https://doi.org/10.17221/35/2024-RAE

# Advancements in fuzzy expert systems for site-specific nitrogen fertilisation: Incorporating RGB colour codes and irrigation schedules for precision maize production in Bangladesh

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**Citation:** Biswas B., Khan M.T.A., Momen M.B.H., Tanvir M.R.R., Alam A.M.S., Islam M.R. (2024): Advancements in fuzzy expert systems for site-specific nitrogen fertilization: Incorporating RGB colour codes and irrigation schedules for precision maize production in Bangladesh. Res. Agr. Eng., 70: 155–166.

**Abstract:** The research was conducted at the Department of Agronomy and Agricultural Extension, Rajshahi University, from December 2021 to April 2022. The objective was to develop a fuzzy expert system for site-specific N fertilisation using leaf colour code (RGB) and irrigation frequencies for maize yield. The experiment encompassed two primary factors: nitrogen fertiliser application rates ($N_1$: 100%, $N_2$: 75%, $N_3$: 50% of conventional rates) and irrigation frequencies ($I_1$: 100%, $I_2$: 75%, $I_3$: 50% of pan evaporation). A completely randomized design (CRD) with three replications was used to arrange the experimental pots, each receiving recommended doses of phosphorus, potassium, and sulfur, with urea applied per treatment instructions. Results revealed significant chlorophyll content and grain yield differences among the various nitrogen fertiliser rates. The highest grain yield (219.27 g·pot$^{-1}$) was observed with $N_1$, whereas the lowest (186.6 g·pot$^{-1}$) was with $N_3$. Similarly, irrigation frequencies significantly influenced chlorophyll content and cob characteristics, with $I_1$ resulting in the highest grain yield (211.27 g·pot$^{-1}$) and $I_3$ the lowest (184.6 g·pot$^{-1}$). Furthermore, the interaction between fertiliser application rates and irrigation frequencies had notable effects on various parameters, leading to the highest grain yield of 227.62 g·pot$^{-1}$ with the combination of $N_1$ and $I_1$ and the lowest (168.00 g·pot$^{-1}$) with $N_3$ $I_3$. The agricultural experiments were facilitated using the Matlab fuzzy toolbox, employing the Mamdani inference method. Fuzzy rules were delineated for nitrogen application rates and irrigation frequencies, with three fuzzy sets each. Membership functions were developed utilising Matlab's fuzzy interface system (FIS) editor and membership function editor, optimising leaf chlorophyll content, evaporation rate as input tiger N fertilisation, and irrigation frequencies as output for precise maize production in Bangladesh.

**Keywords:** fuzzy decision support system; leaf chlorophyll content; maize; nitrogen management

Supported by the Grant for Advanced Research in Education (GARE), Bangladesh Bureau of Educational Information and Statistics (BANBEIS), Ministry of Education, Peoples republic of Bangladesh (Grant No. : LS20211689).

https://doi.org/10.17221/35/2024-RAE

In the realm of agricultural innovation, precision farming techniques have become increasingly imperative for enhancing crop productivity and sustainability, particularly in regions like Bangladesh, where agricultural resources are finite and the population's reliance on staple crops such as maize is significant (Hossain et al. 2021). Within this context, the integration of advanced technologies such as fuzzy expert systems (FES) holds immense promise for optimising agronomic practices, particularly in the realm of nitrogen (N) fertilisation, a critical determinant of maize yield and quality (Mana et al. 2024 ).

This manuscript delves into the pioneering research conducted in Bangladesh, focusing on developing and applying a novel fuzzy expert system tailored for site-specific N fertilization in maize cultivation. Unlike traditional approaches that rely solely on conventional agronomic practices, this system incorporates innovative elements such as RGB (red-green-blue) colour codes and precise irrigation schedules to fine-tune N application rates, thereby maximising crop yield while minimising environmental impact (Dahal et al. 2020).

Nutrient management, an essential component of precision agronomy, entails the precise application of fertilizers tailored to the specific requirements of crops. Farmers can customize nutrient applications by comprehending the intricate interactions among soil health, plant needs, and environmental factors, thereby averting overuse and reducing nutrient runoff. This practice amplifies crop yields and fosters environmental preservation by curbing soil degradation and water pollution (Rahman et al. 2022).

A crucial facet of this optimisation process revolves around the discerning application of fertilizers, with nitrogen playing a pivotal role in the growth and development of crops such as maize. Conventional nitrogen fertilisation methods often lack the precision necessary for optimal crop health, thus prompting the exploration of innovative approaches (Giordano et al. 2021). This study delves into the evolution of a fuzzy expert system devised to streamline decision-making in site-specific nitrogen fertilisation for maize cultivation within the realm of precision agriculture in Bangladesh, with RGB color codes serving as a primary input (Figure 1).

Bangladesh, characterised by diverse agroecological zones and varying soil conditions, poses a distinct set of challenges for farmers striving

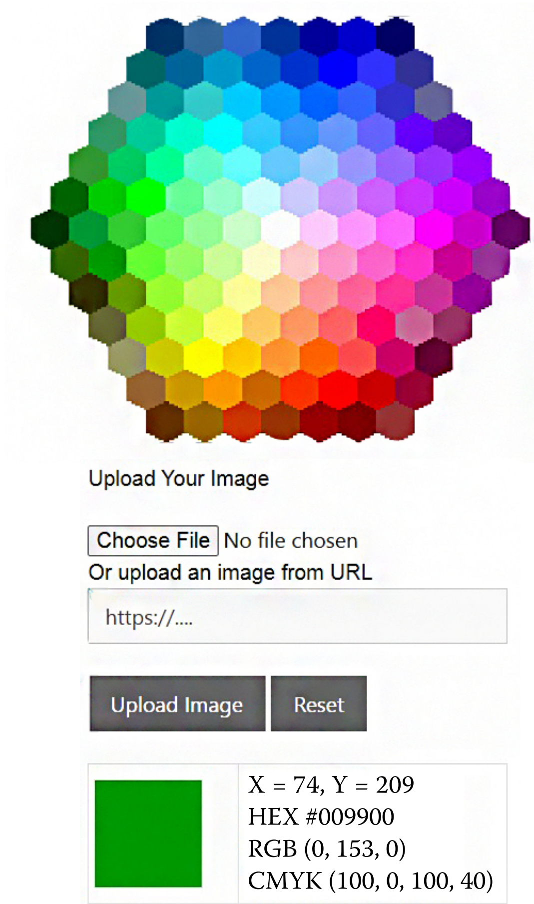


Figure 1. Use of RGB colour code to determine foliar greenness

to refine nitrogen application strategies (Jahan et al. 2018). Incorporating RGB colour codes derived from on-site images of maize plants furnishes a dynamic and visually comprehensive dataset for analysis (Figure 1). These codes capture subtle variations in plant health and vigour, offering a non-invasive and real-time approach to assessing the nitrogen needs of maize crops.

Traditionally, plant nutrient assessments have relied on labour-intensive and time-consuming methods, often resulting in delayed insights into nutrient deficiencies (Henry 2020). However, the integration of RGB colour information presents a promising alternative, leveraging the visual cues inherent in plant foliage. Derived from on-site images, RGB colour codes serve as a rich data source that can be analysed to infer nutrient status (Barbedo 2019).

In precision agriculture, optimising water management is crucial for enhancing crop productivity and resource efficiency, particularly amid rising global populations and unpredictable climate patterns

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(Rastogi et al. 2024). Evaporation pan readings serve as reliable indicators of atmospheric water demand and, consequently, the potential water requirements of crops (Krishna 2019). By incorporating these readings into irrigation scheduling, real-time adjustments can be made to ensure crops receive optimal water tailored to their growth stages and environmental conditions. Moreover, the strategic application of nitrogen fertiliser complements this approach, given nitrogen's pivotal role in plant growth and water-use efficiency (Wang et al. 2017). Synchronising nitrogen application with the irrigation schedule based on evaporation pan readings thus presents a holistic strategy to enhance crop health, nutrient absorption, and overall agricultural sustainability.

In addressing the inherent uncertainty and imprecision in agricultural data, fuzzy expert systems emerge as powerful tools (Janssen et al. 2010). By applying fuzzy logic principles within an expert system framework, these systems can better handle the vagueness inherent in colour-based assessments, providing a more nuanced and accurate representation of nutrient conditions. Fuzzy logic (FL) is a precise problem-solving technique that handles numerical data and linguistic knowledge simultaneously. It offers a method for controlling complex systems without requiring precise mathematical descriptions, resembling human reasoning in its ability to handle uncertainties, vagueness, and judgments. Originating from the work of Professor Dr. Lotfi Zadeh at the University of California, Berkeley, in 1965 (Zadeh 1965), fuzzy logic integrates intermediate possibilities between digital values, departing from the binary logic foundation of modern computers (Figure 2).

In line with the preceding discussion, the advancement described involves a multifaceted approach encompassing the design of a fuzzy logic system, its integration into an expert system architecture, rule-based development, and the incorporation of domain expertise. A feedback mechanism within the system facilitates its adaptability and learning over time, ensuring continual enhancement and relevance in the dynamic agricultural landscape (Araújo et al. 2021). The overarching objective of this progression is to craft a robust and user-friendly tool empowering farmers and agronomists to make informed decisions regarding nutrient management. By leveraging the capabilities of fuzzy expert systems alongside RGB colour codes, this innovative approach holds the potential to revolutionise on-site nutrient assessments, fostering more efficient and precise agricultural practices conducive to sustainable crop production (Fawzy et al. 2022).


Figure 2. The main difference between fuzzy logic and Boolean logic

The evaluation of the fuzzy expert system entails an exhaustive exploration of fuzzy logic principles and their integration into the expert system architecture. Drawing on domain-specific knowledge from agronomists and farmers, the system establishes a resilient rule base linking RGB colour codes to site-specific nitrogen fertilisation recommendations (Tan et al. 2022).

The system's adaptive nature, facilitated by a feedback mechanism, ensures ongoing learning and refinement of recommendations based on real-world performance. The implications of this evolutionary journey extend beyond mere technological innovation; they underscore the potential to revolutionise decision-making processes for farmers, enabling them to achieve both economic and environmental sustainability in their agricultural practices. As we explore the fuzzy expert system's evaluation, we aspire to contribute to the ongoing dialogue on precision agriculture, offering a practical solution tailored to the unique challenges of nitrogen fertilisation in maize cultivation in Bangladesh.

This research investigates strategies to facilitate the efficient transfer and adoption of fuzzy expert systems for fertiliser application and optimal irrigation management for maize production in Bangladesh.

## MATERIAL AND METHODS

**Plant materials and growth condition.** The research was carried out within a controlled environment in a net house of the Agronomy Field Laboratory, Department of Agronomy and Agricultural Extension, Rajshahi University, Rajshahi, during the December 2021 till April 2022, utilising loamy sand soil obtained from the nearby experimental field. The soil composition contained ($gm \cdot kg^{-1}$) 0.4 organic carbon, 0.7 nitrogen, 1.8 ppm K, 7.5% Ca, and negligible phosphorus. The soil exhibited a slightly alkaline pH level of 7.6 and an electrical conductivity

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of 0.04 milliSiemens (mS) per cm (mS·cm$^{-1}$). Plastic pots, measuring 30 cm in height and 25 cm in diameter, were filled with 15 kg of air-dried, free-draining soil for the experiment.

Hybrid maize variety NH-7720, marketed by Syngenta Bangladesh Ltd., was used. The experiment encompassed three nitrogen fertiliser application rates ($N_1$: 100%, $N_2$: 75%, $N_3$: 50% of conventional rates) and three irrigation frequencies ($I_1$: 100%, $I_2$: 75%, $I_3$: 50% of pan evaporation). A completely randomized design (CRD) with three replications was utilised to arrange the experimental pots. Each pot received recommended doses of phosphorus, potassium, sulfur, and organic fertiliser, while urea and irrigation were applied as per treatment instructions.

The collected data were analysed statistically following the analysis of variance (ANOVA) technique, and the mean differences were adjudged using Duncan's Multiple Range Test (DMRT), using SPSS statistical software (version 22.0).

**Determination of leaf chlorophyll content.** The nitrogen content of maize leaves was determined using digital image analysis based on the numeric values of RGB colours. The analysis was conducted using RGB colour picker software (version 1.0) on scanned images of the maize leaves (Figure 3). The following formula, as described by Ali et al. (2013), was used for the determination of nitrogen content:

$$ChN_{RGB} = G - \frac{R}{2} - \frac{B}{2} \quad (1)$$

where: $ChN_{RGB}$ – the chlorophyll content; $G$ – green; $R$ – red; $B$ – blue

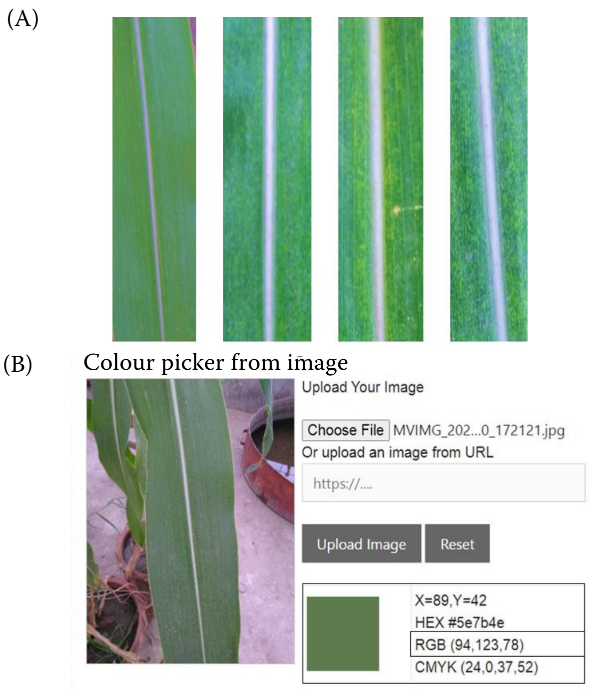


Figure 3. (A) Scanned image of the maize leaf, (B) measurement of the composition of red, blue and green colours using RGB color picker software

**Irrigation measurement with evaporation pan.** Irrigation water requirement was calculated based on cumulative pan evaporation (CPE). The daily pan evaporation was measured from an evaporation pan and rainfall was measured using a standard rain gauge (Figure. 4) Pan evaporation was adjusted by using the following equation (Michael 1985):

$$CPE = EV_p \times K_p \quad (2)$$

where: $EV_p$ – pan evaporation; $K_p$ – pan co-efficient ( 0.7.)

**Collection of experimental data.** Plant physiological parameters: Leaf chlorophyll content, yield components and yield: Number of grains cob$^{-1}$, 1 000 grain weight (g), grain yield (t·ha$^{-1}$), stover yield (t·ha$^{-1}$) and Biological yield (t·ha$^{-1}$) were recorded.

**Computerised experimental setup.** The fuzzy logic toolbox within Matlab was utilised to define the membership functions and construct the fuzzy rule-based system. Several sequential steps were undertaken to compute the output of this fuzzy inference system (FIS). Initially, a set of fuzzy rules was determined. Subsequently, the input data was fuzzified using the input membership functions. Following this, the rule strength was calculated by aggregating the fuzzified inputs according to the fuzzy rules. Then, the consequence of each rule was determined by combining the rule strength with the output membership functions. Finally, the output distribution was obtained by aggregating all the consequences.

**Fuzzy logic control system.** Figure 5 illustrates the structure of a fuzzy logic control system. The development of fuzzy rule-based systems

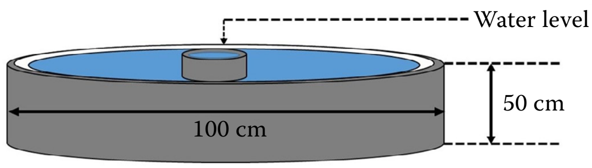


Figure 4. Schematic diagram of the evaporative pan

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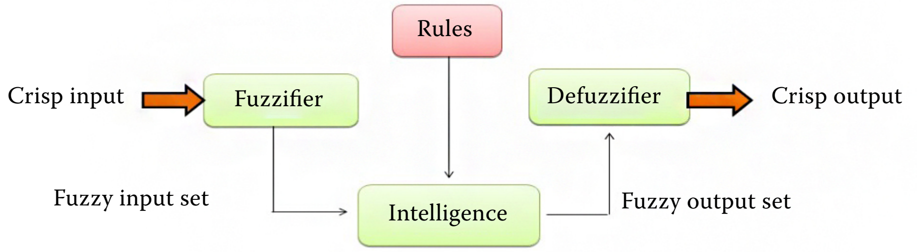


Figure 5. Fuzzy Logic controller block diagram

(FRBS) comprises four main components: An input processor (or fuzzification), a set of linguistic rules, a method of fuzzy inference, and an output processor (or defuzzification) that generates an actual number as output.

**Membership function**. A fuzzy set membership function serves as a generalisation of the indicator function for classical sets. It represents the degree of truth as an extension of valuation in fuzzy logic. The membership function applies across the domain of all possible values (Zadeh 1965).

**Input and fuzzification.** The input invariably consists of a crisp numerical value confined to the input variable's discourse universe. Fuzzification involves allocating the crisp input into the appropriate fuzzy set.

**Output and defuzzification.** The outcome manifests as fuzziness in the degree of membership in the qualifying linguistic set. The process of converting a fuzzy quantity into a crisp value is termed the defuzzification of a fuzzy set. The controller's output undergoes defuzzification to be presented in crisp form.

## RESULTS AND DISCUSSION

**Plant response to experimental treatments.** This section presents the outcomes of the experimental treatments administered to the plants, focusing on their responses and performance under various conditions. It encompasses observations related to growth parameters, yield, and any other relevant plant metrics.

**Chlorophyll content ($ChN_{RGB}$).** The chlorophyll content ($ChN_{RGB}$) in maize leaves was evaluated at 21 and 42 days after sowing (DAS), considering varying nitrogen fertiliser rates and irrigation frequencies. For $N_1$, the maximum chlorophyll contents were recorded at 76.6 DAS and 78.83 at 21 and 42 DAS, while the corresponding minimum values were 59.57 and 67.95 for $N_3$. Regarding irrigation frequency, $I_1$ exhibited the highest levels at 73.87 and 77.08, contrasting with $I_3$, which yielded the lowest at 62.15 and 67.95. The interaction between $N_1$ and $I_1$ displayed the highest content at 78.63 and 80.5, respectively, while $N_3$ and $I_3$ exhibited the lowest at 43.11 and 57.

The observed differences in chlorophyll content across different nitrogen fertiliser rates highlight the significant impact of nitrogen availability on plant photosynthetic activity. Our results are consistent with the findings of Urban et al. (2021) and Muhammad et al. (2022), who also reported that higher chlorophyll content at higher nitrogen application rates compared to lower rates suggests that adequate nitrogen application promotes chlorophyll synthesis and accumulation in maize leaves, thereby enhancing photosynthetic efficiency and potentially leading to increased biomass production and yield. Similarly, the variations in chlorophyll content associated with different irrigation frequencies underscore the importance of water management in influencing plant physiological processes. Our results align with the findings of Chen et al. (2023) and Lan et al. (2024), who demonstrated that higher chlorophyll levels observed under more frequent irrigation compared to less frequent irrigation indicate that adequate water availability positively influences chlorophyll synthesis and retention in maize leaves, thus supporting optimal photosynthetic activity and plant growth. Furthermore, the interaction between nitrogen fertiliser rates and irrigation frequencies reveals synergistic effects on chlorophyll content. This finding is consistent with the number of previous results (Nasar et al. 2020; Candiani et al. 2022; Ye et al. 2022), emphasising the combined effects of nutrient and water management on chlorophyll content in plants. The highest chlorophyll levels observed under the combination of $N_1$ and $I_1$ suggest that optimal nitrogen availability and sufficient

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water supply promote maximal chlorophyll accumulation in maize leaves. Conversely, the lowest chlorophyll content observed under the combination of $N_3$ and $I_3$ indicates that inadequate nitrogen supply and limited water availability negatively impact chlorophyll synthesis and retention, potentially compromising plant photosynthetic capacity and overall growth performance.

Incorporating fuzzy expert systems in decision-making for site-specific nitrogen fertilisation, guided by RGB colour code analysis, has positively affected chlorophyll content in maize crops. Chlorophyll serves as a vital indicator of plant health and photosynthetic activity, which is crucial for overall crop performance. The nuanced and adaptable approach facilitated by fuzzy logic has played a pivotal role in optimising nitrogen application, leading to enhanced chlorophyll synthesis. Real-time feedback from RGB colour code analysis has enabled more precise assessments of chlorophyll levels, ensuring nitrogen is applied following the specific needs of each plot (Zermas et al. 2020). This targeted approach has likely bolstered photosynthetic efficiency, consequently improving chlorophyll content.

**Number of grains per cob.** The number of grains per cob showed a significant effect on nitrogen fertilisation (Table 1). The maximum number of grains per cob (476.61) was counted from $N_{1,}$ and the minimum number of grains per cob (440.15) was counted from $N_3$. The number of grains per cob was also significant due to irrigation frequencies (Table 1). Therefore, the maximum number of grains per cob (482.20) was with $I_1$ and the minimum number of grains per cob (435.48) was counted from $I_3$. The interaction effect of nitrogen fertiliser application and irrigation frequencies differ significantly in the number of grains per cob (Table 1). $N_1$ with $I_1$ had the highest number of grains per cob (501.16), while $N_3$ with $I_3$ had the lowest number of grains per cob (430.11 %). Our findings are consistent with

Table 1. Effect of different nitrogen fertiliser application rates, irrigation frequencies and interaction on yield components and yield of maize

| Nitrogen fertilizer AR | Chlorophyll content (DAS) 21 | Chlorophyll content (DAS) 42 | No. grains cob$^{-1}$ | 1 000 gw (g) | Grain yield (g pot$^{-1}$) | Stover yield (g·pot$^{-1}$) | BY (g·pot$^{-1}$) |
|---|---|---|---|---|---|---|---|
| $N_1$ | 76.06$^{a}$ | 78.83$^{a}$ | 476.61$^{a}$ | 320.5 | 219.89$^{a}$ | 263.56$^{a}$ | 483.45$^{a}$ |
| $N_2$ | 71.16$^{b}$ | 74.06$^{a}$ | 454.61$^{ab}$ | 314.41 | 198.19$^{ab}$ | 249.40$^{a}$ | 447.59$^{ab}$ |
| $N_3$ | 59.57$^{c}$ | 67.95$^{b}$ | 440.15$^{b}$ | 304.02 | 184.38$^{b}$ | 227.23$^{b}$ | 411.60$^{b}$ |
| Irrigation frequencies | | | | | | | |
| $I_1$ | 73.87$^{a}$ | 77.08$^{a}$ | 482.20$^{a}$ | 320.21 | 211.27$^{a}$ | 249.63 | 460.89 |
| $I_2$ | 71.77$^{a}$ | 75.12$^{a}$ | 453.68$^{ab}$ | 309.5 | 204.6$^{ab}$ | 243.94 | 448.54 |
| $I_3$ | 61.15$^{b}$ | 67.95$^{b}$ | 435.48$^{b}$ | 309.21 | 186.6$^{b}$ | 246.61 | 433.21 |
| Interaction effect | | | | | | | |
| $N_1I_1$ | 78.63$^{a}$ | 80.50$^{a}$ | 501.16$^{a}$ | 326.55 | 227.62 | 269.99$^{a}$ | 497.61$^{a}$ |
| $N_1I_2$ | 75.60$^{ab}$ | 79.77$^{ab}$ | 477.68$^{ab}$ | 317.4 | 225.75 | 256.27$^{ab}$ | 482.02$^{ab}$ |
| $N_1I_3$ | 73.93$^{abc}$ | 76.23$^{abc}$ | 441.99$^{bc}$ | 317.55 | 206.31 | 264.41$^{abc}$ | 470.72$^{ab}$ |
| $N_2I_1$ | 74.67$^{abc}$ | 76.07$^{abc}$ | 482.3$^{abc}$ | 321.92 | 211.64 | 254.01$^{abc}$ | 465.65$^{ab}$ |
| $N_2I_2$ | 72.40$^{abcd}$ | 75.50$^{abc}$ | 447.98$^{bc}$ | 309.76 | 197.46 | 244.98$^{abc}$ | 442.44$^{ab}$ |
| $N_2I_3$ | 66.40$^{cd}$ | 70.60$^{bc}$ | 433.55$^{bc}$ | 311.56 | 185.48 | 249.88$^{abc}$ | 434.68$^{ab}$ |
| $N_3I_1$ | 68.300$^{bcd}$ | 74.67$^{abc}$ | 454.16$^{bc}$ | 312.16 | 194.54 | 224.88$^{c}$ | 419.42$^{ab}$ |
| $N_3I_2$ | 67.30$^{cd}$ | 70.10$^{c}$ | 435.39$^{bc}$ | 301.36 | 190.59 | 230.58$^{c}$ | 421.17$^{ab}$ |
| $N_3I_3$ | 43.11$^{e}$ | 57.00$^{d}$ | 430.89$^{c}$ | 298.52 | 168 | 226.22b$^{c}$ | 394.22$^{c}$ |
| CV% | 5.97 | 6.61 | 7.14 | 16.45 | 7.38 | 10.55 | 7.57 |

$^{a-d}$Mean values in a column having the same letters or without letter do not differ significantly at 0.05 level of probability; CV – Co-efficient of variation; AR – aplication rate; BY – biological yield; gw – grain weight; $N_1$ (100 % of conventional nitrogen rate – 550 kg·ha$^{-1}$/standard rate); $N_2$(75 % of conventional nitrogen rate – 412.5 kg·ha$^{-1}$/medium rate); $N_3$ – (50 % of conventional nitrogen rate – 275 kg·ha$^{-1}$/low rate); $I_1$ – (irrigation based on 100% of pan evaporation/standard); $I_2$ – (irrigation based on 75% of pan evaporation/medium); $I_3$ – (irrigation based on 50% of pan evaporation/low)

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the report by Iqbal et al. (2014), who found that increased nitrogen fertilisation significantly impacted the number of grains per cob. Similarly, Shen et al. (2020) observed a significant effect of irrigation frequency on grain count.

**1 000 grain weight.** 1 000 grain weight did not vary significantly in terms of nitrogen fertiliser application rates or irrigation frequencies (Table 1). The highest 1 000-grain weight (320.50 g) was found from $N_1$, and the lowest (304.02 g) was found from $N_{3.}$ Among the irrigation frequencies, the maximum grain weight (320.21 g) was obtained from the $I_1$ minimum value (309.21) from $I_{3.}$ The combination of $N_1$ and $I_1$ yielded the highest weight of 1000 grains (326.55 g), while the combination of $N_3$ and $I_3$ yielded the lowest weight of 1 000 grains (298.52 g) (Table 1). No remarkable variation in 100-grain weight following both nitrogen fertilisation and irrigation has also been reported by Jahangirlou et al. 2020.

**Grain yield.** The grain yield exhibited notable variations corresponding to different nitrogen fertiliser application rates (Table 1). The highest grain yield (219.89 g·pot$^{-1}$) was achieved with the application of $N_1$ (100% nitrogen fertiliser), whereas the lowest grain yield (184.38 gpot$^{-1}$) was observed with $N_3$ (50% Nitrogen fertiliser). Furthermore, the irrigation frequency demonstrated significant effects on grain yield (Table 1), with the highest yield (211.27 g·pot$^{-1}$) associated with $I_1$ and the lowest yield (186.6 g·pot$^{-1}$) observed with $I_3$.

A noteworthy observation emerged from the combined application of nitrogen fertilizer and irrigation frequency (Table 1). The highest grain yield of 227.62 g·pot$^{-1}$ was attained with the combination of $N_1$ and $I_1$, while the lowest grain yield of 168 g·pot$^{-1}$ was recorded with the combination of $N_3$ and $I_3$.

Several previous findings in maize have supported variations in grain yield concerning different nitrogen fertiliser application rates and irrigation (Davies et al. 2020; Li et al. 2020; Ren et al. 2022). These studies also emphasize the optimisation of resource allocation to enhance crop productivity (Shah and Wu 2019). Furthermore, these results can be elucidated and leveraged through the integration of a FLCS in agricultural decision-making processes, as described by Seyedmohammadi and Navidi (2022).

The fuzzy logic control system offers a sophisticated approach to managing the uncertainties inherent in agricultural systems, such as variations in soil conditions, weather patterns, and crop responses to inputs. By incorporating fuzzy logic principles into decision-making frameworks, the FLCS can effectively analyse and interpret the intricate relationships between nitrogen fertilizer application, irrigation frequency, and grain yield (Prabakaran et al. 2018).

The ultimate measure of the success of any agricultural intervention is its impact on crop yield. In this study, implementing the fuzzy expert system, RGB colour code analysis, and customised irrigation schedule has demonstrated a positive correlation with maize yield. By tailoring nitrogen fertilisation based on site-specific requirements, the fuzzy expert system has likely contributed to a more balanced nutrient supply, positively influencing crop development and yield (Prabakaran et al. 2021). The visual insights provided by RGB colour code analysis have allowed farmers to adjust their management practices promptly, optimising the conditions for maximum yield potential. Furthermore, incorporating a customised irrigation schedule complements the precision agriculture framework. Efficient water management ensures crops receive adequate moisture at critical growth stages, preventing water stress and optimising yield potential (Farooq et al. 2019). The synergy between nitrogen fertilisation and irrigation practices within the fuzzy expert system has likely created a conducive environment for maximising maize production in Bangladesh.

**Stover yield.** Stover yield did not vary significantly due to different irrigation methods; however, it caused remarkable variation in nitrogen fertilisation (Table 1). Results revealed that the highest stover yield (263.56 g·pot$^{-1}$) was obtained from $N_{1,}$ and the lowest stover yield (227.23 g·pot$^{-1}$) was obtained from $N_{3.}$ Considering the irrigation frequencies, the highest stover yield (249.63 g·pot$^{-1}$) was recorded for $I_{1,}$ and the lowest Stover yield (246.61 g·pot$^{-1}$) was recorded for $I_{3.}$ The interaction effect between nitrogen fertilizer application rates and irrigation frequencies on stover yield was significant, and maximum stover yield (269.99 g·pot$^{-1}$) was produced from the combination of $N_1$ with $I_1$, and minimum Stover yield (224.88 g·pot$^{-1}$) was produced in the combination of $N_3$ with $I_1$(Table 1).

**Biological yield.** Results revealed that the highest biological yield (483 g·pot$^{-1}$) was produced for $N_{1,}$ and the lowest biological yield (411.60 g·pot$^{-1}$) was obtained for $N_3$. Biological yield showed an insig-

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nificant response to irrigation frequencies (Table 1). The maximum biological yield (460.89 g·pot$^{-1}$) was obtained from $I_{1,}$ and the minimum value (433.21 g·pot$^{-1}$) was obtained from $I_{3.}$ The interaction between $N_1$ and $I_1$ produced the highest biological yield (497. 61 g·pot$^{-1}$). However, the lowest biological yield (394.22 g·pot$^{-1}$) was obtained for the interaction between $N_3$ and $I_3$ (Table 1).

Greater stover yield and biological yield of maize in response to nitrogen may be due to the fact that nitrogen plays an important role in plant growth and development. Ren et al. (2022) reported that nitrogen helps to promote more biomass by supporting chlorophyll production in leaves. In contrast, the small difference in stover yield and biological yield for greater irrigation frequencies may suggest that maize plants might exhibit a threshold beyond which surplus water negatively impacts crop growth. Kaur et al. (2020) reported that available water is essential for optimum plant growth and nutrient uptake. However, over-irrigation results in water logging and reduced oxygen supply to the root zone, followed by leaching of nutrients. Consequently, the influence of irrigation frequency on stover yield may not have as high an impact as nitrogen rates since water availability has a dual role in nutrient and plant physiological process interactions.

**Fuzzy expert system (FES) – based decision systems.** This section elucidates the findings regarding the performance and effectiveness of the fuzzy rule-based decision systems implemented in the experiment. It discusses the system's ability to interpret input data, generate appropriate decisions, and its overall impact on optimising plant management practices.

**Data analysis and simulation with Matlab fuzzy toolbox.** In this part, crisp values from the agronomic field research have been applied to the fuzzy logic control system. In the thesis paper, nitrogen fertilization and irrigation schedule were measured with leaf chlorophyll content based on RGB colour code, and evaporation pan reading was described in the fuzzy logic system among all parameters. Chlorophyll (Chl) is an important photosynthetic pigment for plants, largely determining photosynthetic capacity and plant growth (Li et al. 2018).

We use Matlab's fuzzy toolbox to implement our algorithm. Figure 6 depicts a fuzzy inference system with two Matlab inputs ($ChN_{RGB}$ value for nitrogen fertilisation and pan evaporation level for irrigation frequencies) and two outputs (nitrogen fertilisation & irrigation frequencies).

Membership functions were created using Matlab's FIS Editor and membership function editor.

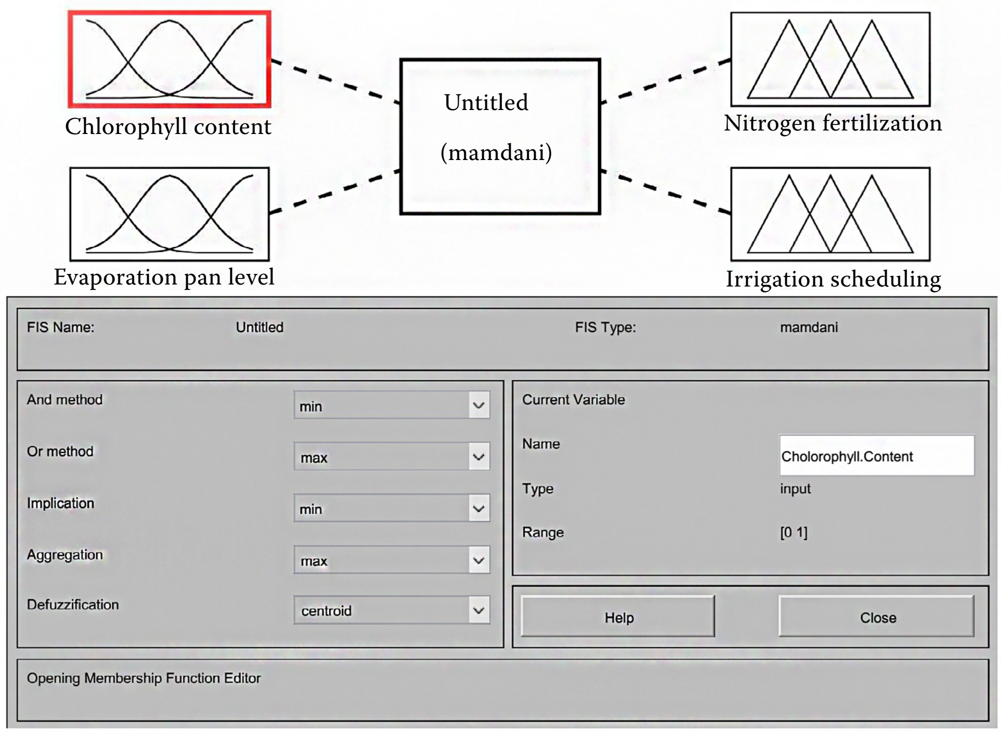


Figure 6. The fuzzy inference system consists of two inputs ($ChN_{RGB}$ value for N fertilisation and pan evaporation level for irrigation frequencies) and two outputs (nitrogen fertiliser and irrigation frequencies)

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To obtain the membership function of the output category, the range of the output variable was first set to 100. The parameters for each category were then configured (Othman et al. 2014). A triangular membership function was used in this study.

**Fuzzy set of the input variable.** Fuzzy-based modelling variables were developed to schedule irrigation frequencies for nitrogen fertilisation and pan evaporation levels. For both variables, three fuzzy sets were defined: low, medium, and standard, with numerical values derived from experimental analysis (Table 1, and Figure 7).

**Fuzzy set of the output variable.** Generalizing the methodology of the FRBS output variables, three fuzzy sets were defined for both nitrogen fertiliser rates and irrigation frequency: low, moderate, and standard (Figure 8). Furthermore, fuzzy triangular sets were used to reduce complexity because they are widely used and require only the peak value and the width of its base to be determined. (Viais et al. 2019)

**Fuzzy rules base.** We considered the 9 (3 × 3) combinations among the fuzzy sets of the two input variables to obtain the rules base. Thus was created 9 pairs of the form nitrogen fertiliser rate × irrigation frequencies according to methodology (Khoshnevisan et al. 2014). The rules were created after the input and output membership functions were developed. In total, 15 rules statements were created in step 4 to classify maize N fertilization and irrigation (Figure S1 in Electronic supplementary material – ESM). The rule viewer also consists of the defuzzification results (Figure S2 in ESM). The first and second columns represent leaf chlorophyll content and evaporation rate values, while the third and fourth columns represent the Nitrogen rates and irrigation frequencies for maize cultivation. Finally, the last two columns, the category column, show the defuzzification results.

**Surface view.** The surface rule viewer of the fuzzy inference system in Matlab produces a 3D surface

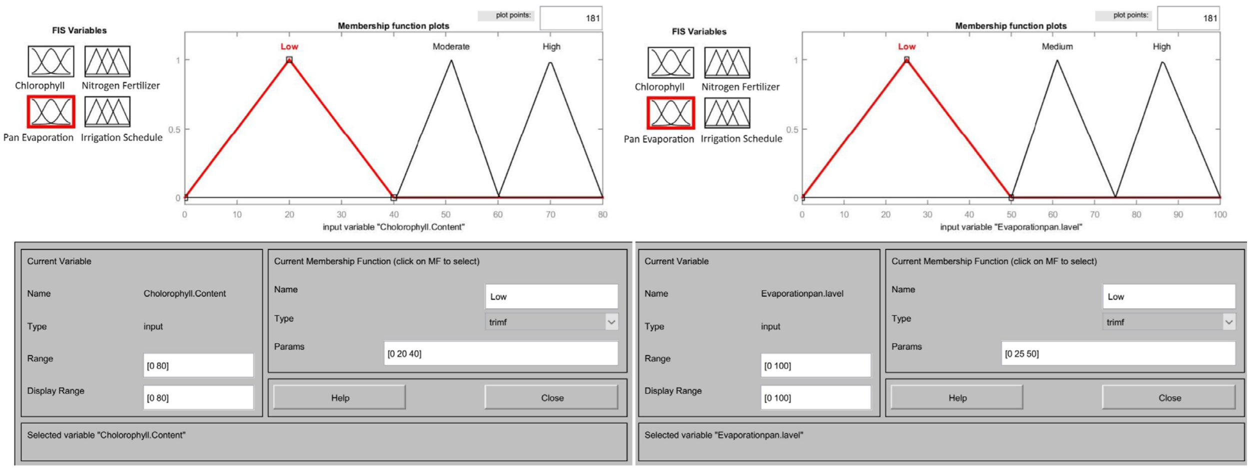


Figure 7. Triangular membership function of input fuzzy set

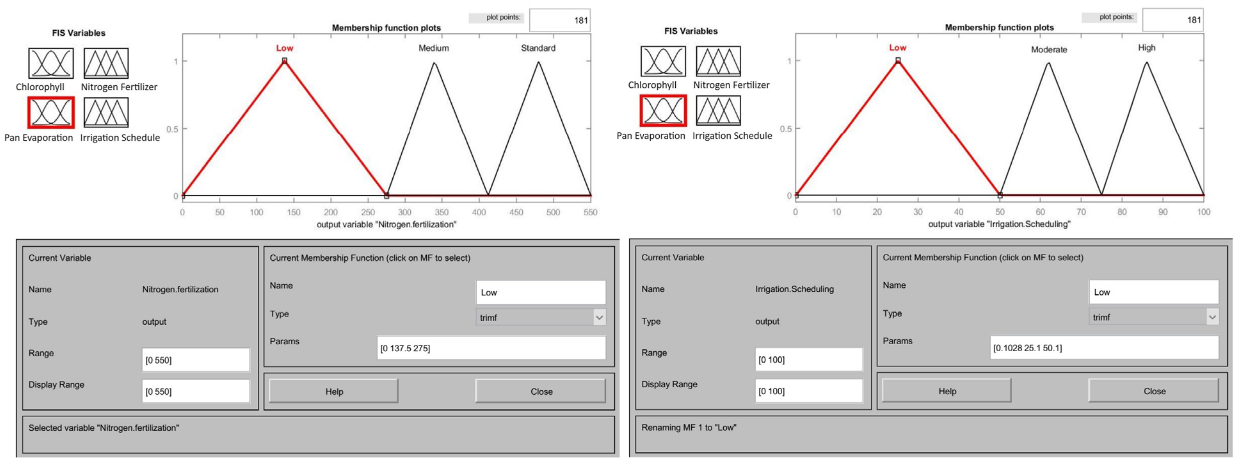


Figure 8. Triangular membership function of the fuzzy output set

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Table 2. Fuzzy set of input and output with percentages

| Input fuzzy set | | Output fuzzy set | |
|---|---|---|---|
| leaf chlorophyll content | evaporation (%) | nitrogen fertiliser rate (kg·ha$^{-1}$) | irrigation frequencies (%) |
| standard (60–80) | high (75–100) | low (0–275) | standard ( 75–100) |
| medium (45–60) | medium (50–75) | medium (275–412) | medium (50–75) |
| low (0–4) | low (0–50) | standard (412–550) | low (0–50) |

plot to visualise the relationships among chlorophyll content, N fertilizer application rates, and evaporation levels (Figure S3 in ESM).

The agronomic experiment method is used to compute the pertinence functions of the fuzzy sets of this study's outcome variables (Daniel et al. 2019). Figures 7 and 8 show that it was possible to determine the intervals indicating the most significant degree of pertinence of each item of the input and output variables of a given fuzzy set. Suppose an experiment was carried out under the same conditions during the same period described. In that case, the classifications presented in (Table 2) are possibly invariant or have no significant changes, making the result relevant. We have the following values (Table 2.) measured for some combinations of input fuzzy sets for leaf chlorophyll content and yield output variable (for other output variables and combinations of fuzzy input sets, the procedure performed was analogous).

Setting up the rules for the fuzzy system (Table 2) shows how the fuzzy sets of inputs relate to the output variables and how the median values for each combination of fuzzy input sets are determined.

## CONCLUSION

The evaluation of fuzzy expert systems combined with RGB colour code analysis and a customised irrigation schedule has shown significant promise in transforming precision maize production in Bangladesh. This integration merges traditional agricultural wisdom with advanced technologies, offering a more adaptive and efficient method to enhance crop yield and ensure sustainable resource management. Fuzzy expert systems refine decision-making in nitrogen fertilisation, allowing optimal nitrogen use and reducing environmental and economic impacts. RGB colour code analysis provides visual insights into maize health, enabling real-time decisions tailored to each field's conditions. This research developed the need-based optimum dose of nitrogen fertilisation and irrigation at the proper time for maize growth and yield with the fuzzy expert system. This holistic approach combines traditional knowledge with technology, addressing food security, economic sustainability, and environmental resilience in maize production.

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Received: April 12, 2024
Accepted: July 22, 2024
Published online: September 29 , 2024