Neural networks based-simple estimated model for greenhouse gas emission from irrigated paddy fields

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ABSTRACT

The current study aims to develop a simple model for estimating greenhouse gas emissions originating from paddy fields, utilizing backpropagation neural networks. The model integrated three input parameters: soil moisture, soil temperature, and soil electrical conductivity (EC), while generating estimations for two output parameters: methane (CH_4) and nitrous oxide (N_2O) emissions. The model was put into practice across three different irrigation systems, i.e., continuous flooded (FL), wet (WT), and dry (DR) regimes. For model training and validation, the input parameters were measured by a single 5-TE sensor. Concurrently, CH_4 and N_2O emissions were determined utilizing a closed chamber, and gas samples were subjected to laboratory analysis. Findings unveiled that the developed model accurately estimated CH_4 and N_2O emissions, demonstrating commendable coefficient of determination (R^2) values ranging from 0.60 to 0.97 for validation process. Notably, the WT irrigation system exhibited the highest precision, boasting R^2 values of 0.97 for CH_4 and 0.73 for N_2O estimation, respectively. Conversely, the FL irrigation system has the lowest accuracy with R^2 values of 0.66 and 0.60. Despite variances in accuracy across irrigation systems, the overall performance remained deemed acceptable, warranting the model's applicability for estimating greenhouse gas emissions under diverse irrigation scenarios.

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1. INTRODUCTION

Rice cultivation stands out as a significant contributor to greenhouse gas emissions, primarily methane (CH_4) and nitrous oxide (N_2O). This poses a pressing concern prompting the scientific community to seek strategies for both adaptation and mitigation. Studies reveal that rice fields account for approximately 30% of global agricultural CH_4 emissions and 11% of N_2O emissions [1], surpassing emissions from wheat and maize fields [2]. The emission dynamics from paddy fields are influenced by various factors, including rice varieties, organic matter content, soil management practices, water regimes, and fertilizer applications. Specifically, continuous flooding, a prevalent water management technique, is the primary driver of CH_4 emissions, while nitrogen fertilizer application significantly contributes to N_2O emissions [3]. Additionally, the choice of irrigation systems, particularly intermittent irrigation, plays a notable role in N_2O emissions [4]. Efforts to mitigate these emissions must address these multifaceted factors comprehensively.

CH_4 typically arises in anaerobic environments, such as those fostered by the widespread practice of inundating paddy fields with standing water. Conversely, N_2O is generated via microbiological processes encompassing nitrification and denitrification, occurring in both aerobic and anaerobic conditions [5]. The emission peaks for CH_4 coincide with continuous flooding, whereas N_2O production surges during intermittent flooding phases and periods of plant rotations [6]. Consequently, irrigation systems emerge as the pivotal factor influencing CH_4 and N_2O emissions. Numerous studies have underscored an inverse correlation between emission levels of CH_4 and N_2O and the treatment of irrigation systems [7], [8].

In the pursuit of adapting and mitigating the emissions of these two gases through irrigation system, precise measurements and quantification are imperative. Typically, measurements of CH_4 and N_2O emissions entail the use of closed chambers constructed from polycarbonate and acrylic plates for gas sampling, followed by analysis via gas chromatography (GC) to determine their concentrations and fluxes [9]. These measurements can be conducted either continuously [10] or through periodic sampling [11]. However, this method is notably intricate and costly, primarily due to the high expense associated with gas analysis equipment.

Hence, there is a pressing need to develop greenhouse gas emission models that enable quantification using more accessible and economical equipment. Among various modeling techniques, neural networks emerge as particularly suitable models, as they facilitate the estimation of multiple parameters simultaneously. Previous efforts have seen the development of greenhouse gas emission models tailored to paddy fields utilizing neural networks model [12]–[17]. However, these models typically require input parameters measured by multiple sensors or diverse instruments, thus incurring substantial costs. Therefore, the objective of this study is to develop a simple model employing neural networks to predict CH_4 and N_2O emissions from paddy fields using input variables from a single sensor that provides simultaneously three variables including soil moisture (SM), soil temperature (ST), and soil electrical conductivity (EC). The use of these three variables from a single sensor will be promising a more practical and cost-effective model.

2. METHOD

2.1. Collecting data for training and validation

During the rice planting season spanning from January 20th to May 13th, 2018, data collection was meticulously conducted at Kinjiro Farm in Bogor, Indonesia. Greenhouse gas emission was identified from three distinct irrigation systems, each characterized by varying water levels: flooded (FL), wet (WT), and dry (DR). In the FL system, water was consistently maintained at a level 2 cm above the soil surface, inundating the plot from the time of transplanting until the 70th day after transplanting (DAT). Subsequently, the water level was reduced to 0 cm at the soil surface until the 113th DAT. Within the WT system, the water level was regulated at 1 cm above the soil surface from transplanting to the 20th DAT, followed by a maintenance of 0 cm from the 21st to the 113th DAT. Conversely, in the DR system, the water level was kept at 1 cm from transplanting to the 20th DAT, then lowered to 0 cm from the 21st to the 30th DAT, and further decreased to -5 cm below the soil surface from the 31st to the 113th DAT.

Within the scope of these three treatments, the 5-TE sensor was meticulously positioned at a depth of 5 cm beneath the soil surface. 5-TE and its data logger provided by Decagon Device Inc, USA (currently changed as METER group, and the sensor is renamed became Teros-12). This sophisticated sensor served the crucial function of monitoring SM, ST, and soil EC, providing essential input parameters for the developed neural network model. Concurrently, greenhouse gas emissions, specifically CH_4 and N_2O for model training and validation, were meticulously quantified. A closed chamber, with the dimensions of 30 cm x 30 cm x 120 cm, was employed for this purpose across each treatment. Gas samples were systematically collected from the chamber on a weekly basis and subjected to rigorous analysis in the laboratory with GC. This meticulous gas sampling regimen spanned a duration of 17 weeks, encapsulating the entirety of the 119-DAT.

2.2. Developing neural networks model

The developed neural network model employed the backpropagation learning algorithm to facilitate its training process. Comprising three layers -input, hidden, and output- the model was structured to effectively process and predict greenhouse gas emissions. The input layer encapsulated crucial parameters including SM, ST, and soil EC, while the output layer focused on predicting CH_4 and N_2O emissions as shown in Figure 1. The selection of these input parameters was suggested by prior research, demonstrating their significant influence on CH_4 and N_2O emissions, thereby ensuring the model's robustness and relevance [13]–[15], [17].

The procedure for estimating CH_4 and N_2O emissions via the backpropagation algorithm unfolds as:

– Weight Initialization: The weights denoted as V_{ij} and W_{jk} (refer to Figure 1) are initialized with random values ranging from -1 to 1.

– Calculation of hidden layer values (Feedforward): Node of hidden value (H_j) is calculated by the (1) and (2).

$$Z_{ij} = \sum_{i=1}^{n} X_i V_{ij} \tag{1}$$

$$H_j = \frac{1}{1+exp^{-\sigma(Z_{ij})}} \tag{2}$$

Where, Xi is node of input, σ is constant of activation function.

– Calculation of output layer values (feedforward): Value of output node is calculated by the (3) and (4).

$$Z_{jk} = \sum_{i=1}^{n} H_j W_{jk} \tag{3}$$

$$Y_k = \frac{1}{1+exp^{-\sigma(Z_{jk})}} \tag{4}$$

Where, Y_k is the value of output nodes.

– Updating weight values (backward): Each weight is adjusted by accounting for the disparity between the model's output node and the observed data, utilizing the (5).

$$E = \frac{1}{2}\sum_{k=1}^{n}(Y_o - Y_k)^2 \tag{5}$$

Where, Y_o is observed output data.
Then, adjusted weight value in between node of output and node of hidden by the (6) to (8):

$$\Delta W_{jk} = \alpha \delta_k Y_k \tag{6}$$

$$\delta_k = (Y_o - Y_k)Y_k' \tag{7}$$

$$W_{jknew} = \beta \Delta W_{jk} + W_{jkold} \tag{8}$$

Where, α is constant of training rate, β is constant of momentum, W_{jknew} is new weight (after adjusted), and W_{jkold} is old weight (before adjusted).
Meanwhile, adjusted weight in between node of hidden and node of input by the (9) to (12):

$$\Delta V_{ij} = \alpha \delta_j X_i \tag{9}$$

$$\delta_j = \delta_{inj} H_j' \tag{10}$$

$$\delta_{inj} = \sum_{k=1}^{n} \delta_k W_{jk} \tag{11}$$

$$V_{ijnew} = \beta \Delta V_{ij} + V_{ijold} \tag{12}$$

Where, V_{ijnew} is new weight (after adjusted), and V_{ijold} is old weight (before adjusted).
The above process iterates with updated output weighting values (V_{ij} and W_{jk}), which are then employed to estimate CH_4 and N_2O emissions.

2.3. Performance of model

The evaluation of the developed model was conducted utilizing the coefficient of determination (R^2), a metric ranging from 0 to 1, by assessing the concordance between model predictions and observed data with the (13):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_k - y_o)^2}{\sum_{i=1}^{n}(y_o - y_{ave})^2} \tag{13}$$

Where y_{ave} is mean value of observed data.

A higher R^2 value indicates a stronger alignment between the model's estimations and the actual data, signifying superior performance. The assessment of model performance encompassed both training and validation phases. For this purpose, the cross-validation technique was implemented, adhering to the approach employed by Prabuwono *et al.* [18] in similar neural network applications. This methodology involved partitioning the dataset into 70% for training and 30% for validation [19], a strategy recognized for yielding superior outcomes compared to alternative partitioning schemes.

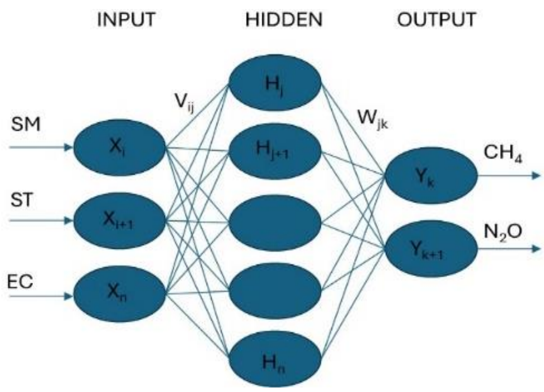


Figure 1. Developed simple neural networks to estimate CH_4 and N_2O emissions

3. RESULTS AND DISCUSSION

3.1. Greenhouse gas emissions among the treatments

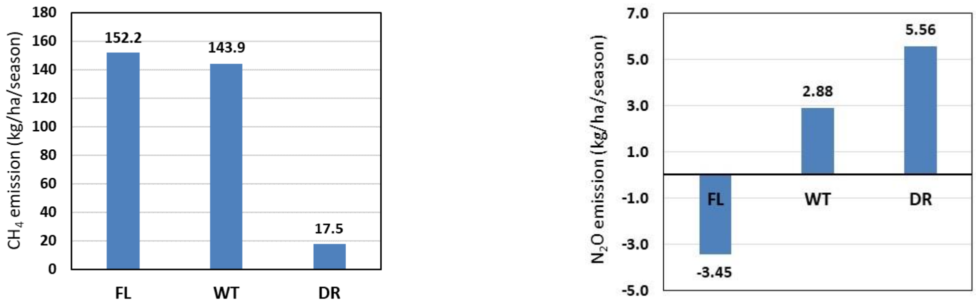
Greenhouse gas emissions within rice fields were notably influenced by water management practices, as illustrated in Figure 2. Among the treatments, the FL system, characterized by continuous inundation, exhibited the highest CH_4 emissions, followed by the WT and DR treatments as shown in Figure 2(a). Specifically, emissions totaled 152.2, 143.9, and 17.5 kg/ha/season for FL, WT, and DR, respectively. The pronounced CH_4 emissions in the FL treatment can be attributed to the prolonged presence of standing water, fostering anaerobic conditions ideal for methanogenic bacteria proliferation and subsequent CH_4 production [20], [21]. This finding was consistent with prior studies indicating a surge in CH_4 emissions upon the initiation of flooding [22], corroborating Wu *et al.* [23] observation that continuous flood irrigation systems yield greater CH_4 emissions compared to systems with reduced water levels. Conversely, the DR treatment, characterized by minimal water levels, yielded the lowest CH_4 emissions among the treatments. The diminished CH_4 emissions in DR were attributed to the absence of standing water, even post-transplanting, despite maintaining elevated water levels below the ground surface. This condition was akin to the practice of alternate wetting and drying irrigation (AWDI), known to curtail CH_4 emissions by up to 32% [24]. Hasanah *et al.* [25] conducted water level optimization studies aimed at mitigating greenhouse gas emissions, pinpointing a water level of -5 cm below the ground surface as optimal for emission reduction while preserving land productivity. The present study bolsters these optimization efforts, particularly in the context of CH_4 emission reduction.

A contrasting trend emerges in the total N_2O emissions results, where the lowest water level treatment within the DR regime released the highest total N_2O emissions, trailed by the WT and FL treatments as shown in Figure 2(b). This observation aligns with findings reported by Xing *et al.* [26], suggesting an inverse relationship, or trade-off, between CH_4 and N_2O emissions. N_2O emission formation stems from the soil's nitrification and denitrification processes, involving denitrifying bacteria that convert nitrate (NO_3-) into N_2O. During this conversion, oxidation transpires, liberating oxygen into the environment, particularly in conditions characterized by lower water levels. Consequently, the DR treatment, with its minimal water level, exhibits the highest N_2O emissions. This finding was further corroborated by prior research indicating AWDI system may elevated N_2O emissions by up to 62% compared to FL irrigation systems [27].

3.2. Estimating greenhouse gas emissions

Table 1 illustrated the model's performance during both the training and validation phases. Notably, the training phase exhibited superior performance, boasting an R^2 range of 0.93 to 1.00. Conversely, the validation process had an R^2 value ranging from 0.60 to 0.97. This discrepancy in performance can be attributed to the continuous refinement of weight values within the neural network model during the training phase, achieved through iterative comparison between observed and modeled data. In contrast, the validation phase employed weights derived from the training process to assess data that had not been previously examined by the model. This methodology echoes findings from prior hydrological research [28], underscoring the importance of iterative training for optimizing model performance.

The WT treatment exhibited the highest accuracy, primarily due to the moderate levels of total CH_4 and N_2O emissions compared to other treatments. However, the accuracy of estimating N_2O emissions was relatively lower compared to CH_4 due to its lower flux value. Moreover, the formation of N_2O emission was intricately influenced not only by the input parameters specified in the developed model but also by various other factors, further complicating its estimation.



(a) (b)

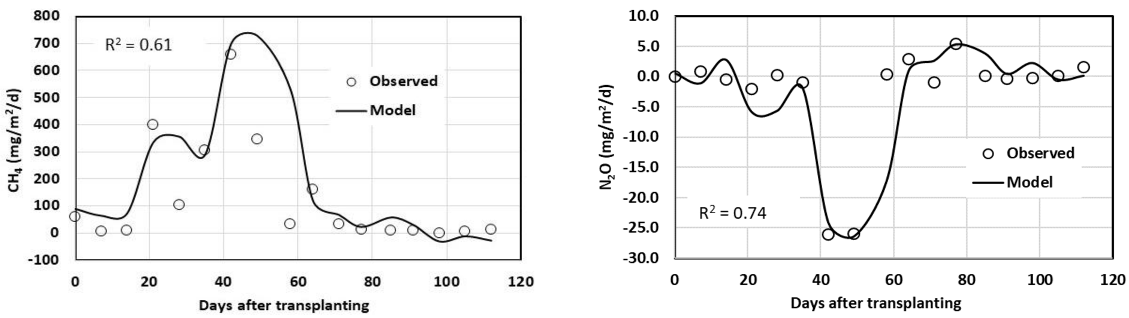
Figure 2. Total of (a) CH_4 emission and (b) N_2O emission among the treatments during a season

Table 1. Performances of developed model

Process Estimation	R^2 CH_4	R^2 N_2O
Training:		
- FL	0.97	0.93
- WT	1.00	0.93
- DR	0.98	0.96
Validation:		
- FL	0.66	0.60
- WT	0.97	0.73
- DR	0.91	0.71

Figure 3 shows comparison between observed and model prediction data both for CH_4 and N_2O under FL treatment. In detail Figure 3(a) presents a comparison between observed CH_4 flux and model predictions for the FL treatment, encompassing both the training and validation processes. The estimated flux data generally mirrors the trend observed in the actual data, albeit instances of both overestimation and underestimation. The recorded measurements range from 0.40 to 660.2 mg/m^2/d, with minimum, average, and maximum values of 0.40, 127.8, and 660.2 mg/m^2/d, respectively. In contrast, the model's predictions has minimum, average, and maximum values of -31.67, 199.1, and 729.4 mg/m^2/d, respectively. Despite discrepancies between measurements and predictions, the model achieves a moderate level of agreement, as indicated by an R^2 value of 0.61.

Similarly, the comparison between observed N_2O data and model predictions for the FL treatment reveals a consistent trend in Figure 3(b). The observed and estimated N_2O fluxes exhibit a similar pattern, with smaller deviations compared to CH_4. The measured N_2O flux values range from -25.99 to 5.40 mg/m^2/d, with minimum, average, and maximum values recorded at -25.99, -2.63, and 5.40 mg/m^2/d, respectively. In contrast, the model-predicted values range from -26.47 to 5.30 mg/m^2/d, with minimum, average, and maximum values of -26.47, -3.80, and 5.30 mg/m^2/d, respectively. Notably, the R^2 value in this comparison is higher than before, reaching 0.74, indicating a stronger agreement between observed and predicted N_2O fluxes under FL treatment.

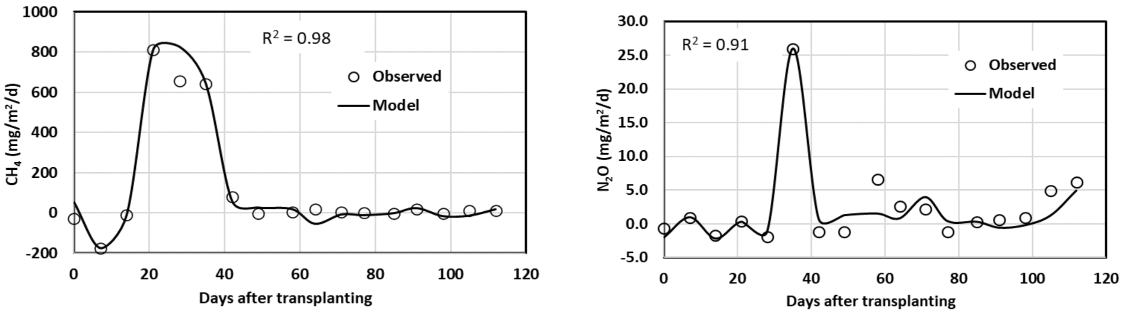


(a) (b)

Figure 3. Comparison of (a) CH_4 emission and (b) N_2O emission in between observed and model under FL treatment

The close alignment between the observed and model data was also found in the WT treatment, as presented in Figure 4. The WT treatment earned the most accurate results in predicting CH_4 flux, boasting an impressive R^2 value of 0.98 in Figure 4(a). This is evidenced by model predictions closely aligning with measurement results, exhibiting minimal deviation. Within this treatment, the observed CH_4 flux values ranged from -174.2 to 812.9 mg/m^2/d, with minimum, average, and maximum values of -174.2, 120.6, and 812.9 mg/m^2/d, respectively. Meanwhile, the model's predictions earned values ranging from -176.0 to 827.0 mg/m^2/d, with minimum, average, and maximum values of -176.0, 128.5, and 827.0 mg/m2/d, respectively.

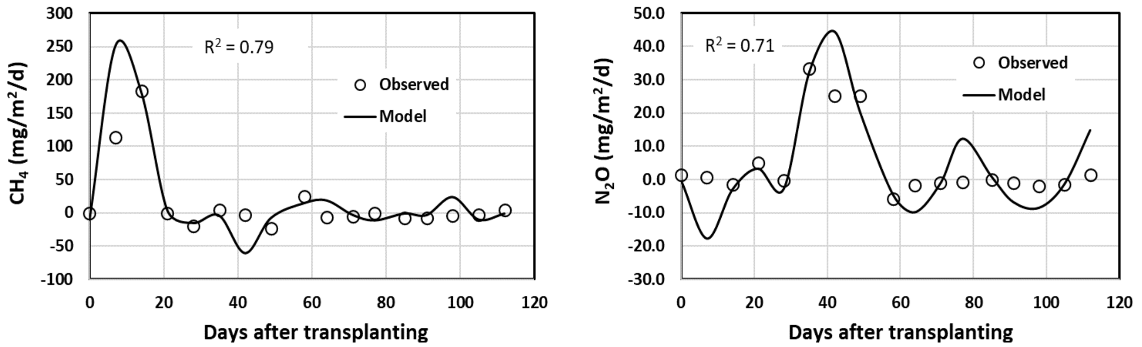
The WT treatment also exhibited accurate results in N_2O estimation, albeit with a slightly lower R^2 value of 0.91 compared to CH_4 estimation as shown in Figure 4(b). However, the deviation between measurements and model predictions remained minimal. This is evident from the close alignment between most of the model-predicted flux values and the measured values. Specifically, the minimum, average, and maximum flux values for both measurements and models were recorded at -1.89, 2.58, and 25.98 mg/m^2/d and -2.13, 2.17, and 25.96 mg/m^2/d, respectively.



(a) (b)

Figure 4. Comparison of (a) CH_4 emission and (b) N_2O emission in between observed and model under WT treatment

For the DR treatment, the observed and predicted emissions trends for both CH_4 and N_2O were notably similar, indicating the acceptability of the models in Figure 5. Accuracy levels within this treatment were moderate for both CH_4 and N_2O predictions, with respective R^2 values of 0.79 and 0.71. As illustrated in Figure 5(a), the model predictions for CH_4 fluxes tended to be higher, indicating lower deviation values. Most of the predicted CH_4 fluxes closely aligned with the measurements. Specifically, the minimum, average, and maximum values of measured CH_4 flux were recorded at -22.9, 14.8, and 183.1 mg/m^2/d, while the model predictions were -60.7, 21.5, and 251.7 mg/m^2/d, respectively. Meanwhile, in the case of N_2O predictions in Figure 5(b), instances of both overestimation and underestimation were observed around the 7th DAT and after the 60th DAT. The measured N_2O flux values ranged from -5.74 to 33.37 mg/m^2/d, with minimum, average, and maximum values of -5.74, 4.55, and 33.37 mg/m^2/d, respectively. In contrast, the model predictions ranged from -17.64 to 44.46 mg/m^2/d, with minimum, average, and maximum values of -17.64, 4.30, and 44.46 mg/m^2/d, respectively.



(a) (b)

Figure 5. Comparison of CH_4 emission (a) and N_2O emission in between observed and model under DR treatment

The predicted total emissions across all treatments aligned precisely with the observed data as shown in Table 2. The FL treatment exhibited the highest total CH_4 emissions, followed by the WT and DR treatments. Conversely, total N_2O emissions were highest in the DR treatment, followed by WT and FL treatments. Notably, the WT treatment demonstrated the highest accuracy for total greenhouse gas emissions, with minimal deviation between observed and estimated data. The total differences for CH_4 and N_2O were recorded at 7.2 kg/ha/season and 0.4 kg/ha/season, respectively. In contrast, the FL treatment displayed the least accuracy in estimating total emissions, characterized by the largest total difference. This consistency in model estimation underscores the reliability of the results. Despite varying R^2 values, the accuracy values remained within an acceptable range, as suggested in similar studies [29]. Hence, the developed simple neural networks model presents a practical method for estimating greenhouse gas emissions with simplicity, cost-effectiveness, and accuracy. This method offers greater simplicity and accuracy compared to earlier models. Abbasi *et al.* [17] developed a neural network model to estimate greenhouse gas emissions from rice fields. However, their model demands more extensive input data, including soil characteristics, the amount of fertilizer, and the type of rice variety. In contrast, the new method requires fewer inputs, making it a more straightforward and efficient solution. This approach proves especially valuable in areas where direct emission measurement is impractical due to limited access and high costs. For broader applicability, it is recommended to validate the current model in diverse locations with varying environmental conditions and soil types.

Table 2. Comparison of total emissions between observed and model among the treatments

	Treatments		
Total Emissions	FL	WT	DR
Total CH_4 (kg/ha/season)			
Observed	152.2	143.9	17.5
Estimated	243.7	151.1	25.9
Differences	91.5	7.2	8.5
Total N_2O (kg/ha/season)			
Observed	-3.45	2.88	5.56
Estimated	-4.91	2.48	4.87
Differences	1.46	0.40	0.68

4. CONCLUSION

A straightforward model has been developed for estimating CH_4 and N_2O emissions using backpropagation neural networks from irrigated paddy fields. This model incorporates three input parameters, all of which can be conveniently measured using a single sensor, thus streamlining the gas emission estimation process. During validation across three distinct irrigation systems i.e., FL, WT, and DR, the model demonstrated accuracy, with R^2 values ranging from 0.60 to 0.97. Despite variations in R^2 values, the estimation outcomes remained consistently reliable, both in predicting flux values and total emissions over a single season. Consequently, this model presents a practical and cost-effective solution for estimating greenhouse gas emissions from paddy fields, simplifying the process significantly.

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