite indices rather than nutrient-specific fertilizer priorities.

At the same time, advances in agricultural sensing technology enable higher-resolution data for precision agriculture [20]. Internet of Things (IoT)-based soil sensors [14] provide near-real-time soil measurements at fine spatial resolution, reducing reliance on labor-intensive laboratory analyses [10], [15], [19]. Unmanned aerial vehicle (UAV) remote sensing also supplies high-resolution information on field structure and crop condition, supporting detailed mapping at the scale of individual beds or plots [11]-[13], [18]. Recent studies highlight the promise of integrating IoT sensing, UAV imagery, and data analytics into decision-support systems for precision agriculture [17], [18].

Despite these advancements, a gap remains between soil data analysis and the generation of actionable fertilizer recommendations. Few studies have demonstrated direct integration of fuzzy clustering with nutrient-priority logic for N, P, or K at the level of individual spatial units. Additionally, most existing applications operate at coarse spatial scales, which limits their applicability in smallholder vegetable systems where management occurs at the bed scale.

This study addresses these gaps by proposing a spatial classification and decision-support method for mapping fertilizer needs. The method uses Fuzzy C-Means clustering of soil NPK data. It is applied to a 500 × 500 m shallot field in Srikayangan, Kulon Progo, Indonesia. The field is divided into 10 × 10 m blocks for smallholder bed-scale use. Soil N, P, and K were measured with IoT sensors and combined with high-resolution UAV imagery. FCM clustering on normalized NPK data created fertility zones. A nutrient-priority logic then found the most limiting nutrient (N, P, or K) at each block.

This study offers three primary contributions. First, it develops a nutrient-priority logic that translates fuzzy membership degrees into actionable recommendations. Second, it applies FCM clustering at a fine spatial scale consistent with smallholder bed operations. Third, it integrates IoT-based soil sensing and UAV imagery into a straightforward, map-based decision-support output.

This study does not introduce a new clustering algorithm. Rather, it enhances the practicality of FCM-based soil fertility zones by linking fuzzy clustering results with site-specific fertilizer prescriptions. The proposed approach is adaptable to various crops, regions, and sensor configurations where soil nutrient variability necessitates more efficient fertilizer management.

II. Methodology

A. Study Area and Data Acquisition

The study was conducted in an intensively cultivated vegetable field used for seasonal shallot and leafy vegetable production in Desa Srikayangan, Kecamatan Sentolo, Kabupaten Kulon Progo, Yogyakarta, Indonesia. The field in our experiment spans approximately 500 × 500 m and is subdivided into narrow beds and furrows, following local farming practices. The objective of the data acquisition campaign was to capture the spatial variability of soil macronutrients—Nitrogen (N) [16], Phosphorus (P), and Potassium (K), which are essential nutrients plants require in relatively large amounts—and relate it to crop-condition patterns observable from high-resolution UAV (unmanned aerial vehicle) imagery.

A regular sampling grid with a nominal spacing of 10 × 10 m was designed to cover the entire field. Each grid cell (block) was represented by a single sampling point located near the center of the crop bed. At every sampling point, an in-situ NPK soil sensor probe was inserted vertically into the topsoil (0–20 cm) after removing surface residues and ensuring good contact between the probe and the soil [10].

For each point, the probe was held in place until the readings stabilized, and the values of N, P, and K were recorded. To reduce random noise, the insertion and reading process was repeated two or three times within a radius of about 1 m, and the average of these readings was used as the NPK value for the corresponding block. Between sampling points, the probe was cleaned to avoid cross-contamination.

To obtain reference values and assess the consistency of sensor readings, composite soil samples were collected from a subset of grid points. These samples were air-dried and analyzed in the laboratory using standard procedures [4], [5]. The resulting dataset thus consists of triplets, each associated with georeferenced coordinates for a sampling location.

The geographic coordinates of all sampling points were measured using a GNSS receiver mounted on a survey pole, ensuring sub-meter positional accuracy. The in-field NPK sensing and GNSS positioning procedure is illustrated in Fig. 1.

Fig. 1. In-situ soil NPK data acquisition and GNSS-based georeferencing during field sampling.

To obtain a spatially continuous representation of crop condition and field structure, aerial images of the study area were acquired using a fixed-wing unmanned aerial vehicle (UAV) equipped with a nadir-looking RGB camera (Fig. 2). The UAV was programmed to fly an autonomous mission over the 500 × 500 m field along parallel flight lines. The flight altitude was set to approximately 100–120 m above ground level, resulting in a ground sampling distance of a few centimeters per pixel [11],[13].

Forward and side overlaps were configured to at least 70% and 60%, respectively, to ensure reliable image matching. Several ground control points (GCPs) were placed at clearly visible locations within and around the field and surveyed using the same GNSS equipment as the soil sampling points. These GCPs were later used to improve the geometric accuracy of the photogrammetric products.

The raw UAV images were processed using a standard structure-from-motion (SfM) photogrammetry workflow, which includes feature detection and matching, bundle adjustment, dense point cloud generation, and orthorectification. The resulting orthomosaic was georeferenced in the same projected coordinate system as the GNSS measurements. The georeferenced soil NPK points were then overlaid on the orthomosaic in a geographic information system (GIS), and each 10 × 10 m block was associated with both its NPK values and its corresponding location in the UAV image. This integration enabled subsequent Fuzzy C-Means clustering on the block-level NPK data and the visualization of fertilizer recommendation points directly on the high-resolution UAV map.

Fig. 2. Fixed-wing UAV platform used for high-resolution RGB image acquisition.

B. Data Preprocessing and Block Generation

To support block-level decision making, the study area was discretized into a regular grid of 10 × 10 m cells, hereafter referred to as blocks. Each soil sampling point was assigned to its corresponding block based on spatial location. For blocks with more than one sample, the average values of N, P, and K were computed. Blocks without observations were either excluded from the analysis or filled using simple spatial interpolation (nearest neighbor), depending on their position and the density of surrounding samples.

The raw N, P, and K values may have different units and numerical ranges. To prevent any single nutrient from dominating the clustering process, all variables were normalized prior to analysis. In this study, min–max normalization was used:

$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$ Where x_{ij} is the original value of nutrient $j \in \{N, P, K\}$ in block i, and x'_{ij} is the normalized value within the interval $[0,1]$. Each block is then represented as a three-dimensional feature vector.

$$\boldsymbol{x}_i = [N'_i,\ P'_i,\ K'_i]$$

Basic quality control was applied to detect and handle outliers (e.g., physically unrealistic values due to sensor error). Outliers were inspected against the laboratory reference data and field notes. If a value was clearly erroneous and could not be confirmed, the corresponding block was removed from further analysis.

C. Fuzzy C-Means Clustering

The core of the proposed approach is the use of the Fuzzy C-Means (FCM) algorithm to partition the blocks into a set of soil fertility clusters based on their normalized N, P, and K values. FCM seeks to minimize the following objective function:

$$J_m = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{m} \ \| \mathbf{x}_i - \mathbf{v}_k \|^2$$

where,

- n is the number of blocks,
- c is the number of clusters,
- u_{ik} is the membership degree of block i in cluster k,
- $m > 1$ is the fuzziness exponent (typically $m = 2$),
- $\boldsymbol{v}_k$ is the center of cluster k, and
- $\|\cdot\|$ denotes the Euclidean norm.

In this study, the number of clusters (c) was chosen to represent distinct patterns of nutrient status in the field (e.g., three clusters to capture relatively low, medium, and high fertility combinations or characteristic N–P–K imbalances). The algorithm proceeds iteratively as follows:

- Initialization: Initialize the membership matrix $\mathrm{U}[=\mathrm{u}_{\mathrm{ik}}]$ with random values such that $\sum_{\mathrm{k}=1}^{/\mathrm{c}} \mathrm{u}_{\mathrm{ik}} = 1$ for all i.
- Cluster center update: Compute cluster centers

$$\mathbf{v}_k = \frac{\sum_{i=1}^{n} u_{ik}^{m} \mathbf{x}_i}{\sum_{i=1}^{n} u_{ik}^{m}}$$

for each cluster k.

- Core Membership update: Update membership degrees

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\| \mathbf{x}_i - \mathbf{v}_k \|}{\| \mathbf{x}_i - \mathbf{v}_j \|} \right)^{\frac{2}{m-1}}}$$

for all blocks i and clusters k.

- Stopping criterion: Repeat steps 2–3 until the change in the membership matrix between two successive iterations falls below a small threshold ε(e.g., 10^{-5}) or a maximum number of iterations is reached.

The implementation was carried out in Python using a custom FCM routine and executed in Google Colab. The output of this step is a set of cluster centers $\{\mathbf{v}_k\}$and a membership matrix that describes the degree to which each block belongs to each cluster.

D. Derivation of Nutrient Priority Classes

To transform the fuzzy clusters into actionable fertilizer recommendations, the nutrient composition of each cluster center was analyzed. For each cluster k, the relative status of N, P, and K was assessed by comparing the normalized values N'_k, P'_k, and K'_k in v_k to the field-wide distribution or target fertility levels. Clusters in which a particular nutrient exhibits comparatively low values were interpreted as zones where that nutrient is more likely to be limiting.

A simple decision rule was then defined to assign a nutrient priority to each block:

- For each cluster k, determine the "most limiting" nutrient j_k, which is the nutrient with the lowest normalized value in $\mathbf{v}_k$.
- For each block i, compute a nutrient priority score by combining its membership degrees with the cluster-level limiting nutrients. For example, the priority score for nutrient j in block i can be defined as,

$$S_{ij} = \sum_{k:j_k=j} u_{ik}$$

- Assign block i to the nutrient with the highest score $\arg\max_j S_{ij}$, yielding one of three recommendation classes: N-priority, P-priority, or K-priority.

This procedure preserves the fuzzy nature of the underlying clusters while providing a crisp, interpretable label for operational use. Blocks with similar scores for multiple nutrients can be flagged as mixed or flexible zones for further agronomic evaluation if needed.

E. Spatial Mapping and Visualization

The FCM cluster labels (dominant cluster per block) and the nutrient-priority classes were joined back to the 10×10 m spatial grid and visualized in a GIS. The fertility clusters were displayed as a zonation map of the shallot field. At the same time, the nutrient-priority classes were represented in a separate map showing whether N, P, or K should be emphasized in each block.

To make the output usable in the field, representative fertilizer recommendation points were selected from within contiguous patches of each nutrient-priority class. In each patch, a few blocks with the highest nutrient-priority scores were chosen as application points. These points were then overlaid on the UAV orthomosaic, allowing farmers and field technicians to locate the recommended areas directly on a detailed image of the shallot beds. The final maps form the basis for suggesting differentiated fertilizer rates (e.g., higher urea doses at N-priority points, higher SP-36 at P-priority points, and higher KCl at K-priority points) instead of a single uniform NPK recommendation for the whole field.

III. Results and Analysis

A. Fuzzy C-Means Zoning of Soil Fertility

The Fuzzy C-Means (FCM) algorithm successfully partitioned the 500×500 m field into three main fertility zones based on the N, P, and K measurements at each 10×10 m block. Visual inspection of the resulting clusters (Fig. 3) shows that the field is clearly structured into red, green, and blue zones with gradual transitions rather than abrupt boundaries.

Cluster-level analysis indicates that:

- Cluster 1 (Red) corresponds to blocks with high N and relatively low K.
- Cluster 2 (Green) represents blocks with high K but lower N.
- Cluster 3 (Blue) is characterized by relatively high P with more balanced N and K values.

These patterns align with the agronomic interpretation in the field, where some areas receive high N fertilization but remain undersupplied with P and K. In contrast, other areas have accumulated K from previous applications.

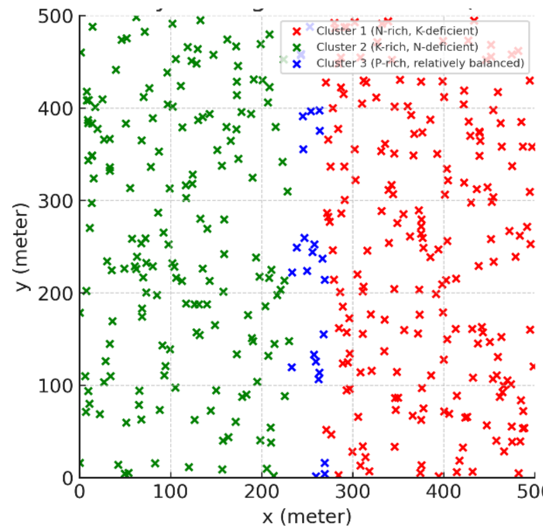

Fig. 3. Soil fertility zoning based on Fuzzy C-Means clustering.

The quality of the clustering was evaluated using two internal indices. The Silhouette Score of 0.61 and Dunn Index of 0.03 suggest that the three clusters are reasonably well separated while still capturing the gradual variability that exists in real soil conditions. These values suggest that FCM offers a reliable representation of the underlying fertility structure and is suitable as a basis for informed spatial decision-making.

B. Spatial Pattern of Nutrient Deficiencies

By comparing the cluster centers with the most fertile reference condition, it is possible to identify which parts of the field are more likely to be deficient in specific nutrients. The cluster map in Fig. 4 shows that:

- The western part of the field is dominated by Cluster 2 (green), indicating high K but relatively low N, and simultaneously showing P deficiency in some blocks.
- The eastern part of the field is dominated by Cluster 1 (red), where N is high but P and K are lower, suggesting a need to supplement P and K rather than N.
- Cluster 3 (blue) appears in intermediate zones with higher P and relatively balanced N and K, acting as a transition between the red and green zones.

This pattern confirms that nutrient limitations are not uniform: the west is mainly limited by P and K, whereas the east is more constrained by N. Such differences justify the need for site-specific fertilizer management instead of uniform application. Table I summarizes the qualitative interpretation of each cluster based on the N, P, and K status.

TABLE I. INTERPRETATION OF FCM FERTILITY CLUSTERS

Cluster	Dominant color	N status	P status	K status	Interpretation
C1	Red	High	Low–medium	Low	N-rich, K-deficient zone (needs P and K)
C2	Green	Low–medium	Low–medium	High	K-rich, N-deficient zone
C3	Blue	Medium	High	Medium	P-rich, relatively balanced, and stable zone

C. Fertilizer Recommendation Points

To translate the cluster information into operational recommendations, fertilizer application points were determined by selecting blocks with the highest nutrient-priority scores inside each deficiency zone. These points are located near the centers of areas with the strongest shortage, representing locations where additional fertilizer will have the most significant effect while still covering surrounding blocks.

The resulting fertilizer recommendation map is shown in Fig. 4. The background colors represent the FCM clusters as in Fig. 3, while overlaid symbols indicate specific application points for each nutrient:

- Red squares mark N application points, where additional urea is recommended.
- Blue triangles mark P application points, where SP-36 is prioritized.
- Green circles mark K application points, where KCl is prioritized.

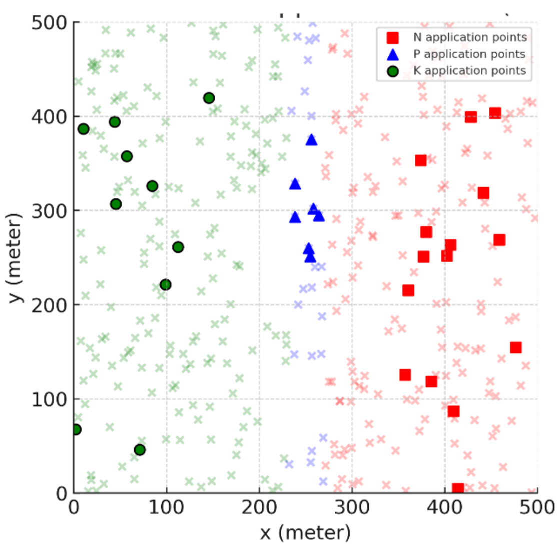

Fig. 4. Fertilizer recommendation points over the FCM zonation map.

Based on the nutrient-priority classification, the corresponding fertilizer types and application rates are summarized in Table II.

TABLE II. FERTILIZER RECOMMENDATION RATES BY NUTRIENT PRIORITY

Nutrient priority	Symbol/color in Fig. 4	Recommended fertilizer and rate (per ha)
N-priority	Red square	Urea 300–350 kg/ha
P-priority	Blue triangle	SP-36 100–120 kg/ha
K-priority	Green circle	KCl 150–200 kg/ha

These recommended doses are intended for the core application points and can be adjusted proportionally for the surrounding blocks, depending on equipment capability and field conditions.

D. Visualization on High-Resolution Spatial Agricultural Map

To make the results directly interpretable by farmers and local extension workers, the nutrient-priority recommendation points were finally overlaid on a high-resolution aerial orthomosaic of the study area (Fig. 5). The orthomosaic was generated from UAV imagery and represents individual crop beds and management units within the 500 × 500 m field.

The coordinates of the 10 × 10 m blocks and the selected fertilizer application points (Section III-C) were transformed into the same spatial reference system as the orthomosaic. Each point was then plotted on top of the image and symbolized according to its recommended nutrient:

- blocks with N-priority were marked as N application points,
- blocks with P-priority were marked as P application points, and
- Blocks with K-priority were marked as K application points.

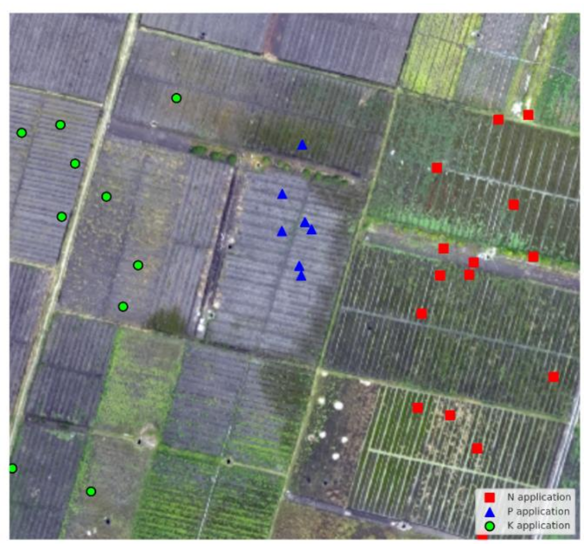

Fig. 5. UAV orthomosaic with FCM-based fertilizer recommendation points.

Fig. 5 shows that many N-priority points coincide with visually lighter or less vigorous plots in the eastern portion of the field. In contrast, P- and K-priority points are concentrated in the western and central plots where crop growth appears uneven or patchy. This spatial correspondence between visual crop condition and the FCM-based nutrient recommendations provides an additional qualitative validation of the proposed method.

By combining the orthomosaic with the fertilizer recommendation points, the resulting map becomes a practical tool for field operations: farmers can visually locate specific beds or parcels that require N, P, or K and adjust their applications accordingly. The map can also be integrated into mobile or web-based interfaces, allowing operators to navigate to the recommended positions using GPS while viewing the underlying UAV image.

E. Discussion

The FCM-based spatial classification clearly revealed that the 500 × 500 m field cannot be treated as a uniform management unit. The three clusters obtained from NPK data describe distinct fertility regimes that are consistent with both the historical fertilization practices and the visual crop patterns observed in the UAV imagery. Cluster 1 (red) represents blocks with relatively high N. However, Cluster 2 (green) corresponds to blocks with high K but lower N, and Cluster 3 (blue) contains blocks with relatively high P and more balanced N and K. These patterns suggest that the field has experienced heterogeneous nutrient accumulation, with specific areas receiving repeated N applications while others have accumulated K or P.

When the cluster information is translated into nutrient-priority classes, a transparent spatial gradient emerges: the western part of the field is dominated by blocks that require additional phosphorus (P) and potassium (K). In contrast, the eastern part shows a concentration of N-priority blocks. The central area is characterized by P-priority points associated with Cluster 3, which has a higher P. However, only moderate N and K. This configuration implies that a uniform NPK recommendation would inevitably over-fertilize some zones (e.g., N in the western plots) and under-fertilize others (e.g., P and K in the west, N in the east). Instead, the proposed method provides differentiated targets: more P and K in the west, more N in the east, and fine-tuned doses in the transition zones.

A key advantage of FCM in this context is its ability to handle gradual transitions and uncertainty. Traditional hard clustering or simple thresholding of nutrient values would force each block into a single, crisp category, creating sharp boundaries between zones that may not exist in reality. In contrast, FCM assigns membership degrees to multiple clusters for each block. The nutrient-priority scores derived from these memberships enable the method to highlight "core" deficiency zones, where a single nutrient is clearly limiting, while also acknowledging mixed or ambiguous areas. This is reflected in the placement of fertilizer recommendation points, which tend to appear in the centers of homogeneous patches, rather than directly on the boundaries between different fertility regimes. This is agronomically reasonable because edge blocks can often be managed with intermediate or blended doses.

The overlay of fertilizer recommendation points on the UAV orthomosaic further strengthens the interpretation. In the eastern plots where N-priority points cluster, the imagery shows lighter coloration and less vigorous canopy growth, typical of N deficiency. Conversely, several P- and K-priority points are located in western or central plots, where the vegetation pattern is patchy or where crop rows appear uneven. The spatial agreement between model-derived recommendations and visual symptoms from high-resolution imagery serves as an independent, qualitative validation of the approach. It also demonstrates how proximal sensing (soil sampling and FCM analysis) and remote sensing (UAV imagery) can be combined into a single, intuitive decision-support product for farmers.

From a management perspective, the generated maps enable site-specific fertilization at a resolution that is compatible with the scale of individual beds or farmer-owned subplots. By applying urea only around the N-priority points in the east (300–350 kg/ha), and focusing SP-36 and KCl around P- and K-priority points in the west and center, the farmer can reallocate a fixed fertilizer budget more efficiently rather than increasing total input. This has two important implications: 1) potential economic benefits, through savings in fertilizer where it is not needed and yield gains where deficiencies are corrected; and 2) environmental benefits, by reducing the risk of nitrate leaching and K or P accumulation in already fertile zones. Although yield measurements are not yet included in this study, the spatial pattern of recommendations is consistent with these expected outcomes.

At the same time, several limitations should be acknowledged. First, the analysis is based on a single sampling campaign, which captures spatial but not temporal variability; nutrient dynamics across seasons or cropping cycles are not yet modeled. Second, the block size of 10 × 10 m represents a compromise between spatial detail and sampling feasibility. Smaller blocks could reveal finer heterogeneity but would require more intensive sampling, while larger blocks might mask important within-block variability. Third, the fertilizer doses used in the recommendation map are derived from general agronomic guidelines; they would ideally be adjusted using response curves or economic optimization to quantify the benefits of site-specific management fully. Finally, the clustering quality, although supported by the Silhouette Score (0.61) and Dunn Index (0.03), could be further evaluated by comparing alternative clustering methods (e.g., k-means, Gaussian mixture models) and by validating the zones against actual yield data.

Despite these limitations, the study demonstrates that integrating FCM clustering with nutrient-priority analysis and UAV imagery can produce operationally meaningful fertilizer recommendation maps. The methodology is generic and can be extended to other fields, additional nutrients, or different sensor sources, and can be embedded into an IoT-based platform, such as Agri Watch Net, to support near-real-time decision-making. Future work will focus on multi-seasonal data, yield-based validation, and coupling the nutrient-priority maps with variable-rate application technologies to quantify the economic and environmental benefits of adopting this approach.

Although this study is demonstrated using a shallot field in Srikayangan, Indonesia, the contribution of this work is not limited to a specific crop or geographic context. The proposed framework is methodologically generic and can be applied to any agricultural system where 1) soil macronutrients can be measured at spatial sampling points (via sensors or laboratory analysis), 2) a management grid can be defined according to operational field units, and 3) spatial transitions in soil fertility are expected. The use of Fuzzy C-Means clustering combined with nutrient-priority decision logic is independent of crop type and location, and therefore transferable to other horticultural crops, cereal systems, and smallholder or commercial farming contexts. In this sense, the Srikayangan field serves as a representative testbed to demonstrate the operational feasibility of translating fuzzy soil fertility classification into actionable fertilizer recommendations, rather than as a location-specific solution.

IV. Conclusion

This study presented a spatial classification and decision-support framework for fertilizer requirement mapping based on Fuzzy C-Means clustering of soil NPK data integrated with IoT-based sensing and UAV imagery. By applying the proposed approach at a fine spatial resolution compatible with smallholder bed-scale management, the results demonstrate that soil fertility within a single field can exhibit substantial spatial differentiation, making uniform fertilizer application inefficient and potentially wasteful.

The use of fuzzy clustering enables the representation of gradual transitions in soil nutrient availability, while the introduced nutrient-priority decision logic bridges the gap between fuzzy classification outputs and actionable fertilizer recommendations. Rather than producing only generalized fertility zones, the proposed framework identifies which macronutrient—Nitrogen, Phosphorus, or Potassium—should be prioritized at each management block, thereby enhancing the operational relevance of site-specific nutrient management.

Although the framework was demonstrated using a shallot field in Srikayangan, Indonesia, its contribution lies in the methodological integration and decision-support logic rather than the specific field context. The approach is generic and transferable to other crops, regions, and agricultural systems where spatial variability in soil nutrients necessitates more targeted fertilizer management. By combining fuzzy clustering with high-resolution sensing and intuitive spatial visualization, this work provides a practical pathway for translating soil data into actionable management decisions.

Overall, the proposed framework advances the practical usability of FCM-based soil fertility zonation for precision agriculture by linking data-driven spatial analysis with fertilizer decision-making, thereby supporting more efficient, economical, and sustainable nutrient management practices.

V. Future Work

Future research will focus on extending the proposed framework in several directions. First, multi-season soil and crop data will be incorporated to capture temporal nutrient dynamics and improve the robustness of fertilizer recommendations. Second, the derived nutrient-priority zones will be validated against measured yield and economic return data to quantify agronomic and financial benefits. Third, comparative experiments with alternative clustering and interpolation methods, such as k-means and geostatistical kriging, will be conducted to evaluate methodological trade-offs. Finally, the integration of the proposed approach with variable-rate fertilizer application technologies and mobile decision-support interfaces will be explored to facilitate real-time, data-driven nutrient management at scale.

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