NITROUS OXIDE PREDICTION FROM FARMLAND USING FUZZY LOGIC

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Declaration of Authorship

I, Rose Chong-Wu, declare that this thesis titled ”Nitrous Oxide Prediction From Farmland Using Fuzzy Logic” and the work presented in it are my own, I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

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Abstract

Undoubtedly, agriculture is vital for sustaining humanity, but how often do we concern ourselves with the negative consequences of arable farming, particularly the amount of greenhouse gas emissions that result from it? Nitrous oxide (N_2O) is a greenhouse gas (GHG) emitted from farmland as a result of natural soil processes, including nitrification and denitrification. The amount of this potent GHG that is emitted into the atmosphere is exacerbated by the widespread application of nitrogen-rich fertilizers to crops using the conventional broadcast method.

It is alarming to know that from 2005 to 2019, fertilizer use in Canada increased by 71%, and this caused a 54% increase in N_2O emissions. The Government of Canada has decided to take action against climate change and set a goal to reduce N_2O levels by 2030. Note that this target does not mean there is a ban or mandatory reduction in fertilizer use. Their goal is to reduce fertilizer-related emissions without jeopardizing the success of maximizing food production, while improving the sustainability of farming. To accomplish it, there must be ways to monitor N_2O from farmland.

The work presented in this article is indirectly related to this goal, as I will explore the use of a fuzzy logic (FL) model to predict N_2O from relatively easily obtained inputs: daily average soil temperatures and moisture readings. This is not intended to replace traditional measurement methods, such as trace gas chambers, but to provide an alternative means of obtaining a rough estimate of N_2O emissions, since traditional methods are very costly. If this yields sufficiently accurate results, it can be deployed in real-world settings.

Between the years of 2021 and 2023, data was collected during the growing season on many different parameters, including soil temperature and moisture. These two variables are known to impact the flux of N_2O. In this research project, a FL model was developed, and daily average soil temperature and moisture data for each year were obtained and input into the model. The output was the predicted amount of N_2O emitted from the farmland. These predicted values were compared statistically with real, daily-averaged N_2O readings. The results indicate that this model is promising as a cost-effective technology for predicting N_2O emissions from farmland.

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Chapter 1

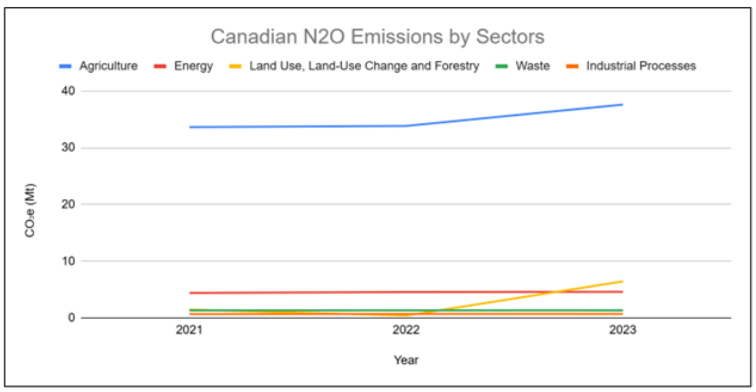
Introduction

Of the prominent greenhouse gases (GHGs), nitrous oxide (N_2O) emissions resulting from agricultural activities have become a significant global concern. Crop production is responsible for approximately 50% of agriculture-related N_2O emissions, primarily due to fertilizer-induced discharges. Since the Industrial Revolution, atmospheric N_2O concentrations have increased by 60 parts per billion (ppb), with an annual rise of 0.73 ppb (Ramzan et al., 2020). N_2O is a critical GHG due to its long atmospheric lifetime of over 114 years and its global warming potential, which is 298 times greater than that of carbon dioxide (CO_2) (Signor & Cerri, 2013). In Canada specifically, the agriculture sector is the largest contributor of N_2O emissions and accounts for approximately 75% of N_2O emissions as a result of fertilizer use (Office of the Auditor General of Canada, 2024) (Figure 1.1).

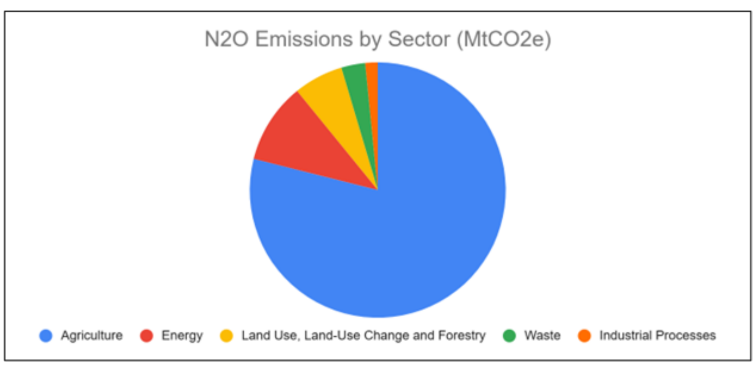
Soil studies are inherently complex and interdisciplinary, often requiring the integration of mathematical models from the hard sciences with subjective, rule-based frameworks from the soft sciences. These hybrid models, while essential for capturing the multifaceted nature of soil systems, can be difficult to interpret and may not always provide an accurate representation of real-world soil properties and processes. Soil science modeling is characterized by numerous, often conflicting, attributes and relies on uncertain and imprecise data. Given the inherent variability and ambiguity present in natural systems, addressing uncertainty in soil modeling remains a fundamental challenge (McBratney & Odeh, 1997). However, the introduction of fuzzy logic by Zadeh (1965) provided a mathematical framework for quantifying uncertainty and imprecision. Fuzzy logic has since been applied across various domains within soil science, including soil classification, soil mapping, land assessment, fuzzy geostatistics, and soil physical processes modelling (McBratney & Odeh, 1997).

Table 1.1: N_2O emissions from Canadian sectors in $\mathrm{MtCO_2eq}$ for the years 2021, 2022, and 2023. Average values are used in Figure 1.1. *Data from Climate Watch (2024)*

Sector	2021	2022	2023	Average
Agriculture	33.65	33.85	37.60	35.03
Energy	4.41	4.57	4.62	4.53
Land Use, Land-Use Change and Forestry	1.47	0.42	6.45	2.78
Waste	1.33	1.34	1.35	1.34
Industrial Processes	0.69	0.70	0.70	0.70
Total	**41.55**	**40.88**	**50.71**	**44.38**



(a) N_2O emissions by sector (2021–2023).



(b) Average N_2O emissions by sector.

Figure 1.1: N_2O emissions from Canada by sector for the years 2021 to 2023 in $\mathrm{MtCO_2eq}$. (a) Annual emissions by sector, showing that agriculture is the dominant source across all years. (b) Average sectoral contributions, with agriculture accounting for 78.9%, followed by energy (10.2%), land use (6.3%), waste (3.0%), and industrial processes (1.6%). *Data from Climate Watch (2024).*

1.1 Motivation & Importance

Extensive literature on N_2O emissions from agriculture already exists; however, the accurate prediction of farmland-derived N_2O emissions remains a relatively unexplored research area. Developing predictive models for N_2O emissions using fuzzy logic programming offers a promising approach to enhancing the speed and reducing the cost of emission estimates. Such an approach could improve decision-making related to fertilizer application strategies, irrigation management, and other agronomic practices that influence N_2O emissions. Furthermore, fuzzy logic-based modeling offers a cost-effective and resource-efficient alternative to existing technologies for direct soil N_2O measurements, thereby increasing its potential for widespread application in agricultural research and management.

This research contributes to sustainable agriculture by addressing the environmental and climatic challenges associated with fertilizer-derived emissions. Accurate estimation and monitoring of agricultural N_2O emissions are essential for informing mitigation strategies. However, predicting N_2O emissions remains a persistent scientific and technical challenge (Lin et al., 2024).

1.2 Thesis Statement

Research Problem:

As agriculture intensifies to feed a growing population, it is only logical that increased fertilizer is used, thus increasing nitrous oxide emissions from farmland operations. Agriculture mainly accounts for approximately 60% of global anthropogenic N_2O emissions, primarily due to nitrogen fertilizer applications to agricultural soils. Consequently, agriculture represents the largest opportunity to reduce N_2O emissions. However, crop nitrogen-use efficiency is generally low, with less than 50% of applied nitrogen typically taken up by crops under normal farming conditions. As a result, an important mitigation challenge is reducing N_2O emissions per unit of fertilizer applied while maintaining agricultural productivity (Reay et al., 2012).

As governments urge farmers to voluntarily reduce N_2O emissions from agricultural activities, there must be scientific advances to help achieve and adapt to these goals. This research project focuses on developing a cost-effective, prediction-based method for estimating N_2O emissions from local-scale areas, farming operations, as opposed to global N_2O estimation strategies.

Accurate measurement of N_2O gas emissions from farmland is now feasible using multiple methods, including chamber, micrometeorological, and flux-gradient approaches. Other analytical techniques used to measure N_2O include chromatographic, optical, and amperometric methods. However, each of these methods for accurately measuring N_2O is not affordable, not easily deployable, and cannot collect emission data over wide areas (Rapson & Dacres, 2014).

To mitigate the costs of developing and deploying accurate N_2O measurement tools, several researchers have focused on developing predictive models that are much less costly. Some work includes using a variety of machine learning techniques such as regression, shallow and deep machine learning by Hamrani et al. (2020). Additionally, work has been done by Lin et al. (2024), focusing on the use of an agricultural-informed neural network and by Killeen et al. (2025), who utilized federated learning for training models for N_2O emission prediction. Jadhav and Lal (2019) have begun work on greenhouse gas predictions using farm data as inputs for a fuzzy logic-based system.

This project focuses solely on using minimal readily available weather and soil data as inputs to a custom rule-based fuzzy logic model to predict N_2O emissions from farmland. The objective of this project is to create a cost-effective yet reasonably accurate alternative to deploying expensive machinery. Note that precision would be lost as these are predictions only, not actual measurements of GHG emissions.

Limitations of Current Solutions:

Time and computational demands can limit the development of more detailed predictive models, especially when rapid results are required. In many cases, there is only a need for approximate values rather than precise measurements. By limiting the model inputs to two variables and keeping computational requirements low, this approach enables rapid generation of results with minimal data. As a result, it is well-suited for users who simply need reasonable estimates of N_2O emissions from arable agricultural activities.

Key Idea:

As Canada's federal government aims to reduce the amount of GHGs emitted as a result of agricultural activities, while maintaining successful and profitable crop yields, there is a desire for cost-effective methods to know how much GHGs are being emitted. Accurate measuring devices are available, but they are very expensive, and thus they are not feasible for widespread use. Especially since the government is not restricting fertilizer application (in which over-fertilization leads to increased N_2O emissions), reasonably accurate predictions should suffice. Not only would a fuzzy logic system for N_2O predictions be a cost-effective alternative, the model that is being proposed also uses only two very common types of weather data as inputs, thus the required data is easy to obtain, and moreover, the model itself is very quick, and not computer-intensive, so even non-experts can easily use it. The objective of this project is to analyze how well this custom fuzzy logic model can predict N_2O emissions given weather data as inputs, identify any limitations or shortcomings, and recommend improvements for future iterations, as needed.

1.3 Objectives

This thesis' main objectives include:

1. **Utilizing simple weather data in a fuzzy logic system to make predictions of the greenhouse gas, N_2O,**

from farmland.

2. **Analyze the model's predictive ability:**

   (a) On a day-to-day basis for each growing season.

   (b) Of the accuracy of the cumulative N_2O simulated during each growing season.

3. **Explore the relationships between the input variables (soil temperature and moisture) with N_2O emissions.**

This research focuses on the potential of a new outlook for predicting N_2O emissions using fuzzy logic. Although fuzzy logic has long existed and has been used in many other applications, there has been little work to date on its use in agriculture, particularly for predicting greenhouse gas emissions. This study aims to develop a fuzzy logic-based modeling approach to predict N_2O emissions from agricultural soils using a single impulse measurement and daily average temperature and soil moisture as inputs. The model will be designed to simulate N_2O emissions based on the known rate of decay of nitrogen by microorganisms in the soil after a known fertilizer concentration is applied, along with daily inputs of two major factors that affect the rate of decay.

At the end of the growing season, the daily predicted N_2O emissions generated by the fuzzy logic model will be evaluated against actual emission measurements obtained from LI-COR gas analyzers from the research area. Statistical analysis will be conducted to assess the model's daily predictive accuracy, by calculating metrics such as mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), mean bias error (MBE), and coefficient of determination (R^2), and Spearman's rank correlation (ρ).

In addition, absolute and percentage errors were calculated by comparing each season's cumulative observed emissions with the cumulative simulated emissions to assess the model's ability to capture overall N_2O release across the entire growing season. This comparison is particularly relevant for management and reporting purposes, as it reflects the model's ability to estimate total emissions over time rather than day-to-day variability.

Peripheral to the most important objectives was to perform a limited data analysis of the input variables and their relationship to N_2O emissions. These revealed trends consistent with prior literature; results across growing seasons aligned with studies reporting divergent conclusions.

1.4 Contributions

The main contribution of this research would be the exploration of the innovative development of a cost-effective and relatively simple method of predicting N_2O emissions that could be used by many users due to its low complexity. This tool can be used to predict N_2O emissions from the arable land of interest.

Based on the results, the if fuzzy logic model will be deemed to provide a high enough degree of accuracy for predictive modeling of N_2O emissions for wider application, or as a future direction, will be adjusted until it can more accurately do so. The findings of this research will provide insights into the efficiency of fuzzy logic modeling for predicting N_2O emissions and its potential as a rapid, cost-effective alternative to direct measurement techniques. The results will contribute to the broader understanding of how computational intelligence methods can enhance greenhouse gas monitoring, be used to predict N_2O emissions in comparison experiments, and furthermore, be used to implement sustainable agricultural practices.

1.5 Methodology

This research project investigated the innovative approach of utilizing a fuzzy logic system to predict N_2O emissions, in which only two weather data types were used as inputs, and the output analysis would hopefully lead to the conclusion of having created a reasonably accurate predictive model.

The original datasets implemented consisted of (a) soil temperature measured at six different depths and (b) precipitation (rainfall) measurements over the course of several growing seasons (2021 - 2023). These variables were measured every 30 minutes throughout the growing seasons at Area X.O., a research farm located in Ottawa, Ontario, Canada.

These datasets were pre-processed to obtain the daily averages: (a) average soil temperature, calculated across the six soil depths, and (b) average daily rainfall. An impulse function measurement was required for the fuzzy logic system. It refers to the maximum amount of N_2O emitted from the soil, which was an accurate measurement of the GHG (using a measuring device), taken after fertilizer application and after a real or simulated rainfall event, which stimulates a high amount of N_2O released from the soil.

The impulse measurement along with the processed datasets, were input into the fuzzy logic system. The rule-based system would generate outputs, which were daily N_2O predictions for each specific growing season. The predictions were then compared with the actual N_2O emissions datasets for each season, which were obtained from trace gas chamber analyzers deployed in the same field as the weather data. Afterward, the predictions were compared with the empirical N_2O emissions to assess accuracy and shortcomings, including peak-valley comparisons and prediction lags or leads.

The simulated predictions showed promising results, with clearly similar peaks and valleys when compared with the actual N_2O measurements. However, there were noticeable time discrepancies, indicating that the identifiable predictive patterns were offset relative to the actual emissions. This is not a major issue if the objective of this research project is solely to find out how much N_2O is emitted over the whole growing season, as this technology is intended for predictions to help farmers or other users know a relatively accurate estimation of the N_2O emitted from their farmland to abide by the government's goal to reduce the amount of N_2O emissions. However, if accurate daily predictions are desired, more fine-tuning of the fuzzy logic model or more detailed datasets would be required. If the model in its current state, is adequate for users, some applications would include testing N_2O emissions under different conditions, such as fertilizer types, applied concentrations, or application methods.

1.6 Thesis Outline

The remaining parts of the thesis are structured as follows: Chapter 2 is an extensive literature review detailing relevant aspects of nitrous oxide, followed by fuzzy logic, then mentioning related work. This will lead to Chapter 3 in which problem formulation and methodology of the experiment are discussed. Chapter 4 focuses on a further in-depth description of predicting nitrous oxide emissions using fuzzy logic. The results of the emissions calculations and their discussion will appear in Chapters 5 and 6, respectively. Final thoughts of the experiment and suggestions for future work conclude this research project in Chapter 7.

Chapter 2

Literature Review

This literature review will begin by covering background knowledge of nitrous oxide in great detail, followed by an explanation of fuzzy logic, and then a review of available information on related work to date done by my colleagues, who have taken a higher-level approach to predict nitrous oxide emissions. I will also describe work that is highly similar to mine, in which fuzzy logic is used to predict greenhouse gas emissions from rice paddies.

2.1 Nitrous Oxide

Nitrous oxide is a potent greenhouse gas that contributes to global warming. Agricultural soils are a huge source of nitrous oxide emissions, which are generated by natural processes that are amplified with the application of nitrogen-based fertilizers. With the growing demand to feed the world population, the overall problem is exacerbated. The topics of N_2O's role in global warming, the nitrogen cycle, factors influencing N_2O emissions, and strategies for measuring and estimating N_2O will be discussed.

2.1.1 Global Warming, Greenhouse Gases & the Greenhouse Effect

Oftentimes, the terms "global warming" and "climate change" are used interchangeably. However, global warming is only one facet of climate change. Increasing concentrations of greenhouse gases within the atmosphere have caused a rise in global temperatures, which is referred to as "global warming". The escalating changes of climate measures over extended time are referred to as "climate change" and include changes regarding temperature, precipitation, and wind currents (U.S. Geological Survey, 2022b).

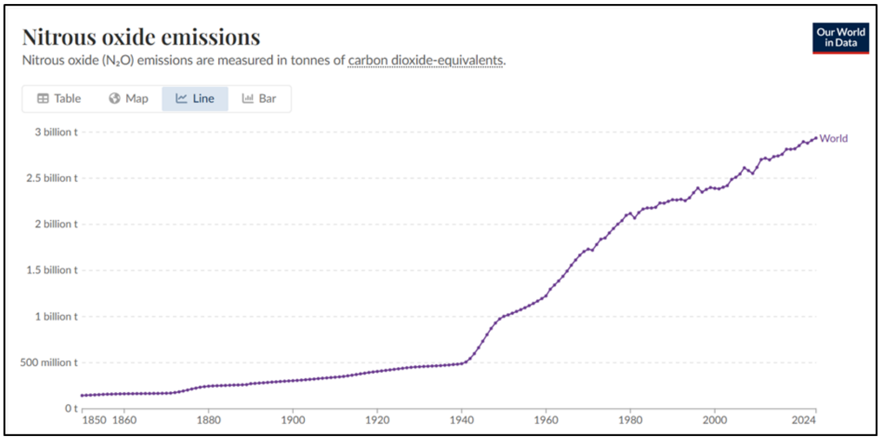
Changes in global climate threaten the well-being of life on earth and are primarily the result of human activities. Natural sources of greenhouse gases exist, but the primary driver of global warming is the large amounts of greenhouse gases released into the atmosphere by anthropogenic activities. While greenhouse gases are naturally occurring in the atmosphere and are vital for maintaining Earth's temperature suitable for its inhabitants, human activities have significantly increased the concentrations of four of them. The most abundant greenhouse gases (GHGs) are water vapour, carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (U.S. Geological Survey, 2022a).

While the most important GHGs are water vapour and CO_2, other gases including CH_4 and N_2O, also contribute to atmospheric warming, due to rises of their atmospheric levels caused by anthropogenic activity (Le Treut et al., 2007). The most abundant GHG in the atmosphere is water vapour, but it is not significantly affected by human activities (Forster et al., 2007). However, the other three GHGs are influenced by anthropogenic activities to a great extent and are therefore pertinent to the greenhouse effect (Signor & Cerri, 2013). The mechanism by which these gases warm the Earth is called the "greenhouse effect" (Kweku et al., 2018).

The greenhouse effect is the phenomenon that provides a suitable global temperature for life on Earth. Of incoming solar radiation toward Earth, approximately one-third is reflected back into space, while the remaining two-thirds is absorbed by the atmosphere and surface (Le Treut et al., 2007). A portion of this energy is trapped and re-radiated by GHGs, which capture solar heat, and trap it in the atmosphere. This cycle of trapping heat continues, thereby raising global temperature. Increases in GHGs released into the atmosphere as a result of human activities have been correlated with the enhanced greenhouse effect, thereby raising global temperatures (Kweku et al., 2018).

The effect of each GHG on atmospheric temperature is quantified using a measure called the global warming potential (GWP) (Snyder et al., 2009). This measure is determined by its atmospheric lifetime and is expressed relative to CO_2, the most abundant GHG. For a chosen time horizon of 100 years for CO_2 and has a GWP of 1 (because it is the reference gas), the lifetime of CH_4 is 12 and GWP of 25, while N_2O has a longer lifespan of 114 years and a GWP of 298 (U.S. Environmental Protection Agency, 2023) (Forster et al., 2007). Although there is less N_2O in the atmosphere than CO_2 (U.S. Environmental Protection Agency, 2025), on a per-mole basis, N_2O is approximately 300 times more potent.

Below, we examine how N_2O emissions have increased over the years (Figure 2.1). As shown in Figures 2.1b and 2.1a, N_2O emissions in Canada and globally have increased steadily. This trend has been ongoing since the start of the Industrial Revolution (Ramzan et al., 2020). By putting things into perspective with Figure 2.1c, it is evident that Canada plays a part, but it is the accumulated effects of many countries that are responsible for attributing the massive amounts of N_2O into the World.



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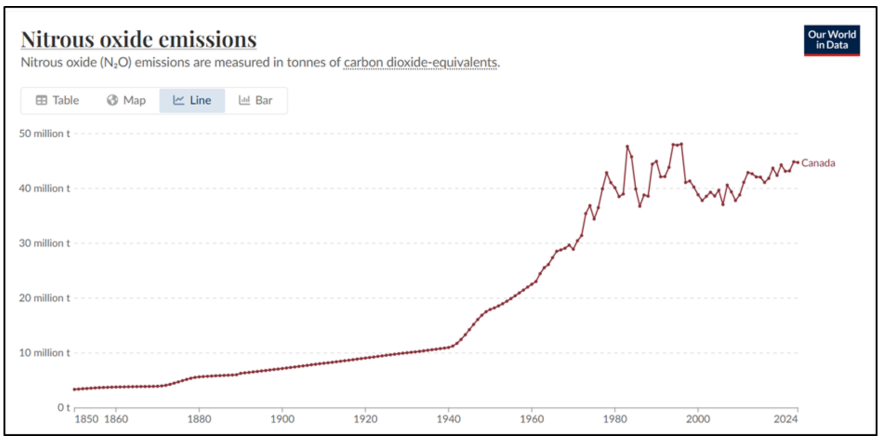

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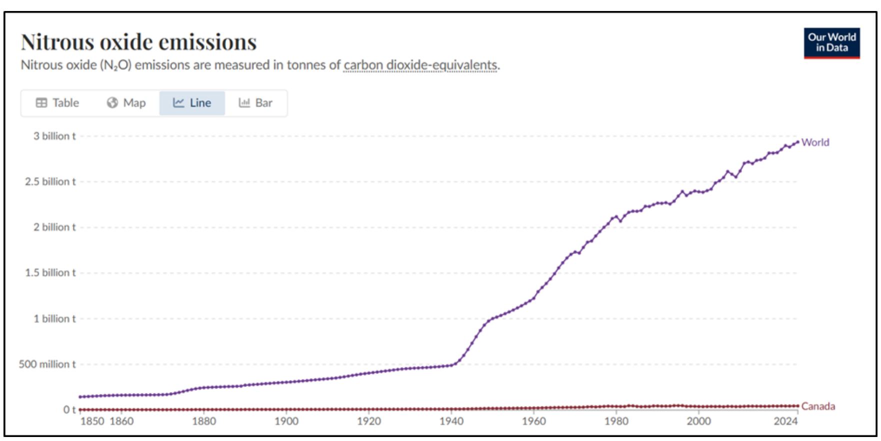

(c)

Figure 2.1: Nitrous oxide emissions trends (1850–2024). (a) Global N_2O emissions show a gradual increase from 1850 to the 1940s, followed by a rapid rise to present. (b) Canadian emissions increase steadily until the 1940s, rise more sharply until the 1970s, and then fluctuate in recent decades. (c) Comparison of global and Canadian emissions highlights the relatively smaller contribution of Canada to total global emissions. *Data from Jones et al. (2025), processed by Our World in Data (2025).*

Note: In the early 1900s, it was discovered that the lack of nitrogen availability was a key factor that limited plant growth. During that period, there was a desire to increase agricultural production, which led to the pursuit for inexpensive, efficient, and readily available nitrogen sources. Ammonium nitrate was discovered in the 1940s and became one of the largest sources of nitrogen for agrarian use (Transport Canada, 2022). According to Hedlin (1995), fertilizers containing nitrogen and phosphorus became widely available in Canada by the 1930s. However, the effects of fertilizer, such as whether they would enhance crop yields or other aspects like the type and amount/concentration to apply, had not been examined at that point in time.

N_2O is a greenhouse gas that contributes to the greenhouse effect and, consequently, to global warming. Since the Industrial Revolution, its atmospheric concentration has risen dramatically, raising serious concerns due to its contribution to global warming. In 2023, 4.0% of Canada's GHG emissions were attributed from N_2O. The emissions amounted to 28 $MtCO_2e$ (megatonnes of CO_2 equivalents) of which agricultural soil management is the main contributor (Environment and Climate Change Canada, 2025). Given the significant environmental risks associated with N_2O, this study focuses specifically on its dynamics within the agricultural sector, the main driver of anthropogenic N_2O emissions in Canada.

2.1.2 Nitrous Oxide from Agriculture

Nitrous oxide (N_2O) is one of the greenhouse gases emitted from Canadian agricultural practices and is very impactful, as it accounts for approximately half of the total global warming impact associated with agricultural emissions. This greenhouse gas (GHG) is naturally produced by soil microorganisms in the ground during processes that transform nitrogen. It is normal for all soils to emit N_2O; however, agricultural soils emit substantially more because of the addition of nitrogen-based fertilizers. It is necessary to return these fertilizers to the soil to replace the nitrogen removed from fields by harvested crops; otherwise, crop yields would decline. However, as nitrogen application increases, the potential for nitrogen losses to the environment also increases. This includes the emissions of N_2O into the atmosphere (Agriculture and Agri-Food Canada, 2012).

Scientists assume that approximately 1% of the nitrogen applied to agricultural soils is emitted as N_2O, but this estimate varies widely with soil and landscape conditions. Aside from direct soil emissions, agricultural systems can also contribute to indirect N_2O emissions when nitrogen that was applied to the field is leached to surrounding areas or volatilized as it is converted to ammonia, which subsequently becomes N_2O elsewhere. Technically, the indirect emissions occur outside farm boundaries, but they originate from nitrogen fertilizers applied to agricultural land and are therefore still considered farm-derived N_2O emissions (Agriculture and Agri-Food Canada, 2012).

There are many pathways within agricultural systems through which N_2O can be produced, as shown in Figure 2.2. Since N_2O in agricultural systems primarily results from applying nitrogen-based fertilizers, we will further elaborate on the nitrogen cycle and the factors that affect N_2O emissions.

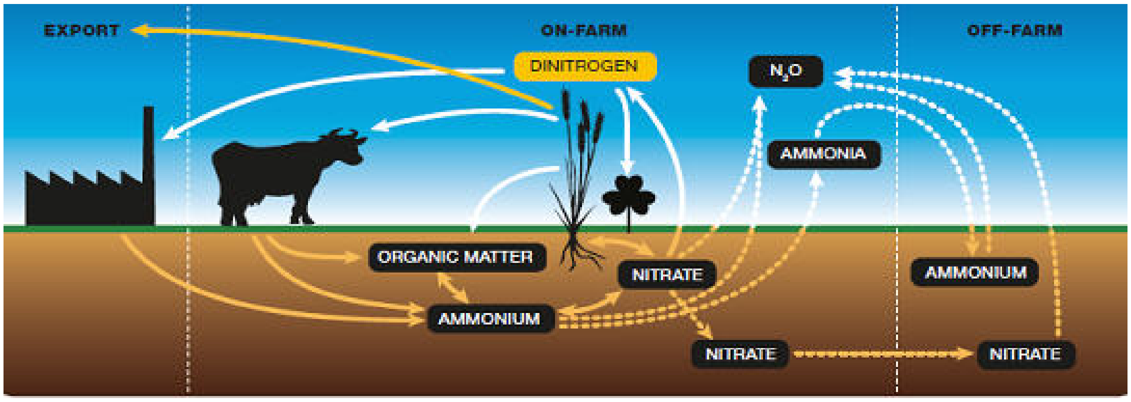

Figure 2.2: Conceptual view of the pathways within the nitrogen cycle on Canadian agricultural farms. Nitrogen movement includes inputs to the system, transport within, and losses from the system. Nitrogen inputs into the farm system primarily by application of ammonium and nitrate fertilizers to the soil. Additional input is by certain crops such as legumes, that atmospheric dinitrogen (N_2) incorporates it into the soil as organic matter after plant residues decompose. Within the system, nitrogen can originate from fertilizer, manure, and plants take up soil organic matter. Nitrogen leaves the farm system when crops are harvested and as livestock products, ammonia and gaseous N_2O losses to the air, and nitrates leached from the soil. *Image from Agriculture and Agri-Food Canada (2012).*

2.1.3 Nitrous Oxide in the Nitrogen Cycle

Nitrous oxide is a part of the nitrogen cycle (Figure 2.3). The nitrogen cycle begins with atmospheric nitrogen (N_2) being fixed into ammonia (NH_3) through biological nitrogen fixation by nitrogen-fixing microorganisms called diazotrophs, which include free-living and symbiotic bacteria and archaea (Imran et al., 2021). This process breaks the strong N_2 triple bond. In the soil, ammonia (NH_3) can be converted into ammonium (NH_4^+) and subsequently oxidized to nitrate (NO_3^-) through a three-step process known as nitrification. Nitrite (NO_2^-) and nitrate (NO_3^-) ions are produced during nitrification, both of which can subsequently be reduced by a process called denitrification. Denitrification entails the stepwise reduction of nitrate (NO_3^-) to N_2 by a series of four enzymes, generating intermediate compounds including nitrite (NO_2^-), nitric oxide (NO), and nitrous oxide (N_2O). Additionally, during nitrate (NO_3^-) ammonification to ammonium (NH_4^+), via nitrite (NO_2^-), a partial reduction of nitrate (NO_3^-) can also occur, which is another way for N_2O to be produced in the nitrogen cycle (Thomson et al. (2012), as cited by Signor and Cerri (2013)).

2.1.4 Nitrous Oxide Synthesis in Soil

There are multiple simultaneous processes happening in soil that contribute to the emission of nitrogen-based compounds. The majority of nitrous oxide emissions are the result of two natural biological processes called nitrification and denitrification. Aerobic autotrophic nitrification is carried out by ammonia-oxidizing and nitrite-oxidizing bacteria. Denitrification takes place in anaerobic conditions and is mediated by denitrifying bacteria. These processes represent the primary microbial pathways within the soil nitrogen cycle (Signor & Cerri, 2013).

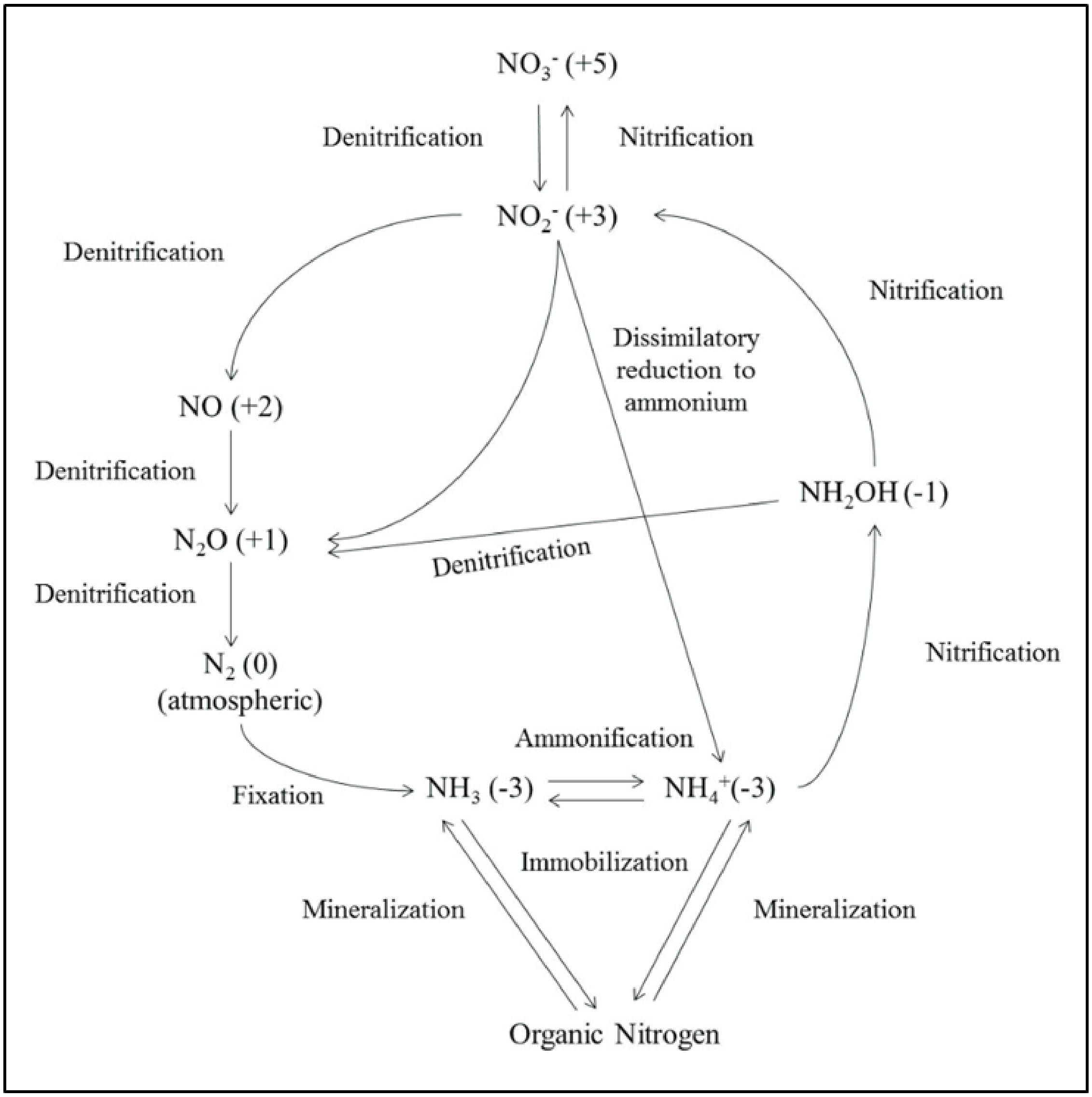

Figure 2.3: The nitrogen cycle with processes labelled as well as the oxidative states included next to chemical formulas of different nitrogenous compounds. The nitrogen cycle consists of two main processes, nitrification and denitrification, both of which take place in the soil and are mediated by different soil microorganisms. *Image from Signor and Cerri (2013).*

Nitrification

Nitrification is an aerobic process in which ammonium (NH_4^+) is oxidized to nitrate (NO_3^-) by chemoautotrophic microorganisms and occurs in two sequential stages. The first stage, known as nitritation, involves the oxidation of NH_4^+ to nitrite (NO_2^-) and is carried out primarily by *Nitrosomonas* spp., *Nitrosospira* spp., and *Nitrosococcus* spp. The second stage, nitratation, consists of the oxidation of NO_2^- to NO_3^- and is mainly mediated by *Nitrobacter* spp., *Nitrosospira* spp., and *Nitrococcus* spp. (Moreira & Siqueira, 2006, as cited by Signor and Cerri (2013)).

The nitrification process can be summarized by the following reactions:

$$\begin{aligned} \text{Nitritation:} &\quad 2NH_4^+ + 3O_2 \rightarrow 2NO_2^- + H_2O + 4H^+ + \text{energy} \\ \text{Nitratation:} &\quad 2NO_2^- + O_2 \rightarrow 2NO_3^- + \text{energy} \end{aligned} \tag{2.1}$$

As nitrification proceeds, NO_2^- concentrations initially increase as NH_4^+ is oxidized and subsequently decrease as NO_3^- is formed. Nitrification is not the main contributor of N_2O formation, but still can produce some, particularly under conditions of limited oxygen availability (Signor & Cerri, 2013).

Denitrification

Denitrification is a microbial process that reduces nitrate to gaseous nitrogen, thereby shifting bioavailable nitrogen from the soil and restoring it to the atmosphere. While dinitrogen gas (N_2) is the final end product of denitrification, several intermediate gaseous nitrogen compounds can be formed during the process, including N_2O (Bernhard, 2010).

Denitrification is a reductive process in which nitrate (NO_3^-) is converted to dinitrogen (N_2) and is carried out by facultative anaerobic bacteria, which typically comprise approximately 0.1–5.0% of the total soil bacterial population (Moreira & Siqueira (2006), as cited by Signor and Cerri (2013)). Denitrification is carried out by a range of microorganisms, including species within the genera *Bacillus*, *Paracoccus*, and *Pseudomonas* (Bernhard, 2010).

Denitrification can be complete or incomplete. If completed, the result is N_2. If the process is incomplete, a portion of nitrogen is released as intermediate gaseous products such as nitric oxide (NO) and nitrous oxide (N_2O). Denitrification accounts for the majority of N_2O produced in soils (Firestone & Davidson, 1989).

The denitrification reaction sequence is:

$$\begin{gathered} NO_3^- \rightarrow NO_2^- \rightarrow NO \rightarrow N_2O \rightarrow N_2 \\ \text{Nitrate} \quad \text{Nitrite} \quad \text{Nitric Oxide} \quad \text{Nitrous Oxide} \quad \text{Nitrogen Gas} \end{gathered} \tag{2.2}$$

(International Plant Nutrition Institute (IPNI), n.d.)

As a general statement, N_2O is primarily produced by nitrifying organisms in aerobic or semi-aerobic conditions, but in anaerobic conditions, denitrifying microorganisms produce it (Bremner, 1997; Stevens et al., 1997; and Khalil et al., 2004, as cited by Signor and Cerri (2013)).

2.1.5 Influencing Factors of Nitrous Oxide Production

The production and emission of N_2O through microbial processes are governed by complex interactions among multiple factors, including temperature, moisture, pH, and texture of the soil, as well as nitrogen availability, and decomposable organic matter within (Bøckman & Olfs, 1998). Management practices such as crop rotation, soil disturbance, nitrogen source and application rate, and the timing and depth of nitrogen application further interact to significantly influence soil N_2O emissions (Liu et al., 2006; Tan et al., 2009, as cited by Signor and Cerri (2013)).

N_2O formation in soil occurs primarily through nitrification and denitrification. Temperature and soil density are the main factors that influence N_2O emissions from nitrification (Davidson & Swank, 1986). As for denitrification, the main influence is water filled pores space (WFPS) (Signor & Cerri, 2013).

Note: Water-filled pore space. Soil particles are separated by pore spaces that contain water and air. After rainfall or irrigation, these pores can become nearly saturated; over time, water drains, evaporates, or is taken up by plants, allowing air to reenter. Soil texture influences this balance: clay soils have small pores that retain water and limit aeration, while sandy soils have large pores that drain quickly. Typically, pore space accounts for 30–60% of soil volume, and well-structured soils contain a mix of macropores and micropores that balance drainage, aeration, and water availability for plants (Umasankareswari et al., 2022)

Although there are numerous factors that contribute to N_2O production, we will only go over the most important and relevant ones for this research project.

Temperature & Moisture

Two key factors that influence nitrification and denitrification are temperature and moisture, because they determine the activity of microorganisms, thus impacting the amount of N_2O production. Additionally, soil temperature and moisture strongly influence diffusion of N_2O into the atmosphere (Davidson & Swank, 1986).

Temperature

With regard to temperature, the rate of nitrogen conversion is low at mild temperatures and increases as the temperature rises (Akiyama et al. 2000, Brentrup et al. 2000, Hao et al. 2001, as cited by Signor and Cerri (2013)). When considering a wider range of temperatures (e.g., 0-50 °C), N_2O emissions have been reported to increase exponentially (Liu et al. 2011, as cited by Signor and Cerri (2013)). The close relationship between seasonal variation in N_2O flux and soil and air temperatures can be explained by these seasonal temperature shifts (Wolf & Brumme 2002, Zhang & Han 2008, as cited by Signor and Cerri (2013)). Also note that there is a positive feedback loop with temperature and the denitrification rate. Microbial activity is stimulated by rising soil temperatures, which also increase anaerobic sites for denitrification (Signor & Cerri, 2013).

Moisture

With moisture, the dynamics of how it relates to N_2O production are more complex. Generally speaking, increasing soil moisture is associated with higher N_2O emissions (Baggs et al., 2000 and Giacomini et al., 2006, as cited in Signor and Cerri (2013)), as both nitrification and denitrification processes are strongly influenced by soil water content (Davidson & Swank, 1986).

However, under conditions of very high soil moisture, N_2O production tends to decrease, whereas alternating wet and dry periods often result in elevated N_2O emissions (Brentrup et al., 2000, as cited by Signor and Cerri (2013)). This pattern occurs because increasing soil moisture initially stimulates microbial activity, while excessively high moisture levels can inhibit microbial processes.

N_2O emissions increase with soil moisture up to a threshold, after which emissions decline. The highest N_2O fluxes follow rainfall events or periods of elevated soil temperature. Large N_2O emissions have also been linked to rain or irrigation events, with N_2O diffusion from soil to the atmosphere increasing sharply immediately after rainfall before returning to baseline levels within approximately three days (Liu et al., 2011; Liu et al., 2006; Perdomo et al., 2009, as cited by Signor and Cerri (2013)).

As soil aeration decreases, dinitrogen (N_2) becomes the dominant nitrogen gas emitted, reflecting the close relationship between soil moisture and aeration. Greater water-filled pore space (WFPS) reduces the number of air-filled pores, thereby increasing N_2O production via denitrification. Nevertheless, extremely high soil water content ultimately suppresses N_2O emissions (Liu et al., 2011, as cited in Signor and Cerri (2013)). It is generally assumed that N_2O formation in soils is maximized when WFPS reaches approximately 80% (Bøckman & Olfs, 1998).

Denitrification is the dominant source of N_2O when WFPS exceeds 70%, whereas nitrification becomes the primary contributing process as WFPS decreases to approximately 60% (Ruser et al., 2006, as cited in Signor and Cerri (2013)). However, it is important to note that a process being dominant does not necessarily imply that it produces the highest overall N_2O emission rates (Signor & Cerri, 2013).

Soil Type

Clay loam soils produce more N_2O than loamy sand soils. Clayey soil has few macropores, thus increasing anaerobic microsites for N_2O production by denitrification (Tan et al., 2009, as cited (Signor & Cerri, 2013)).

Note: The Ottawa Smart Farm is located in Nepean, where their soil has been described as loamy or sandy (Fraser, 2024). This coincides with the fact that generally speaking, till soils should have a loamy to sandy texture (Thie, n.d.). By visual inspection, the soil at Area X.O is light coloured, like sand so it would be reasonable to say it leans more sandy in nature.

Relief Position

Low-relief areas tend to retain more moisture and contain higher levels of organic matter than elevated areas. As a result, microbial respiration and oxygen consumption are often higher in these low-lying zones, thereby enhancing conditions favorable for N_2O production (Davidson & Swank, 1986).

Note: Ottawa is considered a low-relief area because it is part of the Great Lakes - St. Lawrence Lowlands, more specifically, the sub-region called the Central Lowlands, which includes the area between the Ottawa River and the St. Lawrence River (Natural Resources Canada, 2016).

2.1.6 Model to Explain Factors that Influence Nitrous Oxide Emissions

Firestone and Davidson (1989) proposed a model that they called "hole-in-the-pipe", which represents the interactions and control level of the numerous factors involved in N_2O emissions from soil. The model encapsulates the impact of microbiological and ecological factors on soil emissions of nitric oxide (NO) and nitrous oxide (N_2O) (Figure 2.4), indicating that the production of these gases is closely linked to soil nitrogen availability. The rate at which nitrogen flows through the system represents the first level of control on NO and N_2O emissions and broadly reflects overall nitrogen cycling. A second level of control is represented by the proportion of NO and N_2O lost from the system, which is primarily governed by soil moisture conditions. Ultimately, emissions of these gases depend on the balance between their production, consumption, and diffusive transport within the soil.

In dry, well-aerated soils, the dominant process is nitrification and gas diffusion is relatively high, allowing greater emission of the more oxidized nitrogen form, NO, before it can be consumed by other processes. In contrast, under moist soil conditions, gas diffusion and aeration are reduced, thereby increasing the likelihood that NO reacts within the soil before atmospheric release. Under these conditions, the more reduced version, N_2O, becomes the dominant gas emitted. When soils become supersaturated and anaerobic, much of the N_2O produced is further reduced to dinitrogen (N_2) before being released to the atmosphere (Davidson et al., 2000) (Signor & Cerri, 2013).

2.1.7 Soil as a Sink for Nitrous Oxide

Although soils are commonly regarded as sources of N_2O, they can also act as sinks by consuming atmospheric N_2O. This process is not yet well understood but may be pertinent to consider in agricultural systems and N_2O emission studies. Negative N_2O fluxes have been reported under a range of conditions, often associated with low nitrogen and oxygen availability, which favor the full reduction of N_2O to dinitrogen (N_2). Soil N_2O consumption is influenced by factors such as soil properties, temperature, moisture, pH, and organic carbon and nitrogen availability. In general, the longer N_2O persists within the soil, either due to deeper production or limited diffusion, the greater potential there is for its full reduction to N_2 (Chapuis-Lardy et al., 2007, as cited in Signor and Cerri (2013)).

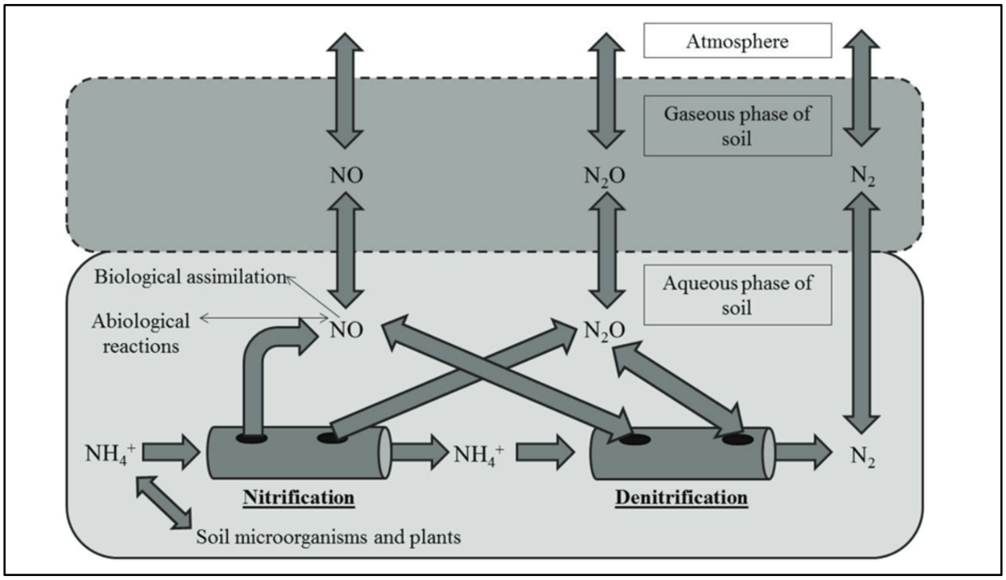

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Figure 2.4: Diagram of the “hole in the pipe” model. This figure describes the factors and levels of control that impact N_2O emissions from soil. *Image from Signor and Cerri (2013), which was adapted from Davidson et al. (2000).*

2.1.8 Impact of Nitrogen Fertilizer Application

We now recognize that N_2O emissions from nitrification and denitrification depend on the soil’s nitrogen content (Akiyama et al., 2000, as cited in Signor and Cerri (2013)). Furthermore, the rate of N_2O emitted from the soil is related to the amount of nitrogen fertilizer applied. The application of nitrogen fertilizers affects the availability of ammonium (NH_4^+) and nitrate (NO_3^-) in the soil. Fertilizers with higher ammonium content tend to have increased nitrification take place, leading to loss of N_2O, since it is possible that denitrification takes places afterwards if the conditions are favourable (Mosier, 2001; Khalil et al., 2004; Liu et al., 2005, as cited in Signor and Cerri (2013)). In addition, nitrogen fertilization promotes greater plant biomass production, resulting in increased crop residue and associated carbon inputs to the soil. These added carbon sources contribute to elevated N_2O emissions over extended periods, even long after fertilizer application occurred (Hellebrand et al., 2008, as cited in Signor and Cerri (2013)).

The mathematical relationship describing N_2O emissions as a function of the amount of nitrogen applied in fertilizer form is poorly understood and not well defined. Some researchers postulate it is linear, while others say it is exponential, but the general consensus is that as the amount of fertilizer applied increases, so does the amount of N_2O emitted from the soil. Many researchers have found that, within a few weeks after fertilizer application, N_2O emissions induced by these fertilizers are concentrated, with the largest fluxes happening within the first two weeks following application. An experiment found that the effect of nitrogen fertilizer on N_2O emissions vanishes after two months (Akiyama et al. 2000, Brentrup et al. 2000, Hao et al. 2001, Liu et al. 2011, Baggs et al. 2000, as cited by Signor and Cerri (2013)).

Interactions between nitrogen fertilizer application and other environmental factors play an important role in regulating N_2O emissions. Fertilizer applied under dry soil conditions generally results in lower N_2O emissions than under moist conditions (Smith et al., 1998; Schils et al., 2008; Zhang & Han, 2008, as cited in Signor and Cerri (2013)). The highest N_2O emissions are typically observed when fertilizer application coincides with precipitation events or when after the first rainfall following nitrogen application (Metay et al., 2007; Passianoto et al., 2003, as cited in Signor and Cerri (2013)). However, even under high soil moisture conditions, N_2O emissions remain low when nitrogen availability is limited (Denmead et al., 2010, as cited in Signor and Cerri (2013)).

2.1.9 Mitigation Strategies

In addition to climate, there are a few soil management practices that influence microbial activity that can impact N_2O emission from agricultural systems such as tillage, nitrogen recycling from crop residues, and mineral or organic fertilizer application. However, understanding of how these dynamic factors regulate denitrification remains limited, largely due to the high spatial and temporal variability observed in field conditions and the insufficient representation of microbial functional diversity in current N_2O emission models (Groffman et al., 2009; Cavigelli & Robertson, 2001, as cited in Signor and Cerri (2013)).

Take a deeper look into nitrogen-based fertilizer application as a factor that affects N_2O emissions. Nitrogen is often the most limiting nutrient in agricultural production systems. To achieve maximum crop yields, large amounts of nitrogen fertilizer are typically applied; however, fertilizer nitrogen use efficiency is generally only between 30-50% for most agricultural sites (Y. Li et al., 2020).

Several management strategies can be used to reduce N_2O emissions associated with nitrogen fertilizer application. One important approach is the use of slow-release fertilizers, which reduce emissions by releasing nitrogen more gradually into the soil. These fertilizers can be grouped into three main categories: low-solubility organic nitrogen compounds that decompose biologically or chemically, physically coated fertilizers that slow nitrogen release through polymer or mineral barriers, and inorganic low-solubility compounds such as metal ammonium phosphates (Shaviv, 2001, as cited in Signor and Cerri (2013)).

Another effective strategy is the use of stabilized or bioamended fertilizers containing inhibitors, commonly referred to as slow-acting nitrogen fertilizers. In particular, nitrification inhibitors have been shown to reduce N_2O emissions (Zanatta et al., 2010, as cited in Signor and Cerri (2013)). Reducing emissions can also be achieved by selecting fertilizer types with lower N_2O emission potential. Nitric fertilizers produce more N_2O emissions than urea and ammonia fertilizers (Zanatta et al., 2010, as cited in Signor and Cerri (2013)). When comparing ammonium nitrate to urea, the former produced more intense and quicker emissions (Signor & Cerri, 2013). When feasible, the use of manure or organic fertilizers is preferred, as these sources typically yield lower N_2O emissions than mineral nitrogen fertilizers (Signor & Cerri, 2013).

Furthermore, fertilizer application practices play a key role in controlling N_2O emissions. Applying nitrogen fertilizers below the soil surface rather than on the surface can reduce emissions, particularly when heavy rainfall is expected. Splitting fertilizer applications and placing nitrogen deeper in the soil profile can further reduce nitrogen losses and the proportion emitted as N_2O (Signor & Cerri, 2013).

2.1.10 Measuring Effectiveness of Mitigation Strategies

Greenhouse gas (GHG) emissions from agriculture are quantified in part to meet international reporting requirements, such as Canada's obligation to provide reliable annual emission estimates from major sources, including farms. Emission measurements are also essential for scientific purposes, as accurate data are required to identify effective mitigation practices and to understand the processes controlling GHG production and release. Measuring GHG emissions from farms is challenging due to the diversity of emission sources, including soils, livestock, and machinery, as well as the highly variable nature of gas release. To address this, a range of measurement techniques has been developed, including chamber-based methods, tower and aircraft measurements, long-term soil carbon analyses, high-frequency atmospheric sampling, and subsurface or airborne air collection. No single method is sufficient; however, by combining multiple approaches, researchers can obtain robust emission estimates and identify key controlling factors. This knowledge is typically incorporated into predictive models, which are widely used and continue to be refined to improve their reliability (Agriculture and Agri-Food Canada, 2012).

2.1.11 Measuring Nitrous Oxide Emissions

Several methods to empirically measure N_2O emissions exist, such as chamber methods, static core methods, and micrometeorological techniques (Groffman et al., 2006, as cited in Wang et al. (2021)). Chambers are widely used to study N_2O fluxes spatially at different scales. To locally estimate potential N_2O emissions from managed soils, the static core method is utilized, accounting for nitrification and denitrification processes. The preferred methods for measuring N_2O fluxes on a landscape scale are micrometeorological techniques (Beauchamp, 1997, Skiba, et al., 1992, as cited in Wang et al. (2021)).

For the purposes of this study, particular attention is given to the chamber method, which is a widely used sampling approach for measuring soil gas emissions. Chambers are the most common method for quantifying gas fluxes from the soil surface, as they allow gases of interest to accumulate within a known volume over a defined period.

In practice, a chamber is placed over the soil surface and sealed for a short duration, during which gas samples are collected and then analyzed to determine changes in N_2O concentration (Turner et al., 2008, as cited in Rapson and Dacres (2014)). One of the main advantages of chamber-based measurements is that they are relatively easy to deploy and do not require highly precise or rapid analytical instrumentation (Denmead, 2008; Jones et al., 2011, as cited in

Rapson and Dacres (2014)).

Automated chambers enable more frequent measurements over extended study periods; however, their operational requirements and high costs limit their application to relatively small areas, typically less than 25 m^2 (Meyer, 2001, as cited in Rapson and Dacres (2014)). It is also important to note that chamber deployment can disturb the soil surface and alter the soil microclimate. As a result, chambers should only be closed for short periods. The appropriate chamber closure time depends on the detection limits and precision of the analytical technique used to measure N_2O concentrations (Denmead, 2008; Jones et al., 2011; Meyer, 2001, as cited in Rapson and Dacres (2014)).

2.1.12 Approaches for Estimating Nitrous Oxide Emissions

Estimates of N_2O emissions from soils are generally categorized into two main methodologies. Bottom-up methods are based on direct measurements of soil-surface gas fluxes or on models that relate emissions to nitrogen inputs applied to soils. In contrast, top-down approaches estimate emissions from observed changes in atmospheric N_2O concentrations combined with assessments of sink strength (Del Grosso et al., 2008).

N_2O emissions exhibit strong spatial and temporal variability, which often leads to poor agreement among estimation methods, particularly at smaller spatial scales. However, agreement between approaches improves at larger scales, where convergence between top-down, atmosphere-based estimates and bottom-up, soil-based estimates has been observed. Because these approaches rely on different assumptions, their agreement indicates some degree of confidence in the emission estimates. Furthermore, this also suggests that large-scale N_2O emissions are reasonably well understood (Del Grosso et al., 2008).

This research project adopts a bottom-up approach to estimating N_2O emissions at a small spatial scale. Noting this is important, as emission estimates can exhibit considerable variability in accuracy when different estimation methods are applied to the same dataset. Recognizing and accounting for this variability is therefore essential for evaluating the reliability and limitations of small-scale N_2O emission predictions.

2.2 Fuzzy Logic

Fuzzy logic (FL) is a type of logic that allows partial truths, and this unique quality thus allows computers to make decisions and "think" more like humans. The history, motivations, how it works, and implementations will be discussed.

2.2.1 History of Fuzzy Logic

Lofti A. Zadeh, a computer science professor from the University of California in Berkeley, first initiated fuzzy logic in 1965 (Zadeh, 1965). The inventor describes it as “a precise logic of imprecision and uncertainty” (Hellmann, 2001) (Zadeh, 2009). This technology was not well accepted for about two decades, until the late 1980s, when it proved itself successful in various applications (Yen and Langari, 2004, as cited in Kaur and Kaur (2012)).

2.2.2 Conceptual Motivation for Fuzzy Logic

Fuzzy logic (FL) aims to emulate two extraordinary human capabilities. First is the capacity of humans to make rational decisions in uncertain situations; second is the ability to carry out various physical tasks without relying on computation. The core concept of FL is to formalize and eventually mechanize these abilities, thereby bridging natural human intelligence and machine intelligence. The purpose of FL is to deal with imprecision and uncertainty in a precise manner. Thus, it is a favourable choice to use FL when modeling ill-defined objects (Zadeh, 2009).

FL is a multivalued logic that differs from traditional bivalent logic by allowing intermediate values in computer calculations, thereby enabling a more human-like way of thinking (Zadeh, 1984). FL is a computational method that aims to mimic human thinking and is quite beneficial for problems that model reality because, unlike traditional bivalent logic, which only allows 1 or 0, which translates to membership in a category or not, it works on the premise of allowing degrees of membership, ranging from 0 to 1. Fuzzy logic is all about the formalization of approximate reasoning (Zadeh, 1988) (Hellmann, 2001).

Classical logical systems cannot make decisions involving imprecision and uncertainty because they operate on binary inputs. Whereas conventional bivalent logic is defined by strict bivalent notions such as true/false, yes/no, 1/0, and so on, fuzzy logic allows for values in between (degrees of membership) (Zadeh, 1984). FL can overcome this limitation of binary logical systems because its constraints are elastic and flexible rather than rigid (Zadeh, 1988). In terms of emulating human thinking and natural language patterns, FL is much better at these kinds of tasks than conventional logic systems (Mohandas & Karimulla, 2001, as cited in Kaur and Kaur (2012)). Thus, in cases where precise reasoning may be limiting to the problem at hand, FL is appropriate to use (Zadeh, 1988). FL is very useful when approximate but quick solutions are needed, as well as in circumstances where systems are highly complex, and the behaviors of the systems are poorly understood (Ross, 2000).

Although the term implies vagueness, fuzzy logic is not inherently vague. The term “fuzzy” refers to its ability to handle imprecision and uncertainty precisely. The basis of FL is a fuzzy set, in which the boundaries of a class are not discrete but are fuzzy, and membership in a class is a graded function. The information regarding the objects under analysis in FL is allowed to be fuzzy, but the mandates governing deduction are specific. In the words of its creator, “fuzzy” refers to the information that is to be analyzed, which can be “imprecise, uncertain, incomplete, unreliable, partially true or partially impossible" (Zadeh, 2009). With fuzzy logic, computers can think in a more human-like manner because it allows the mathematical formulation and processing of statements based on graded scales (Hellmann, 2001) (Zadeh, 2009).

2.2.3 Fuzzy Sets and Membership Functions

In fuzzy logic, everything is considered a matter of degree, even truth (Zadeh, 1988). As previously mentioned, classical mathematics used for classic logic systems is defined by the use of strict yes/no, true/false, 1/0, and more. These are called crisp sets. However, fuzzy sets are more flexible, which is meant to make computers more "intelligent" (Hellmann, 2001).

Each input for the decision has a membership function, which describes the magnitude or "how much" the input partakes. The membership function for a fuzzy set will take values between 0.0 and 1.0, representing the degree to which the input value is a member of the set. Each input is weighted and processed to determine the response. The weighting of the input values as factors determines how much they influence the fuzzy output sets of the final concluding output (Hellmann, 2001).

Note: It is important to differentiate fuzzy logic from probability. Both systems occur over the same numeric range, but for one event of probability, 0 represents false and 1 represents true. In the case of fuzzy logic, 0 represents non-membership in the group whereas 1 represents full membership, and there can be intermediate degrees of membership (Hellmann, 2001).

2.2.4 Fuzzy Set Theory

Fuzzy set theory uses quantitative variables as well as linguistic variables to represent imprecise concepts. Membership of objects in fuzzy sets can be approximate, which means that fuzzy sets have objects that can satisfy imprecise properties of membership (Ross, 2000).

Fuzzy logic is based in fuzzy set theory, in which therein lies the concept of fuzzy sets. Whereas in traditional, crisp sets, the object is either completely in the set or not at all, in fuzzy sets, the element can belong to a set to some degree, which is called the degree of membership in the set. Other names for the degree an element belongs to a set are degree of truth or the alpha value (Zadeh, 1988) (Tanaka, 1993).

Membership functions describe the degree of membership of elements in a given set. The fuzzification process refers to when the degrees of membership of a variable in relation to its membership function are calculated (Tanaka, 1993).

Just as operations can be performed on crisp sets, basic operations can be introduced to fuzzy sets such as *AND*, *OR*, or *NOT*. The variables can be combined and formulated as rules to determine outputs (Hellmann, 2001). The use of these operators can be manipulated and combined and applied to fuzzy logic statements, just as they would be for traditional logic statements (Tanaka, 1993).

As described by Tanaka (1993), the rules of operations can be written as:

$$a \text{ AND } b = \min(a, b)$$

$$a \text{ OR } b = \max(a, b)$$

$$\text{NOT } a = 1 - a$$

Another formulation of these operations is:

$$a \text{ AND } b = a \cdot b$$

$$a \text{ OR } b = a + b - (a \cdot b)$$

$$\text{NOT } a = 1 - a$$

There are many beneficial aspects to using fuzzy logic, however the major con is that finding the correct rule set and determining the range of fuzzy variables to include in the approach to the solution can be time consuming (Kaur & Kaur, 2012).

2.2.5 Fuzzy Logic Process

While fuzzy logic systems are often described as consisting of four components: fuzzification, rule base, inference engine, and defuzzification, some authors, including Tanaka (1993), group the first three components under the fuzzy inference process, treating defuzzification as a separate final stage. See Figure 2.5.

Fuzzy Inference

A rule base typically contains rules whose consequences are mutually contradictory. With traditional logic, the rule base is typically designed so that under any circumstance, no multiple contradicting rules are "true" at the same time. However, in a fuzzy logic rule base, due to partial degrees of truth being allowed, it is common for multiple contradicting rules to occur, by having a non-zero value. Thus, there is need for a mechanism to settle or mediate these conflicts. The consolidation of contradictory information is deemed output composition. Defuzzification is the interpretation of this composition. The sequence of three steps (fuzzification, rule evaluation, and output composition) prior to defuzzification is called the fuzzy inference. A distinction is usually made between fuzzy inference and defuzzification since various inference methods and various defuzzification methods can be used with each other (Tanaka, 1993).

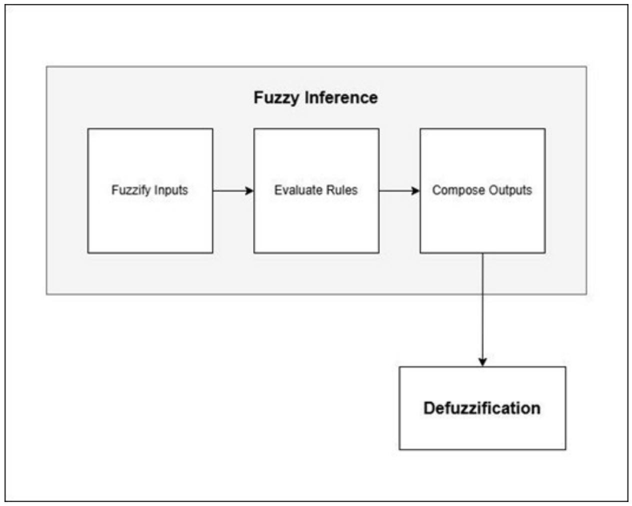


Figure 2.5: Fuzzy inference (which is made up of fuzzification, rule evaluation, and output composition) and defuzzification. Fuzzification is converting a crisp value into a fuzzy one. The fuzzy value is evaluated by a predetermined rule base which determines the relationship between the fuzzy input and the fuzzy output. A value is output after the model has evaluated it against the rule base. This is converted back to a crisp output, in the defuzzification step. *Image adapted from Tanaka (1993).*

Fuzzy Inference System Architecture

The architecture of a Fuzzy Inference System (FIS) is described below.

Fuzzification

Fuzzification is the transformation of a crisp quantity into a fuzzy input, recognizing that quantities are not deterministic and can carry uncertainty. This uncertainty arises from imprecision or ambiguity, we represent the variable as a membership function (Ross, 2000). This step converts precise, crisp input values into fuzzy linguistic values. This is achieved by relating the input with a membership function that maps values between 0 and 1 to dictate the degree of association with a linguistic term (Guo & Wong, 2013).

Rule Base Evaluation

At first glance, each fuzzy rule appears to be the same as ordinary rules. However, in fuzzy logic reasoning, the rule base often contains rules whose consequences are contradictory because partial truths are allowed. A fuzzy rule can be created by combining various fuzzy statements to form the antecedent and consequent of the rule (Tanaka, 1993) (Hellmann, 2001). A fuzzy rule base, sometimes referred to as the knowledge base, is a collection of fuzzy rules (Hellmann, 2001).

Output Composition

To resolve conflicts arising from contradictory rules, conflicting information is consolidated; this step is called output composition (Tanaka, 1993).

Defuzzification

Interpreting the result of the final step of the fuzzy inference process follows and is called defuzzification (Tanaka, 1993). This step involves converting fuzzy results to crisp ones. This can be done by reducing a fuzzy set to a crisp single-valued quantity or a crisp set, or alternatively by turning a fuzzy number into a crisp number (Ross, 2000). There are four methods of defuzzification, described by Ross (2000).

1. **Max-membership principle:** Also known as the height method. This is limited to output functions that are peaked and takes the maximum.

2. **Centroid Method:** Also known as the center of area or center of gravity method and uses algebraic integration to get the centroid. This is the most prevalent method.

3. **Weighted Average Method:** Weighting each membership function is required to obtain a weighted average in the output by its respective maximum membership value. This method can only be used for output membership functions that are symmetrical.

4. **Mean-max membership:** Also called middle-of-maxima method. This is related to the first method, but the locations of the maximum membership can be non-unique.

Note: This research project uses the weighted average method for defuzzification.

2.2.6 Types of Fuzzy Inference Systems

There are two types of fuzzy interface systems (system architectures) that have been developed: Sugeno-type and Mamdani-type. The rule bases for them are the same, but they differ in other aspects (Kaur & Kaur, 2012).

Mamdani-Type FIS

To best capture expert knowledge, the Mamdani-type is widely accepted, as it can describe human expertise in a human-like manner. The rule base is interpretable and intuitive, making it suitable for decision-support applications. The con of this type of FIS is the computational burden (Kaur & Kaur, 2012). It is superior to the Sugeno FIS in terms of expressive power and interpretability because the rule consequents are fuzzy (Haman & Geogranas, 2008, as cited in Kaur and Kaur (2012).

Note: This research project utilizes the Mamdani-Type FIS.

Takagi-Sugeno FIS

The Sugeno method is very efficient computationally and is widely used for optimization and adaptive processes. These qualities make this method attractive for control problems, especially for dynamic, non-linear systems. Membership functions can be customized to enable the fuzzy system to model the data effectively. The processing time for this FIS type is shorter because the weighted average replaces defuzzification, which is time-consuming. An advantage of Sugeno-type FIS over Mamdani is that it can be integrated with neural networks, genetic algorithms, or other optimization processes (Kaur & Kaur, 2012).

Key Differences

The main difference between the two types of FIS lies in how crisp outputs are generated from fuzzy inputs. Defuzzification is required with a Mamdani-type FIS to defuzzify a fuzzy output, whereas a Sugeno-type FIS computes a crisp output using a weighted average. Another difference is that Mamdani-type FIS has output membership functions, but Sugeno-FIS does not Kaur and Kaur, 2012.

2.2.7 Fuzzy Logic Implementation into Project

Generally speaking, fuzzy logic implementation can be useful for very intricate processes when a simple mathematical model does not exist for the problem at hand, for exceptionally nonlinear processes, or when linguistic expert knowledge must be processed (Hellmann, 2001). Fuzzy logic is a great option for reducing the development time and optimization of performance of non-linear or time-variant systems, and systems that are complex to model (Tanaka, 1993).

Since nitrous oxide emissions from farmland depend on multiple variables for which no straightforward mathematical model exists and the intermingled processes are nonlinear, the deployment of fuzzy logic should be serviceable to the research area of predicting this greenhouse gas from farmland.

2.3 Related Work

Related work will be split up into two sections. The first will provide an overview of some work that is performed by members of the same research lab, using the same datasets, but with different approaches to creating predictive models. Following that, one piece of literature was identified as most similar in terms of model and overall procedure to the research project discussed here.

2.3.1 Research from Area X.O Data

Colleagues of mine have also done some research using the same dataset from the same smart farm location, Area X.O., Ottawa, Ontario, Canada, albeit their work is more complex, being at the doctoral level. Lin et al. (2022) contributed to this field of knowledge at a higher level with their published research article called “Stacked Bi-directional LSTM for Predicting Emission of Nitrous Oxide”, in which they addressed that traditional machine learning models did not capture the dynamic, time-series nature of nitrous oxide emissions. A stacked Bidirectional Long Short-Term Memory (BDLSTM) model was proposed to more accurately encompass the temporal dependencies of N_2O emissions. This model used N_2O flux, soil temperature, and water flux as input features. The results showed that this stacked BDLSTM outperformed a Multilayer Perceptron (MLP) and was highly effective at predicting N_2O emissions from agricultural soils. The ability for it to capture the dynamic relationships of time-series data led to high N_2O prediction accuracy, and thus it is deemed to be a suitable tool for GHG predictions.

Lin et al. (2024) also contributed to this area of study in a work titled “Agriculture-informed neural networks for predicting nitrous oxide emissions,” where it was acknowledged that traditional machine learning models, including LSTM, have limitations such as lacking interpretability and generalization. A hybrid model was proposed that combined an RNN and DLEM (recurrent neural network and dynamic land ecosystem model) to create an AINN (agriculture-informed neural network) that can perform data-driven learning along with processing agricultural knowledge. This solution enhances the interpretability of output measures that reveal underlying soil processes (nitrification and denitrification). This AINN was successful in merging ML and process-based modeling for accurate, interpretable and general N_2O emission prediction.

Additionally, Killeen et al. (2025) performed research along similar lines in their paper titled “IoT-Based Smart Farming Architecture Using Federated Learning: a Nitrous Oxide Emission Prediction Use Case”. Federated learning was chosen to address the drawbacks of cloud, fog, and edge computing for model training, including poor privacy and loss of geographical trends. They proposed a privacy-aware Internet of Things (IoT)-based smart-farming architecture that employs federated learning. The results were positive, indicating that federated and ensemble learning could keep up with centralized learning. Thus, their prototype, which incorporated relatively inexpensive sensors and predictive modeling, could replace expensive N_2O emission-sensing equipment.

F. Li et al. (2024) is also experimenting with fuzzy logic to predict N_2O emissions, however, this differs from my project in that the input features of Li’s research include an additional feature that influences emissions, pH of the soil. The work of my colleagues is highly advanced and falls beyond the scope of this research project, yet all have been working on shared raw datasets. This demonstrates that there are many potential ideas and solutions to address and achieve a common goal: developing an accurate yet affordable method to predict N_2O emissions from farmland.

2.3.2 Fuzzy Logic to Predict Methane and Nitrous Oxide from Rice Paddy Fields

As previously mentioned, fuzzy logic deals with imprecision and uncertainty, thus it is a favourable choice to utilize fuzzy logic when modeling objects that are ill-defined (Zadeh, 2009). Fuzzy logic is often used in instances of complex processes, where there are no mathematical models to solve the issue, or in cases where processing of expert knowledge is required (Hellmann, 2001). Fuzzy logic can be applied across a range of research areas, including agriculture. Jadhav and Lal (2019) applied fuzzy logic to analyze methane (CH_4) and nitrous oxide (N_2O) emissions from rice paddy fields.

It is widely known that the greenhouse gases CH_4 and N_2O result in global warming; corrective measures are needed. This work explored the application of Internet of Things (IoT) technology and fuzzy logic for monitoring and analyzing these emissions from rice paddy fields. They measured CH_4 and N_2O emission rates across different stages of rice cultivation in paddy fields using sensors. From the sensors, real-time data was collected, including methane, ammonia, carbon monoxide, carbon dioxide, temperature, humidity, and soil moisture as the initial dataset. The collected data would serve as essential inputs for predicting future CH_4 and N_2O emissions. The aim of their efforts is to provide a cost-effective approach to tracking and implementing corrective actions on farms to address these emissions.

Rice paddy fields are known to be substantial contributors to CH_4 and N_2O emissions. CH_4 has a global warming potential 21 times that of carbon dioxide (CO_2), whereas N_2O is 298 times more potent. Given the significant role of these gases in climate change, their accurate monitoring and analysis are essential for developing effective mitigation strategies. However, conventional methods for gas emission measurement, such as gas detection chambers and remote sensing, tend to be expensive, spatially limited, and technically complex for average users. The study proposes an IoT-based monitoring system to collect data from rice paddy fields across different growth stages. Coupled with a fuzzy logic model, they aimed to develop a more efficient, accessible, and cost-effective alternative to the previously mentioned technologies for predicting GHG emissions. Jadhav and Lal (2019) developed a model that combines these technologies to monitor and analyze CH_4 and N_2O emissions from rice paddy fields.

Internet of Things (IoT) sensors acquire real-time environmental data. An electrochemical sensor, such as an Arduino or Raspberry Pi, transmits the collected raw data to the cloud via an IoT platform for subsequent processing. By using fuzzy logic and data from IoT, an intelligent system can be created that can recognize patterns, predict events, and thus help with decision-making for corrective measures in farming management.

Data was collected in real time using sensors measuring soil temperature, air and soil humidity, soil pH, and gas concentrations. Electrochemical sensors were used to measure gas concentrations in parts per million (ppm). Humidity sensors captured moisture levels in both the air and soil, while temperature sensors recorded soil temperature. Soil pH sensors were used to determine soil acidity. All sensors were connected to microcontroller hardware, such as Arduino or Raspberry Pi systems, and transmitted data to a cloud-based environment through an IoT platform. The collected raw sensor data were stored in the cloud, where they were made available for subsequent processing and analysis. Using the collected data from IoT as inputs for a fuzzy logic model, an intelligent system can be created that can recognize patterns, predict events, and therefore help with decision-making.

Compared with existing methods, the proposed IoT-fuzzy logic system is more cost-effective, reliable, and accessible. Traditional gas monitoring systems often require specialized expertise and expensive equipment, making them difficult to adopt widely, particularly in developing regions. In contrast, the IoT-based system is designed to be portable and user-friendly, enabling farmers and researchers to monitor gas emissions in real time and make informed decisions regarding crop management practices. Furthermore, the collected data early-warning systems and future predictions of GHG emissions, thereby aiding climate change mitigation efforts.

Jadhav and Lal (2019) developed a model that combines these technologies to monitor and analyze CH_4 and N_2O emissions from rice paddy fields. They had access to sensing technology that provided numeric readings of CO_2 gas concentration, temperature, relative humidity, soil temperature, soil pH, and water level in rice paddy fields. Sensor nodes were placed in farmland to collect real-time data on the listed variables, and then values such as minimum, average, and maximum were determined for each (excluding soil pH, for which there is no average).

The collected data are fed into a fuzzy decision-making methodology. Fuzzy logic is a computational approach that is well-suited for real-life applications because it handles uncertainty and imprecision well, where an element's strength of membership in a set affects the final predicted output. They described their fuzzy logic system as consisting of four components. Fuzzification, fuzzy interface engine, fuzzy output engine, and defuzzification. Fuzzification refers to the conversion of numerical values (raw data) from sensors and output values into linguistic terms such as low, moderate, and high. Also, membership functions are determined. A fuzzy rule set is the collection of multiple if-else statements that define various conditions and constraints. For example, they gave some of their rules to determine the emission of methane:

1. If the temperature is average, and CO_2 is maximum, then a high amount of methane will be emitted.
2. If soil temperature is maximum and soil pH is minimum, then a moderate amount of methane will be emitted.
3. If the temperature is average and the water level in the field is maximum, then a moderate amount of methane will be emitted.

The third step is the fuzzy inference engine, mapping inputs to outputs by using fuzzy set theory. The fuzzy inference engine applies the rules in the fuzzy rule base to map the input to the corresponding output. Lastly, defuzzification takes the linguistic output and translates it to a crisp output (converting a fuzzified output to a crisp value), which are the predicted values of the greenhouse gases emitted.

This work by Jadhav and Lal (2019) addresses the issue that traditional methods for analyzing gas emissions are costly, non-portable, and require specialized training, whereas the proposed model can be used by anyone. Their proposed system will be more reliable, cost-efficient, portable, and easy to use. Additionally, the data that they collect from sensors will be useful for methane and nitrous oxide emissions, which will help with identifying early warning signs and determining future actions.

In conclusion, the study details the combination of IoT technology and fuzzy logic for monitoring CH_4 and N_2O emissions in rice cultivation. By leveraging real-time sensor data and intelligent decision-making algorithms, the system provides a practical, cost-efficient, and scalable solution for GHG monitoring in agriculture. The article contributes to smart farming initiatives by offering innovative approaches to data-driven decision-making for emission control, irrigation management, and fertilizer application. This initial research lays the groundwork for further advancements in IoT-based environmental monitoring and for sustainable agriculture.

This related work represents the closest related research to the present study, aside from the work of a colleague within the same research group who is also applying fuzzy logic techniques to predict nitrous oxide emissions. In comparison to my colleague, both studies share a common computer processing foundation, but there are key differences that exist in the model design and data requirements. In particular, my research colleague incorporates another impactful input variable that influences N_2O emissions, and the model relies on sub-hourly measurements, whereas my research focuses on a simplified framework using fewer inputs and daily averaged data. These distinctions highlight the different trade-offs between factors such as model complexity, data availability, and computational efficiency. This research project is efficient for balancing accuracy, practicality, user-friendliness, and computer processing time.

2.4 Concluding Remarks

This chapter presented background information on several key topics relevant to this research. It first discussed the role of nitrous oxide as a greenhouse gas and its significance in agricultural systems. The chapter also reviewed the history and fundamental principles of fuzzy logic, including how fuzzy inference systems can be applied to model complex environmental processes. In addition, related work similar to this project was examined, including studies conducted by colleagues within the same research laboratory. A detailed account of a closely related experiment was provided as well, which builds on the same fundamental ideas. This leads to the next chapter, which explains the rationale behind conducting this research project.

Chapter 3

Problem Formulation & Methodology

The research problem is formulated after identifying gaps in the existing literature related to the prediction and measurement of agricultural N_2O emissions. While current measurement technologies can provide highly accurate emission data, they are often costly, require specialized expertise to operate, and are limited in their spatial and temporal coverage. As a result, there is a need for alternative approaches that can estimate emissions using more accessible environmental information.

Based on this gap, the research problem focuses on developing a predictive modelling approach that can estimate N_2O emissions using commonly available environmental variables that are related to soil processes. To address this problem, the methodology proposes the development of a fuzzy logic–based model that integrates environmental inputs such as temperature and moisture conditions with observed impulse measurements that characterize the initial site-specific soil states. The proposed approach for executing this work is detailed.

3.1 Problem Definition

Reliable, farm-scaled, N_2O prediction is still hard, and part of the problem is the cost and coverage of measurements. Rapson and Dacres (2014) note the need for a N_2O measurement tool that is cost-effective, easily deployable, and usable over wide areas. The hypothetical sensor would allow a more accurate understanding of N_2O emissions over broad landscapes, not just in isolated studies. They also tell us that developing such a technique would be very challenging, and perhaps some sensor precision would need to be sacrificed. Their review aimed to showcase the challenges of such techniques so that new developments to meet the shortfalls could be created. They tell us that researchers should consider broad-scale development when creating new technologies. Although this project is not about creating a sensor, it does address the three main challenges highlighted by these authors.

3.1.1 Conceptual Design

The conceptual design of this research project is based on integrating environmental observations with a computational modelling framework to estimate daily N_2O emissions from agricultural soils. The study combines measured field data, environmental variables, and a fuzzy logic inference system to simulate emission dynamics over the timeframe of growing seasons. this particular model assumes that N_2O emissions are influenced by the initial soil emission state after fertilizer application and two driving environmental conditions that influence microbial activity. The initial soil state is represented using impulse measurements collected in the field, which provide a baseline indication of the soil's maximum emission potential. Environmental drivers are daily temperature and moisture conditions, which are included to govern emission rates.

Within this framework, fuzzy logic is used as the modelling approach because it allows complex environmental relationships to be represented through linguistic rules (rather than strict mathematical equations). The fuzzy inference system translates environmental inputs into emission response factors using overlapping membership functions and rule-based reasoning. These responses are then combined with a temporal activation function representing fertilizer-driven emission dynamics.

Overall, the design of the study incorporates field measurements, environmental drivers, and fuzzy inference modelling to generate daily, next-day N_2O emission predictions. This structure allows the model to incorporate the underlying soil conditions and short-term environmental variability. The rule-based fuzzy logic model provides a simple, interpretable framework for estimating emissions in agricultural systems.

3.2 Methodology

This section will provide details on the overall methodology and procedure that took place for the research project. The detailed formulation of the fuzzy logic model is presented in the subsequent chapter, while this section focuses on steps taken, data collection, and overview of evaluation metrics.

3.2.1 Procedure

The initial impulse measurement will account for gas concentration, soil temperature, and soil moisture. A single-impulse measurement for this approach will be beneficial, as it reduces resource use (human time, machine usage, and monitoring) in the long run if the predictive model is accurate enough to be successfully deployed in real life.

With this initial context that characterizes the state of the soil, fuzzy logic can be used to predict the amount of nitrous oxide emitted. If the fuzzy logic model can successfully predict the amount of nitrous oxide emitted with a good accuracy rate, then it can be used for further research, such as testing different fertilizers, different fertilizer amounts,

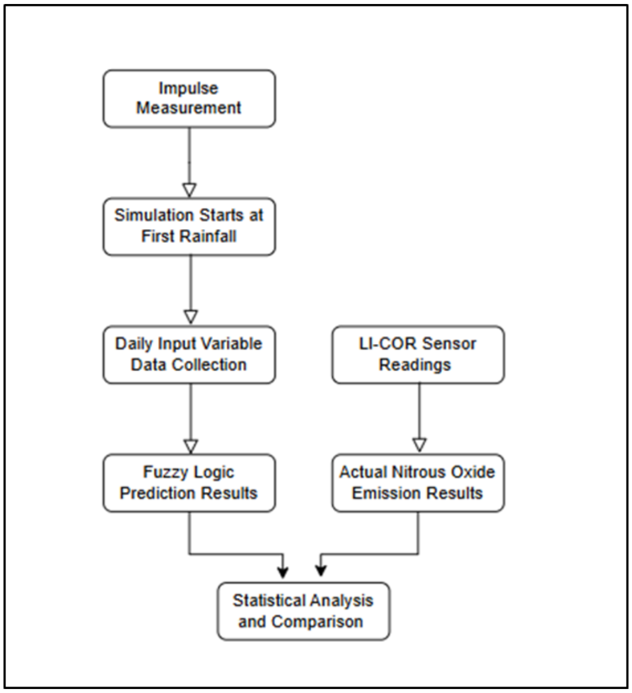


Figure 3.1: Proposed approach. A single impulse measurement will be taken at the beginning of the growing season. Fuzzy logic predictions of N_2O emissions from the soil will start once the first major precipitation event is simulated by watering a plot of soil, which will create the maximum amount of N_2O emitted. Daily temperature and moisture readings will be collected to refine the model's emission predictions. Simultaneously, LI-COR gas chambers will provide data on N_2O emitted from the soil. At the end of the growing season, the predictions from the fuzzy logic model will be assessed against the empirical data from the LI-COR gas sensors.

or patterns of fertilizer application, to aid in decision-making processes in the midst of global climate concerns.

The proposed approach is shown in Figure 3.1. It starts by obtaining a single impulse measurement under known field conditions (fertilizer type applied and application method) and combining this information with established nitrogen decomposition rates and weather data to predict N_2O emissions. The initial impulse measurement will account for gas concentration, soil temperature, and soil moisture. The impulse measurement will be taken after an area of soil is watered or after a rainfall event because it is known that this is when the most N_2O is emitted.

With this initial context as the baseline for the experiment, the custom fuzzy logic model can predict the amount of N_2O emitted from the soil using daily temperature and moisture measurements continuously fed into the model. The fuzzy logic model predictions are based on the known rate of decay of atmospheric nitrogen by microorganisms in the soil, as well as how much the input variables play a factor in determining N_2O emission output. The predicted N_2O measurements will be statistically compared with actual readings from LI-COR sensors at the end of the growing season to assess the accuracy and reliability of the fuzzy logic model for estimating emissions.

Figure 3.2: Area X.O satellite view. The headquarters office of Area X.O is 1740 Woodroffe Ave Building 400, Nepean, ON K2G 3M5, located in Ottawa, Ontario.. The coordinates are latitude 45.3 and longitude -75.8. The research farming soil is located onsite. *Image courtesy of Google Maps*.

3.2.2 Data Description

The study site where the data were collected will be described, including the measurements taken and the instruments used for data collection.

Site Description

The testing site will be the Smart Farm of Ottawa, Ontario, Canada, called Area X.O (45○19'8.17"N, 75○45'22.40"W) (Figure 3.2). During the 2021 to 2023 growing seasons, the test plot (approximately $20\,\mathrm{m} \times 20\,\mathrm{m} = 400\,\mathrm{m}^2$) of land was planted with corn. Aerial view seen in Figure 3.2.

Soil Characteristics

The texture of the soils in the Nepean area is generally moderately coarse to coarse and often contains a significant amount of angular sandstone fragments. The subsoil colour typically ranges from dark brown to yellowish-brown. Across this region, loamy sand is the most prevalent soil texture, although sandy loam and sand can also be found. The surface soil is considered fine in texture, with sandy loam being the most common (Schut and Wilson, 1987). The soil located in Area X.O is considered sandy loam.

Fertilizers & Tilling Technique

The fertilizer used in the years 2021 and 2022 was urea and poly-coated urea applied in a concentration of 225 kg/ha, while for 2023 urea coated with urease inhibitor was applied in a concentration of 150 kg/ha. In all cases, the tilling technique was used side strip.

Notes: Urea is the most commonly used nitrogen fertilizer worldwide because it has a high nitrogen content, is relatively inexpensive, and is easy to transport, store, and apply. However, despite these benefits, it is not a very efficient nitrogen source since a portion of the applied nitrogen can be lost through several pathways, including N_2O emissions once it is in the soil. These losses not only reduce how effectively the fertilizer is used but also contribute to environmental concerns. For this reason, better nitrogen management strategies are needed to improve nitrogen use efficiency while still maintaining crop yields and reducing environmental impacts.

To address these issues, enhanced efficiency nitrogen fertilizers (EENFs) have been developed to reduce nitrogen losses and make nutrients more available to plants over time. These fertilizers include options such as polymer-coated urea and stabilized urea formulations that contain urease and/or nitrification inhibitors. For example, urease inhibitors work by slowing down the conversion of urea into ammonia and ammonium, which helps prevent a rapid release of nitrogen in the soil and reduces early spikes in emissions. (Y. Li et al., 2020). .

Description of Required Data

Several types of field data need to be collected for this experiment. They are: initial impulse measurement to characterize the starting state of the soil, which is taken *after* fertilizer application and *after* the first rainfall (or area of soil will be watered to simulate a rainfall event), which will produce a large N_2O reading. Daily measures of soil temperature and rainfall (which serves as a proxy for soil moisture) are required as well.

For the fuzzy logic model:

- **Initially, once**
  1. Known fertilizer concentration applied
  2. Impulse measurement to characterize soil starting state
  3. Soil temperature
  4. Soil rainfall
- **Daily, continuous**
  1. Soil Temperature
  2. Soil rainfall

For comparison to the fuzzy logic model:

- **Daily, continuous**
  1. N_2O emissions

3.2.3 Data Collection

Now that the required data has been introduced, the instruments used to collect the data and more details regarding the data will be discussed.

Figure 3.3: LI-COR sensor. LI-COR Gas Analyzers are high-precision instruments used for measuring greenhouse gas (GHG) fluxes, including nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2), from soil, water, and air. These sensors can detect gas concentrations with high accuracy. In agricultural and environmental research, LI-COR chambers are commonly deployed to capture real-time N_2O emissions from soil, providing direct, empirical measurements that are essential for validating predictive models. These sensors are widely used due to their high sensitivity and ability to operate in field conditions. However, this technology is costly. *Image and description from LI-COR Environmental (2026).*

Nitrous Oxide Impulse and Flux Measurements

The proposed experiment is to use a single impulse measurement which will give us the initial reading that will be given to the fuzzy logic model. It is taken by a LI-COR automated trace gas chamber, as seen in Figure 3.3, after a rainfall event (or simulated rainfall event by heavy watering), which will provide the maximum amount of N_2O emitted.

Additionally, this will provide accurate, empirical measurements of N_2O throughout each growing season. These measurements are taken continuously at sub-hourly intervals. The purpose of collecting this data is for comparison of predicted versus actual N_2O emissions at the end of each season.

Soil Temperature & Moisture Readings

Sub-hourly temperature and moisture levels will be taken from the on-site weather station data, which includes weather and soil sensor data. Soil temperature and soil moisture data were collected using nearby cloud-connected Pessl sensor nodes located approximately 15 to 200 m from the sampling sites. Measurements were recorded at sub-hourly intervals, with soil readings available at multiple depths, including 10 cm, 20 cm, 30 cm, 40 cm, 50 cm, and 60 cm.

3.2.4 Data Pre-Processing

Field data were collected during the 2021, 2022, and 2023 growing seasons using in-field sensor networks. Soil temperature, soil moisture, and weather data were collected using nearby (within 15-200 m) cloud-connected Pessl sensor networks. These measurements were recorded at sub-hourly intervals, with soil data available at multiple depths, including 10 cm, 20 cm, 30 cm, 40 cm, 50 cm, and 60 cm. N_2O flux measurements were obtained using a LI-COR automated gas chamber system. Emission samples were recorded at 30-minute intervals throughout each growing season (Killeen et al., 2025).

Prior to being used in the fuzzy logic model, the dataset underwent cleaning to ensure consistency and completeness. Following this, daily averages of temperature and rainfall were calculated. These aggregated environmental variables were then aligned and merged with the daily N_2O data, ensuring that all observations corresponded correctly by day of year (Figure 3.4). Consequently, the datasets were relatively simple to understand. This is particularly useful for those who are inexperienced with data analysis, since the complexity is low.

The dataset consists of daily observations of environmental conditions and corresponding N_2O emissions. Each row represents a single day within the growing season, identified by the day of year (DoY), which provides a temporal reference for the measurements. The dataset includes three main input features: average daily temperature, average daily rainfall, and time (DoY), along with one output variable, N_2O emissions. The average temperature (°C) represents the mean of daily minimum and maximum temperatures and serves as a key indicator of microbial activity in the soil. The average rainfall (mm/day) reflects precipitation levels, which influence soil moisture conditions and oxygen availability. The day of year (DoY) captures the temporal progression of the growing season and can help identify seasonal trends or patterns in emissions. The target variable, N_2O emissions (ppb/m^2), represents the *measured* values released from the soil for each day. This variable serves as the ground truth used to evaluate model performance. The dataset is structured as a time-series dataset with environmental inputs and a corresponding emission output, allowing for analysis of both temporal trends and relationships between environmental drivers and N_2O emissions.

The minimal pre-processing required for this dataset supports the overall objective of developing a simple, cost-effective, and deployable modeling framework, making it more accessible for real-world agricultural applications. This intuitive framework allows accessibility to non-expert users. See Figure 3.4 for an example dataset.

3.2.5 Data Analysis & Evaluation Metrics

The primary statistical analysis conducted in this study focuses on evaluating the accuracy of the fuzzy logic model predictions of N_2O emissions compared with the measured emissions obtained using LI-COR gas chamber sensors. First, the accuracy of the model in predicting daily N_2O emissions will be examined. Subsequently, the cumulative end-of-season emission totals will be analyzed to assess how well the model captures overall seasonal

	A	B	C	D	E
1		DoY	Avg Temperature	Avg Rainfall	N2O Emissions
2	0	160	17.9	0.3	0.0024255
3	1	161	18.45	0.5	0.001465406
4	2	162	19.6	0	0.088382708
5	3	163	20.1	2.6	0.154767297
6	4	164	20.1	11.2	0.163438181
7	5	165	18.05	0.4	0.147664359
8	6	166	15.65	0	0.149895715
9	7	167	17.2	0	0.139890834
10	8	168	17.4	26.4	0.144017451
11	9	169	20.75	0	0.21578194

Figure 3.4: Example of dataset required for predictive model. This is an example dataset from the year 2021.

emission trends. Additional statistical analysis will also be performed to examine potential correlations among the collected environmental input variables and to evaluate their relationships with observed N_2O emissions.

Error Analysis of Daily Predictions

To evaluate the effectiveness of the model's daily predictions, statistical differences between the predicted and measured values will be analyzed using several error metrics. These metrics will be used to quantify how closely the predicted N_2O emissions align with the observed values.

Mean Absolute Error (MAE)

The Mean Absolute Error represents the average absolute difference between predicted and measured values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \tag{3.1}$$

where P_i represents the predicted value, O_i represents the observed value, and n is the total number of observations.

Root Mean Squared Error (RMSE)

The Root Mean Squared Error measures the square root of the average squared differences between predicted and observed values. This metric places greater emphasis on larger prediction errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{3.2}$$

Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error expresses the prediction error as a percentage of the observed values.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{P_i - O_i}{O_i}\right| \tag{3.3}$$

Note: MAPE was calculated with an adjustment to reduce distortion from near-zero emission values. Because N_2O fluxes close to 0 ppb/m^2 are common, small absolute errors can lead to disproportionately large percentage errors. To address this, measured emissions within ± 1 ppb/m^2 were set to -1 or 1 (whichever was closest) prior to computing MAPE, following Killeen et al. (2025). This is done in effort to treat low baseline emissions appropriately to prevent inflation of the metric.

Mean Bias Error (MBE)

The Mean Bias Error represents the average difference between predicted and observed values and indicates whether the model tends to overestimate or underestimate emissions.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{3.4}$$

The aim is to perform this based on point by point (real versus predicted) and also do these calculations on the final amount of predicted N_2O versus real because during preliminary insights of the graphical outputs, there are obvious matching trends seen but they are imperfect by having lags or advances, or over and under predictions. If we are just concerned about overall nitrous oxide predictions for a season, and questioning whether just the final amount emitted will be a good predictor, we should calculate the metrics based on the total amount of N_2O predicted in each season as well, not just how the model performs daily.

Error Analysis of Seasonal Predictions

To evaluate the effectiveness of the model's seasonal predictions, statistical differences between the cumulative predicted and measured values will be analyzed using several error metrics. These metrics quantify how closely the predicted N_2O emissions correspond to the observed values. Calculate the sum of predicted N_2O emissions and measured emissions of each growing season. Then perform the following error calculations to see how well the model did at predicting total N_2O emissions over each season.

Absolute Error

The Absolute Error measures the magnitude of the difference between the predicted and measured values without considering the direction of the error.

$$AE = |P - M| \tag{3.5}$$

where P represents the predicted value and M represents the measured value.

Percent Error

The Percent Error expresses the difference between predicted and measured values relative to the measured value.

$$PE = \frac{P - M}{M} \tag{3.6}$$

where P represents the predicted value and M represents the measured value.

Prediction Ratio

The Prediction Ratio represents the ratio between the predicted and measured values and provides a simple measure of model bias. Positive ratio indicates model over-prediction, while negative ratio indicates model under-prediction.

$$R = \frac{P}{M} \tag{3.7}$$

where P represents the predicted value and M represents the measured value.

Input Data Exploration Analysis

Additional analysis may be conducted to identify patterns among input variables that influence N_2O emissions after plotting the measured data obtained from the LI-COR gas chamber sensors. Correlation calculations aim to identify dependencies between variables (FlexMR, n.d.). Potential relationships that may be explored include those between temperature and N_2O emissions, as well as soil moisture and N_2O emissions.

The strength and nature of the relationship between variables are quantitatively assessed using Pearson's r and Spearman's rank correlation coefficient (ρ). Both metrics range from -1 to $+1$, where values closer to $|1|$ indicate stronger relationships (linear for Pearson and monotonic for Spearman) while values near 0 suggest little or no consistent association between investigated variables. It is important to note that a correlation near zero does not necessarily mean there is not a relationship, but rather it indicates the absence of a clear linear or monotonic trend (SurveyMonkey, n.d.).

In the context of regression analysis, the slope represents the rate of change in the dependent variable with respect to the independent variable. However, the overall explanatory power of the model is more appropriately evaluated using the coefficient of determination (R^2), which ranges from 0 to 1 and represents the proportion of variance in the data explained by the model. In environmental datasets, moderate R^2 values are common due to the inherent variability in natural systems; therefore, values in the range of approximately 0.6 to 0.9 can still indicate meaningful model performance. Higher R^2 values suggest a better fit, although they should be interpreted in the context of the data and model structure (Biology for Life, n.d.).

Spearman's Rank Correlation (ρ)

Spearman's Rank correlation measures the strength and direction of a monotonic relationship between two variables. It is useful when variables increase or decrease together but do not necessarily follow a linear relationship (Laerd Statistics, 2018).

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{3.8}$$

where d_i is the difference between the ranks of paired observations and n is the number of observations.

Pearson's Correlation Coefficient (r)

Pearson's correlation coefficient measures the strength and direction of the linear relationship between two variables (Turney, 2022b).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{3.9}$$

where x_i and y_i represent paired observations and $\bar{x}$ and $\bar{y}$ represent their respective means.

Coefficient of Determination (R^2)

The coefficient of determination describes how well a regression model explains the variability of the observed data (Turney, 2022a).

$$R^2 = 1 - \frac{SSE}{SST} \tag{3.10}$$

where the sum of squared errors (SSE) and the total sum of squares (SST) are defined as:

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3.11}$$

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{3.12}$$

The regression sum of squares (SSR) is given by:

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 \tag{3.13}$$

such that:

$$SST = SSR + SSE \tag{3.14}$$

3.3 Concluding Remarks

This chapter presents the motivation for conducting this research, the general methodology employed, and the approach used to evaluate the effectiveness of the proposed model for daily and seasonal accuracy. Explanation of data exploration metrics were included as well. The next chapter provides a detailed explanation of the structure and operation of the fuzzy logic model.

Chapter 4

Nitrous Oxide Predictions Using a Fuzzy Logic Model

It has been established that nitrous oxide emissions are unusually elevated due to the usage of fertilizers on crops. There is a need for accurate methods to predict N_2O emissions to align with government goals to reduce these GHGs. Currently, there are very accurate technologies that can measure N_2O emissions from the ground, but they are expensive and cannot be used over large areas.

The objective of the fuzzy logic model is to estimate N_2O emissions from readily available environmental measurements. The model is designed to achieve a level of predictive accuracy, "ballpark" estimates of N_2O emissions. One such application is for agricultural producers who voluntarily monitor N_2O emissions associated with crop production but may not have access to specialized or high-cost measurement equipment.

The structure of the fuzzy logic model is intentionally kept simple to support usability and scalability. An impulse function measurement is incorporated to represent the maximum potential N_2O emission for a given experimental plot. The primary input variables to the model are daily average soil temperature and soil moisture, which are known to influence microbial processes that produce N_2O. Empirical measurements for inputs and N_2O undergo pre-processing to obtain averages. The model outputs a predicted daily N_2O emission value. When supplied with continuous daily averages of soil moisture and temperature, the model can generate N_2O emission estimates throughout the growing season, which are compared with the calculated daily averages of the empirical counterparts. In this section, an in-depth explanation of the fuzzy logic model will be provided (Figure 4.1).

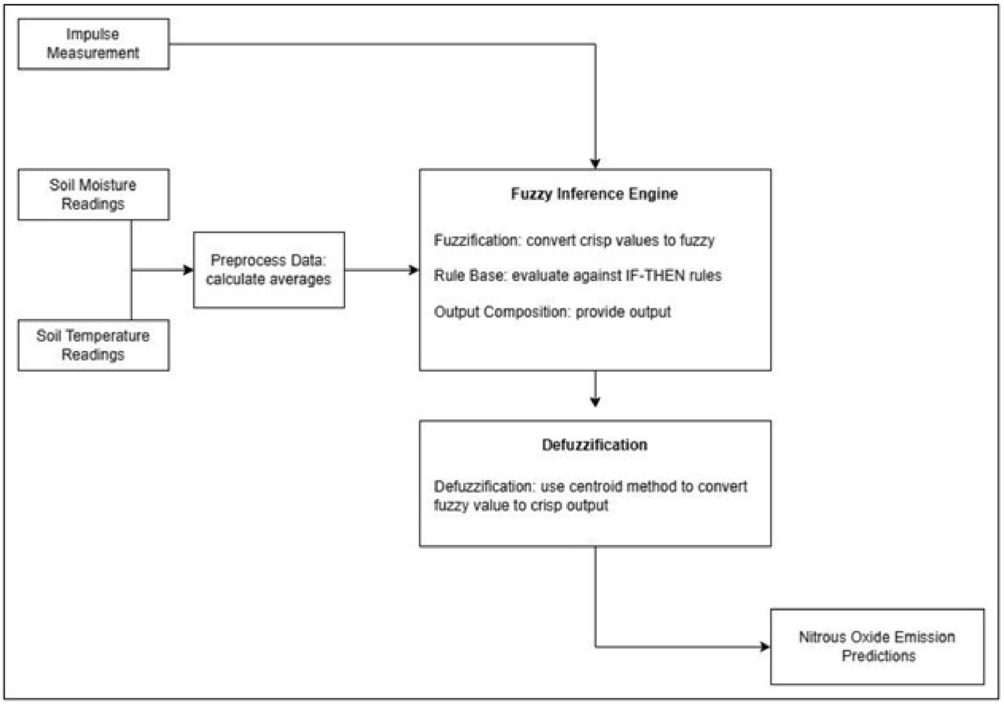


Figure 4.1: Schematic of the fuzzy logic pipeline.

4.1 Overview of the Modeling Framework

The modelling framework consists of two connected components. First, a fuzzy inference system estimates daily N_2O emission potential from environmental inputs. Second, this fuzzy output is embedded within a seasonal simulation framework that incorporates fertilizer timing through a temporal activation function. Together, these components generate daily predicted N_2O emissions over each specific growing season.

The fuzzy inference system uses daily average temperature and daily rainfall (as a proxy for soil moisture) as its two environmental inputs. These variables were selected because they are strongly related to the microbial and soil conditions that influence N_2O production. The model converts these crisp inputs into linguistic categories, applies a set of IF-THEN rules, aggregates the resulting fuzzy outputs, and defuzzifies the result into a single normalized emission estimate for the following day.

IF-THEN rules with:

- Antecedent AND operation: $\min(\cdot)$
- Consequent sets: N_2O emission $\{$Low, Medium, High$\}$

Linguistic variables:

- **Input: Temperature** - Low / Medium / High
- **Input: Rainfall (24h)** - Light / Medium / Heavy

- **Output: N_2O emission (next day, %)** - Low / Medium / High

The second component of the framework introduces temporal fertilizer dynamics. A Gaussian activation function is used to represent the rise and decline in fertilizer-driven emission potential after fertilizer application. The daily fuzzy response rate was subsequently modulated by a fertilizer activation and decay function, represented by the Gaussian window. This is to account for the temporal dynamics of fertilizer-driven emission potential following application, and then produces a simulated daily N_2O emission series for each growing season.

Separate simulation parameters were specified for each growing season to reflect differences in data availability, fertilizer timing, and environmental conditions. By adjusting the simulation start and end days, fertilizer activation period, and Gaussian spread, the framework allows year-specific calibration while maintaining a consistent underlying modeling structure. This structure allows the model to combine short-term environmental suitability with time-dependent fertilizer effects. The combined output represents a simulated daily N_2O emission estimate that integrates environmental drivers and fertilizer dynamics over time.

4.2 Fuzzy Logic Model Formulation

Fuzzy logic was used to accommodate the inherent uncertainty associated with soil-to-atmosphere greenhouse gas fluxes. The fuzzy logic model implemented in this study is a Mamdani-type fuzzy inference system designed to estimate daily N_2O emission potential as a function of temperature and rainfall within a rule-based inference system and a temporal fertilizer activation function. The modelling framework consists of four stages: fuzzification, rule evaluation, aggregation, and defuzzification. This approach is well suited to the present application because N_2O emissions respond to environmental conditions in gradual ways rather than through abrupt thresholds.

Temperature and rainfall are first transformed into linguistic variables using predefined membership functions, after which a rule base that encodes qualitative relationships between environmental conditions and N_2O emissions is evaluated. The resulting fuzzy outputs are aggregated and defuzzified using the centroid method to produce a single crisp emission estimate. This structure enables the model to represent gradual transitions between environmental states and to produce continuous emission estimates.

4.2.1 Input Variables and Fuzzification

The model uses two environmental input variables: daily average temperature (°C) and daily average moisture, which is calculated by averaging the amount of rainfall over each 24-hour period (mm). These variables were selected because they are known to influence soil microbial activity, moisture availability, and denitrification. All of these factors contribute to N_2O production. The model treats both inputs as continuous variables, with the influence of emissions on each varying gradually across their respective ranges.

The input variables temperature (T) and rainfall (R) are defined as:

$$T = \text{daily average temperature (°C)} \tag{4.1}$$

$$R = \text{daily rainfall (mm)} \tag{4.2}$$

Each crisp input is converted into fuzzy membership values using triangular (*trimf*) and trapezoidal (*trapmf*) membership functions. This fuzzification step allows one input value to belong partially to more than one linguistic category. This is important for representing gradual transitions in environmental conditions. The *degree of membership* for any given input value is calculated using basic linear algebra.

The triangular membership function is defined as:

$$\mu(x; a, b, c) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a < x \leq b \\ \dfrac{c-x}{c-b} & b < x < c \\ 0 & x \geq c \end{cases} \tag{4.3}$$

The trapezoidal membership function is defined as:

$$\mu(x; a, b, c, d) = \begin{cases} 0 & x \leq a \\ \dfrac{x-a}{b-a} & a < x \leq b \\ 1 & b < x \leq c \\ \dfrac{d-x}{d-c} & c < x < d \\ 0 & x \geq d \end{cases} \tag{4.4}$$

The triangular and trapezoidal membership functions are composed of linear segments.

The degree of membership along these segments is computed using the equation of a straight line:

$$\mu(x) = mx + b \tag{4.5}$$

where $\mu(x)$ represents the degree of membership for input value x, m is the slope of the line, and b is the y-intercept.

The slope between two points (x_1, y_1) and (x_2, y_2) is calculated as:

$$m = \frac{y_2 - y_1}{x_2 - x_1} \tag{4.6}$$

Once the slope is known, the intercept is determined by:

$$b = y_1 - mx_1 \tag{4.7}$$

Substituting these values into the linear equation produces the degree of membership for a given input value:

$$\mu(x) = mx + b \tag{4.8}$$

This formulation is used in the implementation to compute the rising and falling edges of the triangular and trapezoidal membership functions used for the inputs (temperature and rainfall) as well as for the output (emission intensity).

In fuzzification, the input variables will be taken from their crisp values to linguistic variables (*Low*, *Medium*, or *High*). Each input is converted into fuzzy membership values using the aforementioned triangular (*trimf*) and trapezoidal (*trapmf*) membership functions.

Temperature and rainfall are each represented using three linguistic categories within the fuzzy inference system (Figure 4.2). Temperature is partitioned into three linguistic categories across a range of 0-40 °C. Low temperatures are modeled using a left-shoulder trapezoidal function to reflect reduced microbial activity under cooler conditions. Medium temperatures are represented by a triangular function centered on intermediate values, while high temperatures are modeled with a right-shoulder trapezoidal function to capture the increased emission potential associated with warmer conditions (Figure 4.2a). Higher temperatures generally promote greater microbial activity and therefore tend to increase N_2O production.

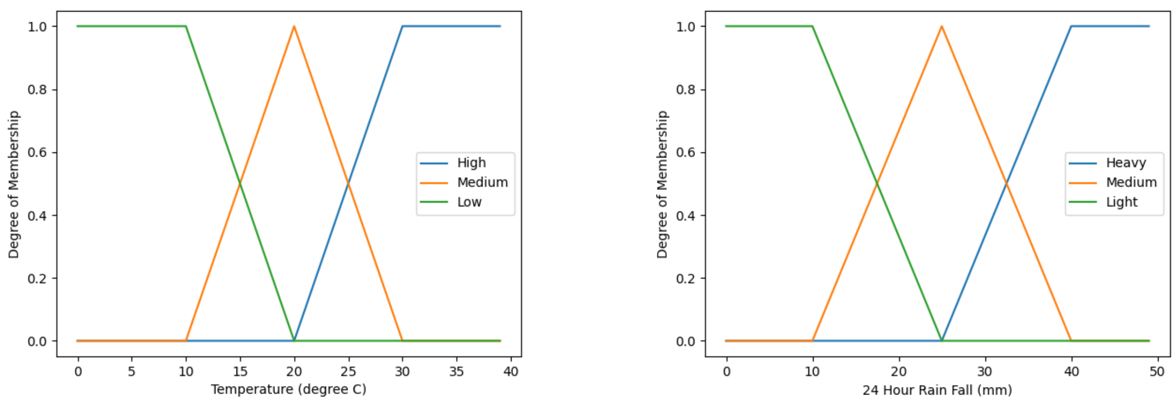
Temperature is represented using three fuzzy sets over the range 0-40°C. These overlapping sets allow the model to capture the gradual effect of warming conditions on microbial activity and N_2O production:

- Low: `trapmf([0,0,10,20])` (approximately 0–20°C)
- Medium: `trimf([10,20,30])` (approximately 10–30°C)
- High: `trapmf([20,30,40,40])` (approximately 20–40°C)

Rainfall is represented in a similar manner using the same three linguistic categories, over an approximate range of 0–60 mm. Light rainfall is modeled with a left-shoulder trapezoidal function, medium rainfall with a triangular function, and heavy rainfall with a right-shoulder trapezoidal function (Figure 4.2b). While the structural design of the membership functions is similar to that used for temperature, rainfall represents soil moisture conditions rather than thermal effects. Increasing rainfall can lead to more saturated soils and reduced oxygen availability, which promotes anaerobic conditions favourable for microbial processes such as denitrification that contribute to N_2O emissions.

Rainfall is represented using three fuzzy sets over the approximate range 0-60 mm (although the Figure shows 0-50 mm):

- Light: `trapmf([0,0,10,25])` (approximately 0–25 mm)
- Medium: `trimf([10,25,40])` (approximately 10–40 mm)
- Heavy: `trapmf([25,40,60,60])` (approximately 25–60 mm)



(a) Temperature membership functions

(b) Rainfall membership functions

Figure 4.2: Fuzzy membership functions used in the model for (a) temperature and (b) rainfall inputs.

The ranges for temperature and rainfall were determined from the observed environmental conditions in the area combined with agronomic knowledge of conditions that influence N_2O production. For temperature, the fuzzy sets span approximately 0–40 °C, reflecting the realistic bounds of daily soil or air temperatures observed in the agricultural datasets used for the model, in this geographical location, accounting for several degrees less and more than the usually observed ranges. The membership functions were then divided into low (0–20 °C), medium (10–30 °C), and high (20–40 °C) with overlapping transitions. This overlap allows the model to represent gradual biological responses.

For rainfall, the range of approximately 0–60 mm over 24 hours was selected to represent the typical distribution of daily precipitation events that were previously known. Most rainfall events from this context fall within this range. The rainfall variable was divided into light (0–25 mm), medium (10–40 mm), and heavy (25–50 mm) categories using overlapping fuzzy sets. These categories were chosen to approximate different soil moisture conditions that can influence microbial activity and gas diffusion in soils.

Temperature is more prominent in determining the emission level, while the role of rainfall as an input adjusts how strongly a rule is activated. The use of overlapping membership functions for both variables allows environmental conditions to belong partially to multiple categories, enabling the model to represent gradual transitions rather than strict thresholds.

Note: To reflect the day-to-day soil moisture conditions that drive N_2O production, average rainfall is used instead of summed precipitation. The reason is that microbial processes (like nitrification and denitrification) respond to existing soil dampness instead of accumulated rainfall, so using daily averages allows the fuzzy logic model to capture these kinds of dynamics. In contrast, summed precipitation can hide how rainfall is distributed over time. For example, a heavy storm one day versus light rain over several days could have the same total precipitation, but different effects on soil conditions that drive N_2O emission responses. Averaging also helps keep the fuzzy membership functions more robust and less influenced by extreme events, so the model reflects the overall environmental state.

4.2.2 Rule-Based Evaluation

The fuzzy rule base contains nine IF-THEN rules corresponding to all combinations of the three temperature categories and three rainfall categories.

Each rule takes the form:

> IF temperature is (Low/Medium/High) AND rainfall is (Light/Medium/Heavy), THEN N_2O emission is (Low/Medium/High).

The 9 rules listed explicitly are:

1. IF Temperature is Low AND Rainfall is Light THEN Emission is Low
2. IF Temperature is Medium AND Rainfall is Light THEN Emission is Medium
3. IF Temperature is High AND Rainfall is Light THEN Emission is High
4. IF Temperature is Low AND Rainfall is Medium THEN Emission is Low
5. IF Temperature is Medium AND Rainfall is Medium THEN Emission is Medium
6. IF Temperature is High AND Rainfall is Medium THEN Emission is High
7. IF Temperature is Low AND Rainfall is Heavy THEN Emission is Low
8. IF Temperature is Medium AND Rainfall is Heavy THEN Emission is Medium
9. IF Temperature is High AND Rainfall is Heavy THEN Emission is High

Again, although rainfall is a part of every antecedent, the output class is determined entirely by the temperature category. This suggests that temperature is a more significant factor in N_2O emissions. Rainfall affects firing strength, but its role is to scale the strength of each of the three temperature-to-emission output activations. Rule firing strengths are computed using the minimum operator, which represents a logical conjunction between the antecedent conditions. This approach allows multiple rules to be partially activated simultaneously, reflecting the complex and interacting effects of temperature and moisture on N_2O emissions. Partial firing and belonging to multiple rules are key characteristics of fuzzy logic.

The firing strength of each rule is calculated using the minimum operator:

$$\alpha_{ij} = \min\left(\mu_{T_i}(T), \mu_{R_j}(R)\right) \tag{4.9}$$

where $i \in \{\text{low, medium, high}\}$ and $j \in \{\text{light, medium, heavy}\}$.

The rule base and firing strengths are summarized in Table 4.1. While temperature largely influences the emission regime, rainfall modulates how strongly the rules are activated by representing the degree of soil wetness associated with denitrification-favourable conditions.

Table 4.1: Fuzzy rule base used in the model.

Rainfall / Temperature	Low Temperature	Medium Temperature	High Temperature
Light Rainfall	Rule 1 Strength	Rule 2 Strength	Rule 3 Strength
Medium Rainfall	Rule 4 Strength	Rule 5 Strength	Rule 6 Strength
Heavy Rainfall	Rule 7 Strength	Rule 8 Strength	Rule 9 Strength

4.2.3 Aggregation

The output membership functions form part of the aggregation stage of the fuzzy inference process, where the contributions from activated rules are combined to produce the final fuzzy emission response.

Output Membership Functions

The output variable of the fuzzy inference system represents the predicted N_2O emission potential for the following day. Emission potential is defined on a normalized scale ranging from 0 to 100, where larger values correspond to greater expected N_2O emissions. Three fuzzy sets are used to represent the possible emission states: *Low*, *Medium*, and *High*. These sets are defined using triangular and trapezoidal membership functions in order to capture gradual transitions between emission regimes (Figure 4.3).

Low emissions are represented using a left-shouldered trapezoidal membership function, medium emissions are represented using a triangular membership function. The overlap between the low and high emission sets allows emission levels near the boundaries to belong partially to multiple categories. High emissions are represented using a right-shouldered trapezoidal membership function. This configuration captures conditions associated with the highest expected N_2O emission potential.

Together, these three membership functions partition the output domain while maintaining overlapping regions that allow the fuzzy inference system to represent gradual changes in emission potential. When fuzzy rules are evaluated, each activated rule contributes to one of these emission categories.

The model output is a normalized N_2O emission index on a 0–100 scale. Three output membership functions are defined:

- Low emission: `trapmf([0,0,25,50])`
- Medium emission: `trimf([25,50,75])`

- High emission: `trapmf([50,75,100,100])`

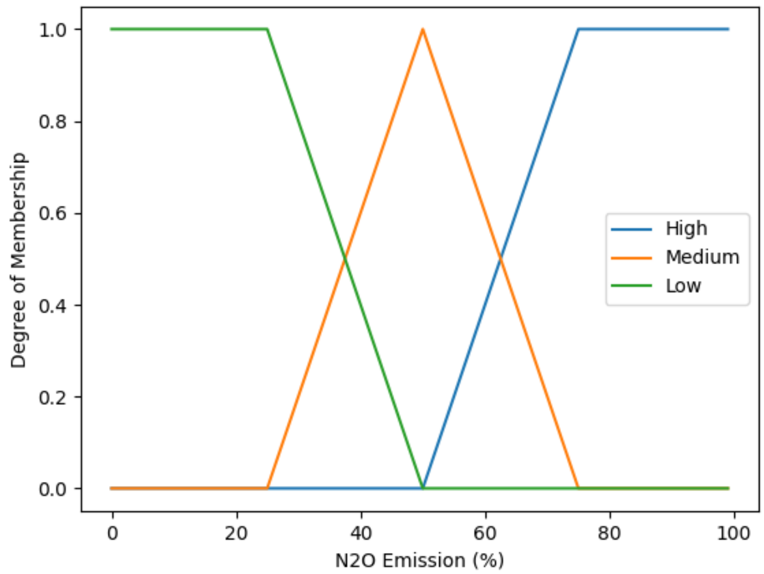


Figure 4.3: N_2O output membership functions.

For each activated rule, the corresponding output membership function is clipped according to the rule's firing strength, following the Mamdani implication method. The clipped output sets are then combined to form a single aggregated fuzzy output, representing the combined influence of all active rules. In other words, the resulting aggregated membership function represents the combined influence of all applicable rules under the given environmental conditions.

Each rule contributes to the output fuzzy set representing emission intensity E, defined by the categories low, medium, and high. The aggregated output membership function is calculated as:

$$\mu_E(x) = \max_{i,j} \left(\min(\alpha_{ij}, \mu_{E_k}(x)) \right) \tag{4.10}$$

where k corresponds to the emission category associated with each rule.

Output membership functions refer to the predicted N_2O emissions. The inference engine evaluates the activated rules using a Mamdani-type inference approach. Antecedent conditions are combined using fuzzy logical operators, and the resulting rule outputs are aggregated to form a single fuzzy representation of N_2O emission potential. The fuzzy inference system follows a Mamdani architecture in which rule consequents are expressed as fuzzy output sets, combined through standard min–max operations, and subsequently converted into a single crisp emission estimate using centroid defuzzification.

4.2.4 Defuzzification

To obtain a single crisp emission estimate, the aggregated fuzzy output is defuzzified using the centroid method. This method computes the weighted average of the output domain values, using membership degrees as weights. Centroid defuzzification was selected because it produces smooth, continuous outputs and is well-suited for modeling gradual changes in emission behavior. When no rules are activated and the aggregated membership function is zero across the output domain, the emission estimate is set to zero to ensure numerical stability and interpretability.

The centroid method for defuzzification is defined as:

$$E^* = \frac{\sum x_i \mu_E(x_i)}{\sum \mu_E(x_i)} \tag{4.11}$$

where E^* is the final normalized emission response and $\mu_E(x_i)$ is the aggregated membership value at output position x_i. This method was selected because it produces smooth and continuous predictions, which is appropriate for environmental processes that vary gradually through time. This converts the final, fuzzy shape of the emission potential back to a crisp value. The final output of the fuzzy logic model is relative N_2O emission potential for the following day.

4.3 Integration Within the Seasonal Simulation Framework

The fuzzy inference system produces a daily normalized emission response based on environmental conditions. To convert this response into a seasonal emission simulation, it is coupled with a fertilizer activation term that varies through time.

The fertilizer response is represented using a Gaussian activation function (Figure 4.4):

$$G(t) = Ae^{-\frac{(t-t_0)^2}{2\sigma^2}} \tag{4.12}$$

where A is the amplitude, σ controls the spread of the response, and t_0 is the timing of peak fertilizer influence.

Two Gaussian pulses are used to represent both immediate and delayed fertilizer responses:

$$G_{\text{total}}(t) = G_1(t) + G_2(t-d) \tag{4.13}$$

where d is the delay parameter. This allows the model to represent more than one fertilizer-related emission pulse during the season.

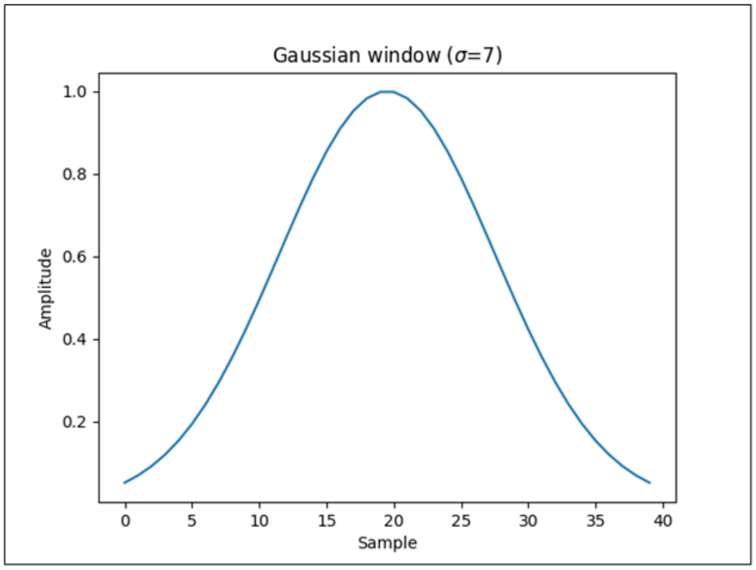


Figure 4.4: Gaussian window function used to represent fertilizer activation over time. The curve is normalized between 0 and 1 and illustrates the temporal rise and decline in fertilizer influence following application.

4.3.1 Final Emission Predication

The final predicted daily N_2O emission is calculated as:

$$N_2O(t) = G_{\text{total}}(t) \cdot E^*(t) \tag{4.14}$$

In this formulation, the fuzzy system determines how favourable the daily environmental conditions are for N_2O production, while the Gaussian activation term determines how much fertilizer-driven emission potential is available on that day. The model is applied separately to each growing season using year-specific simulation windows and fertilizer timing parameters.

4.4 Worked Example of Fuzzy Inference

To illustrate how the fuzzy inference system operates, consider a case where the temperature is 26°C and rainfall is 8 mm. This example only illustrates the operation of the fuzzy inference system and does not incorporate the additional year-specific calculations used in the full seasonal simulation framework.

4.4.1 Fuzzification

For temperature, the memberships are:

$$\mu_{T,\text{low}}(26) = 0 \tag{4.15}$$

$$\mu_{T,\text{medium}}(26) = \frac{30 - 26}{30 - 20} = 0.4 \tag{4.16}$$

$$\mu_{T,\text{high}}(26) = \frac{26 - 20}{30 - 20} = 0.6 \tag{4.17}$$

Thus,

$$(\mu_{T,\text{low}}, \mu_{T,\text{medium}}, \mu_{T,\text{high}}) = (0, 0.4, 0.6) \tag{4.18}$$

For rainfall, the memberships are:

$$\mu_{R,\text{light}}(8) = 1 \tag{4.19}$$

$$\mu_{R,\text{medium}}(8) = 0 \tag{4.20}$$

$$\mu_{R,\text{heavy}}(8) = 0 \tag{4.21}$$

Thus,

$$(\mu_{R,\text{light}}, \mu_{R,\text{medium}}, \mu_{R,\text{heavy}}) = (1, 0, 0) \tag{4.22}$$

4.4.2 Rule Evaluation

The rule firing strengths are obtained using the minimum operator:

$$\alpha_{ij} = \min(\mu_{T_i}(T), \mu_{R_j}(R)) \tag{4.23}$$

which gives:

$$\begin{bmatrix} 0 & 0.4 & 0.6 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{4.24}$$

Only two rules are activated:

- Medium temperature AND light rainfall $\rightarrow$ medium emission, firing strength 0.4
- High temperature AND light rainfall $\rightarrow$ high emission, firing strength 0.6

4.4.3 Aggregation and Defuzzification

The medium emission output set is clipped at 0.4 and the high emission output set is clipped at 0.6. These are aggregated into a single fuzzy output set, and centroid defuzzification is then applied:

$$z^* = \frac{\sum x\mu(x)}{\sum \mu(x)} \tag{4.25}$$

This produces a final normalized emission estimate of:

$$z^* \approx 68.9 \tag{4.26}$$

Therefore, under a temperature of 26°C and rainfall of 8 mm, the fuzzy inference system predicts an emission level of approximately 69% on the normalized output scale.

Once the fuzzy inference system produces the normalized emission response value, this value is used as the environmental response factor for that day. In the seasonal simulation framework, this response is combined with the temporal fertilizer activation function, which represents the rise and decline in fertilizer-driven emission potential following application. The final predicted daily N_2O emission is calculated as the product of the fuzzy environmental response and the fertilizer activation term. This process is repeated for each day within the simulation period for a given year, generating a continuous time series of predicted N_2O emissions that can be compared with measured observations.

4.5 Concluding Remarks

This chapter described the formulation of the fuzzy logic model used to estimate daily N_2O emission potential from temperature and rainfall inputs. It also showed how the fuzzy inference system was integrated with a temporal fertilizer activation function to generate seasonal N_2O predictions. The following chapter evaluates model performance by comparing these predictions with measured emissions across the study years, as well as exploration of the collected data.

Chapter 5

Results

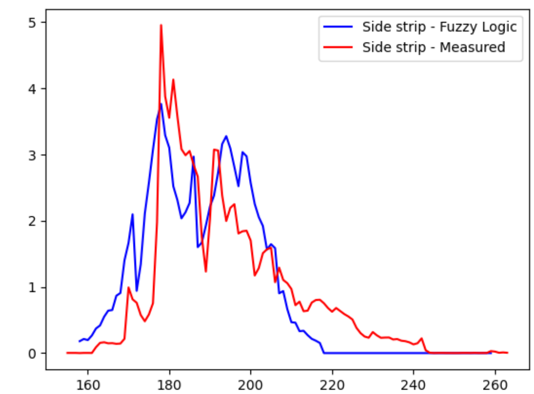
The fuzzy logic model's accuracy will be evaluated in this section. The simulation results for the three growing seasons are presented graphically and then evaluation metrics for the predictions are discussed. In addition, exploratory data analysis has been performed on the acquired data and presented in an effort to ascertain underlying patterns regarding the relationship between the input variables and each one to the output variable.

5.1 Fuzzy Logic Predictions versus Empirical Emissions

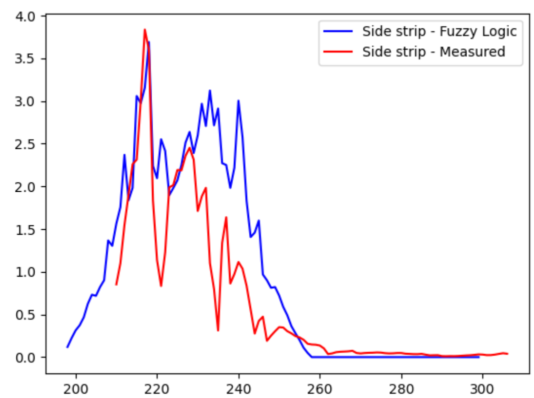
Daily N_2O emissions were evaluated across the growing seasons 2021, 2022, and 2023, with 102, 90, and 75 paired observations (matching days worth of predictions and empirical measurements) respectively. The average air temperature in 2021 was 20.7°C and total rainfall was 267.5 mm (considered a relatively dry year). 2022 was relatively colder with an average air temperature of 14.9°C and had 536.6 mm of rain. 2023 has an average air temperature of 19.4°C and 535.5 mm of rain (Killeen et al., 2025).

5.1.1 Graphical Comparisons

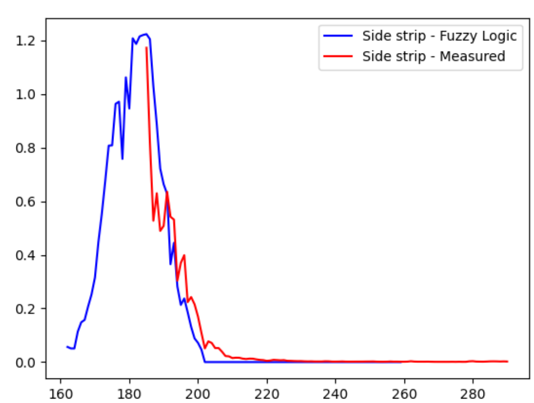
Visually, it is apparent from Figure 5.1 that the fuzzy logic predictions (blue) are not exactly aligned with the empirical N_2O emissions (red), as there are portions of over- and under-predictions. However, the model was able to capture general patterns, as there are many corresponding peaks and dips between the predicted and real emission values. Additional supporting figures are available in the Supplementary Materials section.



(a)



(b)



(c)

Figure 5.1: Plots comparing fuzzy logic predicted N_2O emissions (blue) versus measured N_2O emissions (red) for the years 2021, 2022, and 2023, in order of appearance.

5.1.2 Evaluating Model Performance

Model performance was evaluated using a combination of complementary error, bias, variance, and association metrics (Table 5.1). Mean Absolute Error (MAE) quantify deviations between predicted and measured N_2O emissions, while Root Mean Squared Error (RMSE) preserves the physical units of the observations and emphasizes larger errors that are environmentally meaningful. Mean Absolute Percentage Error (MAPE) was included to provide a relative measure of error magnitude, while acknowledging its sensitivity to low and near-zero flux values. Mean Bias Error (MBE) was used to assess whether the model exhibited systematic over- or under-prediction. The coefficient of determination (R^2) was chosen because it measures the proportion of variance in actual measurements that is explained by the predicted values. Finally, Spearman's rank correlation coefficient (ρ) was used to evaluate agreement in the temporal ordering of predicted and measured emissions, which is particularly appropriate given the nonlinear and regime-based behavior of N_2O fluxes.

Table 5.1: Evaluation metrics for the experiment years regarding predicted versus measured daily N_2O emissions.

	2021	**2022**	**2023**
MAE	0.5038	0.3917	0.0435
RMSE	0.6880	0.6788	0.0970
MAPE	70.35%	77.40%	89.75%
MBE	0.0309	0.3139	-0.0012
R^2	0.6168	0.4503	0.8163
Spearman's ρ	0.7923	0.9045	0.7316
Associated p-value	9.4407×10^{-23}	2.5450×10^{-34}	8.9456×10^{-14}

[a] MAE: Average absolute difference between predicted and measured daily N_2O emissions.
[b] RMSE: Square root of MSE, representing typical daily prediction error in observed units.
[c] MBE: Mean signed difference between predicted and measured emissions, indicating systematic bias.
[d] R^2: Proportion of variance in measured emissions explained by the model.
[e] Spearman's ρ: Rank-based correlation assessing monotonic agreement between predicted and measured emissions.
[f] Associated p-value: Statistical significance of the Spearman rank correlation.

For each year, the MAE is relatively low, indicating that the predicted daily N_2O emissions are generally close to the measured values.

The RMSE values remained relatively low across all three growing seasons, indicating that the model generally produced small prediction errors, with the lowest RMSE observed in 2023 corresponding to the highest overall prediction accuracy.

To reduce the inflation of MAPE caused by near-zero N_2O flux values, measured emissions within $\pm$ 1 ppb/m^2

were snapped to $\pm$ 1 prior to computing MAPE, following the approach adopted in previous studies such as in Killeen et al. (2025). Even with accounting for N_2O emissions near 0 ppb/m^2, these relatively high values (ranging from 70% to 90%) reflect the sensitivity of MAPE to small observed emission values, where even small absolute differences between predicted and measured N_2O emissions can produce large percentage errors.

For 2021 and 2023, the MBE was near 0, indicating that the model minimally under- or over-predicts as a whole, but shows that the model over-predicted in 2022 with a higher value, and this corresponds with Figure 5.1.

R^2 values closer to 1 indicate better predictions, whereas values closer to 0 indicate the model is not performing any better than predicting the mean of the real data. Thus, the model performed the best in 2023 and the worst in 2022.

Spearman's rank correlation coefficient provides insight into the strength of a monotonic relationship between two variables, that is, a relationship in which one variable increases or decreases as the other does and it ranges from -1 to +1. In this case, the predicted values were compared with the actual N_2O emissions. Oftentimes, values $\pm$ 0.7 are considered strong contenders (SurveyMonkey, n.d.), and here, all years showed strong Spearman's rank correlation, and the outcome was statistically significant, the model was reproducing the relative timings of high and low emission periods, effectively capturing temporal patterns.

Now, onto evaluation of the total N_2O predicted per season versus the measured amount (Table 5.2). This is particularly useful if the potential user is not concerned with daily patterns of N_2O emissions and is more interested in keeping track of overall emissions for the growing season. The metrics used were percent error, absolute error, and a ratio between the predicted and measured units of N_2O emmited. Percent error represents the relative difference between the predicted and measured cumulative N_2O emissions at the end of the growing season. It shows the prediction error as a percentage of the measured value, making it easier to understand the magnitude of the error relative to the actual emissions. Absolute error represents the magnitude of the difference between the predicted and measured cumulative N_2O emissions, regardless of direction and reflects the overall size of the prediction discrepancy. Finally, the predicted/measured ratio is the ratio between the cumulative predicted N_2O emissions and the cumulative measured emissions. 1 indicates the model predicted perfectly, values greater than 1 indicate that the model over-predicted emissions, and values less than 1 indicate under-prediction.

Table 5.2: End-of-season metrics calculated from cumulative predicted and measured N_2O emissions for each growing season.

	2021	**2022**	**2023**
Measured Total[a]	96.8454	63.0817	8.5153
Predicted Total[b]	99.9337	91.3319	8.4247
Percent Error (%)[c]	3.1889	44.7835	-1.0639
Absolute Error[d]	3.0883	28.2502	0.0906
Predicted/Measured Ratio[e]	1.0319	1.4478	0.9894

[a] Measured Total: Cumulative N_2O emissions obtained from field measurements over the growing season in ppb m^{-2}.
[b] Predicted Total: Cumulative N_2O emissions estimated by the fuzzy logic model over the growing season in ppb m^{-2}.
[c] Percent Error: Relative difference between predicted and measured cumulative emissions expressed as a percentage.
[d] Absolute Error: Absolute difference between predicted and measured cumulative emissions in ppb m^{-2}.
[e] Predicted/Measured Ratio: Ratio of predicted cumulative emissions to measured cumulative emissions. Values greater than 1 indicate over-prediction and values less than 1 indicate under-prediction.

The percent error was very little and very impressive in the years 2021 and 2023. The model over-predicted slightly in 2021 and much more in 2022. However, it slightly under-predicted in 2023.

5.1.3 Growing Seasons

More details about the results from each growing season are presented.

2021

As seen in Figure 5.1a. The fuzzy logic (blue) shows similar peaks and dips, and overall follows the same general pattern. In this year, the fuzzy logic model over- and under-predicted N_2O emissions across the season. This year had the highest MAE compared to all, but even then, the value is not bad. When calculating metrics based on season totals (measured total against predicted total), the results were astonishing. The fuzzy logic model was very accurate for 2021. The percentage error was approximately 3%.

2022

In Figure 5.1b, the fuzzy logic (blue) does not capture the real emissions (red) perfectly, but does show similar peaks and dips of emissions and overall follows the same general pattern. We see that in this specific year, the fuzzy logic over-predicted the amount of N_2O for most of the season. Visually, we can tell that the fuzzy logic model was over-predicting for the latter part of the season. Recall that the average air temperature for 2022 was notably colder than for the other two seasons; this characteristic may or may not be responsible for impacting the model's tendency to over-predict N_2O for this particular season. As for end-of-season totals, percent error was approximately 45%, and the difference between the predicted and actual emissions was 28 ppb/m^2.

2023

The fuzzy logic (blue) does not capture the real emissions (red) perfectly, but does show similar peaks and dips of emissions and overall follows the same general pattern. From days 165 to 184, there is missing empirical data (where the red line starts) due to an experimental error, where turkeys ate the planted seeds in the research area, thus there is only the predicted fuzzy logic prior to that (blue line). The predicted N_2O emissions are well in line with the rest of the season otherwise, as seen in Figure 5.1c. For seasonal totals, the model performed well, with percent error only as approximately -1%. Trimming the datasets to corresponding days of predicted and empirical was taken into account prior to calculations.

5.1.4 Overview

In 2021 and 2023, percent errors were very low, whereas in 2022 they were much higher, indicating a greater discrepancy between predicted and measured N_2O values. Overall, the model performed well, but the year that it performed the worst was 2022. Perhaps there were some underlying circumstances that would lead to these differences in model accuracy between the years. Next, the input and output data will be examined to determine whether any unusual patterns exist in any year that may explain the variability in the fuzzy logic model's ability to predict N_2O.

5.2 Exploring Relationships of Collected Data

This section will focus on data exploration of the gathered dataset and exploring the relationships between them, for all experimental years, 2021, 2022, and 2023. The two input variables against each other will be explored, followed by how each input variable related with the output variable, N_2O. This portion uses the collected values, after data pre-processing for daily averages. The results are shown in Figure 5.2, then a breakdown of each case will follow.

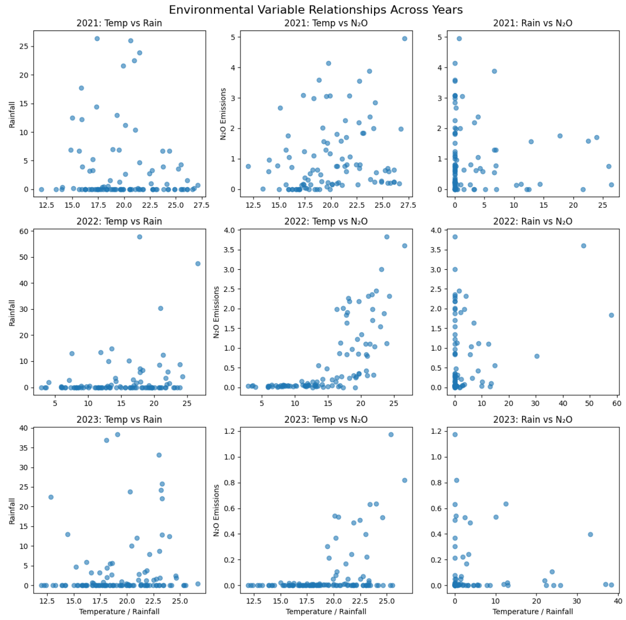


Figure 5.2: Exploratory data analysis.

5.2.1 Temperature versus Moisture

The relationship between temperature and rainfall was examined for each growing season to assess potential dependencies between the model input variables. No discernible pattern was seen when comparing the input variables against each other when viewing the graphs, as seen in Figure 5.3.

In 2021, both the Pearson correlation coefficient (r = –0.0940, p = 0.3522) and Spearman's rank correlation coefficient (ρ = –0.0515, p = 0.6111) indicated no significant linear or monotonic relationship between the variables. Similarly, in 2023, weak correlations were observed (r = 0.1271, p = 0.176; ρ = 0.2289, p = 0.0139), with only the Spearman coefficient reaching statistical significance, although the magnitude remained small.

In contrast, the 2022 dataset exhibited a weak but statistically significant positive Pearson correlation (r = 0.2359, p = 0.0181), suggesting a slight linear association between temperature and rainfall for that season. However, the corresponding Spearman coefficient (ρ = 0.1849, p = 0.0655) was not statistically significant, indicating that this relationship was not consistently monotonic.

Overall, the correlation analysis suggests that temperature and rainfall are only weakly related across all three growing seasons, with no strong or consistent relationship observed. The low magnitude of the correlation coefficients indicates that these variables capture largely independent environmental processes. This supports their use as separate inputs in the fuzzy logic model, as each contributes distinct information to the prediction of N_2O emissions.

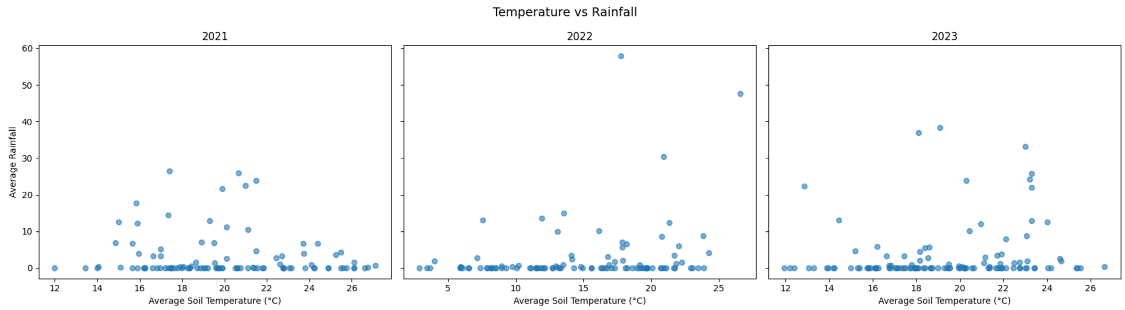


Figure 5.3: Input variables, temperature and rainfall, plotted against each other for all years. 2021 Pearson r: -0.0940 (p=0.3522) Spearman rho: -0.0515 (p=0.6111) 2022 Pearson r: 0.2359 (p=0.01813) Spearman rho: 0.1849 (p=0.06553) 2023 Pearson r: 0.1271 (p=0.176) Spearman rho: 0.2289 (p=0.01388)

5.2.2 Temperature versus Nitrous Oxide

A summary of the statistical relationships between temperature and N_2O emissions across all growing seasons is provided in Table 5.3. Recall that previous studies have reported that at lower, mild temperatures, nitrogen conversion happens slowly, but the rate increases as temperature rises (Akiyama et al., 2000; Brentrup et al., 2000; Hao et al., 2001, as cited by (Signor & Cerri, 2013)). Others have reported that over larger ranges, N_2O emissions increase exponentially with soil temperature (Liu et al., 2011, as cited by (Signor & Cerri, 2013)).

For the 2021 growing season, the relationship between temperature and N_2O emissions was examined using 100 data points, ranging from days of the year 160 to 259. Visual inspection of the scatterplot suggested a weak positive linear trend (Figure 5.4), which was supported by the correlation analysis. The Pearson correlation coefficient (r = 0.2208, p = 0.0273) and Spearman's rank correlation coefficient (ρ = 0.3135, p = 0.0015) both indicated a statistically significant positive association between temperature and emissions, although the strength of the relationship remained weak. The linear regression slope of 0.0707 suggests that N_2O emissions increased slightly with temperature; however, the low coefficient of determination (R^2 = 0.0487) indicates that temperature alone explains less than 5% of the variability in emissions. An exponential model provided a modest improvement in fit (R^2 = 0.1399), suggesting that the relationship may exhibit some nonlinear characteristics, although the overall explanatory power remains limited.

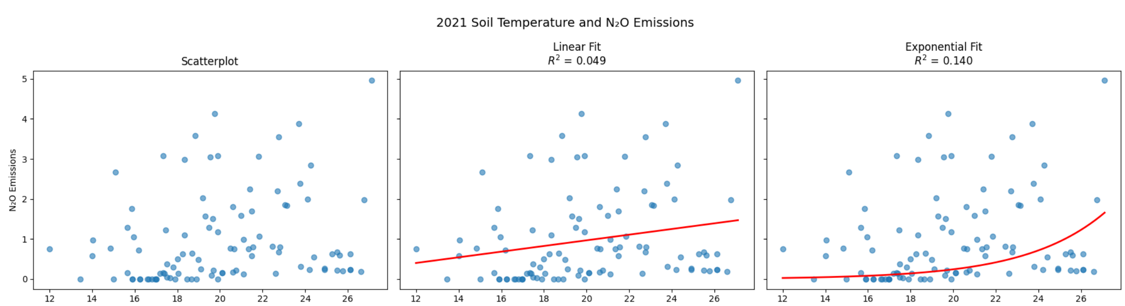


Figure 5.4: 2021 temperature verses N_2O emissions

For the 2022 growing season, the relationship between temperature and N_2O emissions was evaluated using 100 data points spanning days of the year 210 to 309. Visual inspection of the data revealed a clear positive trend (Figure 5.5), which was strongly supported by the correlation analysis. Coinciding with past literature, the trend was exponential. The Pearson correlation coefficient (r = 0.6940, p = 1.188 × $10^{-}15$) and Spearman's rank correlation coefficient (ρ = 0.7765, p = 2.275 × $10^{-}15$) both indicate a strong and statistically significant positive relationship between temperature and emissions. The linear regression slope of 0.1088 suggests that emissions increase slightly with temperature, and is further supported by the coefficient of determination (R^2 = 0.4817), indicating that nearly 48% of the variability in emissions can be explained by temperature alone under a linear assumption. However, an exponential model provided a notably improved fit (R^2 = 0.7152), suggesting that the relationship between temperature and N_2O emissions in 2022 is best characterized as nonlinear. These results indicate that temperature was a dominant driver of emission variability during this season, with increasing temperatures associated with disproportionately higher N_2O emissions.

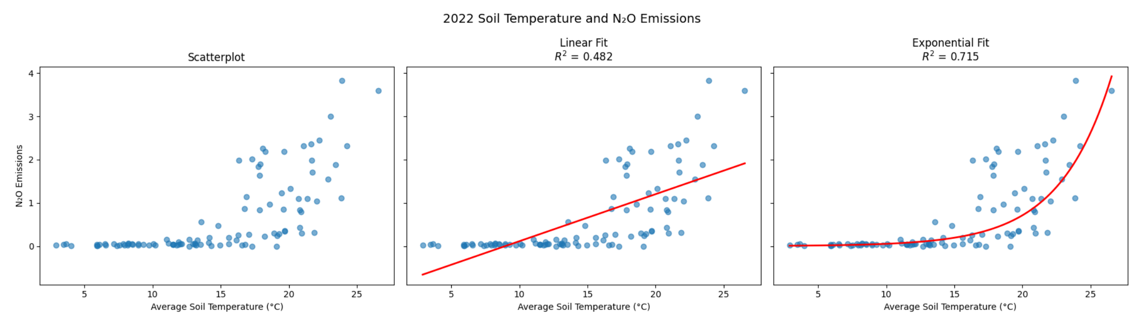


Figure 5.5: 2022 temperature verses N_2O emissions

For the 2023 growing season, the relationship between temperature and N_2O emissions was analyzed using 115 observations spanning days of the year 165 to 279. Visual inspection of the data suggested a weak to moderate positive trend (Figure 5.6). This was partially supported by the correlation analysis, where the Pearson correlation coefficient (r = 0.4086, p = 5.814 × $10^{-}06$) indicated a statistically significant moderate positive linear relationship. In contrast, the Spearman's rank correlation coefficient (ρ = 0.1696, p = 0.0700) was weaker and not statistically significant, suggesting that the monotonic relationship between temperature and emissions was less consistent. The linear regression slope of 0.0235 indicates a relatively small increase in emissions with temperature compared to previous years, with the coefficient of determination (R^2 = 0.1669) showing that approximately 17% of the variability in emissions can be explained by temperature under a linear model. An exponential model provided a slightly better fit (R^2 = 0.2958), indicating some degree of nonlinear behavior, although the overall explanatory power remains low. These results suggest that temperature influenced N_2O emissions in 2023, but the variability shows that emissions are not fully captured by temperature alone. For 2023, the trend cannot be explained by a linear regression slope, nor is it truly exponential. For this year, other factors must have played a role. For example, perhaps the different fertilizer type had to do with this. It is imperative to keep differences in mind when assessing studies.

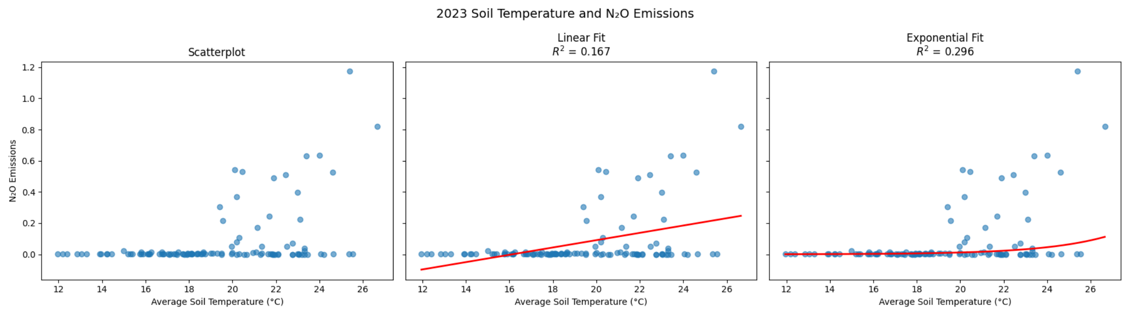


Figure 5.6: 2023 temperature verses N_2O emissions

Across the three growing seasons, the relationship between temperature and N_2O emissions exhibited notable variability in both strength and form. In 2021, the relationship was weak, with low correlation coefficients and minimal explanatory power, indicating that temperature alone was not a strong predictor of emissions. In contrast, 2022 showed a strong and statistically significant relationship, with substantially higher correlation coefficients and R^2 values, and an exponential model providing the best fit. This suggests that temperature acted as a dominant driver of emissions during that season. The 2023 results fell between these two cases, with a moderate linear relationship but weaker monotonic association, indicating a more variable and less consistent influence of temperature. Overall, these findings suggest that while temperature plays an important role in influencing N_2O emissions, although its predictive strength varies across years, and differing behavior may be present under certain environmental conditions. These results indicate that while temperature has a statistically detectable influence on N_2O emissions, it is not sufficient on its own to fully explain emission variability, supporting the inclusion of additional variables such as rainfall in the model.

Table 5.3: Summary of temperature versus N_2O emission relationships across growing seasons.

Metric	**2021 (N=100)**	**2022 (N=100)**	**2023 (N=115)**
Pearson r (p-value)[a]	0.2208 (0.0273)	0.6940 (1.19×10^{-15})	0.4086 (5.81×10^{-6})
Spearman ρ (p-value)[b]	0.3135 (0.0015)	0.7765 (2.28×10^{-15})	0.1696 (0.0700)
Linear slope[c]	0.0707	0.1088	0.0235
Linear R^2[d]	0.0487	0.4817	0.1669
Exponential R^2[e]	0.1399	0.7152	0.2958

[a] Pearson correlation coefficient measuring linear association between temperature and N_2O emissions.

[b] Spearman's rank correlation coefficient measuring monotonic association between temperature and N_2O emissions.

[c] Slope of the linear regression model representing the rate of change in N_2O emissions with temperature.

[d] Coefficient of determination for the linear model, indicating the proportion of variance explained.

[e] Coefficient of determination for the exponential model, indicating goodness-of-fit for nonlinear behaviour.

5.2.3 Moisture versus Nitrous Oxide

The relationship between rainfall and N_2O emissions was examined across all three growing seasons using correlation analysis (Table 5.4). Recall that in general, higher soil moisture leads to higher N_2O emissions (Baggs et al., 2000; Giacomini et al., 2006, as cited by (Signor & Cerri, 2013)). However, at very high moisture levels, N_2O production can actually decrease. In regards to soil moisture fluctuations between wet and dry conditions, emissions tend to increase (Brentrup et al., 2000, as cited by (Signor & Cerri, 2013)).

In 2021, both the Pearson correlation coefficient (r = –0.0601, p = 0.5525) and Spearman's rank correlation coefficient (ρ = –0.0689, p = 0.4961) indicated no significant linear or monotonic relationship between rainfall and emissions. Similarly, in 2023, the Pearson coefficient (r = 0.0568, p = 0.5467) suggested no linear association, while the Spearman coefficient (ρ = 0.2675, p = 0.0038) indicated a weak but statistically significant monotonic relationship.

In contrast, the 2022 dataset exhibited a weak but statistically significant positive Pearson correlation (r = 0.2816, p = 0.0045), suggesting a slight linear association between rainfall and N_2O emissions during that season. However, the corresponding Spearman coefficient (ρ = 0.1380, p = 0.1708) was not statistically significant, indicating that this relationship was not consistently monotonic. Given the absence of a clear trend in the visual analysis, along with weak and inconsistent correlation coefficients, further linear or exponential model fitting was not pursued.

Overall, the results indicate that rainfall exhibits weak and inconsistent relationships with N_2O emissions across all years (Figure 5.7). While some statistically significant correlations were observed, the magnitude of these relationships remains low, suggesting that rainfall alone is not a strong predictor of emission variability. This supports the role of rainfall as a secondary, modulating factor in the model, influencing emission dynamics indirectly rather than acting as a primary driver.

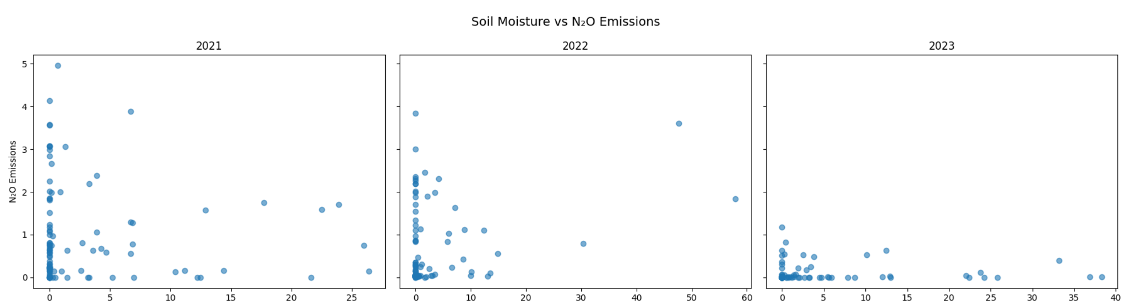


Figure 5.7: Rainfall versus N_2O emissions for all years, 2021, 2022, and 2023.

Table 5.4: Summary of rainfall versus N_2O emission relationships across growing seasons.

Metric	**2021**	**2022**	**2023**
Pearson r (p-value)[a]	-0.0601 (0.5525)	0.2816 (0.0045)	0.0568 (0.5467)
Spearman ρ (p-value)[b]	-0.0689 (0.4961)	0.1380 (0.1708)	0.2675 (0.0038)

[a] Pearson correlation coefficient measuring linear association between rainfall and N_2O emissions.

[b] Spearman's rank correlation coefficient measuring monotonic association between rainfall and N_2O emissions.

5.3 Concluding Remarks

For the different years, the results were not conclusive; for the results of 2021 and 2023 performed better than that of 2022. More research and repeating this experiment to obtain more cases should be done to determine if similar patterns exist to explain how and why this happened. There is always room for improvement with these daily N_2O predictions; however, most of the evaluation metrics were adequate, and from the visual graphs, it is clear and undeniable that the patterns of predicted emissions match peaks and valleys of the real N_2O data. The end-of-season cumulative totals are very accurate in some years, particularly the ones in which temperature has a more linear relationship with N_2O, although more research should be performed before making any hard conclusions as to if that is the reason why the model performed better for those years (2021 and 2023).

For very accurate daily emission predictions, there could be other more complex models that could be used for better accuracy. In regards to cumulative end-of-year total prediction accuracy, the findings from 2021 and 2023 support the overarching idea that this model could be used in real-world settings by interested parties for estimating the amount of N_2O emitted from a farmland site. However, the results from 2022 imply that there needs to be more work to be done for this model. It is a possibility that the over-prediction was due to environmental differences, such as the lower average air temperature reported for that season, but more investigation must be done before making any conclusions about this postulation.

For all years, the soil versus N_2O emissions scatterplots revealed similar patterns, where most of the higher emissions were concentrated at lower soil moisture and less at higher soil moisture levels. This does seem to be in line with previous research, where there exists a threshold of moisture where N_2O production is hindered. However, in this study, it is unclear exactly what the WFPS was at each of the average soil moisture levels, so it is hard to say for certain if it really supports the same notions that other researchers have concluded, which is that emissions peak at around 70-80% water-filled pores.

As for trying to establish any concrete answers as to whether temperature has a linear or exponential relationship with N_2O emissions, this is more puzzling. One year aligned better with a weak linear positive trend, another showed an exponential curve, whereas the last one seemed to be a mix. Thus, from these limited datasets, it is inconclusive and more analysis should be done if provided more data. It is clear that the trend is positive, though, which does align with previous research and is the overall consensus.

A comparison of the input variables shows that temperature has a stronger and more consistent relationship with N_2O emissions than rainfall across all three growing seasons. Temperature shows moderate to strong correlations with emissions, especially in 2022, and generally explains more of the variability based on the regression analysis results. In contrast, rainfall has a less apparent relationship with N_2O, seen by lack of correlation. Overall, these findings suggest that temperature is the main driver of emission variability, while rainfall is a secondary influence. Rather than directly controlling emission levels, rainfall drives emissions indirectly by its effect on soil moisture. This aligns with the structure of the fuzzy logic model, where temperature determines the emission category, and rainfall adjusts the strength of the rule activation.

The following chapter will provide some concluding thoughts and insights as to how to improve the results of this experiment.

Chapter 6

Discussion

In the results section, there were two main comparisons that took place: how the model performed day-by-day when given soil temperature and moisture as inputs for predicting nitrous oxide emissions as well as evaluating how well the model did with seasonal totals of predicted nitrous oxide emissions versus the measured. Additionally, how temperature and moisture related to each other and how each related to nitrous oxide emissions was explored.

The results of this study demonstrate that a simplified fuzzy logic model can reasonably capture the variability in daily N_2O emissions using only temperature and rainfall as input variables. While model performance varied across growing seasons, several consistent patterns emerged regarding the roles of these environmental drivers. In particular, temperature was found to be the dominant factor influencing emission variability, while rainfall exhibited a weaker and more indirect influence. These findings align with the conceptual design of the fuzzy rule base and provide insight into the environmental controls governing N_2O production in agricultural soils.

6.1 Daily & Seasonal Nitrous Oxide Predictions

Based on the graphical results, it is evident that the fuzzy logic model is able to predict similar patterns of nitrous oxide emitted as the real values were, but it is obvious that there are some prediction timing differences, such as lag, advances, under- and over-predictions. However, when comparing the seasonal totals, the evaluation metrics were fairly impressive in some years.

With this information, I can say that this fuzzy logic model lacks extremely accurate predictions of day-to-day nitrous oxide emissions, and that is a point for further research, and other more complex and more computationally intense prediction models would be able to outperform this one. That said, for several years, the temporal agreement was not poor, but there is room for improvement. However, the model performed well when used by interested parties to estimate end-of-season nitrous oxide emissions, and this claim is supported by strong evaluation metrics. If users of this model are not necessarily interested in highly accurate day-to-day predictions, this fuzzy logic model is suitable.

This nitrous oxide predicting fuzzy logic model is great since the input variables are relatively simple to obtain, which include one impulse measurement, soil temperature, and soil moisture. The single-impulse measurement is beneficial because expensive equipment is required only once for this process (rather than continuously for empirical measurements). For pre-processing of the data, what is needed is calculating the averages across the sensors as well as throughout each 24-hour block of time for the days of the growing season. The model is easy to use and computationally efficient, and we now know that its accuracy for seasonal totals is very good. These qualities make it a strong candidate for use and deployment by interested parties seeking a ballpark estimate of nitrous oxide emissions in their area of study or interest.

The fuzzy logic model demonstrated reasonable predictive performance across all three growing seasons, particularly when evaluated using absolute error metrics and cumulative seasonal totals. The model was able to capture general emission trends and approximate total emissions with relatively low error in most cases. However, variability in model performance between years highlights the challenges associated with predicting N_2O emissions in complex environmental systems.

One notable observation was the consistently high MAPE values, which were influenced by the presence of very small measured emission values near zero. In such cases, even small absolute differences between predicted and measured values can result in disproportionately large percentage errors. This limitation suggests that MAPE should be interpreted cautiously in datasets characterized by low baseline emissions, such as this one.

Overall, the model's ability to reproduce general trends using a simplified rule-based structure demonstrates the potential of fuzzy logic as a cost-effective alternative to more complex and data-intensive approaches.

6.2 Variable Relationships

The relationship between average temperature and nitrous oxide emissions varied across years. During the 2021 growing season, the temperature-N_2O relationship was weakly linear, suggesting that temperature influenced emissions proportionally. In contrast, the 2022 growing season exhibited a clear exponential relationship, where increases in temperature corresponded to disproportionately larger increases in N_2O emissions. This indicates that temperature played a more dominant and nonlinear role in driving emissions during that year. The pattern in 2023 sat between linear and exponential, not fitting either curve well, so it was possible that other variables were more important for influencing N_2O emissions this year, but still showed increasing N_2O emissions as temperature increased. Perhaps the temperature variable factored in with the different fertilizer type and concentration used for this particular year impacted the relationship seen. These year-to-year differences show that the effect of temperature on N_2O emissions isn't fixed, and depend on many different conditions and factors in each season. This supports the notion of using flexible models that can capture both linear and nonlinear relationships, such as fuzzy logic implementations.

For all years, the relationship between moisture and nitrous oxide emissions was fairly similar. Visual inspection of the relationship between soil moisture and N_2O emissions suggests a nonlinear, regime-based response rather than a smooth monotonic trend. Elevated N_2O emissions are primarily observed at lower soil moisture levels, while emissions decrease sharply and remain close to zero as soil moisture increases. Consequently, this relationship is not well described by a linear, logarithmic, nor exponential trend line.

6.2.1 Role of Soil Temperature

Across all three growing seasons, temperature consistently exhibited a stronger relationship with N_2O emissions compared to rainfall, although the magnitude and nature of this relationship varied between years. The 2022 dataset demonstrated the strongest dependence on temperature, where correlation analysis indicated a strong positive relationship between input and output in an exponential fashion.

This observation is consistent with established understanding of soil biogeochemical processes. N_2O emissions are largely driven by microbial activity associated with nitrification and denitrification, in which both are temperature-sensitive processes. As temperature increases, microbial metabolism does too, leading to higher rates of nitrogen transformation and thus increased N_2O production.

Although still positive, the weaker relationships observed in 2021 and 2023 suggest that temperature alone is not always sufficient to explain emission variability. This shows that other factors could also be influencing factors, like soil moisture and changing field conditions over time. Nonetheless, the consistent positive relationship between temperature and emissions across all years supports its role as the primary driver in the fuzzy logic model, where it governs the overall emission category.

6.2.2 Role of Soil Moisture

In comparison to temperature, soil moisture (which was approximated by average rainfall) exhibited weak and inconsistent relationships with N_2O emissions across all three growing seasons. Even though some of the correlations were statistically significant, they were still weak overall, and no consistent trend was identified across years. This suggests that rainfall does not directly control emission magnitude in a predictable manner.

Rather, rainfall appears to influence N_2O emissions indirectly through its effect on soil moisture conditions. Soil moisture regulates oxygen availability within soil pores, which in turn controls the balance between nitrification and denitrification processes. In excessively dry conditions and in overly water-saturated soils, microbial activity is decreased.

This interpretation aligns with the structure of the fuzzy logic model, where rainfall does not determine the emission category but instead influences the firing strength of the rules. The indiscernible relationships observed in the data support the design choice of making rainfall as a secondary input that modifies emission behaviour.

6.3 Comparison with Previous Studies

In Chapter 2, two recent studies were introduced that addressed the same problem of predicting N_2O emissions from farmland using similar environmental data. While they shared the same overall objective as this study, they explored different prediction techniques, namely an agriculture-informed neural network and a federated learning approach. The main differences between these approaches and the proposed fuzzy logic model are discussed.

For cumulative end-of season totals, the average accuracy of this approach was 80% and was based on simple inputs, making it a decent contender for N_2O predictions. The daily accuracy varied across growing seasons and could be described as decent but needing improvement. However, the other two studies mainly focused on daily prediction accuracy and were more computationally intensive, thus providing higher daily accuracy.

The agriculture-informed neural network proposed by Lin et al. (2024) achieved higher predictive performance by integrating deep learning with a process-based ecosystem model. It required substantially more environmental inputs, including soil temperature, soil moisture, humidity, water flux, and estimated nitrate concentrations.

Compared with the IoT-based machine learning models presented by Killeen et al. (2025), the fuzzy logic model developed in this study achieved lower daily prediction accuracy but again required substantially fewer input variables and considerably less computational complexity. The machine learning models, particularly Random Forest and LSTM, achieved very high predictive performance through extensive feature engineering, multivariate sensor data, and advanced training procedures.

The proposed fuzzy logic model occupies a different niche than the two machine learning approaches. While both the Agriculture-Informed Neural Network (AINN) and the federated learning framework achieved higher daily prediction accuracy through the use of numerous environmental variables, advanced machine learning algorithms, and extensive model training, they also required substantially greater data availability and computational resources. In contrast, the fuzzy logic model developed in this study relies only on daily temperature and rainfall, requires no training, and produces fully interpretable predictions through its rule base and membership functions. Although its daily prediction accuracy is lower, the model maintained approximately 3% cumulative seasonal prediction error, demonstrating that practical N_2O emission estimates can be obtained using a simple, low-cost approach suitable for applications where sensor availability and computational resources are limited.

Table 6.1: Comparison of the proposed fuzzy logic model with recent machine learning approaches for N_2O prediction.

Characteristic	Proposed Fuzzy Logic Model	Agriculture-Informed Neural Network (AINN)	Federated Learning Framework
Prediction approach	Mamdani fuzzy inference system	Agriculture-informed neural network combining deep learning with the Dynamic Land Ecosystem Model (DLEM)	Machine learning and deep learning models (Random Forest, LSTM, CNN, MLP) trained using centralized and federated learning
Primary objective	Develop a simple, interpretable, and low-cost prediction model	Maximize prediction accuracy by incorporating agricultural process knowledge into deep learning	Demonstrate privacy-preserving N_2O prediction using federated learning while maintaining high prediction accuracy
Primary inputs	Daily temperature and rainfall	Soil temperature, soil moisture, air temperature, humidity, water flux, estimated nitrate, and temporal sequences	Weather, soil temperature, soil moisture, pH, nitrogen, phosphorus, potassium, and numerous engineered features
Model complexity	Low	High	Very high
Model training required	No	Yes	Yes
Interpretability	High; predictions are directly explained by membership functions and fuzzy rules	Moderate; improved over conventional neural networks through DLEM integration	Low to moderate; model behavior depends on complex machine learning algorithms
Data requirements	Minimal	Extensive multivariate time-series	Extensive sensor network with feature engineering
Daily prediction performance	Variable (R^2 = 0.45–0.82 across growing seasons)	Higher than conventional neural networks across all evaluated metrics	Very high; best models achieved R^2 values approaching 0.98–0.99
Seasonal prediction performance	Approximately 3% cumulative seasonal prediction error	Focus was on improving daily prediction accuracy	Focus was on daily prediction accuracy
Computational requirements	Low	High	High
Primary advantage	Simple, inexpensive, and easily deployable	Highest predictive accuracy (while incorporating agricultural process knowledge)	High predictive accuracy (while preserving farmer privacy)
Primary limitation	Lower daily prediction accuracy than advanced machine learning methods	Requires numerous environmental variables, model training, and greater computational resources	Requires extensive sensor infrastructure, feature engineering, and computational resources

6.4 Strengths & Limitations

One of the primary strengths of the proposed fuzzy logic model is its simplicity. Unlike recent machine learning approaches, such as agriculture-informed neural networks and federated learning frameworks, the model requires only daily temperature and rainfall as input variables, eliminating the need for extensive environmental measurements, feature engineering, or model training. This significantly reduces data collection requirements and computational complexity while maintaining good predictive performance. In addition, the fuzzy rule base and membership functions provide a transparent and interpretable prediction process, allowing the influence of each input variable on the final prediction to be readily understood. The model is also computationally inexpensive, making it well suited for deployment in agricultural settings where access to advanced sensing equipment or high-performance computing resources may be limited. Although the proposed approach does not achieve the same level of daily prediction accuracy as more complex machine learning models, it demonstrates that meaningful estimates of N_2O emissions can be obtained using a simple, low-cost, and easily deployable framework.

Several limitations should be considered when interpreting the results of this study. First, the model relies on a limited number of input variables, which do not fully capture the multitude and complexity of factors influencing N_2O emissions. Second, the variability observed between growing seasons suggests that the model may be sensitive to year-specific environmental conditions that may need more accounting for, even though the impulse measurement is taken at the beginning of the fuzzy logic model process to try to characterize specific conditions of the site and year. Additionally, using daily aggregated data can hide short-term fluctuations in emissions that happen at finer time scales, such as differences in mornings, afternoons, evenings, and nights. Finally, while the fuzzy logic model provides a simplified and interpretable framework, it does not incorporate learning or adaptation mechanisms, which may limit its ability to generalize across different datasets or environmental conditions.

Despite these limitations, the findings of this study demonstrate the potential for simplified modeling approaches to estimate N_2O emissions using readily available environmental data. This has important implications for agricultural monitoring, particularly in contexts where access to high-cost measurement technologies is limited.

6.5 Concluding Remarks

This chapter focused on discussing the implications of the results section. The effectiveness of the model's ability to capture daily and seasonal N_2O was reviewed, as well as the role that temperature and moisture had on the emission output. A brief comparison of this study with other studies that focus on the predictions of N_2O was provided. The strengths and limitations of this research were also mentioned. The following chapter will discuss potential ways to expand on this research, since this general framework also provides the stepping-stones to plausible future studies based on the same fuzzy logic ideas.

Chapter 7

Conclusions and Future Work

This section will provide concluding thoughts about the overall project, as well as ideas for future directions for this work.

7.1 Conclusions

Nitrous oxide (N_2O) is a potent greenhouse gas, even more so than carbon dioxide (CO_2), per unit of equal weight. N_2O is released from soils through the natural biological processes of nitrification and denitrification, primarily through denitrification. These processes are mediated by microorganisms in the soil, and their activity is driven by abiotic factors such as soil temperature and soil moisture.

Although these soil processes occur naturally, the rate at which N_2O is emitted from the ground can be exacerbated in agricultural systems due to the application of nitrogen-based fertilizers. As governments set goals to reduce greenhouse gas emissions, measuring N_2O emissions has been a hot topic. Numerous technologies can accurately quantify these emissions, including trace gas analyzers. However, such machinery is often very expensive, not easily portable, and not user-friendly. This is where predictive models can serve as a practical alternative to direct measurement techniques.

This research project utilizes a fuzzy logic model to predict N_2O emissions with few inputs and is computationally efficient. Across all three growing seasons, temperature was identified as the primary driver of N_2O emission variability, while rainfall exhibited a weaker and more indirect influence. This finding aligns with the structure of the fuzzy rule base, where temperature governs emission categories and rainfall modifies rule firing strength.

This model had relatively good accuracy in predicting cumulative N_2O emissions at the end of each season; however, the daily temporal patterns of emissions were not always aligned, although there were similar patterns between the predicted and measured emissions. This indicates that short-term, daily variability is not fully captured by this model.

The contribution of this work is demonstrating that reasonable N_2O emission predictions can be achieved by balancing prediction accuracy with implementation cost, interpretability, and ease of deployment. This thesis shows that a computationally efficient and interpretable fuzzy logic approach can provide meaningful estimates of N_2O emissions without over-relying on expensive measurement technologies or complex data requirements. This suggests that this model is good for providing generalized patterns as well as overall seasonal N_2O emission predictions to a decent degree and can be deployed in scenarios where the participants are interested in N_2O predictions, rather than exact measurements.

7.2 Future Work

There are several avenues to explore for future work. Ideas for future work revolve around potential adjustments to the dataset, additional input variables, modifying the rule base, and expanding the use of this predictive methodology to other areas. Future work could focus on incorporating additional variables, such as soil moisture measurements or nitrogen application data to improve model accuracy. Furthermore, ideas for integrating data-driven components into the fuzzy logic framework may enhance its predictive capabilities while maintaining interpretability are presented.

To address lag and improve the accuracy of day-to-day predictions, I suggest exploring additional readily available inputs to incorporate into the model. Possibilities include soil pH, initial context of organic matter in the soil, or continuous monitoring of water-filled pore space (WFPS). Although adding more inputs would make designing the rule base more complex and increase computational requirements, it is a necessary trade-off to produce more accurate daily predicted nitrous oxide readings.

Another avenue to potentially improve predictions would be to increase the number of records that are used to compute the predictions. For example, instead of using one daily average reading for temperature and moisture, perhaps calculating average temperature and moisture readings in 4 hour blocks per day would increase the number of records 6-fold for more predictions in each 24 hour cycle. Again, although this increases complexity in the input data for the fuzzy logic model, it may be beneficial for higher accuracy.

Direct soil moisture measurements (such as WFPS) would likely improve the model, as soil moisture more directly influences the microbial processes responsible for N_2O production than rainfall alone. In this study, rainfall was used as a proxy for soil moisture because it is a readily available and easily measured environmental variable. While expanding the rainfall membership functions or introducing an additional ”Extreme” rainfall category could improve the representation of large precipitation events, these modifications alone may not fully capture the complex relationship between soil moisture and microbial activity. For example, when soil WFPS exceeds approximately 80%, increasingly anaerobic conditions may promote the reduction of N_2O to N_2, resulting in lower N_2O emissions despite continued microbial activity. In addition, precipitation patterns, including the frequency and timing of rainfall events and alternating wet and dry periods, have been shown to influence N_2O emissions and could be considered in future model development.

Future work could investigate the use of the proposed framework as a decision-support tool for evaluating different fertilizer management practices. By calibrating the fertilizer-related parameters for different application rates, timings, or fertilizer formulations, the model could be used to compare their relative impacts on predicted N_2O emissions for a given field. First, it can be used to predict N_2O emissions across different nitrogen-based fertilizer testing plots. For example, application techniques include broadcast, banding, liquid irrigation, controlled-release fertilizers, and variable-rate or split application of fertilizers (Adika, 2023). Another potential idea is to test the differences between different kinds of nitrogen fertilizers, including the three synthetic types: nitrate, ammonia/ammonium, and urea or organic options like manure or compost (Blalock, 2024).

Another idea is to use this fuzzy logic model in different study sites, which would have different geographical locations, soil types, and weather patterns to predict N_2O emissions. Expanding the model to diverse agricultural systems would help assess its generalizability and potential as a scalable tool for estimating N_2O emissions.

Another avenue of future work could include integration of the fuzzy logic model with a low-cost in-field soil sensor to support automated, near-real-time N_2O emission prediction. A sensor measuring WFPS could provide a direct representation of soil moisture, while temperature could be obtained from the same sensor network or a nearby weather station. The measurements could be transmitted to a small edge-computing device that applies the fuzzy membership functions and rule base to generate daily emission estimates. This approach would reduce reliance on rainfall as a proxy for soil moisture and would better represent conditions following extreme precipitation, prolonged saturation, or rapid drying. Because fuzzy inference requires limited computational resources and no model retraining, the system could potentially be deployed using low-cost agricultural sensor networks.

A useful extension of this work would be to perform a sensitivity analysis to evaluate the robustness of the fuzzy logic model to changes in its inputs and design parameters. One possible approach would be to systematically perturb the boundaries of the temperature and rainfall membership functions while keeping the rule base and all other model parameters unchanged. The model could then be rerun using the original datasets, and the resulting daily and cumulative seasonal predictions compared with those of the baseline model. Such an analysis would quantify the influence of the selected membership function boundaries on model performance and determine whether small changes in the fuzzy set definitions produce significant differences in predicted N_2O emissions. This would provide additional confidence in the stability of the model and help identify opportunities for further refinement of the fuzzy inference system.

I would also suggest investigating why the year 2022 cumulative predictions were not as good as the other years, such as diving deeper into other weather patterns or other possible factors that could have contributed to their relatively worse outcome. A possibility could have been the lower average temperature of this season relating to the model over-predicting. Another thought is to note that a strong exponential relationship was discovered between temperature versus N_2O emissions for this year. There must be some way to further enhance and tweak the model to account for different qualities present in various datasets from different years in the future to make the accuracy of predicted cumulative N_2O emissions better.

Future work based off of this research project focuses on potential ideas on how to improve prediction accuracy, how this technology can be used, how it can be expanded on, and investigate potential reasons for model performance discrepancy in different years .

7.3 Concluding Remarks

As of now, the end goal of this technology is to provide agricultural stakeholders interested in monitoring their N_2O emissions with a low-cost and practical solution, in which fuzzy logic meets this requirement since it is a useful computational method for circumstances where quick approximations are needed. While at this point, initial soil characterization still requires the use of a LI-COR trace gas analyzer, this step can be carried out over a short period by a research facility, agronomist, or government agency. Following this, the methodology only needs affordable soil sensors or publicly available weather data acquired from near the site can be used to predict N_2O emissions with a reasonable degree of accuracy.

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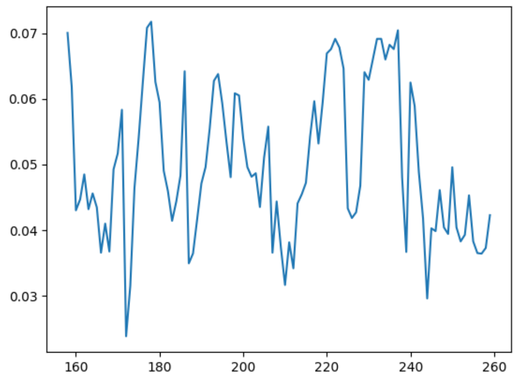
Supplementary Materials

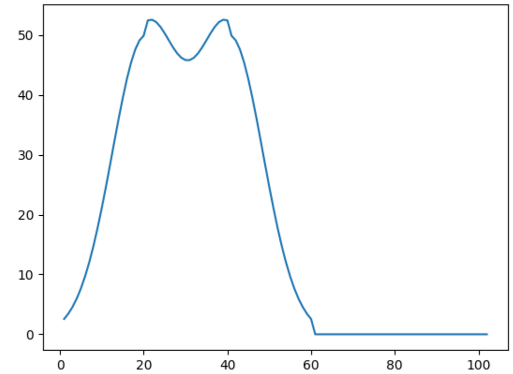
Additional Line Graphs

Additional graphs relating to the Results, Chapter **??**.

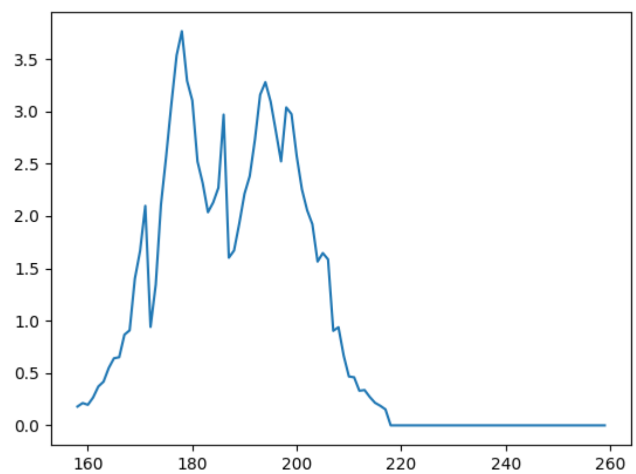
2021



(a) Plot of lsindex versus lsN2Orate for 2021. The x-axis, lsindex, represents days of the year while the y-axis represents the rate of N_2O emitted over the range of that time period, corresponding to day 160 to day 259 of the year 2021.



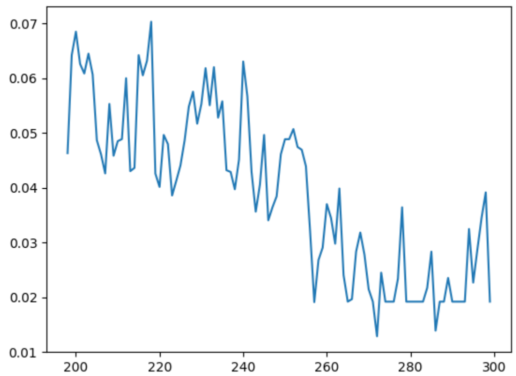
(b) Plot of lsi versus lsdecay for 2021. The x-axis represents the sample index from day 0 to 99 (data for the experiment took place over 100 days). The y-axis represents the decay of nitrogen, thus leading to N_2O emissions. There is a gradual increase in nitrogen decay leading up to day 20. We see elevated decay levels from around day 20 to day 50 of the experiment timeframe. There is a gradual decrease of nitrogen decay from then to around day 60.



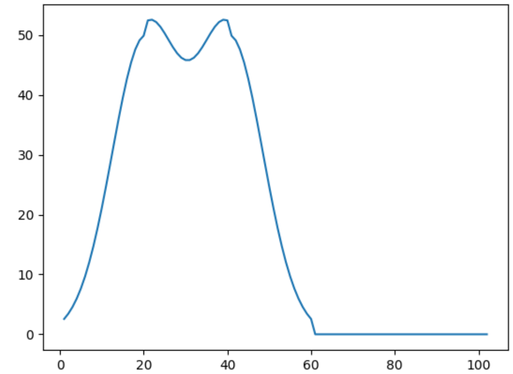
(c) Plot of lsindex versus lsN2O for 2021. The x-axis, lsindex, represents days of the year, corresponding to day 160 to day 259 of the year 2021. The y-axis represents the amount of N_2O emitted across that timeframe. We see peaks earlier in the season, and then negligible amounts of N_2O emitted at the end of the season.

Figure 7.1: Additional plots for the 2021 dataset.

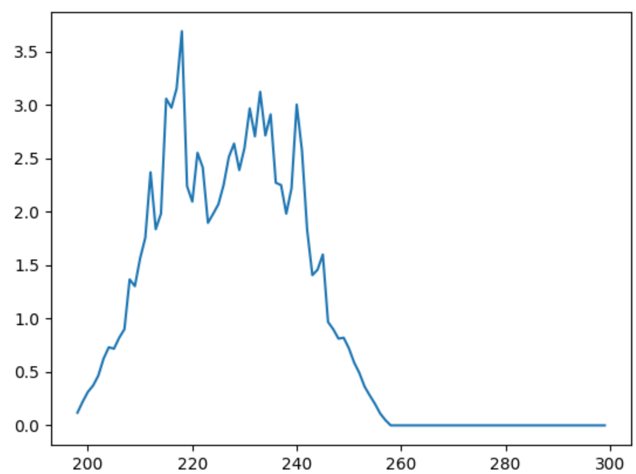
2022



(a) Plot of lsindex versus lsN2Orate for 2022. The x-axis, lsindex represents days of the year while the y-axis represents the rate of N_2O emitted over the range of that time period, corresponding to day 210 to day 309 of the year 2022.



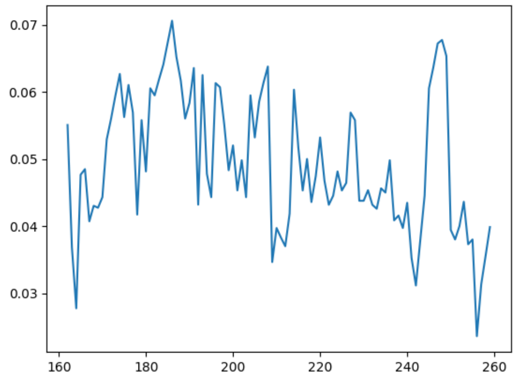
(b) Plot of lsi versus lsdecay for 2022. The x-axis represents the sample index from day 0 to 99 (data for the experiment took place over 100 days). The y-axis represents the decay of nitrogen, thus leading to N_2O emissions. There is a gradual increase in nitrogen decay up until around day 25. We see elevated decay levels from around day 25 to day 45 of the experiment timeframe. There is a gradual decrease in nitrogen decay from then to around day 60.



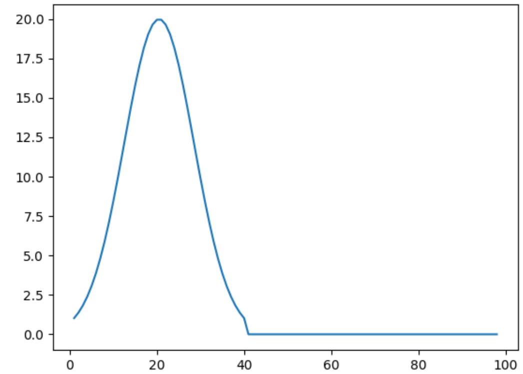
(c) Plot of lsindex versus lsN2O for 2022. The x-axis, lsindex, represents days of the year, corresponding to day 210 to day 309 of the year 2022. The y-axis represents the amount of N_2O emitted across that timeframe. We see peaks earlier in the season, and then negligible amounts of N_2O emitted at the end of the season.

Figure 7.2: Additional plots for the 2022 dataset.

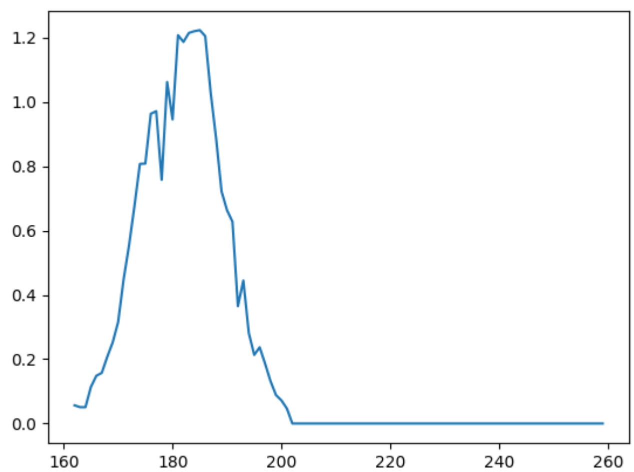
2023



(a) Plot of lsindex versus lsN2Orate for 2023. The x-axis, lsindex represents days of the year while the y-axis represents the rate of N_2O emitted over the range of that time period, corresponding to day 165 to day 260 of the year 2023.



(b) Plot of lsi versus lsdecay for 2023. The x-axis represents the sample index from day 0 to 99 (data for the experiment took place over 100 days). The y-axis represents the decay of nitrogen, thus leading to N_2O emissions. There is an increase in nitrogen decay up until around day 20 then decrease in nitrogen decay from then to around day 40.



(c) Plot of lsindex versus lsN2O for 2023. The x-axis, lsindex, represents days of the year, corresponding to day 160 to day 260+ of the year 2023. The y-axis represents the amount of N_2O emitted across that timeframe. We see peaks earlier in the season, and then negligible amounts of N_2O emitted at the end of the season, slightly after day 200.

Figure 7.3: Additional plots for the 2023 dataset.

Fuzzy Logic Code

```python
# -*- coding: utf-8 -*-
"""
Fuzzy␣Logic␣Temperature␣Controller
"""

from fuzzylogic import *
from matplotlib import pyplot as plt

def trimf(x, points):
    pointA = points[0]
    pointB = points[1]
    pointC = points[2]
    slopeAB = getSlope(pointA, 0, pointB, 1)
    slopeBC = getSlope(pointB, 1, pointC, 0)
    result = 0
    if x >= pointA and x <= pointB:
        result = slopeAB * x + getYIntercept(pointA, 0, pointB, 1)
    elif x >= pointB and x <= pointC:
        result = slopeBC * x + getYIntercept(pointB, 1, pointC, 0)
    return result


def trapmf(x, points):
    pointA = points[0]
    pointB = points[1]
    pointC = points[2]
    pointD = points[3]
    slopeAB = getSlope(pointA, 0, pointB, 1)
    slopeCD = getSlope(pointC, 1, pointD, 0)
    yInterceptAB = getYIntercept(pointA, 0, pointB, 1)
    yInterceptCD = getYIntercept(pointC, 1, pointD, 0)
    result = 0
    if x > pointA and x < pointB:
        result = slopeAB * x + yInterceptAB
```

```
    elif x >= pointB and x <= pointC:
        result = 1
    elif x > pointC and x < pointD:
        result = slopeCD * x + yInterceptCD
    return result


def getSlope(x1, y1, x2, y2):
    #Avoid zero division error of vertical line for shouldered trapmf
    try:
        slope = (y2 - y1) / (x2 - x1)
    except ZeroDivisionError:
        slope = 0
    return slope


def getYIntercept(x1, y1, x2, y2):
    m = getSlope(x1, y1, x2, y2)
    if y1 < y2:
        y = y2
        x = x2
    else:
        y = y1
        x = x1
    return y - m * x


def getTrimfPlots(start, end, points):
    plots = [0] * (abs(start) + abs(end))
    pointA = points[0]
    pointB = points[1]
    pointC = points[2]
    slopeAB = getSlope(pointA, 0, pointB, 1)
    slopeBC = getSlope(pointB, 1, pointC, 0)
    yInterceptAB = getYIntercept(pointA, 0, pointB, 1)
```

```
    yInterceptBC = getYIntercept(pointB, 1, pointC
    , 0)
    for i in range(pointA, pointB):
        plots[i] = slopeAB * i + yInterceptAB
    for i in range(pointB, pointC):
        plots[i] = slopeBC * i + yInterceptBC

    return plots


def getTrapmfPlots(start, end, points, shoulder=None):
    plots = [0] * (abs(start) + abs(end))
    pointA = points[0]
    pointB = points[1]
    pointC = points[2]
    pointD = points[3]
    left = 0
    right = 0
    slopeAB = getSlope(pointA, 0, pointB, 1)
    slopeCD = getSlope(pointC, 1, pointD, 0)
    yInterceptAB = getYIntercept(pointA, 0, pointB, 1)
    yInterceptCD = getYIntercept(pointC, 1, pointD, 0)
    if shoulder == "left":
        for i in range(start, pointA):
            plots[i] = 1
    elif shoulder == "right":
        for i in range(pointD, end):
            plots[i] = 1
    for i in range(pointA, pointB):
        plots[i] = slopeAB * i + yInterceptAB
    for i in range(pointB, pointC):
        plots[i] = 1
    for i in range(pointC, pointD):
        plots[i] = slopeCD * i + yInterceptCD
    return plots
```

```python
def getCentroid(aggregatedPlots):
    n = len(aggregatedPlots)
    xAxis = list(range(n))
    centroidNum = 0
    centroidDenum = 0
    for i in range(n):
        centroidNum += xAxis[i] * aggregatedPlots[i]
        centroidDenum += aggregatedPlots[i]
    return centroidNum / centroidDenum


def evaluateRules(Temp, rainfall):
    rules = [[0] * 3 for i in range(3)]

    fuzzifuedTemperatureLow = fuzzifyTemperatureLow(Temp)
    fuzzifuedTemperatureMedium = fuzzifyTemperatureMedium(Temp)
    fuzzifuedTemperatureHigh = fuzzifyTemperatureHigh(Temp)

    fuzzifuedRainfallLight = fuzzifyRainfallLight(rainfall)
    fuzzifuedRainfallMedium = fuzzifyRainfallMedium(rainfall)
    fuzzifuedRainfallHeavy = fuzzifyRainfallHeavy(rainfall)

    print(rainfall)
    print(fuzzifuedRainfallLight, fuzzifuedRainfallMedium,  fuzzifuedRainfallHeavy)

    print(Temp)
    print(fuzzifuedTemperatureLow, fuzzifuedTemperatureMedium, fuzzifuedTemperatureHigh)

    # RULE 1
    rules[0][0] = min(fuzzifuedTemperatureLow, fuzzifuedRainfallLight)
    # RULE 2
    rules[0][1] = min(fuzzifuedTemperatureMedium, fuzzifuedRainfallLight)
```

```
    # RULE 3
    rules[0][2] = min(fuzzifuedTemperatureHigh, fuzzifuedRainfallLight)
    # RULE 4
    rules[1][0] = min(fuzzifuedTemperatureLow, fuzzifuedRainfallMedium)
    # RULE 5
    rules[1][1] = min(fuzzifuedTemperatureMedium, fuzzifuedRainfallMedium)
    # RULE 6
    rules[1][2] = min(fuzzifuedTemperatureHigh, fuzzifuedRainfallMedium)
    # RULE 7
    rules[2][0] = min(fuzzifuedTemperatureLow, fuzzifuedRainfallHeavy)
    # RULE 8
    rules[2][1] = min(fuzzifuedTemperatureMedium, fuzzifuedRainfallHeavy)
    # RULE 9
    rules[2][2] = min(fuzzifuedTemperatureHigh, fuzzifuedRainfallHeavy)
    return rules



def fuzzifyTemperatureHigh(error):
    return trapmf(error, [20, 30, 40, 40])


def fuzzifyTemperatureMedium(error):
    return trimf(error, [10, 20, 30])


def fuzzifyTemperatureLow(error):
    return trapmf(error, [0, 0, 10, 20])


def fuzzifyRainfallHeavy(error):
    return trapmf(error, [25, 40, 60, 60])


def fuzzifyRainfallMedium(error):
```

```
    return trimf(error, [10, 25, 40])


def fuzzifyRainfallLight(error):
    return trapmf(error, [0, 0, 10, 25])


def fuzzifyN2OEmissionLow():
    return getTrapmfPlots(0, 100, [0, 0, 25, 50], "left")


def fuzzifyN2OEmissionMedium():
    return getTrimfPlots(0, 100, [25, 50, 75])


def fuzzifyN2OEmissionHigh():
    return getTrapmfPlots(0, 100, [50, 75, 100, 100], "right")


def fisAggregation(rules, pcc, pcnc, pch):
    result = [0] * 100
    for rule in range(len(rules)):
        for i in range(100):
            if rules[rule][0] > 0 and i < 50:
                result[i] = min(rules[rule][0], pcc[i])
            if rules[rule][1] > 0 and i > 25 and i < 75:
                result[i] = min(rules[rule][1], pcnc[i])
            if rules[rule][2] > 0 and i > 50 and i < 100:
                result[i] = min(rules[rule][2], pch[i])
    return result


def FuzzyLogicN2OEmission(Temp, Rainfall):
    rules = evaluateRules(Temp, Rainfall)
    #print(rules)
```

```
    aggregateValues = fisAggregation(rules,
                                     fuzzifyN2OEmissionLow(),
                                     fuzzifyN2OEmissionMedium(),
                                     fuzzifyN2OEmissionHigh())

    plt.plot(aggregateValues)
    plt.ylabel("Degree␣of␣Membership")
    plt.xlabel("N2O␣Emission␣for␣the␣Next␣Day␣(%)")
    plt.ylim(0, 1)
    plt.show()

    centroid = getCentroid(aggregateValues)
    return (centroid)

temperaturehigh = getTrapmfPlots(0, 40, [20, 30, 40, 40])
temperaturemedium = getTrimfPlots(0, 40, [10, 20, 30])
temperaturelow = getTrapmfPlots(0, 40, [0, 0, 10, 20])
plt.plot(temperaturehigh, label="High")
plt.plot(temperaturemedium, label="Medium")
plt.plot(temperaturelow, label="Low")
plt.xlabel("Temperature␣(degree␣C)")
plt.ylabel("Degree␣of␣Membership")
plt.legend()
plt.show()

rainfallheavy = getTrapmfPlots(0, 50, [25, 40, 50, 50])
rainfallmedium = getTrimfPlots(0, 50, [10, 25, 40])
rainfalllight = getTrapmfPlots(0, 50, [0, 0, 10, 25])
plt.plot(rainfallheavy, label="Heavy")
plt.plot(rainfallmedium, label="Medium")
plt.plot(rainfalllight, label="Light")
plt.xlabel("24␣Hour␣Rain␣Fall␣(mm)")
plt.ylabel("Degree␣of␣Membership")
plt.legend()
plt.show()
```

```

emissionhigh = getTrapmfPlots(0, 100, [50, 75, 100, 100])
emissionmedium = getTrimfPlots(0, 100, [25, 50, 75])
emissionlow = getTrapmfPlots(0, 100, [0, 0, 25, 50])
plt.plot(emissionhigh, label="High")
plt.plot(emissionmedium, label="Medium")
plt.plot(emissionlow, label="Low")
plt.xlabel("N2O Emission (%)")
plt.ylabel("Degree of Membership")
plt.legend()
plt.show()

Temp = 20
#rain fall of previous day
Rainfall = 10
Emission = FuzzyLogicN2OEmission(Temp, Rainfall)

print(Emission)
```

Seasonal Code - Example: 2021

```
# -*- coding: utf-8 -*-
"""
N2O Fuzzy Logic Model
"""
import numpy as np
import math
import matplotlib.pyplot as plt
import scipy.signal as signal

from weather1 import *
from FuzzyLogicModelOfN2OEmission import *

from scipy.signal.windows import gaussian

weatherdata = select_weather_stations()
tempAve = weatherdata["tempAve"]
rainAve = weatherdata["rainAve"]


#Since dataframe is zero-index. Index starts from startDay - 1
#2021

startday = 160-1
delayday = 200
endday = 260

initvalue = 50

#Gaussian function
activationperiod = 40
standarddev = 8

fertilizerdelay = 20

```

```
index = startday - 1

lsindex = []
lsN2Orate = []

i = 1
lsi = []
lsdecay = []
lsN2O = []
decay = initvalue


window = signal.windows.gaussian(activationperiod, std=standarddev)
plt.plot(window)
plt.title(r"Gaussian window ($\sigma$=7)")
plt.ylabel("Amplitude")
plt.xlabel("Sample")
plt.show()

j = 0

lsBug = []

while index < endday:
    N2Orate = FuzzyLogicN2OEmission(tempAve[index], rainAve[index])/1000
    lsN2Orate.append(N2Orate)
    lsindex.append(index)

    decay = 0
    decay1 = 0
    # urea model
    if j < activationperiod:
        decay = window[j]*initvalue
    else:
        decay = 0
```

```
    # polymer coated urea model
    if j >= fertilizerdelay and j < fertilizerdelay+activationperiod:
        decay1 = window[j-fertilizerdelay]*initvalue
    else:
        decay1 = 0

    totaldecay = decay + decay1
    lsN2O.append(totaldecay*N2Orate)
    lsdecay.append(totaldecay)
    lsi.append(i)
    i += 1
    j += 1
    index += 1

plt.plot(lsindex, lsN2Orate)
plt.show()
plt.plot(lsi, lsdecay)
plt.show()
plt.plot(lsindex, lsN2O)
plt.show()

#2021

with open('MeasuredN2O_BC_2021.npy', 'rb') as f:
    N2O1 = np.load(f)
with open('doy_BC_2021.npy', 'rb') as f1:
    doy1 = np.load(f1)





plt.plot(lsindex, lsN2O, 'b', label="Side strip - Fuzzy Logic")
plt.plot(doy1, N2O1, 'r', label="Side strip - Measured")
plt.legend()
```

```
plt.show()



"""
with open('SimulatedN2O.npy', 'wb') as f:
    np.save(f, N2O)
with open('SimulatedN2O.npy', 'rb') as f:
    N2O1 = np.load(f)
"""
```