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Application of Artificial Neural Networks to Optimize Nitrogen Supply to Meet Plant Needs for Soil Conservation: Case Study, M'Bahiakro Irrigated Perimeter (Central-East, Ivory Coast)

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Abstract

The low nitrogen content of soils in the rice-growing area of M'Bahiakro requires optimized fertilization to improve yields while minimizing environmental impacts. This study proposes an intelligent model based on backpropagation neural networks (BPNN) to predict the nitrogen requirements of rice using seven physico-chemical soil parameters (K, P, Norg, OM, θpf, CEC, and Kc). The model was trained using the Levenberg-Marquardt algorithm, with a sigmoid transfer function for the hidden layer and a linear function for the output layer. Model performance was evaluated using the coefficient of determination (R^2 = 0.98) and the mean squared error (MSE = 0.001), indicating high predictive accuracy. Results show that rice yield no longer improves significantly beyond 118 kg N·ha^{-1}, with R^2 and MSE values stabilizing around 98% and 0.007, respectively. This threshold therefore represents an optimal nitrogen dose, enabling a balance between agricultural productivity and the preservation of natural resources, particularly by reducing soil degradation and groundwater contamination. However, to strengthen the model's robustness, further investigations are essential in the irrigated area of M'Bahiakro, especially during the dry season. Expanding the study to include other rice varieties, soil types, and cultivation practices would not only broaden the model's applicability but also reinforce its role as a decision-support tool in sustainable nitrogen fertilization strategies.

Keywords

Irrigated Perimeter, Artificial Neural Networks, Rice, Nitrogen Fertilization, Soil Conservation, M'Bahiakro

1. Introduction

Irrigated production provides around 75% of the world's rice requirements [1] and plays a particularly important role in global food security. Irrigated crops produce around 40% of total agricultural output and have a major economic and social role to play in terms of consumption, marketing, and the fight against poverty [2].

Of all the nutrients required for rice production, nitrogen is the most restrictive. It is one of the essential constituents of the fundamental molecules of living organisms (nucleic acids, peptides, and proteins). Soil nitrogen availability is a key factor in rice development, growth, and performance [3]. Only mineral forms of nitrogen, such as ammonium and nitrate, can be taken up by the roots of most crop plants, with a preference for nitrate [4]. These elements may already be present in the soil through the degradation of organic matter, either naturally present or supplied in the form of fertilisers. However, it is common to supply an additional quantity directly as a mineral fertiliser. According to [5], the use of these fertilisers in the second half of the 20th century led to an increase in rice yields. However, the excessive use of chemical fertilisers in irrigated rice production is beginning to threaten soil quality and, by extension, reduce yields [6].

In Côte d'Ivoire, rice has become the staple food for the vast majority of the population, both in urban centres and in rural areas [7]. Over the years, national rice consumption has increased from 30 kg/hbt/year in 1960 to 60 kg/hbt/year in 1992, reaching 68 kg/hbt/year in 2002 and over 85 kg/hbt/year in 2015 [8]. However, national production has fallen considerably despite the use of chemical fertilisers. In fact, [9] noted a drop in rice yield from around 7.3 to 6.0 $t \cdot ha^{-1}$ in the Natiokobadara irrigated perimeter (Korhogo in northern Ivory Coast) over the period 2007 to 2013. This drop in rice yield, which is related to the decline in soil fertility, is thought to be due to the excessive use of chemical fertilisers. [6] also reported a downward trend in irrigated rice yields from 3.2 to 2.6 $t \cdot ha^{-1}$ in the irrigated lowlands of Gagnoa (west-central Ivory Coast), probably due to the effects of chemical fertilisers.

The town of M'Bahiakro, the subject of this study, is no exception to this observation. In fact, M'Bahiakro is home to one of Côte d'Ivoire's vast irrigated rice development programmes, with an estimated 450 ha of irrigable land and significant water availability via the N'Zi river [10]. The development of the M'Bahiakro irrigated perimeter includes a 5 m high inflatable dam on the N'Zi with a water retention capacity of 2.76 million m^3, which will remove all constraints on rainfed rice production subject to climatic hazards [11]. However, a concern linked to the sustainability of this irrigated production system relates to the quality of the irrigation water and the production capacity of the soil over time. In fact, in the process of increasing rice production, inputs are often used in excess of nutrient exports to the plots, either through over-fertilization or poor assimilation of the fertiliser by the plants. This could lead to a deterioration in soil and water quality in the M'Bahiakro irrigated area. According to [12], around 0.1% of the inputs used by farmers reach the target organisms, with the remainder contaminating the surrounding environment. Thus, inputs that reach the soil can alter soil microbial diversity and microbial biomass, eventually leading to a disruption of the soil ecosystem and a loss of soil fertility [13]. In addition, excessive concentrations of inputs not recovered by crop plants end up either reaching groundwater through infiltration or watercourses, sometimes causing pollution and eutrophication problems [14].

Furthermore, an increase in the quantity of nutrients in the soil does not necessarily mean an increase in yield in the same proportion. According to Mitscherlich's law, when increasing doses of a fertiliser are applied to the soil, we find that as the quantities applied increase, the yield increases obtained become smaller and smaller ([15] [16]).

In this context, artificial intelligence methods using artificial neural networks (ANNs) offer an advantage in optimising nitrogenous fertilisers to meet the needs of rice in terms of water and soil planning and management. In the field of artificial intelligence, ANNs represent an organised set of interconnected neurons, enabling complex problems to be solved at lower cost. According to [17], ANNs develop self-learning models for exploring the neighbourhood of objects by looking for similarities between objects. In the field of agriculture, these models have the ability to compare the farmer's data with that from a set of similar cases in order to predict the optimal dosage of fertiliser and the associated yield, thus reducing the uncertainties in the fertilisation decision. The models run so far using RNA methods in several research studies have proved to be fairly informative for assessing yield and dosage in support of precision fertilisation ([18] [19]). According to this research, ANN models generate site-specific optimal doses and can verify the stability of these doses under various assumptions, such as climate change or a change in practice.

In our case, nitrogen doses should not only be adjusted as closely as possible to the needs of the rice crop, but should also be synchronised with the development cycle of the rice crop so that soil nitrogen fertilisation is carried out at the right time with the appropriate dose to meet the targeted objectives, thereby reducing soil and groundwater contamination. It is within this framework that this study was initiated, the main objective of which is to optimise the supply of nitrogen fertiliser in the face of the intensification of irrigated rice growing. The importance of this optimisation is to be able to maintain good rice production in the irrigated perimeter of M'Bahiakro while preserving the quality of the soil and water. To the best of our knowledge, no such work has been done to date on the M'Bahiakro irrigated perimeter in central-eastern Ivory Coast. In the course of this work, the general knowledge of the study area and the main theoretical aspects necessary for understanding neural networks.

In the optimization of nitrogen quantity, the processes are described. The optimum amount of nitrogen is then presented and discussed. A conclusion followed by an outlook will mark the end of the work.

2. Methodology

2.1. Location of the Irrigated Perimeter

The study site is an irrigated perimeter located in the Iffou region, in the department of M'Bahiakro in central-eastern Ivory Coast. It lies between longitudes 4018' and 4020' West and latitudes 7026' and 7031' North and includes the first hydro-agricultural inflatable dam in Ivory Coast [10] (**Figure 1**).

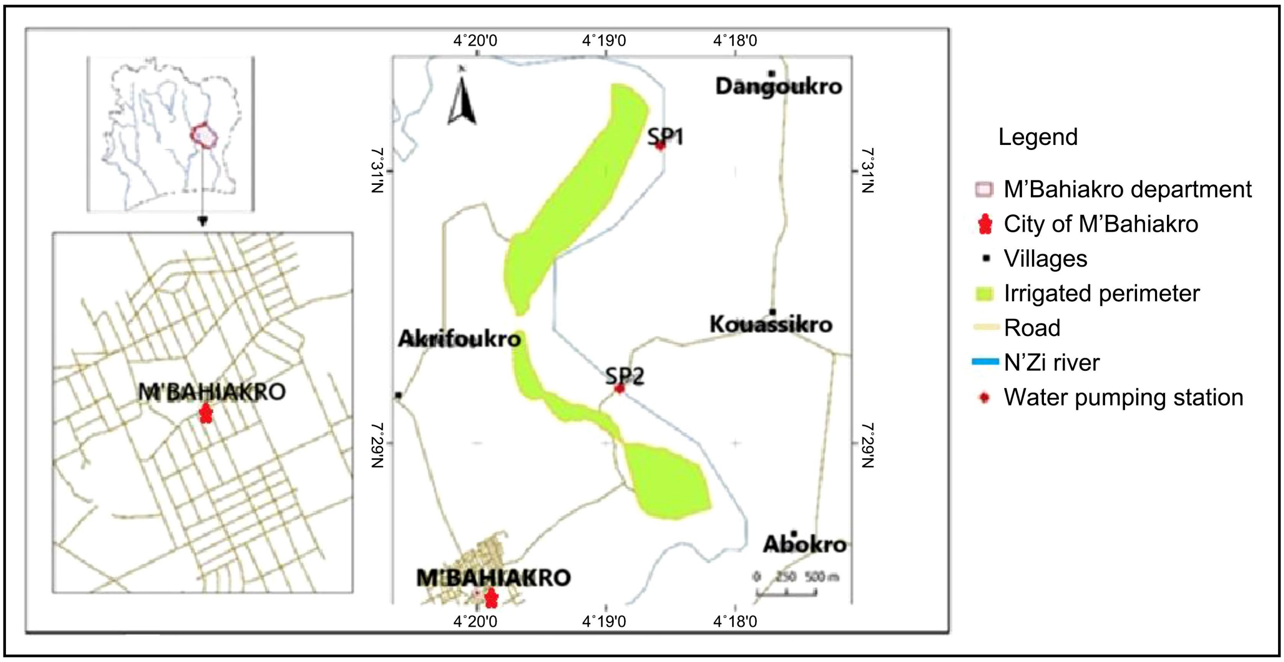

Figure 1. Presentation of the study area.

2.2. Description of the Irrigated Area

The rice-growing perimeter, divided into two sectors, covers an area of 450 ha and is 9 km long and 1 km wide [11]. The irrigation system is gravity-fed, with open canals and two water storage towers. The hydraulic districts are grouped into twelve zones or blocks, with six (06) blocks per sector and two (02) water pumping stations (**Figure 2**). The soils in the irrigated perimeter generally have a clay-loam texture (70%) with hydraulic conductivities varying between 10^{-4} and 10^{-3} m/s

[10]. The drainage porosity of the soil in the irrigated area varies between 40% and 60%. The highest soil porosity values are observed to the north of the irrigated perimeter, with a maximum average value of around 54%.

Figure 2. First water pumping station in the M'Bahiakro irrigated area.

2.3. Data Collection

2.3.1. Physico-Chemical Data for Irrigation Water in the Irrigated Perimeter

The physico-chemical parameters of the water, in particular pH, temperature (T˚C) and electrical conductivity (EC), were measured in situ using a HANNA type HI 9828 portable multiparameter calibrated according to the study season. At the same time, three water samples for nitrogen analysis (nitrites, nitrates, and ammonium) were taken the following day between five and six in the morning. The water samples were taken using three 500 mL polyethylene bottles immersed directly in the water of the dam by means of a rope. Each bottle was rinsed three times with the water to be sampled, then filled to the brim and hermetically sealed before being stored in a cooler. The bottles containing the water samples were stored at a temperature of 4˚C, as indicated by a thermometer in the cooler. This temperature of 4˚C maintained in the cooler with the aid of ice accumulators is useful for maintaining the stability of all the nitrogenous elements in the bottles. The preserved water samples were taken to the laboratory on the day of sampling. In the laboratory, nitrogen parameters were analyzed within twelve hours of sampling, using a flame molecular absorption spectrophotometer in accordance with [20].

2.3.2. Physico-Chemical Data from the Surface Layer of the Soil

Soil samples were taken using an auger at 20 points spread across the study area. The twenty samples were taken to a depth between 0 and 30 cm of soil, equivalent to the organic horizon of the soil. This is also the soil zone (0 - 30 cm) most affected by farming activities [2]. The collection and transport of the twenty soil samples and the analysis of their chemical parameters were carried out in accordance with the protocols defined by the French standards agency (AFNOR). The methods used to analyze the chemical parameters of the soil are summarized in **Table 1**. In addition, physical data relating to fine soil density (Dt), moisture at field capacity (θcc), moisture at the permanent wilting point (θpf), and the cultural coefficient (Kc) at the irrigated perimeter were determined in situ.

Table 1. Methods for analyzing soil parameters.

Parameters	Methods	Standards
Organic matter (OM)	Walkley and Black method	NF ISO 10694
Total nitrogen (Norg)	Kjeldahl digestion method	NF ISO 13878
pH	Electrometric method	NF ISO 10390
Cation exchange capacity (CEC)	Metso method	NF X31-130
Phosphorus (P)	Olsen method	NF ISO 11263
Potassium (K)	Fluoro-nitro perchloric method	NF X31-108

As part of this study, the values of the crop coefficient (Kc) were established in accordance with the recommendations of [21], as presented in FAO Irrigation and Drainage Paper No. 56. These coefficients take into account the different phenological stages of rice, distributed over twelve ten-day periods covering the entire vegetative cycle. Their variation allows for a more accurate estimation of water requirements at each stage of crop development and contributes to optimal irrigation planning (**Table 2**).

Table 2. Rice crop coefficients ([21]).

Decade	1	2	3	4	5	6	7	8	9	10	11	12
Kc	0.6	0.8	1.0	1.0	1.0	1.0	1.05	1.05	1.0	1.0	0.9	0.9

2.3.3. Rice Yield Data as a Function of Increasing Doses of Nitrogen

To obtain data on rice yields as a function of increasing doses of nitrogen, a 1-hectare area of the irrigated perimeter was set aside for rice experimentation with increasing doses of nitrogen. The experiment was carried out over 6 months (from August to February 2020) and consisted first of dividing the 1 hectare of the cleared area into four equal parts of 2500 m^2 each. Three parts of the 1 hectare each received 70 $kg·N·ha^{-1}$, 90 $kg·N·ha^{-1}$ and 140 $kg·N·ha^{-1}$ of nitrogen, and the fourth part, with no nitrogen applied, was chosen as the control according to Figure 3 below. The doses applied were the result of a synthesis of the nitrogen doses applied to each experimental plot from the soil preparation phase through to the ripening of the rice plants. The rice yield results obtained following this experiment were reported for each quantity of nitrogen applied to the different plots.

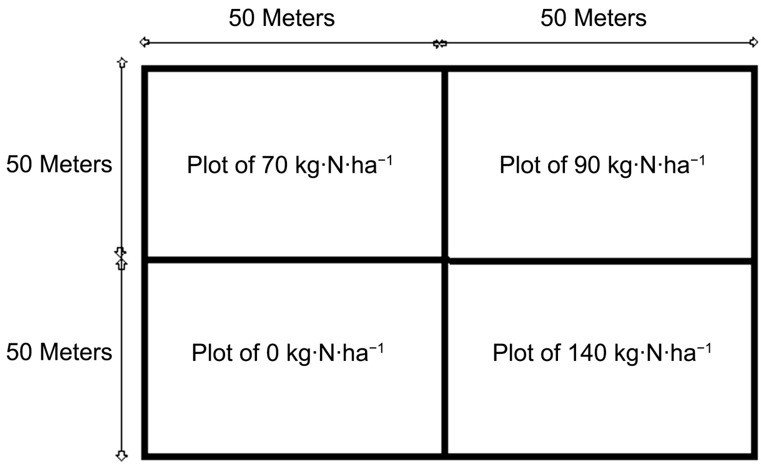

Figure 3. Rice experimentation with increasing doses of nitrogen.

2.4. Model Development Process

This section briefly describes artificial neural networks, in particular, the gradient back-propagation neural network (BPNN) used in this study.

2.4.1. Artificial Neural Networks

Artificial neural network methods are statistical tools used to estimate complex phenomena. Their specificity lies in their ability to estimate non-linear systems. These methods are particularly suitable for reproducing agricultural and hydrological processes and are therefore widely used in soil and water quality modelling ([17] [18] [22]). Among neural models, Multilayer Perceptron models are inspired by the architecture and functioning of the human brain, where the brain attempts to learn from signals coming from its environment in order to provide a response or action to be taken. This type of neural model is made up of interconnected neurons which, following an input signal represented by explanatory variables, produce an output signal, which can only be the variable being modelled. The choice of input variables is generally based on current knowledge of the processes involved. However, when the relationships between the different variables are not well known, a stepwise approach can be used. The stepwise (constructivist) approach consists of testing each of the variables individually in a reference network and combining the variables that obtain the best result for the chosen performance criterion [22].

Typically, the Multilayer Perceptron consists of three types of layers. Each of the variables in the input layer is connected to each of the neurons in the hidden layer(s), which are in turn connected to the neurons in the output layer(s). The connected neurons operate in a specific way and perform a weighted sum of the variables of the previous layer, following the free parameters (weights and biases) initialized beforehand with random values. Then, using a linear or non-linear activation function, they generate a result according to a well-defined algorithm [23].

2.4.2. Error Gradient Back-Propagation Algorithm

The Back Propagation Neural Network (BPNN) algorithm is the most widely used neural network method and determines the optimal weighting of features by iteratively modifying the hidden nodes and the learning rate while calculating the relative weights of the input variables between the neurons in the different layers of the neural network. In statistics, BPNNs are techniques known as classical gradient-based error correction algorithms. This principle forms the basis of gradient algorithm methods, which are effectively used in Multilayer Neural Networks (MLNs) [24]. The aim of the gradient algorithm is to converge iteratively towards an optimized configuration of weights and biases.

The weights and biases used in the model design are given by Equations (1) and (2).

$$w_{ij} = w_{ij} - \alpha \left(\frac{d_{(MES)}}{d_{w_{ij}}} \right), \tag{1}$$

$$b_{j0} = b_{j0} - \alpha \left(\frac{d_{(MES)}}{d_{b_{j0}}} \right), \tag{2}$$

where alpha (α) is the learning rate. The process of forward propagation, cost calculation, and backward propagation is repeated for a fixed number of iterations or until the cost function converges. MES is the mean squared error.

Furthermore, the optimal choice of network parameters, such as the number of layers and hidden nodes in a layer required to achieve a particular objective, is not easy to achieve. Clearly, there is no analytical tool for determining the ideal number of hidden neurons. In this situation, some authors have proposed a few rules. [25] suggest that, in the majority of applications, the optimal number of hidden neurons should be less than or equal to the number of inputs. [26] suggests that the following limit should not be exceeded, depending on the number of inputs according to Equation (3). However, these rules of thumb depend on the nature of the data used and the noise in the data. They cannot, therefore, be generalized. For the optimal choice of network parameters, it is therefore necessary to adopt a "trial-and-error" approach according to [22].

$$m \leq 2\beta + 1, \tag{3}$$

where m is the number of hidden neurons and β is the number of input variables.

2.4.3. Learning BPNN Neural Model

In general, a neural network must be capable of performing a particular function in a given environment. This capability is acquired through the learning algorithm adopted by the neural model. This is the first phase in the life cycle of a neural network (passage from a state of ignorance to a state of knowledge). In the event of a change in function or external environment, this phase must be repeated to adapt the behavior of the neural network to the new parameters (transition between two states of knowledge). Learning a neural network involves subjecting the system to a set of iterative stimuli. By intuition, the network will become better and better informed about the input set. With each learning iteration (feeding the neural network with a stimulus), the neurons in the network adapt their processing to meet the needs of the targeted function [27].

In the majority of existing neural networks, the behavior of a neuron depends on the weights and the activation threshold associated with it. These values, known as the free parameters of the neural model, define the behavior of the neural network on all the inputs. It is therefore difficult, and even impossible, to predict the values of the free parameters during the design phase. Hence, the need to go through the learning phase. During this phase, the free parameters will be modified in order to reduce the error in the system's response to the examples presented at its input and to experience. After a certain number of learning iterations, the margin of error decreases so that it is tolerated by the system. At this point, the neural network no longer needs to learn. Consequently, we can say that the neural network is capable of analyzing real examples from its external environment as an expert. At this point, the decision phase, often called the recall phase, begins [28].

In our case, the neural network is trained by trial and error according to equations 5 and 6 defined above until the best intelligent model is obtained. The intelligent model obtained at the end of training was evaluated according to the performance criteria chosen, namely the coefficient of determination (R2, closer to 1) and the mean square error (MSE, smaller). These performance criteria (MSE and R2), described by Equations (4) and (6), present the best values for testing the performance of a model for optimizing the application of quantities of a chemical fertilizer.

$$\text{MSE} = \frac{\sum_{i=1}^{n}\left(N_{observed,i} - N_{simulated,i}\right)^2}{n}, \quad (4)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(N_{observed,i} - N_{simulated,i}\right)^2}{\sum_{i=1}^{n}\left(N_{observed,i} - \bar{N}\right)^2}}, \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(N_{observed,i} - N_{simulated,i}\right)^2}{\sum_{i=1}^{n}\left(N_{observed,i} - \bar{N}\right)^2}, \quad (6)$$

where n is the number of measurement points, $N_{observed,i}$ is the observed value of nitrogen, $N_{simulated,i}$ is the predicted amount of nitrogen, and $\bar{N}$ is the mean value of $N_{observed,i}$.

The output value giving rise to the quantity of nitrogen supplied, depending respectively on the number of input nodes, hidden nodes, and output nodes, is given by Equation (7).

$$y_k = f_0\left[\sum_{i=1}^{m} W_{kj} \times f_n\left(\sum_{i=1}^{n} W_{ij}x_i + b_{j0}\right) + b_{k0}\right], \tag{7}$$

where y_k are the output values of the *k*th neuron at the nth iteration and x_i are the input values of the network, m and n are the numbers of neurons in the hidden and output layers respectively; W_{ij}, the connection weights between the input layer and the hidden layer; W_{jk}, the connection weights between the hidden layer and the output layer; b_{j0} and b_{k0} are respectively the bias of the *j*th hidden neuron and the bias of the kth output neuron; f_n and f_0 are respectively the transfer function of the hidden neuron and the output neuron.

For this purpose, the MATLAB simulation code was run to find the optimal model according to fixing criteria defined as follows: the maximum number of iterations fixed at 1000, the target error MSE and the minimum performance gradient fixed at 10^{-3} and 10^{-5}, respectively. Levenberg-Marquardt (LM) convergence was used, and logarithmic and linear sigmoid activation functions were used, respectively, for the hidden and output layers.

2.4.4. Database Construction

Nitrogen optimization was carried out following the simulation of rice yield as a function of increasing nitrogen doses. This simulation was carried out using all the data and physico-chemical parameters of the soil and irrigation water obtained during the rainy season (April). The justification for choosing this period was inspired by the work of [29] in France and [30] in Belgium, where the fertilizer requirements of rice would be relatively much more significant for their growth. The data set consists of fine soil density (dt, g·cm^{-3}), moisture at field capacity (θcc, %), moisture at wilting point (θPF, %), organic nitrogen content of the layer studied (Norg, kg·ha^{-1}), cation exchange capacity (CEC, Cmol·kg^{-1}), physico-chemical soil parameters (pH, K, P, OM, TOC), rice cropping coefficient (Kc), rice yields as a function of increasing nitrogen doses (Rd, kg·ha^{-1}), irrigation water parameters (SO_4^{2-}, Mg^{2+}, Ca^{2+}, Na^+, NH_4^+, mg·L^{-1}), rice water requirement (Be, m^3). The input variables were selected using the focused Principal Component Analysis (fPCA) method under R 3.1.3 software. A correlation analysis was carried out in order to identify the variables in the dataset showing significant correlations with rice yields (Rd, kg·ha^{-1}) for a selected significance threshold of $p < 0.05$. Thus, compared with the work of [22], parameters that were highly correlated ($1 \geq |r| > 0.5$) with yield (Rd) were retained as explanatory variables for the construction of the model.

Finally, in order to reduce the complexity of the network and accelerate its convergence, pre-processing was carried out, mainly concerning the normalization of input and target data, based on the Min-Max method. This involves transforming the values of the input parameters and the values of the data into the range 0 to 1 according to Equation (8), given by

$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}}, \quad (8)$$

where $\bar{X}$: normalized value, X: raw analyzed value, X_{min}: minimum value, and X_{max}: maximum value.

3. Results

3.1. Physico-Chemical Parameters of Irrigation Water

Table 3 presents the physico-chemical characteristics of irrigation water from the N'Zi river for the July 2021 season at M'Bahiakro. Analysis of this table shows that the irrigation water is acidic and has an average temperature between 25˚C and 26˚C, with an average acidic pH value of around 6.82. Electrical conductivity (EC) remains below irrigation water standards (<3000 µs/cm). Apart from ammonium (NH_4^+), the irrigation water complies with irrigation standards for nitrite (NO_2^- < 3 mg/L) and nitrate (NO_3^- < 30 mg/L).

Table 3. Values of physicochemical parameters of irrigation water.

Physico-chemical parameters	Min.	Max.	Mean ± Sd	Standards [31]
pH	6.74	6.86	6.82 ± 0.07	6.5 - 8.4
T˚C	25.00	26.00	25.6 ± 1.04	35.0
EC (µs/cm)	129.20	155.60	142.1 ± 13.20	3000
NO_3^- (mg/L)	0.400	1.20	0.77 ± 0.06	30.0
NO_2^- (mg/L)	0.00	0.00	0 ± 0.01	3.0
NH_4^+ (mg/L)	0.81	2.60	1.57 ± 0.07	0.5

3.2. Chemical Parameters of the Surface Layer of the Soil (0 - 30 cm)

The results of analyses carried out on soil samples from the irrigated perimeter are shown in Table 4. The pH values obtained indicate slightly acidic soils with average levels ranging from 5.42 to 7.02, within the optimum growth range for rice species (5.5 ≤ pH ≤ 7.5). The average levels of total organic carbon (TOC) and assimilable phosphorus (P) were higher than the reference standards, with average values of 2.71% and 532.3 ppm, respectively. The average levels of organic matter (OM) (4.63%), cation exchange capacity (CEC) (12.93 Cmol/kg), and potassium (K) (1.17 Cmol/kg) are within the normative range. Furthermore, in all the soil samples studied, the average nitrogen content (0.07%) is generally low compared with the reference range, which is between 0.2% and 0.25%. Nitrogen supplementation would therefore be essential for improving rice production in the M'Bahiakro irrigated perimeter.

Table 4. Values of soil physico-chemical parameters.

Physico-chemical parameters	Min.	Max.	Mean ± Sd	Standards according to [32]
pH	5.42	7.02	6.38 ± 0.46	5.5 - 7.5
K (Cmol/kg)	0.78	1.68	1.17 ± 0.28	0.15 - 0.25
OM (%)	3.89	5.34	4.63 ± 0.48	3.6 - 6.5
CEC (Cmol/kg)	9.23	18.26	12.93 ± 3.44	10 - 25
COT (%)	2.26	3.1	2.71 ± 0.29	1.26 - 2.5
Norg (%)	0.05	0.08	0.07 ± 0.01	0.2 - 0.25
K (ppm)	409	721	532.30 ± 97.48	134 - 179

3.3. Physical Parameters of the Surface Layer of the Soil (0 - 30 cm)

The results of the physical soil parameters used in this study are summarized in Table 5. At the perimeter, the density of fine soil (Dt) between 0 and 30 cm depth averaged 70%. Moisture at field capacity and moisture at the point of permanent wilting were 17.57% and 30.6%, respectively. The crop coefficient for the irrigated perimeter averaged 0.8.

Table 5. Parameters of the soil layer (0 - 30 cm).

Parameters	Details	Mean values
Dt (%)	Density of fine soil	70.00
θcc (%)	Field capacity humidity	17.57
θpf (%)	Humidity at the wilting point	30.60
Kc	Rice crop coefficient	0.80

3.4. Rice Yields as a Function of Increasing Nitrogen Doses

The yields obtained from rice production experiments at M'Bahiakro are summarized in Table 6 below. The application of nitrogen doses to irrigated rice crops in M'Bahiakro indicates an average yield of around 4406 kg·ha^{-1} for increasing doses of nitrogen varying between 70 kg·ha^{-1} and 140 kg·ha^{-1}. The yield responses of rice following application of doses of 70 kg·ha^{-1}, 90 kg·ha^{-1}, and 140 kg·ha^{-1} were 4150 kg·ha^{-1}, 4500 kg·ha^{-1}, and 4570 kg·ha^{-1}, respectively.

Table 6. Rice yields as a function of increasing nitrogen doses.

Nitrogen doses applied (kg·ha^{-1})	Rice yield (kg·ha^{-1})
70	4150
90	4500
140	4570

3.5. Choice of Variables

The choice of input variables for the simulation model of the response of rice to increasing doses of nitrogen was made using the fPCA method (**Figure 4**). This method was used to highlight the relationships between rice yields (Rd) and the physico-chemical parameters of the water and soil studied. **Figure 4** thus shows that Rd is significantly negatively associated with K, P, Norg, OM, θcc ($-1 > r \geq -0.8$) and positively with CEC, Kc ($1 > r \geq 0.8$). These significant correlations reveal the contribution of these different physico-chemical parameters (K, P, Norg, OM, θpf, CEC and Kc) to rice production yield at M'Bahiakro. These parameters are therefore used to design the simulation model.

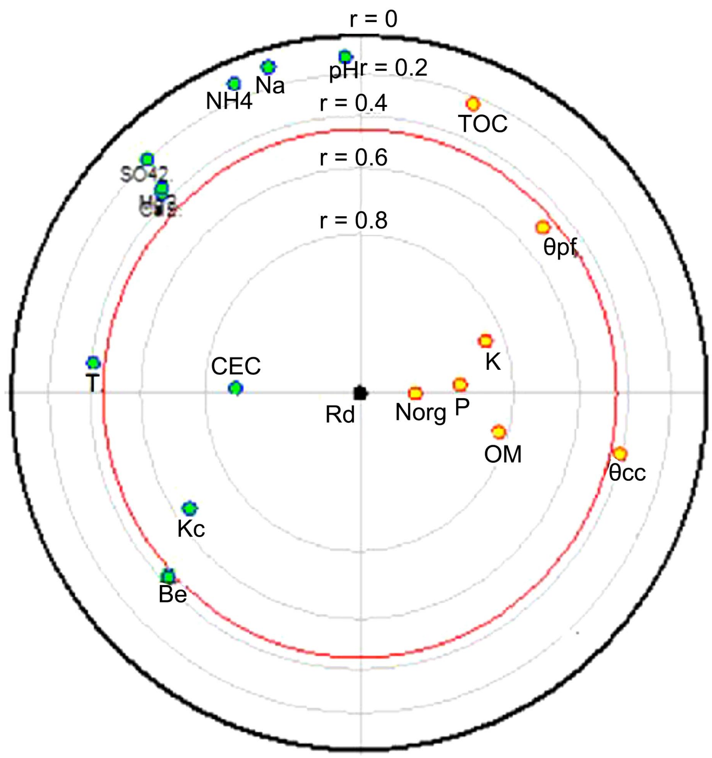

Figure 4. Correlation between explanatory variables and rice yield.

Yellow dots indicate negative correlation values with the dependent variable in the center; green dots indicate positive correlation values with the dependent variable in the center. The red circle indicates the significance threshold ($p < 0.05$); the points inside indicate significant correlations with the score of interest located at the center of the focused PCA.

3.6. Architecture and Performance of the BPNN Model

The BPNN neural model specified by the constructive approach, with seven (7) input variables, one (1) hidden layer of six (6) neurons, and rice yield as the only (1) output variable, is illustrated in **Figure 5**. **Figure 5** defines the architecture of the BPNN model for the season under study. This architecture also shows the weights (wij) generated on the network arrows and the bias (bj) corresponding to variable i and neuron j in the model (Table 7). Minimum values of these free parameters (weights, bias) tend to make the models more coherent and efficient. The weights of these different parameters towards the hidden layer vary between −2.15 and 3.20. From the hidden layer to the output layer, they vary between −1.78 and 2.27. The table also highlights the biases at the level of the six neurons in the hidden layer, which are between −2.77 and 2.72, and the bias at the level of the neuron in the output layer, which is around 0.753. The results of these free parameters were used to simulate rice yields.

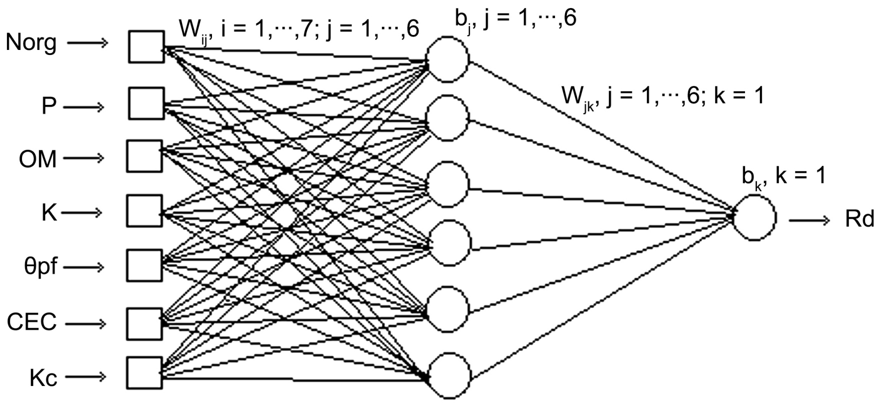

Figure 5. Architecture of the BPNN model developed.

Table 7. Weights and biases of the final training of the BPNN model.

Weight (w_{ij}) of input parameters in the hidden layer						
$w_{1,1} = -2.1411$	$w_{2,1} = -0.5830$	$w_{3,1} = -0.6873$	$w_{4,1} = 0.3036$	$w_{5,1} = 1.4505$	$w_{6,1} = -1.7453$	$w_{7,1} = 0.1412$
$w_{1,2} = 0.8336$	$w_{2,2} = -0.8515$	$w_{3,2} = 2.1763$	$w_{4,2} = 0.6385$	$w_{5,2} = -2.7559$	$w_{6,2} = -1.7348$	$w_{7,2} = -0.3839$
$w_{1,3} = 2.9713$	$w_{2,3} = -0.1183$	$w_{3,3} = -0.0134$	$w_{4,3} = 0.1927$	$w_{5,3} = -0.5977$	$w_{6,3} = 0.6710$	$w_{7,3} = -1.1590$
$w_{1,4} = -0.5140$	$w_{2,4} = 1.2520$	$w_{3,4} = -0.6916$	$w_{4,4} = 2.0591$	$w_{5,4} = 1.6958$	$w_{6,4} = 1.7783$	$w_{7,4} = 0.4111$
$w_{1,5} = 0.3349$	$w_{2,5} = 0.5399$	$w_{3,5} = 0.7842$	$w_{4,5} = 1.3813$	$w_{5,5} = -0.9460$	$w_{6,5} = -0.1066$	$w_{7,5} = -0.3485$
$w_{1,6} = 3.1919$	$w_{2,6} = -1.4355$	$w_{3,6} = -2.1736$	$w_{4,6} = -2.1377$	$w_{6,6} = 1.4527$	$w_{6,6} = 1.5430$	$w_{7,6} = 0.4014$
Weight (w_{jk}) between hidden neurons and the output layer						
$w_{1,1} = 1.3010$	$w_{2,1} = 2.2671$	$w_{3,1} = -1.5012$	$w_{4,1} = -1.7745$	$w_{5,1} = 2.1580$	$w_{6,1} = 2.4241$	$w_{7,1} = 1.6418$
Bias (b_j) in hidden neurons						
$b_1 = 2.7104$	$b_2 = -2.5734$	$b_3 = -1.1307$	$b_4 = -2.7694$	$b_5 = -0.4560$	$b_6 = -0.1230$	$b_7 = 0.6165$
Bias (b_k) in the output layer						
			$b = 0.7525$			

The indices relating to the R and MSE values obtained during the learning phase of the BPNN model (**Figure 6**) indicate the performance of the proposed model. Analysis of the results obtained shows that, for the season studied, the R coefficients are relatively high and greater than 0.90. In addition, the MSE values obtained for this BPNN model are clearly satisfactory (MSE around 0.001 fixed). According to the performance criteria, the BPNN model developed with the input variables Norg, P, OM, K, CEC, θpf, and Kc performs well with R and MSE values ranging from 90% to 100% and from 0.48323 to 0.00174, respectively.

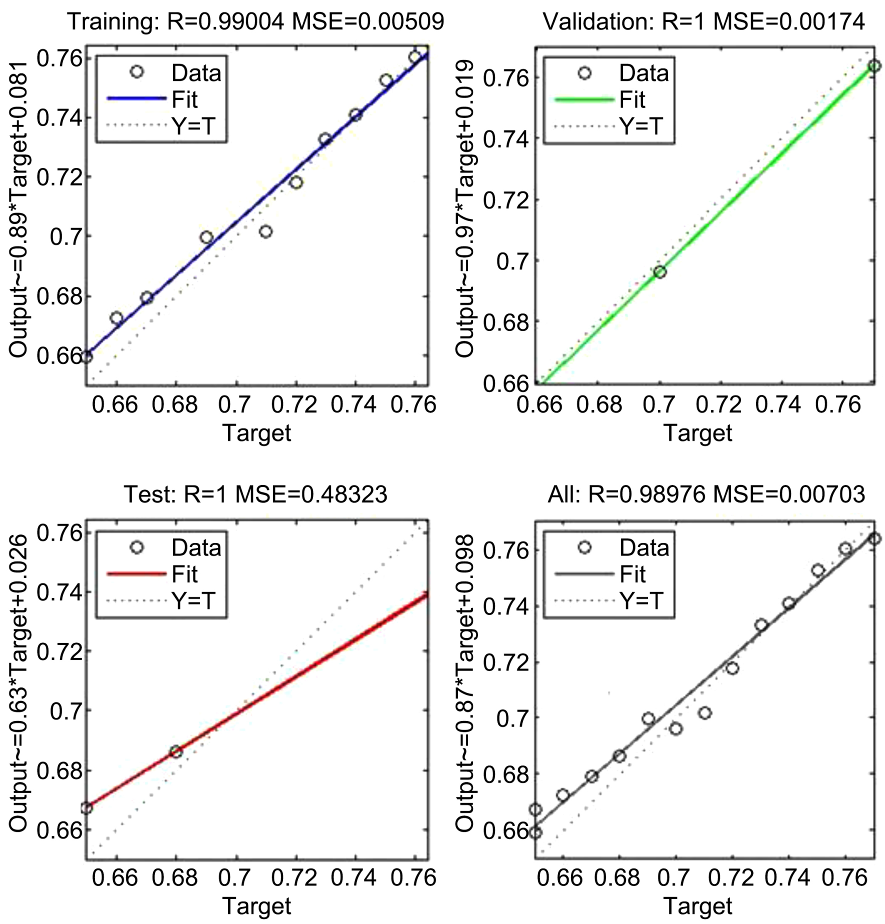

Figure 6. BPNN model learning phase.

3.7. Simulation of Rice Response

Table 8 shows the observed and simulated rice yields for the BPNN model developed. The simulated yields are obtained by varying the nitrogen doses in the model while setting the values of the other input parameters and the free parameters of the model following the learning process. These yields represent the response of the rice to increasing doses of nitrogen.

The difference between the observed and simulated yields is relatively small in relation to the MSE error values close to zero. In general, 80% of the MSE values obtained are satisfactory, with values relatively lower than 0.5. The architecture of the BPNN model developed would therefore confirm the performance of the 7-6-1 configuration neural network in calculating rice yields, with good superposition of the values observed experimentally and those simulated overall, with the exception of the yield obtained for 0 kg·ha^{-1} of Nitrogen (MSE = 0.687 > 0.5). Furthermore, the association between observed and simulated rice yields given by the linear regression line (Figure 7) indicates the reliability of the model developed, with a high coefficient of determination R2 of the order of 98%.

Table 8. Rice yields from the BPNN model.

Nitrogen doses applied (kg·N·ha^{-1})	Rice yield Observed (kg·ha^{-1})	Predicted rice yield (kg·ha^{-1})	MSE
0	-	454.5524	0.6869632*
70	4250	3989.11932	0.1010789**
90	4500	4412.79346	0.0184000***
140	4570	4624	0.0765579****

Error ≤ 0.05 (Excellent), 0.05 < Error ≤ 0.5 (Good), Error > 0.5 (Poor).

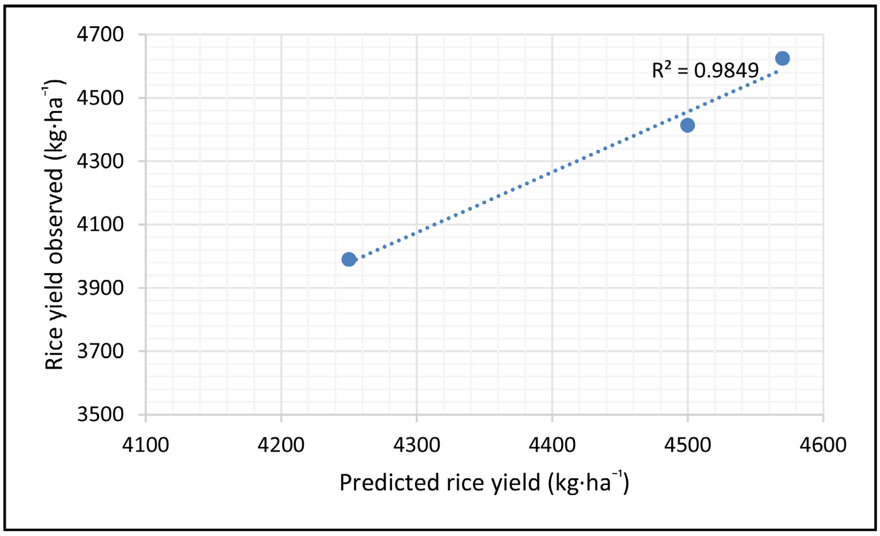

Figure 7. Correlation diagram.

3.8. Nitrogen Optimization

The quadratic regression from the BPNN model illustrates the response of rice to increasing doses of nitrogen (Figure 8). An increase in yield is observed, followed by a stabilization of yield with increasing doses of nitrogen. In the absence of nitrogen, the rice yield is estimated at 454 kg·ha^{-1}. This production increases with an application of 70 kg·ha^{-1} of nitrogen and would reach a yield of around 3989 kg·ha^{-1}. Beyond the dose of 70 kg·N·ha^{-1} of nitrogen, production would stabilize at around 4500 kg·ha^{-1} in terms of yield, whatever the dose of nitrogen applied. Furthermore, the derivative of the equation $y = -0.3364x^2 + 79.405x$ ($y' = -0.6728x$

+ 79.405) cancels out at a value of 118. The biophysical recommendation of nitrogen would then be capped at 118 kg·N·ha^{-1} nitrogen in the irrigated plots of M'Bahiakro.

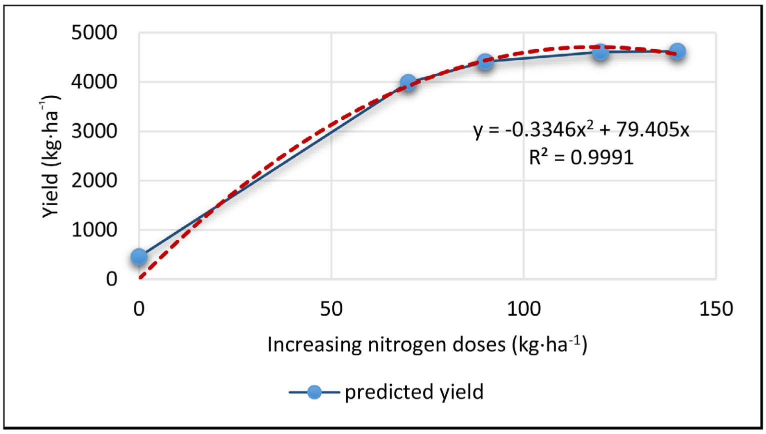

Figure 8. Nitrogen optimization.

4. Discussion

Nitrogen (N) is an essential nutrient for rice growth and development. Due to the low nitrogen content in the cultivated soils of the M'Bahiakro rice-growing area [10], the application of nitrogen fertilizers has become a necessary practice to increase yields. However, rational management of these inputs is required to balance agricultural productivity with environmental sustainability. In this context, a comparative analysis of artificial neural networks, according to [22], revealed that the best results were obtained with an architecture comprising six neurons in the hidden layer, tailored to the agroecological conditions of M'Bahiakro. The developed BPNN (Backpropagation Neural Network) model showed promising performance, with a mean squared error (MSE) of approximately 0.001, a correlation coefficient ($R \geq 0.90$), and a high coefficient of determination ($R^2 = 0.98$).

The effect of removing each input variable on the model's performance was also analyzed using the correlation index (r) within a targeted principal component analysis (PCA). This analysis indicated that rice yield (Rd) is associated with seven physicochemical parameters: K, P, Norg, OM, θpf, CEC, and Kc. Including these variables led to a satisfactory nitrogen optimization model. Compared to other studies, the nitrogen mineralization model in prairie soil proposed by [33], which includes five input variables (clay content, C, N, P, and pH), showed an R^2 of 0.78. This model appears less effective, as it considers fewer variables than the seven used in our case.

Numerous studies have demonstrated the impact of selected parameters on crop performance, particularly organic matter fractions ([34] [35]), organic nitrogen stock [36], and soil moisture [37]. These variables, which are relatively easy to obtain, provide accurate indications of the optimal nitrogen quantity to apply in the irrigated area of M'Bahiakro. The model's performance confirms its ability to accurately predict nitrogen requirements, paving the way for precise fertilizer optimization in irrigated rice systems. Yields varied significantly depending on the nitrogen application levels. They increased with the amount of nitrogen applied, but the yield gain plateaued beyond 118 kg·N·ha^{-1}. These results align with those of [30], who showed that residual soil nitrogen at harvest remains acceptable at 55 kg·N·ha^{-1} but becomes excessive beyond 152 kg·N·ha^{-1}. The work of [38], using a random forest regression algorithm, also identified an average optimal economic dose of 150 kg·N·ha^{-1} for most canola production scenarios during the test year. In our case, nitrogen efficiency decreases when the applied dose exceeds the optimal threshold of 118 kg·ha^{-1}.

However, several recent studies present contrasting or complementary findings. [39] demonstrated that fertilization ranging from 250 to 350 kg·ha^{-1} can reduce yield losses under heat stress by improving leaf hydraulic conductivity. Similarly, [40] reported a significant increase in yield and quality of hybrid rice with a combined nitrogen/potassium application up to 225 kg·ha^{-1}. Furthermore, [41] showed that differentiated nitrogen inputs, even beyond 150 kg·ha^{-1}, promote the formation of quality tillers and grain filling. These observations are reinforced by an analysis by [42], which indicates that innovative management strategies such as deep fertilization, slow-release fertilizers, or targeted split applications can maintain or even improve yields, even with doses exceeding 150 kg·ha^{-1}. Thus, although 118 kg·ha^{-1} appears to be the optimal dose under the agroecological conditions of M'Bahiakro, the literature suggests that higher doses may be beneficial in certain contexts, depending on pedoclimatic factors, cultivation techniques, rice genotypes, and nitrogen application methods.

Furthermore, although the nitrogen requirement prediction model developed in this study demonstrated high performance under the agroecological conditions of M'Bahiakro, its effectiveness can be significantly influenced by external climatic factors. Indeed, interannual climate variability and extreme events (heat waves, droughts, heavy rainfall) simultaneously affect soil nitrogen dynamics and rice physiology, which can lead to a divergence between the theoretical optimal dose and the actual agronomic response of crops. The work of [10], carried out on the irrigated perimeter of M'Bahiakro, highlighted a low nitrogen concentration during the dry season, compared to the rainy season, when levels can be significantly higher. This difference can be explained by reduced mineralization activity during the dry season, when soil samples were taken (December 2018). The study of mineralization dynamics showed that after a phase of microbial inactivity induced by dry conditions, the first rains strongly stimulate microbial processes. This reactivation results in significant mineralization flows, leading to a significant increase in the available nitrogen content in the soil ([43] [44]). This phenomenon clearly illustrates the impact of climate variability on nitrogen dynamics. From this perspective, the nitrogen requirement prediction model could be improved by integrating dynamic climate variables. Adjusting doses according to the seasons and weather forecasts would make it possible to anticipate losses linked to climatic hazards and optimize fertilization efficiency. Such an approach would strengthen the resilience of irrigated rice systems to environmental fluctuations.

5. Conclusions

This study established an optimal nitrogen dose of 118 kg/ha for rice cultivation in the irrigated perimeter of M'Bahiakro, based on a machine learning model of the BPNN type (Backpropagation Neural Network). The model incorporates seven key input variables (K, P, Norg, OM, θpf, CEC, and Kc), a hidden layer composed of six neurons, and a single-neuron output layer. It demonstrated robustness and efficiency, outperforming conventional approaches in agronomic prediction.

The results highlight the potential of intelligent modeling tools for more precise and environmentally responsive nutrient management. Beyond its scientific contribution, this advancement offers concrete prospects for agricultural practice and input governance. It serves as a strategic reference for local policymakers engaged in developing evidence-based agricultural policies, while providing a solid technical foundation for extension services to guide farmers toward more rational fertilization practices.

For producers, the optimal dose of 118 kg/ha represents a practical benchmark for adjusting cultivation practices to optimize yields, reduce input costs, and minimize environmental impacts. The modeling approach based on machine learning has proven to be a relevant strategy for optimized nutrient management, contributing to sustainable agriculture that is more resilient to environmentally induced abiotic stresses.

However, integrating climatic data into BPNN-type neural networks could enhance the model's robustness and adaptability in the face of climatic uncertainties. The development of hybrid models combining artificial intelligence, agroclimatic sensors, and spatial analysis would not only improve the accuracy of nitrogen fertilization recommendations but also strengthen the role of these tools as decision-support instruments. Such an approach would promote more proactive, sustainable, and climate-resilient input management.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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