

**Understanding the Fate and Flow of Nitrogen in Commercial Row Crop Production  
Systems**

by

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## ABSTRACT

Nitrogen (N) fertilizers have significantly advanced modern agricultural productivity, ensuring global food security. Despite these benefits, approximately 48% of the applied N globally is recovered by crops, with the remainder lost through leaching, volatilization, denitrification, and surface runoff, raising critical environmental concerns such as groundwater contamination and greenhouse gas emissions. This research aimed to systematically quantify N dynamics and losses across distinct yield-based management zones (MZ1 – stable high yield; MZ2 – stable low yield; MZ3 – unstable yield) within a 190-hectare commercial row crop farm in northern Alabama over four cropping seasons (2021–2024). Utilizing a partial N mass balance approach, inputs (fertilizers, manure, biological fixation, residues, irrigation, and atmospheric deposition) and outputs (crop uptake, residual soil N, and runoff losses) were assessed to estimate unaccounted-for N. The corn system received the highest input yet exhibited considerable inefficiencies, particularly in lower-yielding zones (MZ2 and MZ3), while the wheat system demonstrated substantial unaccounted N due to poor N synchrony and biomass production. Soybean displayed a negative N balance, suggesting soil N depletion. Field runoff monitoring emphasized that MZ3 had significantly higher runoff and cumulative N losses, especially during fallow and wheat cultivation periods, highlighting the necessity for improved N management strategies.

Nitrogen transformations within soil systems, particularly mineralization, significantly influence plant-available N. This research further explored spatial variability in potential N mineralization

within commercial row crop systems in Alabama, focusing on farms with contrasting cover crop management histories. Results indicated substantial variability in mineralization potential within and between farms, clearly demonstrating higher mineralization rates in farms adopting cover crops and residue retention. These findings validate cover cropping and residue management as pivotal strategies for enhancing soil health and optimizing N cycling, underscoring their critical role in sustainable agriculture.

Further, recognizing the logistical complexity of quantifying N losses at a large scale, this study employed the DSSAT Cropping System Model (CSM) model to simulate crop-soil-weather interactions and associated N dynamics of Maize across management zones under varying climatic scenarios (wet, normal, drought). Model calibration and evaluation using field data confirmed CSM's reliability in predicting crop growth, yield, and N uptake. Simulations identified distinct N loss pathways influenced by zone-specific soil properties and water availability. High-yield zones exhibited greater crop uptake yet higher volatilization and leaching losses, whereas low-yield zones retained more nitrate-N, indicating reduced N efficiency and higher denitrification potential. Weather variability substantially impacted N loss dynamics, underscoring the critical interplay between irrigation management and N dynamics.

Additionally, the research further utilized long-term DSSAT CSM-CERES-Maize model simulations to evaluate optimal N rates and timing under diverse irrigation regimes (50% and 30% deficit, rainfed conditions) across two management zones characterized by contrasting yield stability. The findings revealed substantial yield differences influenced by water availability, with denitrification notably higher for the low-yielding zones. A strategic reduction in N application rates significantly decreased environmental losses without compromising yields. Suggesting the effectiveness of integrated N and irrigation strategies tailored to specific zone conditions. The

optimal N management scenario included moderate irrigation deficits paired with reduced N rates, effectively balancing productivity and sustainability.

Collectively, these comprehensive studies underscore the critical importance of precision agriculture, highlighting the need for site-specific N and irrigation management strategies to enhance nitrogen use efficiency, sustain high productivity, and minimize the environmental impacts of agricultural systems.

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## Table of Contents

ABSTRACT.....	ii
ACKNOWLEDGEMENTS .....	v
Chapter 1. General Introduction.....	1
1.1. Background.....	1
1.2. Objectives.....	6
1.3. References.....	8
Chapter 2. Exploring the bottlenecks of low nitrogen efficiency among yield management zones in a commercial row crop farm using a nitrogen budget approach.....	11
2.1. Introduction.....	13
2.2. Materials and methods.....	17
2.2.1. Study Site.....	17
2.2.2. Management Zone Delineation .....	18
2.2.3. Data Collection .....	18
2.2.4. Soil System Nitrogen Budget.....	19
2.2.5. Nitrogen Inputs .....	19
2.2.6. N Outputs.....	23
2.2.7. Data Statistics.....	27
2.3. Results and Discussion .....	27
2.3.1. Nitrogen Inputs .....	27
2.3.2. Nitrogen Outputs.....	29
2.3.3. Nitrogen Budget.....	35
2.4. Implications for Zone-Specific Nutrient Management .....	38
2.5. Limitations and Uncertainties in Nitrogen Budget Estimation .....	38
2.6. Conclusion .....	39
2.7. References.....	41
2.8. Tables and Figures .....	50
Chapter 3: Potential Nitrogen Mineralization Variability in Commercial Row Crop Fields .....	61
3.1. Introduction.....	62
3.2. Materials and Methods.....	66
3.3. Results and Discussion .....	69

3.4. Conclusion .....	71
3.5. References.....	72
3.6. Tables and Figures .....	74
Chapter 4. Understanding the impact of irrigation on nitrogen losses between high and low-yielding management zones in a commercial maize production system .....	81
4.1. Introduction.....	83
4.2. Materials and Methods.....	87
4.2.1. Study site.....	87
4.2.2. Model operation .....	88
4.2.3. Model calibration .....	90
4.2.4. Model performance statistics .....	92
4.2.5. Climate variability.....	92
4.2.6. Data statistics .....	94
4.3. Results and Discussion .....	94
4.3.1. Model calibration .....	94
4.3.2. Model outputs and performance .....	95
4.3.3. Model evaluation.....	97
4.3.4. Nitrogen balance .....	99
4.3.5. Growing Season Rainfall Categories .....	99
4.3.6. Long-term N dynamics in distinct management zones, irrigation scenarios, and weather conditions.....	100
4.4. Conclusions .....	104
4.5. References.....	106
4.6. Tables and Figures .....	116
Chapter 5. DSSAT-Based Evaluation of Nitrogen Rate and Timing Under Variable Irrigation Scenarios Across Contrasting Management Zones in Maize.....	134
5.1. Introduction.....	135
5.2. Materials and Methods.....	138
5.2.1. Study Site and Experimental Setup.....	138
5.2.2. Management Zone Delineation .....	138
5.2.3. Experimental details.....	139
5.2.4. DSSAT Model Operation .....	140
5.2.5. Statistical Analysis .....	144
5.3. Results and Discussion .....	145

5.3.1. Growing Season Rainfall Conditions.....	145
5.3.2. Model calibration and evaluation.....	146
5.3.3. Nitrogen losses .....	152
5.4. Conclusion .....	156
5.5. References.....	158
5.6. Tables and Figures .....	167
Chapter 6. Summary .....	181

## List of Tables

<b>Table 2.8.1.</b> Soil and topographical characteristics of different management zones. ....	50
<b>Table 2.8.2.</b> Crop management practices for soybean, maize, and wheat during the 2021–2024 growing seasons .....	51
<b>Table 2.8.3.</b> P value table for different components of nitrogen budget.....	51
<b>Table 2.8.4.</b> N inputs (kg/ha and outputs(kg/ha) for different crops and management zones for the study site for the years 2021-2023 .....	52
<b>Table 3.6.1.</b> Field Description .....	74
<b>Table 3.6.2.</b> Timeframes for buried bags installation and incubation period in Field F40. ....	74
<b>Table 3.6.3.</b> Soil texture at all incubation locations in Field F40 .....	75
<b>Table 3.6.4.</b> Field F11 incubation dates .....	75
<b>Table 3.6.5.</b> Soil texture at all incubation locations in Field F11 .....	76
<b>Table 4.6.1.</b> Soil physical and chemical characteristics of MZ1 (high yield zone) .....	116
<b>Table 4.6.2.</b> Soil physical and chemical characteristics of MZ2 (low yield zone) .....	117
<b>Table 4.6.3.</b> Crop Management details for all three crops (2019 & 2022) .....	118
<b>Table 4.6.4.</b> Cultivar coefficients of the maize hybrid Dekalb® DKC 69-16 used in the CERES-Maize model.....	119
<b>Table 4.6.5.</b> Soil hydrological properties calibrated for high yield zone (MZ1) and low yield zone (MZ2).....	120
<b>Table 4.6.6.</b> A comparison of simulated and measured values for maize growth and development parameters for management zone 1 during the year 2022. ....	121
<b>Table 4.6.7.</b> Simulated vs measured growth and development variables for management zone 2 (2022) and management zone 1 (2019).....	122

<b>Table 4.6.8.</b> Model simulated nitrogen mass balance for two management zones (MZ1 and MZ2) for 2022.....	123
<b>Table 4.6.9.</b> Long-term nitrogen dynamics under water deficits for different growing season rainfall categories in MZ1 and MZ2.....	124
<b>Table 4.6.10.</b> P-value summary of fixed effects and interactions in crop response and nitrogen dynamics .....	125
<b>Table 5.6.1.</b> Summary of corn crop management practices for the 2019 and 2022 seasons, including cultivar, planting population, fertilization, irrigation, and harvest dates used in DSSAT model calibration and evaluation. ....	167
<b>Table 5.6.2.</b> Genetic coefficients used to calibrate the DSSAT CSM-CERES-Maize model for the Dekalb® DKC 69-16 corn hybrid. Coefficients were estimated using the GLUE approach based on 2022 field observations from Management Zone 1. ....	168
<b>Table 5.6.3.</b> Nitrogen rate and irrigation deficit treatment combinations used in the simulations for maize production.....	169
<b>Table 5.5.4.</b> Comparison of simulated and observed crop growth and development parameters for corn in Management Zone 1 during the DSSAT-CSM-CERES calibration phase in 2022. ....	170
<b>Table 5.6.5.</b> Comparison of simulated and observed values for corn growth and development parameters in Management Zone 2 (2022) and Management Zone 1 (2019) during the DSSAT-CSM-CERES model evaluation.....	171
<b>Table 5.6.6.</b> Analysis of variance (P-values) for the effects of nitrogen rate (R-I), split timing (RT-I), management zone (MZ), and Growing season rainfall conditions (GSRC) on maize yield, nitrogen uptake, soil residual nitrogen, and nitrogen loss pathways (denitrification, volatilization, and leaching). ....	172

## List of Figures

<b>Figure 2.8.1.</b> Maximum and minimum temperatures (Primary Y-axis) and rainfall amount (Secondary Y-axis) for the study site for 2021-2024.....	53
<b>Figure 2.8.2.</b> Crop Management zones for maize (A) and soybean (B) using historical yield data and zone-specific soil characteristics (C). The numbered dots represent the data collection locations. ....	54
<b>Figure 2.8.3.</b> A comparison of nitrogen inputs (A), outputs (B), and unaccounted nitrogen (C) for various crops across three management zones (MZ). Bars with the same letter are not significantly different at $P < 0.05$ across MZ and crops.....	55
<b>Figure 2.8.4.</b> A comparison of grain and biomass yields(A) and total N uptake (B) of soybean-maize-wheat-soybean across three management zones (MZ) at the study site for study years 2021-2024.....	56
Bars with the same letter are not significantly different at $P < 0.05$ across MZ and crops. ....	56
<b>Figure 2.8.5.</b> Soil inorganic N distribution ( $\text{NO}_3\text{-N} + \text{NH}_4\text{-N}$ ) before planting (A) and after harvest (B) across different years (2021-2023) and management zones (MZ1, MZ2, and MZ3). ....	59
*P and H followed by year represent planting and harvest soil cores during that particular year.	59
<b>Figure 2.8.6.</b> A comparison of rainfall and runoff patterns (A) for and N loss (B ) during years 2021-2024 across two management zones .....	60
<b>Figure 3.6.1.</b> Sampling locations at Field F40 .....	76
<b>Figure 3.6.2.</b> Sampling locations at Field F11 .....	76
<b>Figure 3.6.3.</b> Sample collection a) soil sample collection near the row. ....	77

**Figure 3.6.4.** Sample incubation a) Measure same weight for uniform sample size for all the locations, b) packing and labeling soil in a whirl pak bag, and c) Sealing the bag and burying it parallel to the crop row. .... 77

**Figure 3.6.5.** Sample analysis a) KCl extraction of soil followed by filtration b) N analysis using flow injection analyzer..... 78

**Figure 3.6.6.** N mineralization during different time periods at Field F40..... 78

**Figure 3.6.7.** Weather data during the study period at Field F40. .... 79

**Figure 3.6.8.** N mineralization during different time periods at Field F11..... 79

**Figure 3.6.9.** Weather data during the study period at Field F11. .... 80

**Figure 4.6.1.1.** Maximum, minimum temperature and rainfall distribution at study site for the year 2019 and 2022..... 126

**Figure 4.6.1.2.** Standardized Precipitation Index to characterize meteorological drought for years 1984 – 2022. The red bars represent drought years, blue bars represent wet years, and grey bars represent normal years. .... 126

**Figure 4.6.2.** Maize crop management zones delineated based on historical crop yields and topographic characteristics..... 127

**Figure 4.6.3.1.** A comparison of simulated and observed volumetric soil water content for high yield zone (MZ1 – 2022) at depth 15 (A), 45 (B), and 60 (C) cm..... 127

**Figure 4.6.3.2.** A comparison of simulated and observed volumetric soil water content for low yield zone (MZ2 – 2022) at depth 15 (A), 45 (B), and 60 (C) cm..... 128

**Figure 4.6.4.** A comparison of simulated and observed leaf area index of high yield zone (MZ1 – 2022). .... 129

**Figure 4.6.5.** A comparison of simulated and observed tops weight for A) high yield zone (MZ1, year 2022) (B) Low yield zone (MZ2, year 2022), and C) high yield zone (MZ1, year 2019).. 130

**Figure 4.6.6.** A comparison of simulated and observed soil N at maize harvest for A) nitrate- high yield zone (MZ1, year 2022) (B) and ammonium- high yield zone (MZ1, year 2022)..... 131

**Figure 4.6.7.** A comparison of simulated and observed nitrogen uptake for MZ1, year 2022 (A) and nitrogen uptake for MZ2, year 2022 (B)..... 131

**Figure 4.6.8.1** Long term cumulative effective irrigation (A), and no. of irrigation (B) under different water deficits for different growing season rainfall conditions in MZ1 and MZ2..... 132

**Figure 4.6.8.2.** Long term cumulative nitrogen losses (A), and nitrogen use efficiency (B) under different water deficits for different growing season rainfall conditions in MZ1 and MZ2..... 133

**Figure 5.6.1.** Corn crop management zones delineated based on historical crop yields and topographic characteristics..... 173

**Figure 5.6.2.** Standardized Precipitation Index (SPI) for the corn growing season from 1984 to 2022, used to classify Growing season rainfall conditions (GSRC ) as drought ( $SPI \leq -1$ , red), normal ( $-1 < SPI \leq 1$ , gray), and wet ( $SPI > 1$ , blue). This classification was used to group years for long-term DSSAT simulations evaluating nitrogen and irrigation strategies. .... 173

**Figure 5.6.4.** Simulated maize (A) grain yield and (B) nitrogen uptake under nitrogen rate  $\times$  irrigation deficit (R-I) treatments across management zones (MZ1 and MZ2) and GSRCs (wet, normal, drought). Bars represent treatment means, and different letters indicate significant differences at  $P < 0.05$  based on Tukey’s HSD test..... 176

**Figure 5.6.5.** Soil residual nitrogen at corn harvest as influenced by nitrogen rate  $\times$  irrigation deficit, management zones, and GSRCs. Bars with different letters are significantly different at  $P < 0.05$  according to Tukey’s Honestly Significant Difference (HSD) test. .... 177

**Figure 5.6.6.** Simulated nitrogen denitrification under nitrogen rate × irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments (P < 0.05) based on Tukey’s HSD test..... 178

**Figure 5.6.7.** Simulated nitrogen volatilization under nitrogen rate × irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments (P < 0.05) based on Tukey’s HSD test..... 179

**Figure 5.6.8.** Simulated nitrogen leaching under nitrogen rate × irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments (P < 0.05) based on Tukey’s HSD test..... 180

## List of Abbreviations

ANOVA:	Analysis of Variance
CERES:	Crop Environment Resource Synthesis
CSM:	Cropping System Model
DAP:	Days After Planting
DLL:	Drained Lower Limit
DSSAT:	Decision Support System for Agrotechnology Transfer
DUL:	Drained Upper Limit (Field Capacity)
EPA:	Environmental Protection Agency
Exp:	Experiment (Rate vs. Timing Treatments)
FIA:	Flow Injection Analyzer
FIAlab:	Flow Injection Analysis Laboratory
G1:	Genetic Coefficient: Maximum Possible Kernels per Plant
G2:	Genetic Coefficient: Kernel Filling Rate during Linear Grain Filling
GHCN:	Global Historical Climatology Network
GLIMMIX:	Generalized Linear Mixed Models Procedure in SAS
GLUE:	Generalized Likelihood Uncertainty Estimation
ID:	Irrigation Deficit
KSAT:	Saturated Hydraulic Conductivity

LAI:	Leaf Area Index
LL:	Lower Limit (Wilting Point)
MZ:	Management Zone
MZ1:	High Yield Stability Management Zone
MZ2:	Low Yield Stability Management Zone
n-RMSE:	Normalized Root Mean Square Error
NH <sub>4</sub> <sup>+</sup> :	Ammonium
NOAA:	National Oceanic and Atmospheric Administration
NO <sub>3</sub> <sup>-</sup> :	Nitrate
N:	Nitrogen
NASS:	National Agricultural Statistics Service
NRCS:	Natural Resources Conservation Service
NUE:	Nitrogen Use Efficiency
P:	Precipitation
P1:	Thermal Time from Emergence to End of Juvenile Stage
P2:	Photoperiod Sensitivity Coefficient
P5:	Thermal Time from Silking to Physiological Maturity
PHINT:	Phyllochron Interval (Thermal time between leaf tips)
RMSE:	Root Mean Square Error

SAT:	Saturated Water Content
SAS:	Statistical Analysis System
SPI:	Standardized Precipitation Index
SSURGO:	Soil Survey Geographic Database
TPI:	Topographic Position Index
Trt:	Treatment
TWI:	Topographic Wetness Index
T <sub>max</sub> :	Maximum Temperature
T <sub>min</sub> :	Minimum Temperature
TN:	Total Nitrogen
USDA:	United States Department of Agriculture
V7:	V7 Growth Stage of Corn (7-leaf stage)
WY:	Water Year
R-I:	Nitrogen rate*irrigation deficits
RT-I:	Nitrogen rate applied as split dose*irrigation deficits

## **Chapter 1. General Introduction**

### **1.1. Background**

Nitrogen (N) is essential for crop production and is critical for feeding the ever-increasing human population (Erisman., 2008). Despite its abundance in the atmosphere as dinitrogen gas ( $N_2$ ), it is largely inaccessible to agricultural crops in this form, often limiting primary productivity in ecosystems. The invention of the Haber-Bosch method, in the early 1900s, revolutionized agriculture by converting atmospheric N into fertilizer, significantly reducing farming risks and enhancing food security (Hager T, 2008). Since then, N has become a cornerstone of modern agriculture and its use as agricultural fertilizer has increased eightfold. Today more than half of the total direct input of N to cropland comes from fertilizers (Fowler et al., 2013; Lassaletta et al., 2026). According to the USDA, inorganic fertilizers account for substantial input costs. Approximately 36 percent of a farmer's operating costs for corn, and 35 percent for wheat accounts for inorganic fertilizer input (USDA-FAS, 2022). The most unfortunate fact related to industrial N fertilizers are their low mean global recovery efficiency in crops, which is approximately 48% (Quan et al., 2021). The substantial unrecovered N (52%) is through leaching, volatilization, denitrification, and runoff. These losses result in groundwater contamination, eutrophication of aquatic systems, and heightened greenhouse gas emissions, exacerbating environmental degradation and climate change (You et al., 2023; Karimi et al., 2020; Eagle et al., 2017; Tilman & Isbell, 2015; Fowler et al., 2013; Liep et al., 2011). The extent of these losses depends on various factors, including soil properties, hydrology and weather conditions. In Alabama, intensive N management for row crops production, combined with the region's rainfall patterns, contributes to significant exports of reactive N into the environment. Thus, addressing these inefficiencies is

imperative for sustainable agriculture, emphasizing the need to optimize N management practices in row crop production systems.

Nitrogen balances have been a valuable tool in expanding our knowledge of the N cycle. They have contributed by identifying mechanisms of N transfer and indicating the size of various N reservoirs. Their main use has been in estimating the net N loss, or the unaccounted-for N, in each agricultural production system (Legg & Meisinger, 1982). Quantifying the inputs and outputs of N through partial N budget methods provides valuable insights into potential bottlenecks and inefficiencies within cropping systems. This methodological approach assists in expanding our knowledge of the N cycle, assess the sustainability of nutrient management practices, and quantify potential N losses from agricultural landscapes (Quemada & Lassaletta, 2024; FAO, 2021). Numerous studies highlight the effectiveness of N budgeting in diverse cropping systems, including maize, soybean, and various cereals. For instance, Salazar et al. (2005) demonstrated how management practices significantly influence N losses across different cropping systems, emphasizing that appropriate management practices could markedly reduce environmental risks. Gentry et al. (2009) constructed an N mass budget for Illinois' Big Ditch watershed, revealing soil N depletion in maize-soybean rotations, especially during wet years. They concluded that when N inputs exceeded outputs, the N was carried over to the following year, and when inputs were lower than outputs due to high leaching losses and denitrification, soil N depletion was achieved. Prasad and Hochmuth (2016) evaluated N losses in Florida farms growing potato, sweet corn, and silage corn using the N mass budget approach. They observed that fertilizer N was the primary input for these crops, and crop N uptake ranged from 55.5% to 65.2% of total input N, while environmental N losses averaged around 35% for all crops. Dattamudi et al. (2020) analyzed N budgets in corn-soybean systems in the Midwest over 10 years. They highlighted the importance of N budget

quantification in understanding N cycling in this cropping system. The study revealed inefficiencies of current N management practices, leading to significant subsurface leaching losses, which caused elevated nitrate levels in drainage water.

Additionally, N losses from agricultural runoff have been identified as a leading cause of water impairment in freshwater and coastal ecosystems across the United States. Diaz & Rosenberg (2008) through their intensive study on water quality, highlighted the alarming increase in coastal dead zones since the 1960s. The primary driver for forming dead zones is N loading from agricultural fields. Nutrients not utilized by the crop are often lost via surface/subsurface runoff, leading to harmful algal blooms and hypoxic zones, severely degrading water quality and aquatic habitats. A study conducted by Manninen et al. (2018) to evaluate the effect of land use, soil type, and management practices on surface runoff water found that N losses through surface runoff were significant in cultivated lands, particularly during heavy rainfall events. The inorganic N was the primary form of N lost, and the losses varied between 0.8 and 3.2 kg/ha. Hanrahan et al. (2019) studied the effect of agronomic management on N balances from multiple farmers' fields in Ohio. They reported that the type and rate of fertilizer impacted the N balance and hydrologic N losses. They concluded that the greater the N balance was, the greater the losses, and the surface N loss was prominent in fields receiving organic N or mixed (organic and inorganic N) fertilizer compared to only inorganic application.

As shown by several researchers, using the N budget has been valuable in understanding and implementing efficient N management, especially across different soil types and environmental conditions. However, its application to investigate N losses in field-scale yield zones has been rarely studied. The spatial variability within agricultural landscapes remains a challenge, largely due to differences in soil types, hydrological characteristics, and topography, affecting nutrient

cycling and N dynamics (Khan et al., 2021). Addressing spatial variability through management zone delineation has gained attention for improved resource optimization, nutrient efficiency and reduced environmental impacts. The management zone delineation characterizes the field variability, overcoming the assumption of “one size fits all”. Also, it provides an opportunity to study the N dynamics of each zone of the field and identify the areas that require extra consideration while planning N management strategies (Łukowiak et al., 2024; Zhang et al., 2002).

Along with considering spatial variability, it is important to have a thorough understanding of N transformations in soil. Farmers often apply N uniformly across agricultural fields, assuming that N sources, sinks, and loss mechanisms are consistent throughout the field. However, research clearly shows that variability in soil properties significantly influences N dynamics, complicating effective N management aimed at maximizing NUE (Pal et al., 2020). Key soil properties contributing to this variability include soil organic matter content, residual soil nitrate ( $\text{NO}_3\text{-N}$ ), the amount of crop residue returned to the topsoil, yield variability (representing N sinks), and changes in chemical and physical soil characteristics (Chen et al., 2014; Das et al., 2024).

Therefore, a thorough understanding of N transformations within the soil is critical for optimizing crop management. N mineralization, from organic matter serves as one of primary input of N for crop uptake. the process by which organic N is converted into inorganic forms like ammonium ( $\text{NH}_4^+$ ) and nitrate ( $\text{NO}_3^-$ ), is a key component of soil fertility. These inorganic forms are readily available for plant uptake, making them essential for crop growth and productivity. The primary processes involved include mineralization, immobilization, nitrification, volatilization, and denitrification, each mediated predominantly by soil microbes and influenced by various biotic and abiotic factors. Soil mineralization, the transformation of organic N into inorganic forms like nitrate and ammonium, is influenced significantly by factors such as organic matter availability,

carbon-to-nitrogen ratios, soil temperature, moisture, texture, and microbial diversity. Curtin et al. (2012) and Buzin et al. (2019) illustrated how optimal mineralization rates depend heavily on maintaining favorable soil conditions, notably adequate moisture, temperature, and microbial activity. Agricultural conservation practices, including residue retention, cover cropping, and rotations, especially those incorporating legumes—have been shown to enhance soil organic matter quality, thus boosting mineralization rates and overall soil health. Munera et al. (2020) and Restovich et al. (2022) have documented clear improvements in N cycling efficiency and soil fertility due to these conservation strategies, highlighting their potential in sustainable agriculture.

As we approach 2050, projected global population growth will drive food demand significantly, necessitating further intensification of agricultural practices, especially in staple crops such as corn. Corn is particularly noteworthy due to its extensive cultivation, substantial global market, and high N demand. The United States, as a leading global corn producer, is notably impacted by inefficiencies in N management within corn production systems. Corn fields typically recover only about 50% of the applied N, underscoring significant losses through leaching, volatilization, and denitrification. This inefficiency poses considerable environmental threats and health risks, including elevated nitrate levels linked to cancer risks and atmospheric ammonia contributing to respiratory issues. In regions like Alabama, where unpredictable weather patterns exacerbate N losses, adopting precision N management practices becomes increasingly vital. The need for resilient N management strategies, accounting for spatial variability and climatic factors, underscores the importance of employing advanced agronomic techniques.

The Decision Support System for Agrotechnology Transfer (DSSAT) model emerges as a powerful tool for managing these complexities, providing insights into crop growth, soil-N transformations, water interactions, and the environmental fate of N under varied agricultural

scenarios. Studies employing DSSAT have successfully simulated long-term crop and soil interactions, improving our understanding of N dynamics under different management practices. Re et al. (2020) and Kumar et al. (2024) illustrated DSSAT's efficacy in optimizing N application strategies and minimizing environmental impacts through comprehensive scenario simulations. These studies underscore the potential of precision agriculture and model-based decision-making to significantly enhance N use efficiency and reduce detrimental environmental outcomes.

Optimizing N management thus requires an integrated approach, encompassing precise N application rates, appropriate timing, and efficient irrigation management to enhance productivity and environmental sustainability. Irrigation, in particular, influences N dynamics significantly, affecting nutrient availability and susceptibility to losses. Studies by Dabney et al. (2010), Feng et al. (2023), and Leuthold et al. (2023) consistently demonstrate that precise N application rates and strategic irrigation scheduling substantially improve N recovery, reduce losses, and maintain or enhance crop yields. Addressing spatial variability through targeted management zones further refines these strategies, recognizing the distinct requirements and vulnerabilities of different field areas based on soil and topographic characteristics.

Given these considerations, this research integrates comprehensive field data with advanced modeling techniques to address critical gaps in N management across diverse agricultural landscapes. Specifically, this thesis aims to:

## **1.2. Objectives**

1. Quantify N inputs, outputs, and unaccounted N in distinct yield management zones over multiple cropping seasons, highlighting surface runoff contributions.

2. Investigate the impact of conservation agricultural practices, particularly cover cropping, on soil health and N mineralization potential within Alabama's cropping systems.
3. Calibrate and validate DSSAT CSM-CERES-Maize model simulations to evaluate corn growth, yields, soil water balance, and N dynamics across management zones under varied irrigation scenarios using long-term weather data.
4. Evaluate long-term impacts of N application rates and timing strategies across varying irrigation conditions in distinct management zones, identifying optimal strategies to minimize environmental impacts and reduce yield variability.

By achieving these objectives, this research aims to provide robust, data-driven recommendations that significantly improve N management practices, ensuring sustainable productivity and environmental stewardship within agricultural landscapes.

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## Chapter 2. Exploring the bottlenecks of low nitrogen efficiency among yield management zones in a commercial row crop farm using a nitrogen budget approach

### Abstract

The use of nitrogen (N) fertilizers revolutionized modern agriculture, increasing food production substantially. However, globally, about 48% of applied N is recovered by crops, and the remaining N is lost through leaching, volatilization, denitrification, and surface runoff, raising concerns about water contamination and greenhouse gas emissions. This study aimed to quantify N budgets to evaluate the variability of N losses across three yield-based management zones (MZ1 – stable high yield, MZ2 – stable low yield, MZ3 – unstable yield) in a 190-hectare commercial row crop farm in northern Alabama over four cropping seasons (2021–2024). Using a partial N mass balance approach, N inputs (fertilizers, manure, biological fixation, residues, irrigation, and atmospheric deposition) and outputs (crop uptake, residual soil N, and runoff losses) were quantified to estimate unaccounted-for N representing potential losses. Maize (*Zea mays*) received the highest N input (up to 501±12 kg/ha), yet showed substantial unaccounted-for N losses, particularly in MZ2 (157±19 kg/ha) and MZ3 (121±18 kg/ha), indicating inefficiencies in uptake. Wheat (*Triticum aestivum*) exhibited the highest average unaccounted-for N (up to 172±9 kg/ha), likely due to low biomass production and poor synchrony between N supply and crop demand. In contrast, soybeans (*Glycine max*) showed negative N balance, especially in MZ1 (–15±1 kg/ha), suggesting net addition of N in soil. Edge-of-field runoff monitoring revealed that MZ3 had significantly higher runoff (2166 mm/ha in 2021) and cumulative N losses (6 kg/ha) compared to MZ1 (1 kg/ha). The losses were predominantly observed during the fallow and wheat period (coinciding with the rainy

season). These findings emphasize the importance of site-specific management practices that account for field variability to optimize N use efficiency and minimize environmental impacts.

Keywords: N dynamics; N losses; spatial variability; management zones; surface runoff

## 2.1. Introduction

Nitrogen (N) is a vital nutrient for crop production and ensures food security for a growing population on Earth. The widespread use of N fertilizers has revolutionized modern agriculture, increasing food production substantially. However, the intensified application of N fertilizers and low N recovery efficiency of farming systems (Zhang et al., 2015; Morris et al., 2018) has also increased the risk of N losses in the environment. Currently, the mean global recovery efficiency of N in crops is approximately 48% (Quan et al., 2021). The substantial unrecovered N (52%) is lost from soils through processes of leaching, volatilization, denitrification, and surface runoff. It, thus, raises serious environmental concerns about groundwater contamination, eutrophication of water bodies, and greenhouse gas emissions (You et al., 2023; Karimi et al., 2020; Eagle et al., 2017; Tilman & Isbell, 2015; Fowler et al., 2013; Liep et al., 2011).

Quantifying the inputs and outputs of N in a cropping system is essential in diagnosing the bottlenecks associated with poor N recovery efficiency. It also helps expand our knowledge of the N cycle, assess the sustainability of nutrient management practices, and quantify potential N losses from agricultural landscapes (Quemada & Lassaletta, 2024; FAO, 2021). However, accurate estimation of all the inputs and outputs of N in an agricultural system poses technical and logistical challenges. For example, measuring volatilization and denitrification losses of N gases on a daily time step at the farm scale is challenging. The partial N budget provides valuable information on N imports, exports, and unaccounted N (Singh et al., 2023; Prasad & Hochmuth, 2016). The unaccounted N is calculated by subtracting the known N outputs from the known inputs and typically represents N lost by denitrification, volatilization, leaching, surface runoff, or N stored

in the system (Karimi et al., 2020; Drinkwater et al., 2008; Blesh et al., 2013; Singh et al., 2023; Oenema et al., 2003).

Salazar et al. (2005) used the N budget to evaluate N utilization across three cropping systems (*Secale cereale* (Rye)/*Trifolium* (clover), maize/rye, and maize/bare soil) using different types of cattle manure. The study concluded that the N losses were significantly influenced by crop management practices rather than manure type. The losses were notably higher for maize under tillage practices. Similarly, Follett (2008) highlighted the importance of N budget calculations in row crop systems, especially crops that rely heavily on synthetic fertilizers. He mentioned that N budget calculation can be used as a vital tool for improving N management as it provides a holistic view into N inputs and outputs and helps identify inefficiencies in the system which can contribute to environmental issues. The research emphasized that optimization of balance between N inputs and crop demand can guide farmers in applying the right amount of N, minimizing waste, and reducing the risk of pollution. Gentry et al. (2009) constructed an N mass budget for Illinois' Big Ditch watershed, revealing soil N depletion in maize-soybean rotations, especially during wet years. They concluded that when N inputs exceeded outputs, the N was carried over to the following year, and when inputs were lower than outputs due to high leaching losses and denitrification, soil N depletion was achieved. Prasad and Hochmuth (2016) evaluated N losses in Florida farms growing potato, sweet maize, and silage maize using the N mass budget approach. They observed that fertilizer N was the primary input for these crops, and crop N uptake ranged from 55.5% to 65.2% of total input N, while environmental N losses averaged around 35% for all crops. Dattamudi et al. (2020) analyzed N budgets in maize-soybean systems in the Midwest over 10 years. They highlighted the importance of N budget quantification in understanding N cycling in this cropping system. The study revealed inefficiencies of current N management practices,

leading to significant subsurface leaching losses, which caused elevated nitrate levels in drainage water.

Nitrogen losses from agricultural runoff have been identified as a leading cause of water impairment in coastal ecosystems across the U.S. Diaz & Rosenberg (2008) highlighted the alarming increase in coastal dead zones since the 1960s. The primary driver for forming dead zones is N loading from agricultural fields. Nutrients not utilized by the crop are often lost via surface/subsurface runoff, leading to harmful algal blooms and hypoxic zones, severely degrading water quality and aquatic habitats. A study conducted by Manninen et al. (2018) to evaluate the effect of land use, soil type, and management practices on surface runoff water found that N losses through surface runoff were significant in cultivated lands, particularly during heavy rainfall events. The inorganic N was the primary form of N lost, and the losses varied between 0.8 and 3.2 kg/ha. Hanrahan et al. (2019) studied the effect of agronomic management on N balances from multiple farmers' fields in Ohio. They reported that the type and rate of fertilizer impacted the N balance and hydrologic N losses. They concluded that the greater the N balance was, the greater the losses, and the surface N loss was prominent in fields receiving organic N or mixed (organic and inorganic N) fertilizer compared to only inorganic application.

As shown by several researchers, using the N budget has been valuable in understanding and implementing efficient N management, especially across different soil types and environmental conditions. However, its application to investigate N losses in field-scale yield zones has been rarely studied. Spatial variability within agricultural fields plays an important role in optimizing resource use. Due to differences in soil properties, hydrology, and topography, it is important to understand and address this variability to improve N management (Khan et al., 2021). Mostly, farmers opt for uniform management practices across fields, which often fail to match the specific

needs of different areas of the field, contributing to poor N-use efficiency. Uniform resource application might lead to some areas receiving insufficient N and yielding poor yields, while others receive more N than needed, leading to potential N losses. Thus, it is important to understand the in-field variability to enhance resource optimization and mitigate environmental concerns (Jin et al., 2019). Researchers have reported that spatial variation in agricultural landscapes can be controlled and overcome by delineating management zones based on similar crop response and nutrient potential (Kumar et al., 2022; Farid et al., 2015). The management zone delineation characterizes the field variability, overcoming the assumption of “one size fits all.” Also, it provides an opportunity to study the N dynamics of each zone of the field and identify the areas that require extra consideration while planning N management strategies (Łukowiak et al., 2024; Zhang et al., 2002). However, there are limited studies addressing how N dynamics would differ across management zones under real-world farming conditions. Thus, we hypothesized that various yield zones would exhibit distinct N dynamics and loss characteristics. We tested our hypothesis by quantifying the N budget for each management zone over multiple years in a commercial row crop field, growing maize, soybean, and wheat in rotation.

Hence, the objective of our study was to quantify N inputs and outputs in three distinct yield management zones over four cropping seasons in a commercial farm and identify the unaccounted N using a partial N mass budget approach. A secondary objective was to quantify the N losses from surface runoff over a four-year study period and understand its contribution towards the total N loss.

## 2.2. Materials and methods

### 2.2.1. Study Site

This study is unique as it provides insight into farmer-operated commercial production systems. The four-year study was conducted on a privately owned farm and was initiated in 2021 in Town Creek, Alabama, located at 34° 43' 6.67" N, 87° 23' 13.52" W, and 181 m above sea level. The soil type at the study site ranged from Abernathy Clay loam (Fine-silty, siliceous, semiactive, thermic Oxyaquic Hapludults) to Decatur silty clay loam (Fine, kaolinitic, thermic Rhodic Paleudults), with slopes ranging from 2 to 12 percent and elevations between 169 and 180 m. The farm employs a crop rotation system of soybeans, winter wheat, and maize, where maize is rotated every three years. The cropping sequence and management details are provided in Table 2.8.2. The total area of the study site is 190 ha, of which 125 ha is irrigated using a center pivot system (Figure 2.8.2.). The historic maximum temperature ( $T_{\max}$ ), minimum temperature ( $T_{\min}$ ), and annual rainfall are reported to be 33.0 °C, 10.5 °C, and 1200. mm, respectively.  $T_{\max}$  showed a consistent increase over the study period. In 2021 and 2022, the average  $T_{\max}$  was 33°C; in 2023, it increased to 34°C, indicating a warming trend. Similarly, in 2021 and 2022, the average  $T_{\min}$  was 11°C, but it increased to 12°C in 2023, suggesting a gradual rise in nighttime temperatures. Rainfall patterns demonstrated significant variability across the study years. In 2021, the cumulative annual rainfall was 126 cm, which decreased slightly to 119 cm in 2022. However, a substantial decline was observed in 2023, with cumulative rainfall dropping to 84 cm, indicating drought conditions. Early 2024, in contrast, showed signs of increased rainfall in the initial months. Notably, the spring months consistently received the highest precipitation throughout the study period (Figure 2.8.1).

### **2.2.2. Management Zone Delineation**

The field was delineated into three distinct management zones (Figure 2.8.2, Table 2.8.1) based on historical yield data for maize and soybean using ArcGIS software (version 10.8). These zones were management zone 1 (MZ1), characterized by stable high yields; management zone 2 (MZ2), characterized by stable low yields; and management zone 3 (MZ3), characterized by unstable yields. Crop yield data from six maize years (2010, 2012, 2014, 2018, 2019, and 2020) and four soybean years (2013, 2016, 2017, and 2021) were considered during the management zone delineation process. The management zone categorization was found to be similar for both maize and soybeans (Figure 2.8.2). Two algorithms – the standard deviation algorithm and the two-way outlier algorithm – were used to define the stability of the zones (Maestrini & Basso, 2021). Morata et al. (2020) and Kumar et al. (2022) further evaluated all these zones at the same farm using topographic indices like elevation, slope, topographic position index (TPI), and topographic wetness index (TWI).

### **2.2.3. Data Collection**

Sampling was conducted within each management zone (MZ) to collect data to capture the variability of soil and crop characteristics. Two locations were chosen for data collection in each zone, resulting in six sampling locations, shown as black dots in Figure 2.8.2. MZ1, represented in green in Figure 2.8.2, includes sampling locations 1 and 2, which are high-yield stable zones. MZ2, represented red in Figure 2.8.2, includes sampling locations 5 and 6, which are low-yield stable zones. The coordinates of each sampling point were recorded using a GPS device to ensure accurate and precise measurements. Detailed data collection protocols are described in the subsections on N inputs.

#### 2.2.4. Soil System Nitrogen Budget

Following Oenema et al. (2003), a soil system N budget was developed to study the N dynamics in each management zone. The N budget is based on the principle of mass conservation, where all the known N inputs equal all the known outputs. The difference between the measured N inputs and outputs represents the unaccounted N. The unaccounted N comprises volatilization, denitrification, and leaching loss in our study and indicated potential environmental N losses (Legg & Meisinger, 1982; Meisinger & Randall, 1991; Drinkwater al., 2008; Blesh et al., 2013; Singh et al., 2023). The details of data collection for N inputs and outputs are provided in the section below. The following equations were used to derive the unaccounted N.

$$\sum N_{total\ inputs} = \sum N_{total\ outputs} \quad Eq1$$

Where,

$$\begin{aligned} N_{total\ inputs} = & N_{fertilizer} + N_{manure} + N_{soil\ organic\ N\ at\ planting} + N_{soil\ inorganic\ N\ at\ planting} + N_{crop\ residues} \\ & + N_{irrigation} + N_{atmospheric\ deposition} + N_{fixation\ in\ legume} \end{aligned} \quad Eq2$$

$$\begin{aligned} N_{total\ outputs} = & N_{crop\ removal} + N_{soil\ organic\ N\ at\ harvest} + N_{soil\ inorganic\ N\ at\ harvest} + N_{runoff} + N_{leaching} + \\ & N_{denitrification} + N_{volatilization} \end{aligned} \quad Eq3$$

$$N_{unaccounted} = N_{leaching} + N_{denitrification} + N_{volatilization} \quad Eq4$$

*Rearranging equation 1,3 and 4*

#### 2.2.5. Nitrogen Inputs

##### **Fertilizer and Manure Nitrogen:**

##### ***Fertilizer and Manure Nitrogen:***

The data on fertilizer and manure application rates were obtained from the farmer. A representative sample of poultry manure was collected from the manure pile and analyzed for total N, P, and K

(Peters et al., 2003. The total N concentration (%) of manure was multiplied by the application rate (dry weight) to obtain the total N input from manure. The farmer did not apply any fertilizer or manure for soybean production. Maize and wheat received 4.97 Mg/ha poultry manure before planting. The farmer disked in poultry manure after its application. Additionally, the maize was supplemented with 217 kg/ha N using urea at the V-7 stage. Wheat received 110 kg/ha of N through urea application at the tillering stage. Details of the application rate are provided in Table 2.8.2.

### ***Nitrogen from Residues:***

Crop residues left at harvest also serve as N input in a cropping system. The residues were sampled prior to planting of the next crop. Six replicates were sampled from each location within each management zone using a 1 m<sup>2</sup> quadrant. The subsamples were taken from the replicates to get a representative sample and analyzed for TN content using a vario MAX cube organic elemental analyzer (Elementar Americas Inc., Mt. Laurel, NJ). The total residue biomass (kg/ha) was multiplied with tissue N concentration to calculate residue N input to the succeeding crops.

### ***Legume Nitrogen Fixation:***

There are two methods widely used to determine soybean N<sub>2</sub> fixation. The first is by the difference method, subtracting the amount of aboveground N accumulation of non-nodulated soybean from the N accumulation of nodulated soybean and dividing by the N accumulation of the nodulated soybean (Gentry et al., 2001). The second is the natural abundance method (Shearer & Kohl, 1986; Blesh & Drinkwater, 2013). Values for soybean N fixation at different management zones were calculated based on assumptions made through previous research. Studies on Soybean N fixation by nodulated types suggested that 60-70% of N exported by soybeans is fixed by the plant itself (Thurlow et al., 1985; Gentry et al., 2009 & Ciampitti et al., 2018). By multiplying the

fixation rate and total aboveground N accumulation [grain N divided by N harvest index (Eq.1)], the soybean N<sub>2</sub> fixation was calculated (Eq.2). Therefore, aboveground fixed N inputs for Soybean were calculated using:

$$\text{Harvested N export (kg/ha)} = \text{Soybean pods} \frac{\text{kg}}{\text{ha}} \times \%N \quad \text{Eq.1}$$

$$\text{Legume N fixed (kg/ha)} = (\text{Harvested N export}) \times \% N \text{ from fixation} \quad \text{Eq.1}$$

***Nitrogen from Irrigation:***

To estimate N input through the irrigation water, the irrigation water samples were collected from the pivot at the time of irrigation, transported in an ice box back to the laboratory, and the water sample was filtered and analyzed for NO<sub>3</sub>-N and NH<sub>4</sub>-N within 48 hours of collection following EPA 351.1 protocol, and using the FIAlyzer-1000 flow injection analyzer (FIALab Instruments Inc) within 48 hours of collection.

$$N_{\text{irrigation (kg/ha)}} = \text{Total irrigation (L/ha)} \times [(NH_4-N) + (NO_3-N)]$$

***Nitrogen from Atmospheric Deposition:***

Nitrogen from atmospheric deposition is a small but important N input to agricultural fields. The amount of NH<sub>4</sub>-N and NO<sub>3</sub>-N (mg/L) in rainfall can be obtained from the National Atmospheric Deposition Program (NADP, 2011), specifically from the nearest station, Huntsville, Alabama (AL 99). The total N received via wet atmospheric deposition was calculated by multiplying the monthly precipitation-weighted mean ion concentrations (NO<sub>3</sub>-N + NH<sub>4</sub><sup>+</sup>-N mg L<sup>-1</sup>) by total monthly rainfall (in cm) and dividing the product by 10 to convert results in N kg/ha (Prasad et al., 2016).

### **Nitrogen In Soil at Planting:**

The soil cores (61 cm deep, four replicates) were collected using a tractor-mounted deep soil coring rig from different sampling locations prior to planting. The undisturbed soil cores were sectioned at six different depths (0-5, 5-15, 15-23, 23-30, 30-46, 46-61 cm). Two replicates were used to quantify the bulk density, and the rest were used to analyze mineral-N ( $\text{NO}_3\text{-N} + \text{NH}_4\text{-N}$ ) from the soil. The bulk density (BD) ( $\text{kg}/\text{m}^3$ ) for each depth was determined by drying soil cores at  $221^\circ\text{F}$  ( $105^\circ\text{C}$ ) for 48-72 hours and was calculated as -

$$BD = M/V$$

Where M= mass of oven-dried soil (kg) and V = volume of core sampler ( $\text{m}^3$ )

The rest of the replicates were dried at  $105^\circ\text{F}$  ( $40^\circ\text{C}$ ) for 24 to 48 hours for N analysis. After drying, the samples were extracted with a 2 M potassium chloride (KCl) solution at soil: solution ratio of 1:5 (Keeney & Nelson, 1982), and the filtrate was analyzed for  $\text{NO}_3\text{-N}$  or  $\text{NH}_4\text{-N}$  following the EPA 353.2 protocol and using the FIAlyzer-1000 flow injection analyzer (FIALab Instruments Inc). The concentrations ( $\text{mg}/\text{kg}$ ) were multiplied with bulk density and soil depth and expressed as  $\text{kg}/\text{ha}$  N.

$$\frac{N \text{ (mg/kg)} \times \text{soil depth (m)} \times \text{Soil bulk density (kg/m}^3\text{)}}{100}$$

The subsamples from the same soil core were also analyzed for total N (TN) using a LECO CN analyzer (Schepers et al., 1989), and organic N was obtained by subtracting Inorganic N from TN (Hood et al., 2010; Bly et al., 2024).

$$\text{Organic N} = \text{Total N} - \text{Inorganic N}$$

To simplify quantification in the N budget calculations, organic N used in N inputs was determined by subtracting organic N at planting from organic N at harvest.

### **2.2.6. N Outputs**

#### ***N Crop Removal:***

Data for row crop yield during the study period was collected from multiple locations within management zones- MZ1, MZ2, and MZ3 of the farm. At crop maturity, whole plant samples (excluding root) were collected from six randomly selected 1-meter rows from each location within zones to ensure representation of spatial variability. The collected samples were oven-dried at 60°C to a constant weight to remove all moisture content, after which they were ground to a fine powder using a mechanical grinder. Subsamples of the ground material were analyzed for total N. Similarly, for N uptake in the grain, the samples were separately collected from the same 1-meter row sections used for biomass sampling. The grain samples were oven-dried at 60°C, cleaned, and analyzed for N concentration. The N uptake by the plant tissue and grain was estimated by multiplying the grain/biomass yield (kg/ha) with the respective N (%) concentration. The total N uptake by the crop was then determined as the sum of N uptake in both the biomass and the grain.

#### ***Nitrogen in Soil at Harvest:***

The soil cores (61 cm deep) were collected and processed from different sampling locations in a manner similar to that before planting and analyzed for NO<sub>3</sub>-N and NH<sub>4</sub>-N. The NO<sub>3</sub>-N or NH<sub>4</sub>-N concentrations (mg/kg) were multiplied with bulk density and soil depth to get kg/ha N input.

#### ***Unaccounted-for Nitrogen (denitrification, volatilization, leaching, and surface runoff):***

Denitrification, volatilization, leaching, and surface runoff are key N loss pathways that are highly variable in both spatial and temporal scales. Accurately quantifying these processes in large-scale

commercial farming systems presents significant technical challenges due to the inherent variability of environmental factors (e.g., soil moisture, temperature, and microbial activity) and resource-intensive instrumentation and data collection requirements. For instance, denitrification requires direct measurement of  $N_2$  and  $N_2O$  gases using gas collection chambers and isotopic techniques, volatilization demands continuous monitoring of ammonia emissions, and leaching involves the installation of lysimeters or soil water samplers for subsurface drainage collection. Given the logistical constraints of implementing these detailed methods at the commercial farm scale, these pathways were broadly categorized under "unaccounted N" in this study, as referenced in Dattamudi et al. (2020) and Singh et al. (2023). The unaccounted N fraction includes N losses that could not be directly quantified but are inferred based on the difference between total N inputs (fertilizers, biological fixation, and atmospheric deposition) and known N outputs (plant uptake and residual soil N).

This approach aligns with the mass balance methodology described by Sainju et al. (2016), wherein N inputs and outputs are carefully quantified to estimate the N balance. By accounting for measurable parameters such as fertilizer application rates, crop N uptake, and residual soil N, the remaining N fraction is assumed to represent losses via denitrification, volatilization, leaching, and runoff. While this approach does not directly measure individual loss pathways, it provides a reasonable estimation of overall N loss within the system.

### ***Surface Runoff:***

Based on delineated management zones, two Edge-of-Field (EOF) water quality monitoring stations were installed at the outlet points of two sub-watersheds inside the study field to monitor N loss through surface runoff water from MZ1 and MZ3. We were not able to install another such station in the MZ2 zone owing to limitations due to the topography and cost of monitoring. At the

point of drainage, culverts and water quality monitoring stations were installed to help calculate the quantity and quality of the runoff water discharging out of these zones. EOF monitoring station consisted of a culvert (PVC), an automatic sampler (Teledyne ISCO 6712- Avalanche ISCO 6712), along with a rain gauge (Teledyne ISCO 674, 0.01"tip) and an area velocity meter (Teledyne ISCO 750- 750 Area Velocity Flow Module) that measured the runoff depth and volume during each rainfall event. These culverts, along with the sampling assembly, were installed at the edge of MZ1 and MZ3. The culverts measured 61 and 76 cm in diameter at MZ1 and MZ3, respectively. The runoff samples were pumped from the culvert using a 9.5 mm inside diameter sample tubing into fourteen 900 ml polypropylene wedge bottles housed in a refrigerator that stored the collected samples at a temperature below 4 °C. The autosampler was powered by a solar panel and battery, with sampling triggered when discharge reached 0.05 m<sup>3</sup>/sec. The samples were collected based on flow pacing, which was adjusted and controlled remotely using TerraTerm software based on rainfall frequency, intensity, and particular events.

After rainfall or irrigation events, the surface runoff was directed through the culvert, where the area velocity sensor measured the discharge, prompting the autosampler to collect 200 ml runoff samples at intervals. The bottles in the autosampler hold 12.6 liters of samples in 14 (900 ml each) bottles and six composite samples per bottle. After the sample retrieval from the autosampler, bottles were swapped with another set of 14 bottles. The samples were analyzed for NO<sub>3</sub><sup>-</sup>-N and NH<sub>4</sub><sup>+</sup>-N within 48 hours of collection following EPA 351.1 protocol. The N load was computed by multiplying the discharge with the event means concentration of N. The discharge was calculated using Manning's equation with the water level in the culvert:

## Manning's

$$Q = (1/n) A^2 R^{2/3} S^{1/2}$$

where:

- **Q** is the **discharge** (flow rate) in cubic meters per second (m<sup>3</sup>/s),
- **n** is the **Manning's roughness coefficient** for PVC culvert (0.009 – 0.0015)
- **A** is the **cross-sectional flow area** in square meters (m<sup>2</sup>)
- **R** is the **hydraulic radius** in meters (m), calculated as  $R=A/P$ , where **P** is the **wetted perimeter** (m),
- **S** is the **slope of the energy grade line** (2%)

The runoff flow measurement and nutrient concentration data collected during the study period was calculated using event mass losses and flow-weighted mean nutrient concentrations, as shown in equations 1 and 2. Specifically, event mass losses are computed by summing the product of nutrient concentration and flow rate (Eq 1), providing an accurate assessment of the nutrient load transported during runoff events.

Mass loss = (Eq.1)

where  $C_i$  is the concentration (mg L<sup>-1</sup>) for a given sample

$Q_i$  is the discharge (L) represented by that sample

The data were then used to calculate flow-weighted mean nutrient concentrations (Eq 2), which offer a more representative measure of nutrient concentrations across varying flow conditions. These calculations are essential for evaluating the effectiveness of conservation practices and understanding the dynamics of runoff and nutrient transport, as they help determine the event's nutrient contributions to surface water.

$$\text{Event mean concentration} = \frac{\text{Mass loss}}{\Sigma Q} \quad (\text{Eq.2})$$

where Mass loss (mg) is the sum of all the samples for the monitoring period and  $\Sigma Q$  (L) is the sum of the discharge for the monitoring period.

### **2.2.7. Data Statistics**

Statistical analyses were conducted using the mixed-effects model procedure (PROC GLIMMIX) in SAS 9.4 (SAS Institute, 2013) to evaluate the effects of management practices on N dynamics and crop performance. The model included MZ1, MZ2, and MZ3, crop, year, and soil depth as fixed effects, along with their interactions. Replication along with the interaction between crop and replication were treated as random effects to account for variability across blocks and repeated measures. The Satterthwaite approximation was used to estimate denominator degrees of freedom for fixed effects. Least square means were computed for the main effects and interactions. Mean separations were performed using Tukey's Honest Significant Difference (HSD) test with an alpha level of 0.05. Letter groupings were assigned to indicate statistical differences among treatment means.

## **2.3. Results and Discussion**

### **2.3.1. Nitrogen Inputs**

Nitrogen inputs play a crucial role in crop productivity and nutrient cycling. In this study, key N sources included soil inorganic-N and organic N at planting, crop residue-N, manure-N, atmospheric deposition-N, irrigation-N, and synthetic fertilizers-N (Table 2.8.4). While total N inputs varied by crop, no significant differences were observed among MZs (Table 2.8.3, *p value* = 0.2875), indicating that fertilization rates and input distribution were uniform across the field (Figure 2.8.3A).

Soil N at planting was a major contributor to available N for crop uptake. The MZ2 had the highest soil inorganic-N ( $54\pm 5$  kg/ha) compared to MZ1 ( $49\pm 6$  kg/ha) and MZ3 ( $47\pm 6$  kg/ha). The organic N, representing N released from soil organic matter, followed a similar trend, with highest N reported in MZ2. During the maize season, MZ2 reported  $81\pm 19$  kg /ha organic N, significantly greater than MZ1 ( $54\pm 5$  kg/ha) and MZ3 ( $72\pm 8$  kg/ha). This pattern suggests that MZ2 retained more residual N from previous crops or organic matter decomposition. Residue N was not significantly influenced by the crop or the management zones. Although the highest residues were observed from soybean crop in MZ3 (26 kg/ha) compared to lowest residues left by maize biomass in MZ2 (12 kg/ha).

A key observation was that maize had significantly higher N from organic matter at planting, likely benefiting from soybean root biomass contributing to N availability. Biological N fixation in soybean was highest in MZ1 ( $145\pm 12$  kg/ha) and MZ3 ( $163\pm 2$  kg/ha), suggesting favorable conditions for nitrogen-fixing bacteria. Lower fixation rates in MZ2 ( $138\pm 8$  kg/ha) indicate possible soil constraints affecting nodulation. Minor but consistent N contributions came from atmospheric deposition (5–6 kg/ha) and irrigation (1–6 kg/ha), varying with crop water requirements.

Among crops, maize received the highest total N input ( $443\pm 12$  kg/ha in MZ2), primarily due to heavy applications of inorganic fertilizers (220 kg N /ha ) and manure (80 kg N/ha). Wheat followed with  $306\pm 7$  kg/ha, (110 kg N/ha from inorganic fertilizer and 70 kg N/ha from manure applications). While soybean had the lowest input ( $267\pm 9$  kg/ha), relying mostly on biological N fixation.

### 2.3.2. Nitrogen Outputs

N outputs primarily comprised of total crop uptake and soil inorganic N at harvest. While total N inputs were similar across zones, N outputs varied significantly (Table 2.8.3,  $p$  value = <0.0001), reflecting differences in crop productivity and NUE. Across crops, Maize had the significantly highest total N output ( $353 \pm 7$  kg/ha), followed by soybean ( $242 \pm 35$  kg/ha) and wheat ( $183 \pm 11$  kg/ha) (Figure 2.8.3 B) ( $p$  value = <0.0001). Across management zones, MZ1 exhibited the highest total N output ( $278 \pm 12$  kg/ha), indicating greater nutrient uptake efficiency. MZ3 followed with  $263 \pm 5$  kg/ha, while MZ2 had the lowest output ( $236 \pm 15$  kg/ha), suggesting reduced crop uptake and potential for higher N losses.

### Crop Yields and Nitrogen Uptake

The biomass and yields for soybean-maize-wheat-soybean-wheat (Table 2.8.4) crop rotation revealed significant variability in dry matter production and N uptake across the three MZs, with MZ1 and MZ3 generally outperforming MZ2 in both grain and biomass yields. These findings corroborate with the zones delineated using historical crop yield data. Brock et al. (2005) employed fuzzy c-means clustering to delineate management zones based on maize and soybean yield data. Their results also consistently showed higher yields in stable high-yield zones compared to low-yield zones.

For soybeans in 2021, there were no significant differences in grain yield across the zones, but biomass yield was notably higher in MZ3 ( $3992 \pm 299$  kg/ha), which was 13% greater than MZ1 ( $3534 \pm 289$  kg/ha) and 18% greater than MZ2 ( $3381 \pm 274$  kg/ha), indicating that MZ3's conditions favored biomass production. Maize in 2022 exhibited significant differences, with MZ1 achieving the highest grain yield ( $14168 \pm 320$  kg/ha), followed by MZ3 ( $12154 \pm 287$  kg/ha) and MZ2 ( $10048 \pm 271$  kg/ha), reflecting a 41% increase in grain yield in MZ1 over MZ2. Similarly, biomass

yields were significantly higher in MZ1 ( $9533\pm 290$  kg/ha), with 14% and 59% higher yields compared to MZ2 ( $8337\pm 267$  kg/ha) and MZ3 ( $5994\pm 248$  kg/ha), respectively.

In 2023, wheat grain yield showed no significant variability, but biomass production was highest in MZ3 ( $10761\pm 276$  kg/ha), followed by MZ1 ( $9874\pm 265$  kg/ha) and MZ2 ( $9042\pm 250$  kg/ha) (Figure 2.8.4 A), suggesting that MZ3's conditions were more conducive to wheat total dry matter accumulation. For soybeans in 2023, both grain and biomass yields followed a similar trend, with MZ1 achieving the highest yields ( $2898\pm 185$  kg/ha and  $3408\pm 209$  kg/ha, respectively), while MZ2 underperformed ( $2191\pm 172$  kg/ha and  $2584\pm 198$  kg/ha, respectively). This reinforces the observation that MZ1 consistently supports better overall productivity. In 2024, wheat followed a similar trend as in 2022-2023, with no significant differences in grain and biomass yields. Although the highest wheat biomass was observed in MZ1 ( $7361\pm 232$  kg/ha), it only slightly surpassed MZ2 ( $6968\pm 221$  kg/ha). However, MZ3 recorded the highest biomass ( $7524\pm 246$  kg/ha), followed by MZ1 and MZ2. While MZ1 and MZ3 demonstrated higher productivity across most crops and seasons, MZ2 consistently exhibited lower yields and biomass, reinforcing the impact of soil and topographical variability on crop performance.

Nitrogen uptake, being a product of N% concentration and crop yields, followed a similar trend as of crop yields (Figure 2.8.4 B). MZ1 and MZ3 reported higher uptake ( $239\pm 12$  kg/ha and  $234\pm 14$  kg/ha, respectively) compared to MZ2 ( $196\pm 11$  kg/ha). Among crops, maize and soybeans had significantly higher N uptake ( $292\pm 15$  kg/ha and  $287\pm 14$  kg/ha, respectively) than wheat ( $91\pm 7$  kg/ha). Kumar et al. (2022) also studied crop yields and N uptake in different management zones delineated at Town Creek Watershed, and reported significant variations among zones, with higher yields and uptake in stable high-yield zones. Similarly, Brock et al. (2005) reported significantly higher nutrient uptakes from high-yielding zones, which were characterized by soils with good to

fair drainage, while lower-yielding zones were associated with eroded soils or at high slopes. Likewise, Hornung et al. (2006) examined multiple locations to identify management zones based on yield measurements and variability. They reported significant differences in crop yields and nutrient uptake across all site-years. High-yield zones produced the highest grain yields (1.88 Mg/ha), which were approximately 1.5 times greater than those from low-yield zones.

### **Soil Nitrogen Status**

To evaluate changes in soil N storage, soil cores were collected from all sampling locations within the three MZ at the beginning and end of each cropping season. Total nitrogen (TN) analysis at the end of each season showed no significant differences across crops or MZs. However, at the beginning of the season, TN levels varied significantly, with notably higher values before maize planting (10.2 Mg ha<sup>-1</sup>) than before soybean planting (7.6 Mg ha<sup>-1</sup>). This increase in TN prior to maize cultivation is likely attributed to the mineralization of soybean residues from the previous season. The decomposition of biologically fixed N in soybean residues may have enriched the soil N pool during the fallow period, leading to higher TN at the start of the maize season.

Among MZs, MZ3 had significantly higher TN (10 Mg ha<sup>-1</sup>) compared to MZ1 (9 Mg ha<sup>-1</sup>) and MZ2 (8.2 Mg ha<sup>-1</sup>). These values represent sum of TN measured for individual sections of soil cores taken to a depth of 61 cm. Organic N was quantified by subtracting inorganic N (NO<sub>3</sub>-N + NH<sub>4</sub>-N) from the TN values. Statistical analysis revealed significantly higher ON before wheat planting, followed by maize and soybean. Among management zones, MZ3 consistently showed a significantly higher ON compared to MZ1 and MZ2. End-of-season analyses revealed similar ON patterns as observed at the start of the season.

For N budget calculations, ON was originally quantified in Mg ha<sup>-1</sup>, whereas all other N inputs were in kg ha<sup>-1</sup>. This inconsistency made comparisons and visual representations challenging, with

ON dominating graphical outputs. To address this, the change in ON storage calculated by subtracting end-of-season ON from start of season ON was used in the final N budget. This change value, expressed in  $\text{kg ha}^{-1}$ , was included as a component of total N inputs.

Annually, inorganic N within the 60 cm soil profile, at the start of each cropping season remained consistent with no significant differences across all zones, ranging from 47 kg/ha in MZ1 and 52 kg/ha in MZ2 (Figure 2.8.5) and crops, ranging from 42 kg/ha in maize and 54 kg/ha in Wheat. The end of season soil N did not report any significant differences among MZ. However, significantly higher inorganic N was left in soil profile after maize harvest, especially in MZ2 (81 kg/ha) compared to MZ1 (53 kg/ha).

Depth-wise soil analyses were conducted to examine N movement within six different soil sections taken from 0- 61 cm deep soil cores. These analyses revealed that N concentrations were highest in the surface soil layers (0–5 cm), followed by the 5–15 cm depth, and markedly decreased beyond 15 cm. Additionally, significant year-to-year variability in N concentrations was observed, with 2023 showing notably higher levels compared to 2021 and 2022 (Figure 2.8.5). This variability underscores the importance of soil characteristics, climatic conditions, and management practices in influencing soil N dynamics.

Organic nitrogen (ON), a well-established component of the soil N pool, played a significant role in this study as well. Consistent with existing knowledge, notable differences in organic N were observed across crops and management zones, emphasizing its critical role in soil fertility management. These findings further support the importance of monitoring organic N dynamics when evaluating N availability and cycling under different cropping systems. Maize exhibited significantly higher change (positive) in ON, likely influenced by soybean residue incorporation,

poultry litter applications, and favorable climatic as well as soil conditions, which accelerated organic matter decomposition and microbial activity.

Over the four-year study period, inorganic N measured at planting showed no significant differences among management zones and crops, indicating a consistent amount of mineral N in soil profile each year. However, the mineral N remaining in the soil profile after maize harvest indicated substantial residual N across all MZs. This likely reflects an over-application of fertilizer N relative to crop uptake, particularly in zones where maize yields and N uptake were lower. Among the total N inputs, the contribution from urea-based fertilizer alone ranged from X to Y kg ha<sup>-1</sup> (insert your actual values), which may have exceeded the actual crop demand. While this excess N may not be immediately lost during the growing season, it becomes highly susceptible to leaching or denitrification post-harvest—especially when fields are left fallow for extended periods (Frerichs et al., 2022). Similar outcomes have been reported by Blesh and Drinkwater (2012) and Greer et al. (2018), who observed elevated residual soil N following maize cultivation, attributing it to high fertilizer inputs and poor synchronization between crop demand and N supply, leading to increased environmental losses. Thus, closely monitoring both organic and inorganic N dynamics and synchronizing N application to crop demands can enhance management practices, mitigate environmental impacts, and optimize crop N utilization efficiency.

### **Nitrogen Surface Runoff Losses**

Surface runoff represents an important pathway for N transport from agricultural fields, particularly in the form of nitrate (NO<sub>3</sub><sup>-</sup>-N) and ammonium (NH<sub>4</sub><sup>+</sup>-N). The extent of these losses is strongly influenced by rainfall intensity, field topography, and soil characteristics. Figure 2.8.6 A, illustrates the relationship between precipitation patterns and runoff generation in two MZ (MZ1 and MZ3). Consistent edge-of-field monitoring revealed that MZ3 experienced higher

runoff volumes than MZ1, with the most substantial runoff events following periods of intense rainfall.

Temporal comparisons across crops and years indicated that 2021 was notably wet, with 651 mm of rainfall recorded during the soybean season. This resulted in runoff volumes of 45 mm/ha in MZ3 and 34 mm/ha in MZ1. Despite high rainfall, N losses during this period remained relatively low. In contrast, peak rainfall events in 2022 and 2023 occurred between November and April, coinciding with the fallow period and wheat cultivation, which led to elevated N runoff losses.

N losses via runoff were most pronounced in MZ3 during wheat cultivation, amounting to 1.8 kg/ha in 2022 and 3.1 kg/ha in 2023. The fallow periods also contributed to N losses in this zone, with losses measured at 0.4 kg/ha in 2021 and 0.1 kg/ha in 2022, underscoring the vulnerability of bare soils to surface transport of nutrients. In contrast, soybean and maize systems reported the lowest runoff N losses: 0.2 kg/ha in soybeans (2021), 0.01 kg/ha (2023), and 0.07 kg/ha in maize (2022). Although variation existed across zones and cropping systems, surface runoff did not constitute the dominant N loss pathway at the study site. Over the four-year monitoring period, cumulative N losses via runoff were considerably higher in MZ3 (6 kg/ha) compared to MZ1 (1 kg/ha) (Figure 2.8.6 B). These differences are attributed to the inherent topographical and hydrological features of the zones. MZ3, encompassing a 37 ha watershed with steeper slopes of 6-8% and shorter flow paths, generated greater runoff volumes and N transport relative to the smaller, 11 ha MZ1 representing flat topography (0-2% slope).

N losses in MZ3 were further exacerbated by substantial rainfall events during the wheat-growing season and the application of manure and inorganic fertilizers at the tillering stage. These findings are in agreement with previous studies. For example, Wang et al. (2023) observed that excessive or poorly timed fertilizer applications during periods of heavy rainfall substantially increased N

losses through runoff. Weyers et al. (2021) reported that winter wheat systems experienced the highest cumulative runoff and nutrient exports under intense precipitation conditions. Sherman et al. (2020) also noted that reduced or no-till systems are particularly vulnerable to surface N transport, as fertilizers on the surface remain exposed and are more readily mobilized during rainfall events.

### **2.3.3. Nitrogen Budget**

A comprehensive N budget analysis was conducted across the three MZs (MZ1, MZ2, and MZ3) to quantify total N inputs, total N outputs, and subsequently unaccounted-for N losses. Although fertilizer N rates were uniform across zones, significant differences emerged in N outputs and unaccounted-for N losses, highlighting inefficiencies in N use and crop productivity.

#### **Nitrogen Inputs vs. Outputs Across Crops**

Maize received the highest total N input ( $442 \pm 10$  kg/ha), primarily from inorganic fertilizers and manure applications (Table 2.8.4). However, the estimated total outputs amounted to  $353 \pm 7$  kg/ha, leaving  $90 \pm 6$  kg/ha of unaccounted-for N. This surplus likely reflects substantial N losses through volatilization, leaching, or denitrification, raising concerns about environmental sustainability. Wheat followed a similar trend, with  $306 \pm 7$  kg/ha of inputs and only  $183 \pm 13$  kg/ha of outputs, resulting in  $123 \pm 9$  kg/ha of unaccounted-for N. The high post-harvest soil N observed in wheat plots suggests inefficient N uptake, possibly due to lower biomass accumulation and a shallow root system. Yadav (2024) similarly reported reduced N uptake efficiency in winter wheat, attributing it to limited root proliferation and nutrient demand.

In contrast, soybean—a legume capable of fixing atmospheric N—exhibited a negative N balance in 2021 within MZ1 ( $-15 \pm 3$  kg/ha). This partial balance included external N inputs and estimated

N fixation calculated as 60% of total aboveground N uptake. However, root N uptake was not included in the output estimate, which may have led to an underestimation of total N removal and overstatement of the N deficit. Despite this limitation, the data suggests that soybeans relied on a combination of residual soil N and fixed atmospheric N to meet crop demands. Over multiple seasons, if root N contributions are not replenished or compensated by fixation, soil N depletion could still occur. Zambon et al. (2023) also observed negative N balances in soybean systems, where grain removal often exceeds the amount biologically fixed, especially when root N and belowground contributions are not fully quantified. He emphasized that soybean continuous negative balance or near zero balance in soybean monoculture could lead to potential soil N depletion. To improve early growth and stimulate nodulation, a small starter dose of N is often recommended at planting. This practice helps initiate the BNF process without suppressing microbial symbiosis, supporting a more complete and sustainable N cycling strategy in soybean production systems.

### **Nitrogen Imbalances Across Management Zones and Environmental Implications**

The N budget analysis across management zones revealed considerable spatial variability in unaccounted-for N, indicating inefficiencies in N use and potential for environmental losses. Among the three zones, MZ2 consistently exhibited the highest unaccounted-for N, averaging 34% more than MZ1 and 15% more than MZ3. Despite exhibiting the lowest crop N uptake, MZ2 retained greater amounts of residual soil N at harvest. While losses may not be immediate, the discrepancy between soil N levels at planting and harvest suggests that a substantial portion of N in MZ2 is gradually lost during the fallow winter period. These trends suggest a slow-release mechanism of N loss that is not directly tied to the growing season. This observation aligns with Ruma et al. (2023), who emphasized that variability in soil N mineralization rates across zones

and an insufficient understanding of mineralization capacity can lead to residual mineral N accumulation, which is prone to gaseous emissions and leaching during non-crop periods.

In contrast, MZ1 demonstrated greater N uptake, reflected by lower unaccounted-for N — $79\pm 7$  kg/ha in maize,  $99\pm 31$  kg/ha in wheat, and  $11\pm 16$  kg/ha in soybean—and higher crop productivity. Efficient uptake and removal of N through harvested biomass in this zone limited the potential for environmental losses. MZ3 showed intermediate losses, with unaccounted-for N reaching  $121\pm 18$  kg/ha in maize,  $125\pm 16$  kg/ha in wheat, and  $22\pm 23$  kg/ha in soybean. Although wheat and soybean biomass production was relatively high in MZ3, the elevated N losses suggest that nutrient leaching and surface runoff, particularly during wetter periods, may have contributed to inefficiencies.

The patterns of unaccounted-for N observed across zones were strongly associated with positive N balances, particularly in maize and wheat. These positive balances indicate that fertilizer and other N inputs exceeded crop N removal, increasing the risk of accumulation and subsequent environmental loss. Similar findings have been reported by Poudel et al. (2001), Gentry et al. (2009), and Dattamudi et al. (2020), who emphasized the environmental implications of excessive N surpluses in cereal systems. Notably, unaccounted-for N in wheat systems reached a peak of  $172\pm 9$  kg/ha, further supporting previous studies (Korsaethe et al., 2000; Shi et al., 2012; Sieling & Kage, 2006) that linked high N inputs to significant residual N at harvest and increased post-season losses.

In contrast, the negative N balance observed in soybeans implies that the crop relied heavily on soil N reserves, potentially compromising long-term soil fertility if those reserves are not replenished (Sainji et al., 2017). These findings highlight the need for zone-specific nutrient

management strategies aimed at optimizing N inputs, reducing residual N accumulation, and mitigating environmental losses while maintaining soil health and crop productivity.

#### **2.4.Implications for Zone-Specific Nutrient Management**

The variability in N budgets across management zones and crops highlights the need for tailored nutrient management strategies. Improving nutrient use efficiency in MZ2 through precision management could help reduce losses and enhance productivity. Meanwhile, balancing inputs and outputs across crops is crucial for maintaining soil fertility and minimizing environmental risks. The elevated unaccounted-for N losses in MZ2 call for strategic interventions to improve nutrient retention and reduce inefficiencies. Implementing zone-specific fertilization, cover cropping, or soil amendments could help optimize N use and cycling and enhance system sustainability.

#### **2.5.Limitations and Uncertainties in Nitrogen Budget Estimation**

Nitrogen mass balance calculations are a valuable tool for identifying imbalances in farm-level N management. However, they are subject to certain limitations that introduce uncertainty into the results. One major challenge lies in estimating N losses through volatilization, denitrification, and leaching—processes that are inherently complex and highly variable across time and space. Field-based N budgets rely on estimating several key components, including soil N content, organic N mineralization, crop N uptake, and biological N fixation. Each of these processes carries its own set of uncertainties. For example, biological N fixation is often estimated indirectly, which may result in under- or overestimation. Additionally, due to the difficulty of directly measuring N losses, these are often lumped into an “unaccounted-for N” category, masking the specific contribution of each loss pathway.

Despite these challenges, N budgeting remains a powerful tool. It offers detailed insights into soil N dynamics, crop nutrient demands, and available N sources—critical information for guiding more efficient and sustainable N management. As emphasized by Oenema and Van (1999) and Oenema et al. (2003), improving the accuracy of N budgets requires robust field data, integration of advanced modeling tools, and a system-level understanding of N cycling processes.

Despite these challenges, N budgeting remains a powerful tool. It offers detailed insights into soil N dynamics, crop nutrient demands, and available N sources—critical information for guiding more efficient and sustainable N management. As emphasized by Oenema and Van (1999) and Oenema et al. (2003), improving the accuracy of N budgets requires robust field data, integration of advanced modeling tools, and a system-level understanding of N cycling processes.

## **2.6.Conclusion**

The N budget study conducted from 2021 to 2024 on a commercial farm in North Alabama provided valuable insights into the management practices in a row crop production system and their effect on N dynamics across management zones. The study revealed that there was variability in N outputs and unaccounted-for N across management zones. Among crops, maize had significant unaccounted-for N at MZ3 ( $121\pm 18$  kg/ha), recommending the need for site-specific N management at this farm for more profitable and ecologically sustainable outcomes. Winter wheat received considerably high N inputs ( $314\pm 1$  kg/ha in MZ1,  $331\pm 18$  kg/ha in MZ2, and  $334\pm 2$  kg/ha in MZ3) and had substantial unaccounted-for N ( $108\pm 14$  kg/ha in MZ1,  $154\pm 46$  kg/ha in MZ2, and  $123\pm 10$  kg/ha in MZ3) across all zones, which suggests further research to standardize inorganic or manure N application to this crop is needed. Soybean, being an N-fixing crop, showed a negative budget ( $-15\pm 1$  kg/ha in MZ1,  $3\pm 44$  kg/ha in MZ2, and  $22\pm 23$  kg/ha in MZ3), suggesting soil N depletion. Thus, it is imperative to assess pre-planting soil N status to determine whether

the crop requires a starter N dose to ensure a good crop stand and prevent N mining from the soil. Soil analysis for N each year at the onset of the cropping period showed consistent N concentrations, indicating the soil's inherent capacity to retain N while allowing surplus losses. The findings underscore the importance of establishing an N budget to identify areas within a field that are either sufficient, deficient, or experiencing N losses. Such an approach can help policymakers and farmers make informed decisions regarding N management, optimize the use of this crucial nutrient, and ultimately improve the sustainability and efficiency of agricultural practices.

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## 2.8.Tables and Figures

**Table 2.8.1.** Soil and topographical characteristics of different management zones.

<b>Zone</b>	<b>Soil Series</b>	<b>Soil Texture</b>	<b>pH in water</b>	<b>BD g/cm<sup>3</sup></b>	<b>Slope (%)</b>
<b>Stable High Yield Zone (MZ1)</b>	Abernathy Emory	Silty Clay loam - Clay loam	6-6.5	1.7-1.9	0-2
<b>Stable Low Yield Zone (MZ2)</b>	Decatur silty loam clays	Clay loam - Clay	5-5.7	1.8-2	6-12
<b>Unstable Yield Zone (MZ3)</b>	Decatur Clay	Silty Clay loam - Clay	6-6.7	1.7-1.8	4-8

\*The data is presented for soil core 61 cm in depth

**Table 2.8.2.** Crop management practices for soybean, maize, and wheat during the 2021–2024 growing seasons

<b>Year</b>	2021	2022	2022-2023	2023	2023-2024
<b>Crop</b>	Soybean	Maize	Wheat	Soybean	Wheat
<b>Hybrid</b>	Asgrow 55X9	DK- 6916	Pioneer 26R36	Asgrow 57XF1	Pioneer 26R59
<b>Row spacing</b>	76 cm	76 cm	20 cm	76 cm	20 cm
<b>Plant population (seeds/ha)</b>	326,178	79,074	2,100,393	301,468	2,056,434
<b>Planting date</b>	6/28/2021	4/21/2022	10/15/2022	6/9/2023	11/29/2023
<b>Urea</b>	NA	217 (kg/ha)	110(kg/ha)	NA	110 (kg/ha)
<b>Poultry litter</b>	NA	4480 (kg/ha)	4480 (kg/ha)	NA	4480 (kg/ha)
<b>Irrigation</b>	18mm	140 mm	NA	NA	NA
<b>Harvest date</b>	10/17/2021	08/25/2022	05/28/2023	10/29/2023	05/29/2024

**Table 2.8.3.** P value table for different components of nitrogen budget

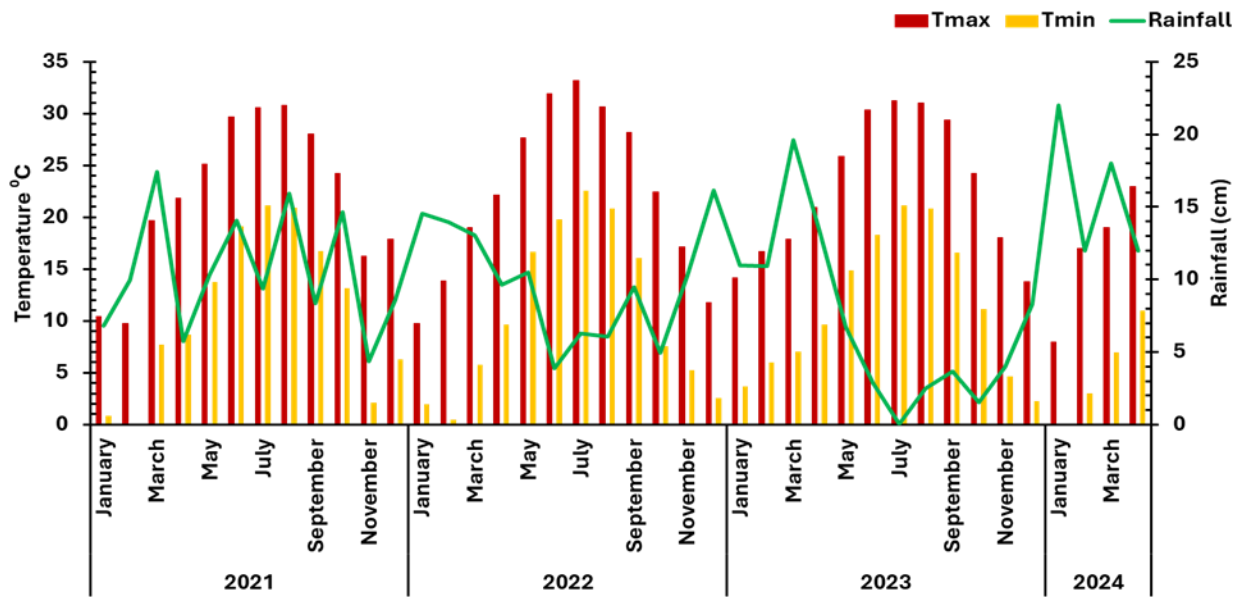
<b>Effect</b>	<b>Yield</b>	<b>N Uptake</b>	<b>N Inputs</b>	<b>N Outputs</b>	<b>Unaccounted N</b>
<b>Crop</b>	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
<b>Zone</b>	<0.0001	<0.0001	0.805	<0.0001	<0.0001
<b>Crop*Zone</b>	0.4452	<0.2203	0.6558	0.6779	0.0923

**Table 2.8.4.** N inputs (kg/ha and outputs(kg/ha) for different crops and management zones for the study site for the years 2021-2023

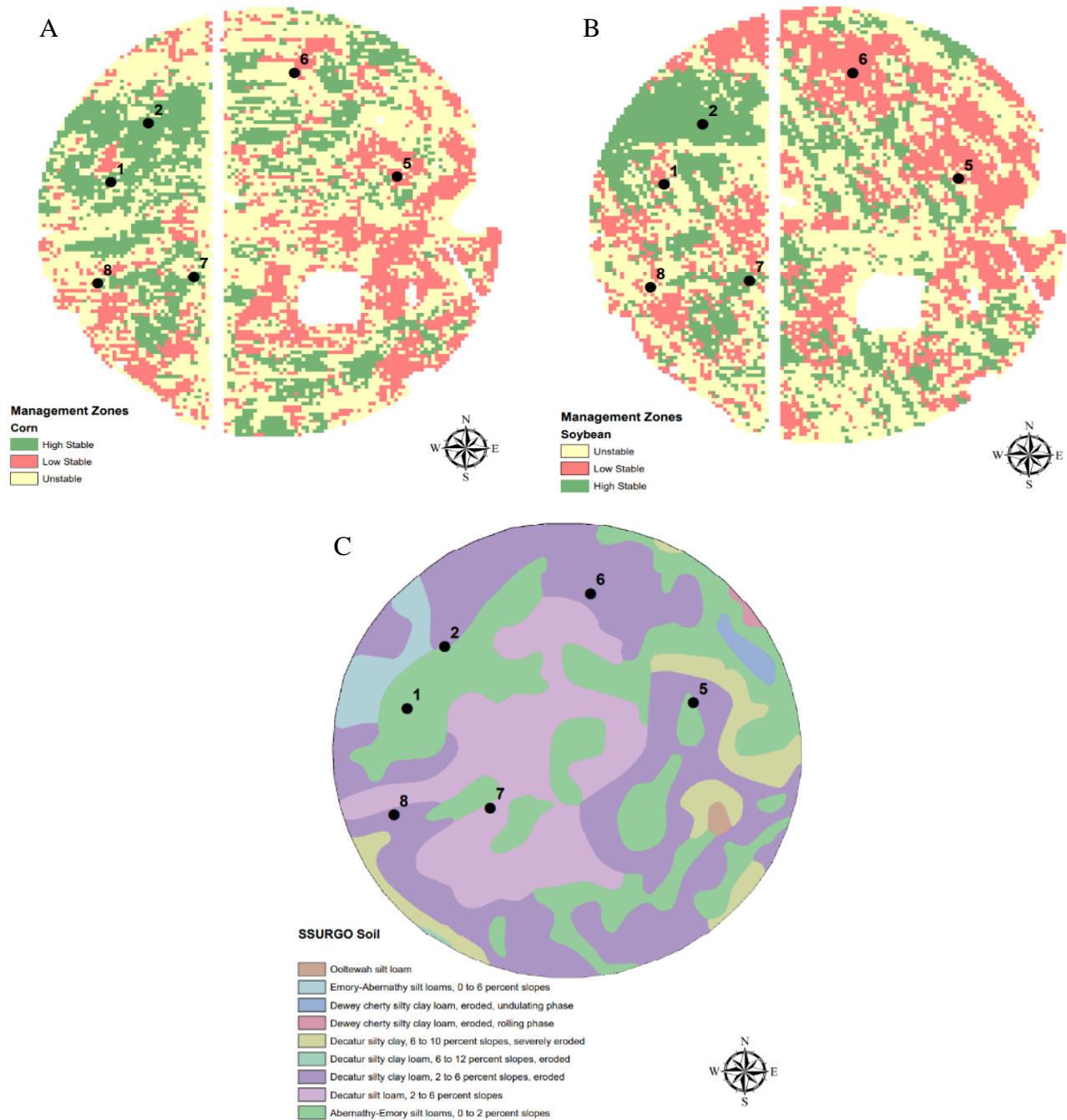
	Crop	Soil N planting	Organic N	Residues N	Manure N	Atm N	Irrigation N	Urea N	Legume N fixed	<b>Total inputs</b>	N uptake	Soil N harvest	<b>Total outputs</b>	<b>Unaccounted N</b>
<b>MZ1</b>	Soybean	59±5	38±5	21±5	NA	6	1	NA	145±12	<b>269±28</b>	247±18	38±11	<b>284±29</b>	-15±1
	Maize	38±5	54±5	22±1	88	5	6	217	NA	<b>429±0.3</b>	303±4	54±11	<b>356±7</b>	72±7
	Wheat	54±5	50±1	17±2	70	5	0	110	NA	<b>305±1</b>	144±11	50±1	<b>194±13</b>	111±14
	Soybean	50±1	47±4	12±1	NA	5	0	NA	153±11	<b>267±18</b>	189±27	47±8	<b>235±35</b>	31±16
	Wheat	47±4	37±0.2	28±4	70	5	0	110	NA	<b>296±7</b>	129±22	54±3	<b>183±24</b>	112±31
<b>MZ2</b>	Soybean	62±26	42±6	30±1	NA	6	1	NA	138±8	<b>278±29</b>	234±3	42±18	<b>276±15</b>	2±44
	Maize	42±6	81±19	12±2	88	5	6	217	NA	<b>451±12</b>	213±3	81±33	<b>293±30</b>	157±19
	Wheat	81±33	51±3	15±5	70	5	0	110	NA	<b>331±18</b>	126±31	51±3	<b>177±28</b>	154±46
	Soybean	51±3	37±0	11±3	NA	5	0	NA	129±13	<b>232±47</b>	136±50	37±0.4	<b>172±50</b>	59±3
	Wheat	37±0.4	54±0	15±1	70	5	0	110	NA	<b>290±0.5</b>	113±17	49±12	<b>162±29</b>	128±28
<b>MZ3</b>	Soybean	48±6	47±7	37±2	NA	6	1	NA	163±2	<b>301±14</b>	238±5	47±4	<b>284±5</b>	16±23
	Maize	47±7	72±8	13±1	88	5	6	217	NA	<b>448±0.4</b>	262±35	72±16	<b>333±35</b>	114±18
	Wheat	72±8	48±2	20±3	70	5	0	110	NA	<b>325±2</b>	162±5	48±2	<b>210±5</b>	115±10
	Soybean	48±2	37±5	15±2	NA	5	0	NA	145±3	<b>250±9</b>	160±5	37±5	<b>197±5</b>	53±1
	Wheat	37±5	49±3	21±0.2	70	5	0	110	NA	<b>291±5</b>	128±0.3	44±20	<b>171±0.3</b>	120±16

\*The data is presented as means ± standard deviation. MZ1 represents a stable high yield zone; MZ2 represents a stable low yield zone; MZ3 represents an unstable/intermediate yield zone;

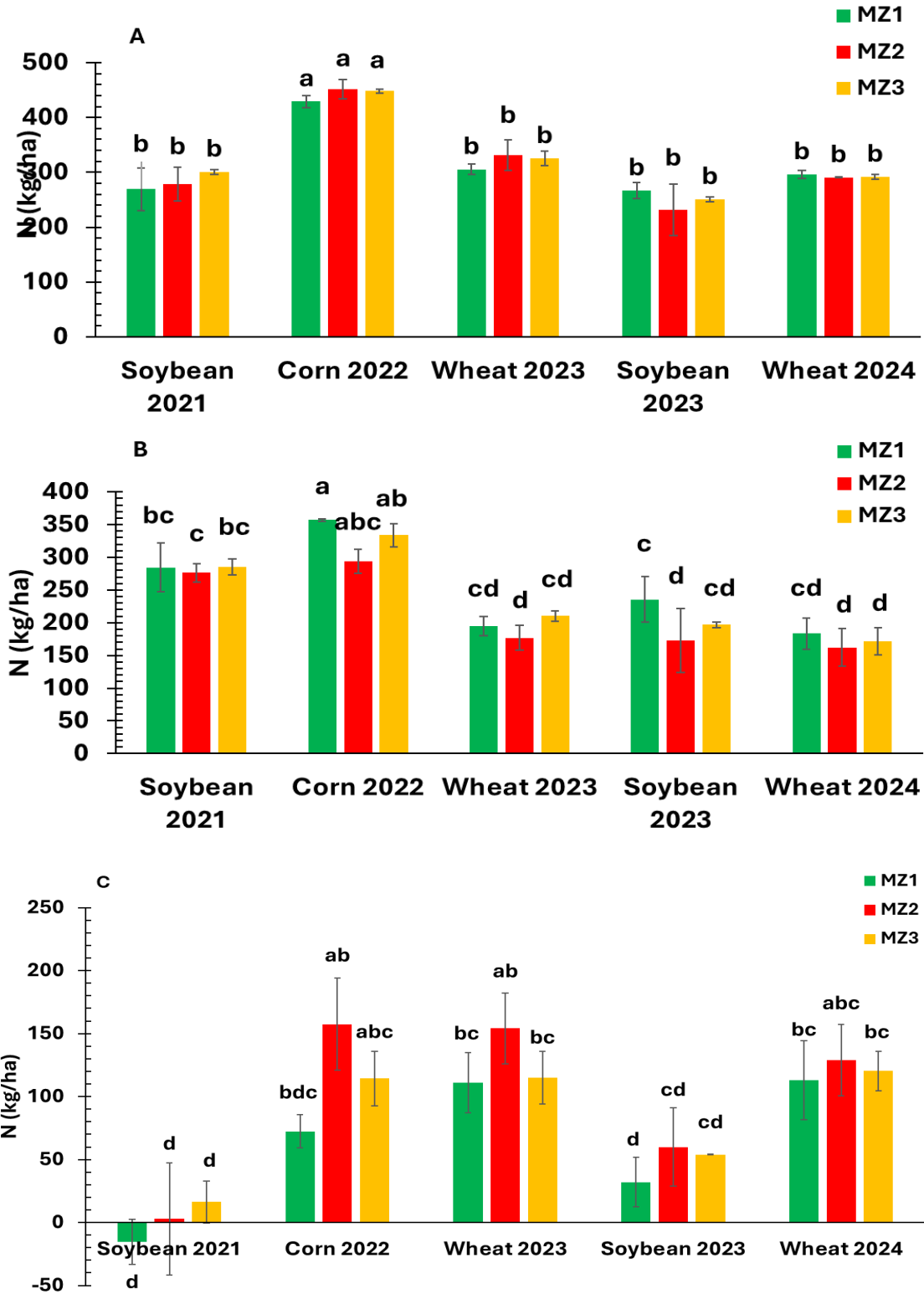
\*All values used in table are expressed in kg/ha.



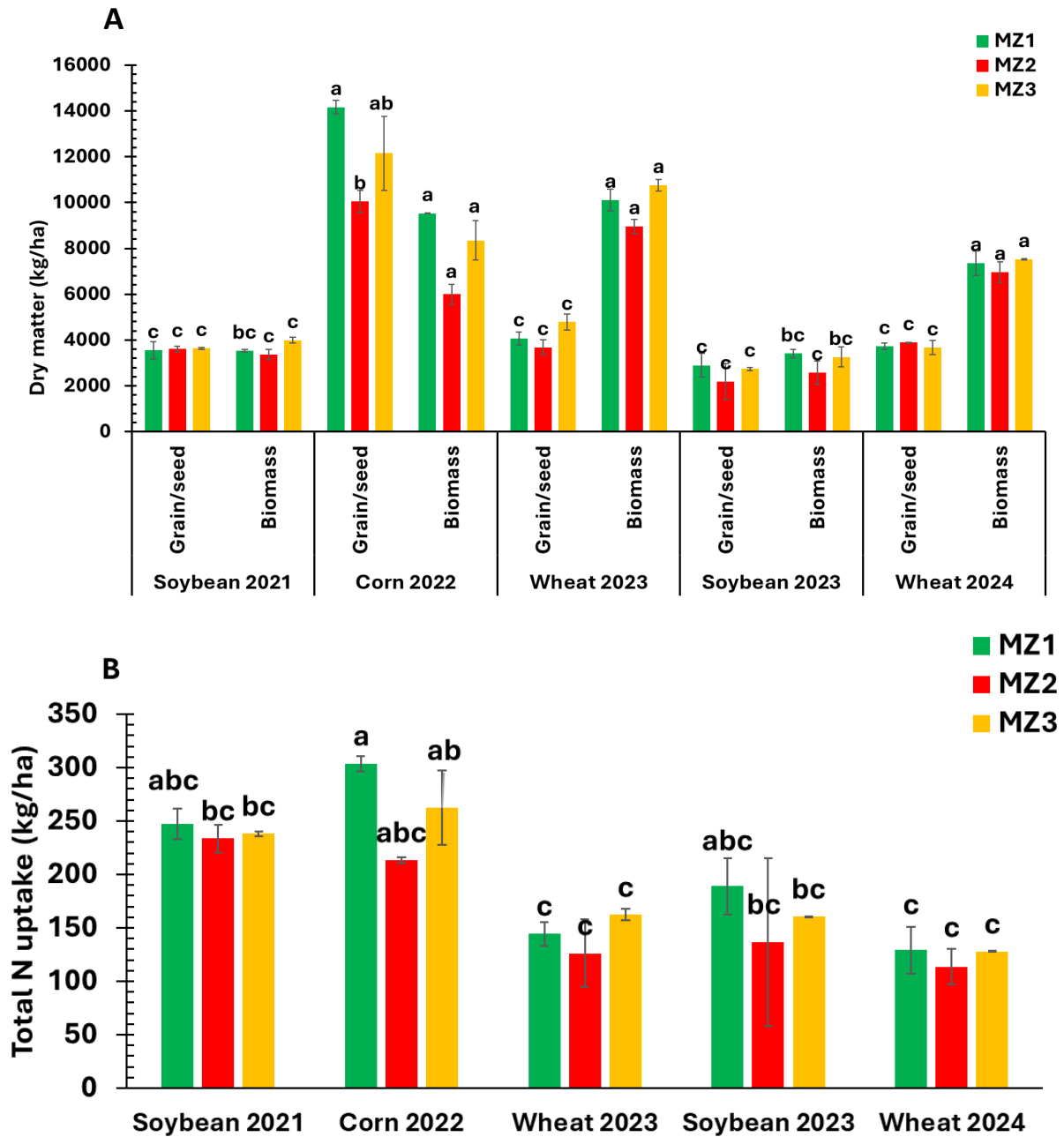
**Figure 2.8.1.** Maximum and minimum temperatures (Primary Y-axis) and rainfall amount (Secondary Y-axis) for the study site for 2021-2024.



**Figure 2.8.2.** Crop Management zones for maize (A) and soybean (B) using historical yield data and zone-specific soil characteristics (C). The numbered dots represent the data collection locations.

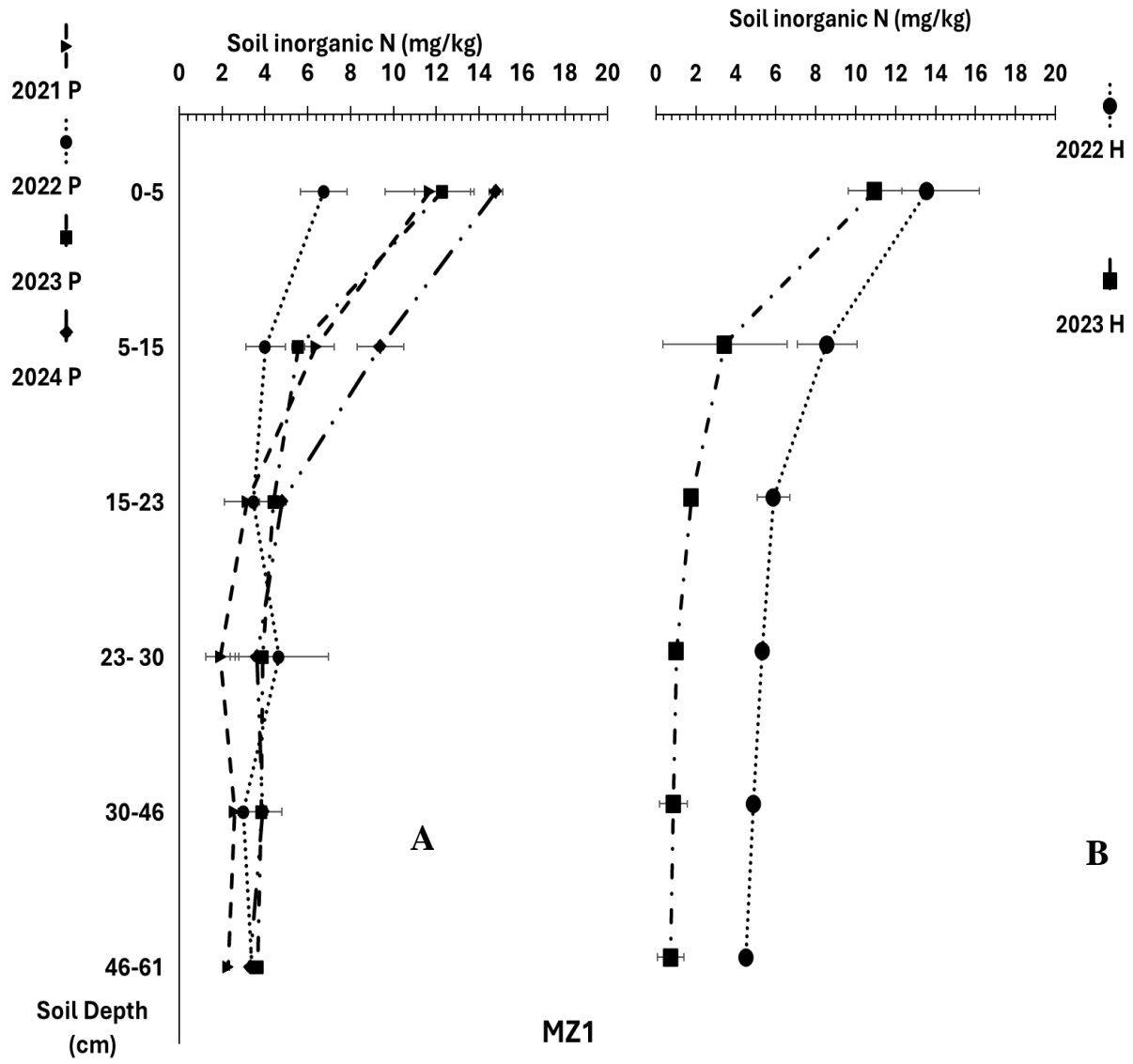


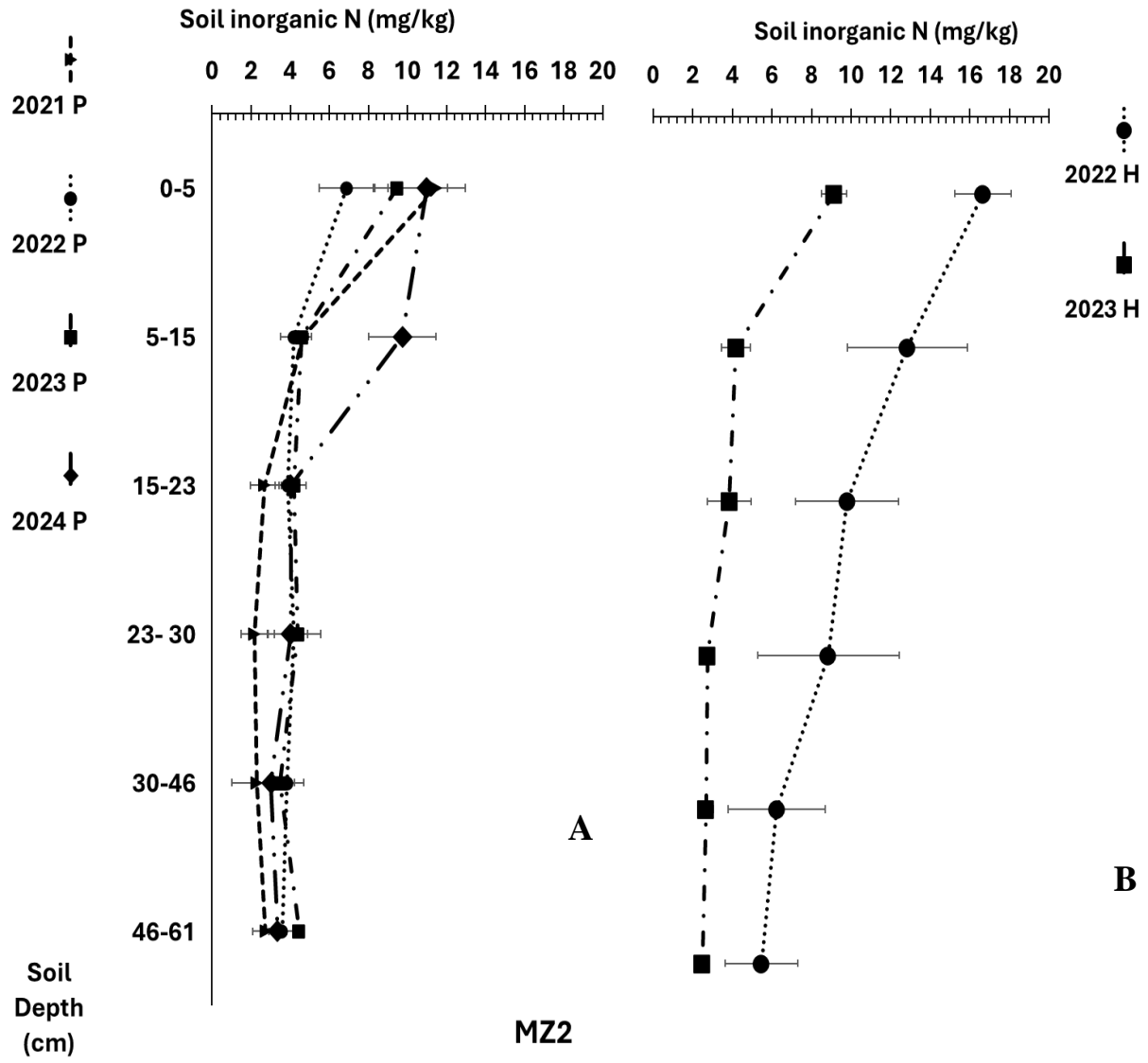
**Figure 2.8.3.** A comparison of nitrogen inputs (A), outputs (B), and unaccounted nitrogen (C) for various crops across three management zones (MZ). Bars with the same letter are not significantly different at  $P < 0.05$  across MZ and crops.

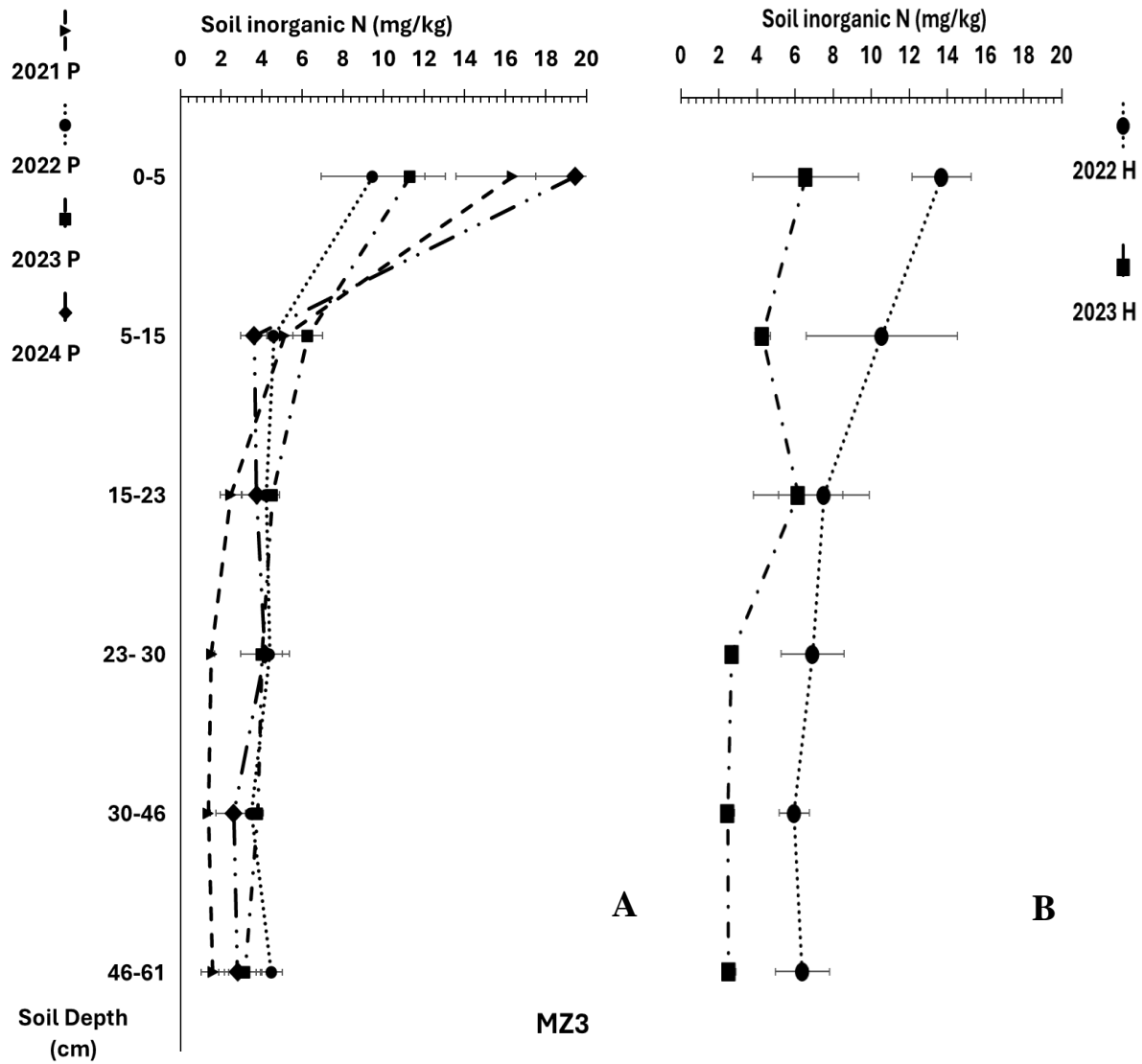


**Figure 2.8.4.** A comparison of grain and biomass yields(A) and total N uptake (B) of soybean-maize-wheat-soybean across three management zones (MZ) at the study site for study years 2021-2024.

Bars with the same letter are not significantly different at  $P < 0.05$  across MZ and crops.

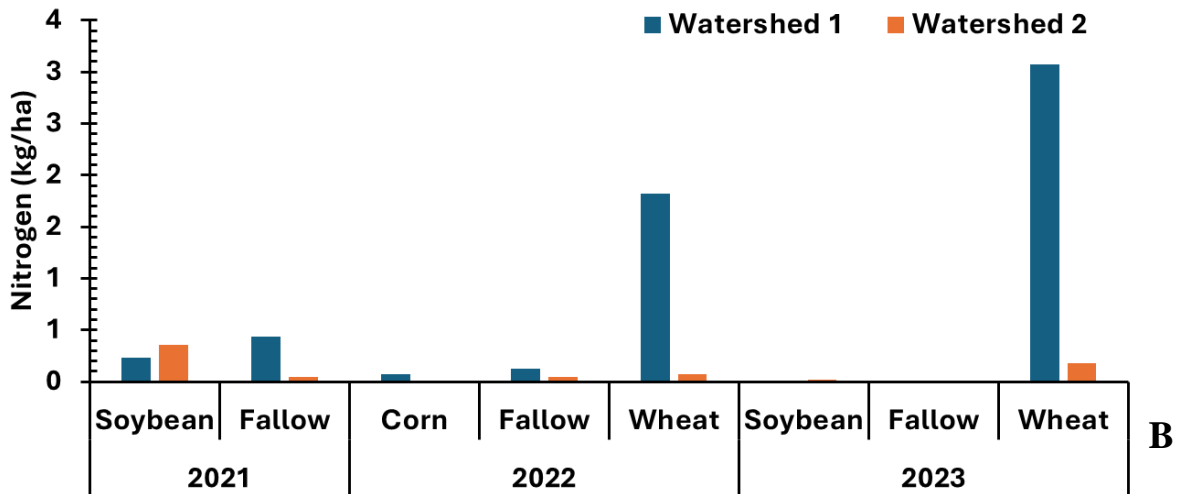
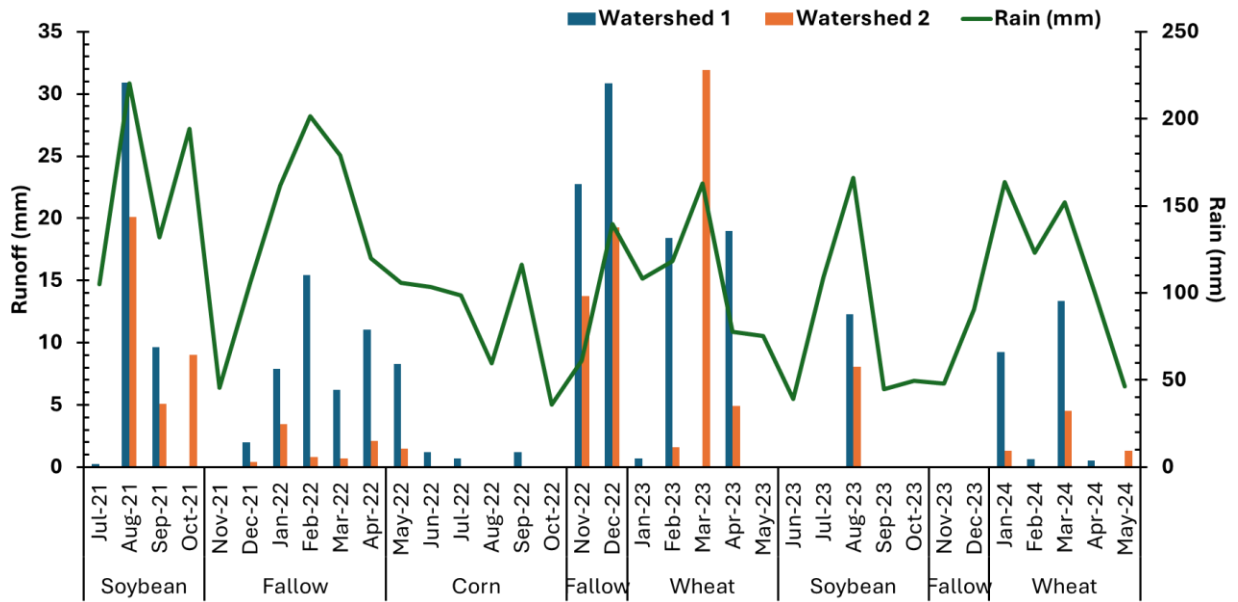






**Figure 2.8.5.** Soil inorganic N distribution ( $\text{NO}_3\text{-N} + \text{NH}_4\text{-N}$ ) before planting (A) and after harvest (B) across different years (2021-2023) and management zones (MZ1, MZ2, and MZ3).

\*P and H followed by year represent planting and harvest soil cores during that particular year.



**Figure 2.8.6.** A comparison of rainfall and runoff patterns (A) for and N loss (B) during years 2021-2024 across two management zones

### **Chapter 3: Potential Nitrogen Mineralization Variability in Commercial Row Crop Fields**

#### **Abstract**

Nitrogen (N) transformation in soils is crucial in determining N availability for plant growth. Row crop producers have widely adopted cover crops across the U.S. However, there is limited knowledge about N transformations in commercial fields with and without cover crops. Furthermore, there is lack of understanding about the spatial variability of potential N mineralization in row crops and how it varies within a field and between cropping systems. An in-situ mineralization study was conducted in two Alabama row crop farms to evaluate the variability of potential N mineralization across locations and within a farm. The results revealed the variability in N mineralization within farms at both the locations. It was reported that a farm with cover crop and residue retention history had a mineralization rate of 1.18 to 3.89 lb/acre/day. In contrast, another farm with no cover crop had a mineralization potential of 0.93 to 1.17 lb/acre/day. These findings underscore the importance of cover crops and residue retention for enhancing N mineralization potential.

Key words: Nitrogen transformation, ammonium mineralization, nitrate mineralization, cover cropping

### 3.1. Introduction

**Nitrogen Transformation in soils** – Nitrogen (N) transformation refers to converting N from an unavailable form to a plant-available form and vice versa. Nitrogen, being the vital nutrient, is required in higher quantities as it directly influences crop yield and productivity. It has various forms and can significantly impact agricultural productivity or contribute to environmental pollution.

**Why is it important to understand N transformations** - Understanding N transformations are essential for several reasons. First, while the dominant component of soil N is organic N, plants primarily utilize inorganic forms such as ammonium and nitrate ( $\text{NH}_4^+$ ,  $\text{NO}_3^-$ ). Soil microbes primarily mediate the biological processes that convert unavailable or organic forms into available forms. Second, N often acts as a limiting factor for plant growth in most terrestrial ecosystems. Consequently, the productive capacity of an ecosystem, known as net primary production, can be regulated by the rates at which soil microbes transform N into forms that plants can utilize. The main concepts associated with N transformations in soil include mineralization, immobilization, volatilization, nitrification, and denitrification. Recognizing these transformations and understanding the various forms of N is crucial for comprehending N movement within the landscape and its environmental implications.

**Soil mineralization and immobilization** -

**Soil mineralization** is the process by which organic N compounds are transformed into simpler inorganic forms, including nitrate and ammonium. According to various studies, the rate of N mineralization in the soil is not constant in time or space, and it depends on many factors, such as

soil type, properties of organic matter, composition of soil microorganisms, and soil temperature and moisture (Robertson & Groffman, 2007, Liu et al., 2016, Buzin et al., 2019, Risch et al., 2020).

These factors and their effect on mineralization are elaborated below:

1. Availability of organic N compounds: Organic N compounds are an energy source for microorganisms, facilitating mineralization.
2. The organic source's carbon-to-nitrogen ratio (C:N): A C:N ratio below 30 promotes mineralization.
3. Soil temperature: Optimal mineralization occurs at around 77°F (25°C), while temperatures below 68°F (20°C) slow the rate of mineralization.
4. Soil moisture: Soils that are poorly drained or too dry experience limited microbial activity, thus slow rates of microbial decomposition and mineralization (Curtin et al, 2012). The ideal moisture level for mineralization is at field capacity or approximately 75% of field capacity. Adequate moisture facilitates microbial activity and nutrient release.
5. Soil texture: Soil texture, such as sand or clay content, influences the stability of organic matter and its decomposition rate. Sandy soils have faster organic matter decomposition than heavy clay soils.
6. Biodiversity: Microbial biodiversity plays a crucial role in mineralization. Healthy soils, particularly those under conservation practices and cover crop systems, harbor a greater diversity of beneficial microbes that greatly influence the potential for mineralization.

**Soil immobilization** - Soil N immobilization is the opposite process of soil N mineralization and involves converting inorganic forms of N into organic forms present in soil microbes. This process is also termed “nitrogen robbing.” In this process, soil microbes utilize the available inorganic N as a nutrient source, leading to its incorporation into their biomass. Immobilization of N reduces

its availability for plant uptake, and it may limit plant growth. It occurs when the soil organic matter or amendments added to the soil contain relatively high amounts of carbon compared to N. Furthermore, N immobilization can intensify during periods of limited moisture availability, such as drought (Zheng et al, 2017).

**Impact of conservation practices on N mineralization rates** - Conservation practices (CP), especially residue retention and crop rotation are known to improve the amount and quality of soil organic matter (SOM), which in turn increases the soil N mineralization. Residue retention involves leaving crop residues, including stalks, leaves, and other plant materials on the field after harvest instead of removing them. These residues, originating from previous crops or cover crops specifically planted for this purpose, contribute to soil health and fertility. On the other hand, crop rotation is a strategy where various crops are cultivated in a specific field over a series of seasons or years that optimizes soil fertility, mitigating pest and disease challenges, and ultimately improving overall crop yields. Cover crops have many excellent benefits and are essential to soil health. Cover crops provide advantages by protecting top fertile soil and adding organic substrate to improve soil beneficial microbes. Overall, it enhances soil aggregate stability, soil biological activity, soil biodiversity, and carbon sequestration (Ghosh et al., 2010). Munera et al., 2020 conducted a study to investigate the effects of CP on the amount and quality of soil organic matter (SOM) and potential N mineralization. Their results suggest that the CPs are more effective in increasing SOM and N mineralization than conventional agricultural systems. Another study by Restovich et al., 2022 highlighted the importance of incorporating legumes as cover crops in crop rotation. The experiment reported that the legume monoculture and legume-dominated mixtures maintained higher soil mineral N stocks at cover crop termination than the grass- or brassica-associated cover crops. Introducing a legume in a mixture with non-legumes enhances N cycling

by maintaining biological N fixation and N retention of potentially leachable N in aboveground biomass of both the legume and the non-legume mixture component.

Understanding soil N immobilization is crucial for managing N dynamics in agricultural systems. By carefully considering the C:N ratios of organic inputs and ensuring adequate moisture conditions, farmers can mitigate the potential adverse effects of N immobilization and maintain a balanced nutrient supply for their crops.

### **Soil health and potential N mineralization –**

Soil health is intricately tied to soil organic matter (SOM). It is vital in soil fertility as it enhances nutrient absorption and release and creates a conducive environment for soil microbes (Geisseler et al. 2021). Soil microbes are key players in maintaining soil fertility as they break down organic residues, which either immobilize N, making it unavailable for plants or mineralize N, making it available for plant uptake. This article explores the advantages of conservation practices and the retention of residues on agricultural lands. More specifically, the focus is on the impact of potential N mineralization by soil microbes. Gaining a deeper understanding of N cycling in agriculture is crucial for improving fertilizer use efficiency and promoting sustainable food production in Alabama.

The N mineralization potential of soils is an estimate of the net production of inorganic N under given conditions, and it provides a means to assess soil N availability. To investigate the N mineralization potential of different soil types, a study was conducted in Alabama in 2022. The study aimed to observe the differences in N mineralization potential between two commercial farms, one with a cover crop adoption and the other without a cover crop history, and determine the within-field variability for mineralized N.

### 3.2. Materials and Methods

The study was conducted on two farmers' fields (Table 3.6.1) in Central (F40) and North Alabama (F11). An in-situ buried bag experiment protocol, as described by Sullivan et al. (2021), was followed.

Field F40 (Figure 3.6.1) was divided into seven locations: high, medium, and low-yielding zones based on multiple years of data collected at this farm (Table 3.6.3). The soil type is classified as loamy sand (Table 3.6.3). The cropping sequence observed in Field F40 involved a peanut-cover crop-cotton rotation. This experiment was conducted during cotton crop. At the beginning of the study, Field F40 had residues retained on its soil surface (cover crop residues – mixture of triticale @ 30 lb/acre, clover @ 5 lb/acre, and radish @ 5 lb/acre) and received an application of two tons per acre of chicken litter (35 days before planting) and recommended dose of urea (217 lb/acre) at the time of planting cotton (05/20/22). The total soil carbon content in Field F40 ranged from 1.0% to 1.8%. To assess the variability in N mineralization potential of the field, all seven locations were selected for the in-situ incubation experiment. The buried bags were collected four times starting in June and continued until the end of September (Table 3.6.2) to assess the N mineralization potential of the soil.

Similarly, based on historical yield data, Field F11 (Figure 3.6.2) was divided into 4 locations: 1 & 2 into high-yielding and 7 & 8 into low-yielding zones. The farm has predominantly silty loam soils (Table 3.6.5). The farm employs a crop rotation system consisting of soybeans followed by corn. There are four months of fallow period (Dec- Mar) between soybean harvest in Nov and corn planting in April. Chicken litter (25 days before planting) and recommended dose of urea (420 lb/acre) was applied to corn (04/21/22). The study was conducted during corn period (Table 3.6.1). The total soil carbon content in Field F11 ranged from 1.2% to 1.6%. All four locations were

chosen for the incubation experiment to capture the variability within the field. The buried bags were pulled twice during the growing season to assess the N mineralization potential. (Table 3.6.4).

**In situ Buried bag method** - This study used 8-inch-long Whirl Pak bags to perform infield incubation. These bags were sealed on one side and had a tie on the other end to secure their contents.

1. The soil samples were collected from the cotton field at various sampling locations at Field F40 and Field F11 (Figure 3.6.1 & 3.6.2) using an auger to extract soil from the top 2 inches of the soil profile. The collected soil from the replicates was combined and passed through a 6 mm sieve to create composite samples. The soil collection and sieving steps are shown in Figure 3.6.3.
2. No additional water was added to the soil samples during collection to maintain similar moisture conditions as surrounding soils. The soil moisture presents at the sampling time, referred to as "as-is" soil moisture, was retained within the samples. At the time of collection, the moisture status of soils was near field capacity to provide adequate moisture availability and promote better aeration within the bag.
3. Subsequently, 100 grams of the sieved soil was tightly packed into the labeled Whirl Pak bags and securely sealed for incubation. The bags were buried near the crop rows to ensure that the soil inside the bags experienced similar temperatures as the surrounding field soil. This in-situ placement allowed for the estimation of N mineralization under natural conditions. The incubation steps are shown in Figure 3.6.4.
4. At burial, the soil samples were analyzed for bulk density, gravimetric water content, nitrate, and ammonium to provide initial N concentration (T<sub>0</sub>).

5. The bags remained buried for a minimum incubation period of 21 days at various periods, as specified in Table 3.6.2 and Table 3.6.4.
6. The bags were carefully retrieved from the field after incubation. The soil contents were analyzed to determine gravimetric water content and the concentrations of nitrate and ammonium, referred to as the final N concentration (T1).
7. Following the first incubation period, a new set of bags was buried, and steps 1 to 6 were repeated to collect mineralization data multiple times during the cropping period, allowing for multiple measurements and a more robust assessment of N mineralization over time.

**N Analysis-** The soil retrieved from bags was used to determine inorganic N accumulation. The soil was extracted at “as-is” moisture to avoid the flush of mineralization that often accompanies soil drying and rewetting. The gravimetric water content of the soil was also calculated to adjust the soil weight on an oven-dried basis for the final N (kg/ha) estimation (Figure 3.6.5). Ammonium + nitrate-N were determined by using 5 g soil (weight later adjusted using gravimetric water content calculations) and 2M KCl extraction, followed by analysis in flow injection analyzer (Nitrate-EPA 353.2- FIAlyzer 1000, Greiss method with cadmium reduction and Ammonium - EPA 350.1-FIAlyzer 1000, Salicylate method)

### **Calculations-**

T0 is when the bag was buried, and T1 is when the bag was retrieved from the soil.

#### ***Net Nitrification***

$$= ([\text{nitrate on T1}] - [\text{nitrate on T0}]) / \text{incubation days}$$

#### ***Net Ammonification***

$$= ([\text{ammonium on T1}] - [\text{ammonium on T0}]) / \text{incubation days}$$

#### ***Net Mineralization***

$$= ([\text{nitrate} + \text{ammonium on T1}] - [\text{nitrate} + \text{ammonium on T0}]) / \text{incubation days}$$

### 3.3. Results and Discussion

By conducting this experiment at Field F40 under actual farming conditions, valuable insights into the N dynamics and mineralization potential were obtained. Mineralization rates were higher at F40, ranging from 1.18 to 3.89 lb/acre/day during the start of the experiment, and declined to 0.93 to 1.77 lb/acre/day during later periods (Figure 3.6.6). In contrast, the mineralization rate in Field F11 (Figure 3.6.8) ranged from 0.40 to 0.47 lb/acre/day during the first time period (33-day incubation period) and increased from 0.93 to 1.17 lb/acre/day during the second time period (55-day incubation period). The initial high mineralization rate at F40 can be attributed to the availability of organic substrate in the form of cover crop residues (Nov – Mar). The presence of organic substrate and a favorable carbon-to-nitrogen ratio promoted microbial population and mineralization. Conversely, F11 lacked cover crops; thus, a low organic substrate for microbes led to low mineralization rates and immobilization at locations 7 and 8 during the first incubation.

Another crucial consideration is the influence of topography, hydrology, and weather on the results. The favorable topography with slopes of less than 6% and the loamy sand texture of soils facilitated adequate drainage and less surface runoff at F40. A total of 20 inches of rainfall was recorded during this experiment with an average  $T_{\text{max}}$  of 89 °F (Figure 3.6.7), which favored the decomposition of cover crop residues on the soil surface and the decomposition of poultry litter applied before planting. Conversely, F11, with heavy textured soils and a slope around 10%, experienced hot and dry conditions during the study period with an average  $T_{\text{max}}$  of 88 °F and only 10 inches of rain (Figure 3.6.9). Before planting corn, the field was fallow from November 2021 to April 2022. During this fallow period, 28.1 inches of rainfall were recorded, leading to surface runoff, which could have carried away topsoil and accumulated inorganic N. This phenomenon

likely resulted in decreased beneficial microbial activity in the soil. This theory is supported by results observed at location numbers 7 and 8 (which falls under steeper slope areas compared to location 1 and 2), ( Fig 2) which experienced immobilization at first incubation and could be attributed to slower rate of decomposition of organic substrate-poultry litter (applied 25 days before planting)

The results also exhibited variation among different locations within both experimental sites. The variation in mineralization followed a similar trend as the yield-based zone delineation. At F40 (Fig 6), the highest mineralization rate was recorded at locations falling under high-yielding zones (3,4,9) compared to the lowest at low-yielding zones (7 &8). The variation was predominantly due to differences in hydrology. The soil texture for all the locations did not vary significantly at the surface layer. Similarly, at F11, high mineralization rates were reported at locations 1 and 2 (high-yielding zones). The mineralization potential at these locations ranged from 0.40 to 0.47 lb/acre/day during the first incubation and 1.17 to 1.54 lb/acre/day during the second incubation compared to locations 7 and 8 that experienced immobilization at first, followed by mineralization (0.38 to 0.89 lb/acre/day) during the later incubation period (Fig 8).

This experiment was conducted to collect baseline data from farmer-managed fields to understand the contribution of mineralized N in the total N inputs in commercial row crop system. There are a few limitations to this experiment. The protocol followed can only make relative comparisons in N mineralization rate and amount among soils sampled from different parts of the fields having variable texture, slope, and hydrology. Under farmers' field conditions, it is difficult to maintain uniform conditions like temperature and soil moisture conditions (e.g., moisture near field capacity) when using soils that vary in texture and water holding capacity. For an in-depth

understanding of soil N mineralization, the protocol should be replicated under laboratory conditions of similar soil temperature and moisture.

### **3.4. Conclusion**

This study emphasizes the variability of N mineralization within a field and between two commercial agricultural farms with dissimilar management practices. Overall, the experiment findings underline the intricate relationship between soil properties, climatic conditions, and organic inputs in shaping the mineralization processes within agricultural systems. F40, with a cover crop history, had enhanced N mineralization potential compared to F11, with no crop during the fallow period. The comparison between F40 and F11 also highlights the importance of adequate moisture conditions and implementing conservation practices and residue retention on agricultural lands. The within field variability emphasizes the heterogeneity in topography and hydrology, indicating varying N dynamics within the field. The applied inorganic N fertilizer is short-lived due to its complex nature and associated losses. However, organic matter provides a slow but steady source of plant nutrients. By comprehending the intricacies of N cycling and field variability, we can improve fertilizer efficiency and foster sustainable agricultural practices for enhanced food production.

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### 3.6. Tables and Figures

**Table 3.6.1.** Field Description

Location	Latitude	Longitude	Area (Acres)	Soil type	Crops
F40	32.419237	-85.416157	14.4	Loamy sand	2021- Peanut 2022- Cotton 2023- Corn
F11	34.715870	-87.393020	118	Silty loam	2021- Soybean 2022- Corn 2023-Wheat- Soybean

**Table 3.6.2.** Timeframes for buried bags installation and incubation period in Field F40.

Time period 1	06/06/23 to 06/27/23
Time period 2	06/27/23 to 07/21/23
Time period 3	07/21/23 to 08/29/23
Time period 4	08/29/23 to 09/20/23

**Table 3.6.3.** Soil texture at all incubation locations in Field F40

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Location	Yield zone	Sand %	Silt %	Clay %	Soil textural class
3	High	81.6	12.16	6.20	Loamy sand
4	High	75.9	15.08	9.00	Sandy loam
5	Medium	75.9	16.04	8.04	Sandy loam
6	Medium	81.7	14.16	4.16	Loamy sand
7	Low	79.9	14.0	6.16	Loamy sand
8	Low	86.9	6.53	6.59	Loamy sand
9	High	81.9	10.0	8.08	Loamy sand

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**Table 3.6.4.** Field F11 incubation dates

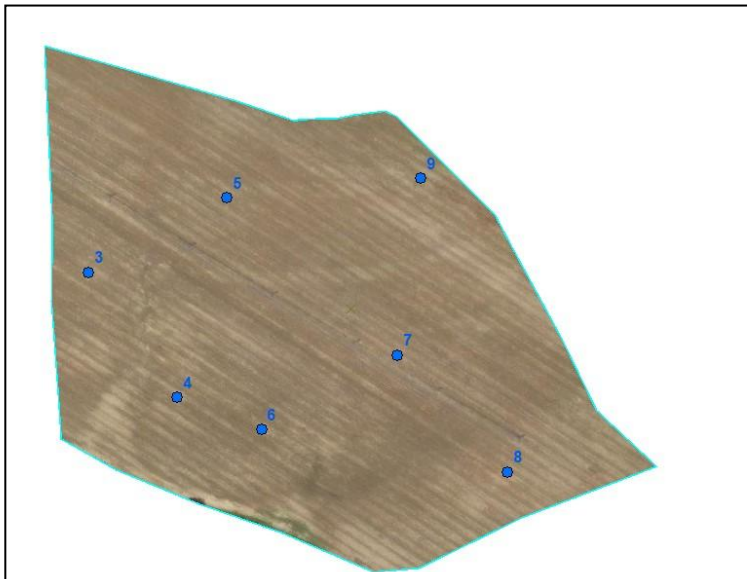
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Time period 1	05/01/22 to 07/07/22
Time period 2	07/07/22 to 09/05/22

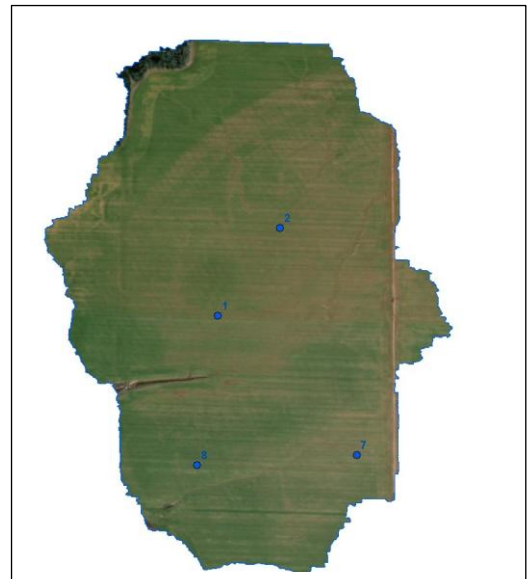
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**Table 3.6.5.** Soil texture at all incubation locations in Field F11

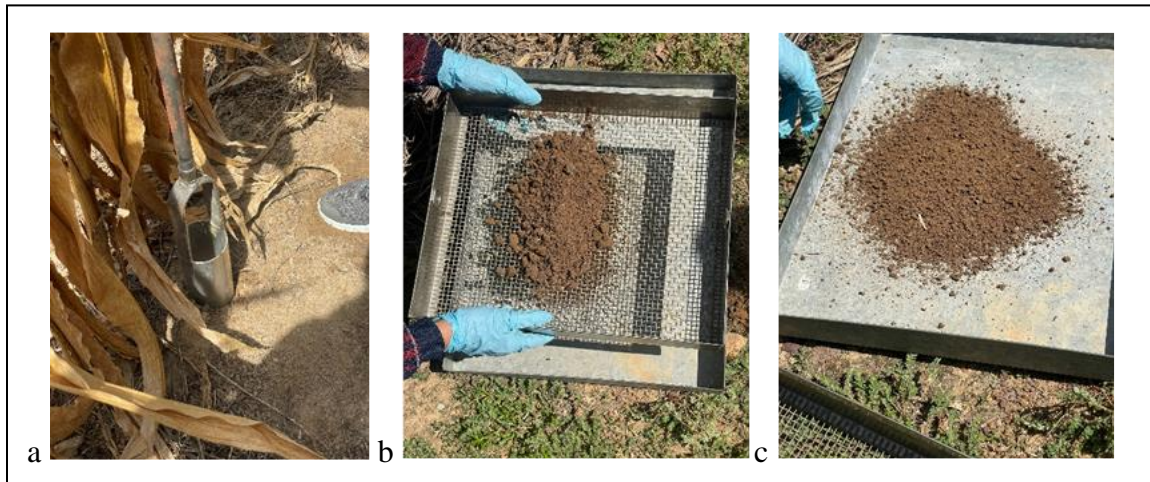
Location	Yield zone	Sand %	Silt %	Clay %	Soil textural class
1	High	23.6	54.1	22.4	Silt loam
2	High	33.4	46.4	20.3	Loam
7	Low	25.4	54.4	20.3	Silt loam
8	Low	23.6	50.0	26.4	Silt loam



**Figure 3.6.1.** Sampling locations at Field F40



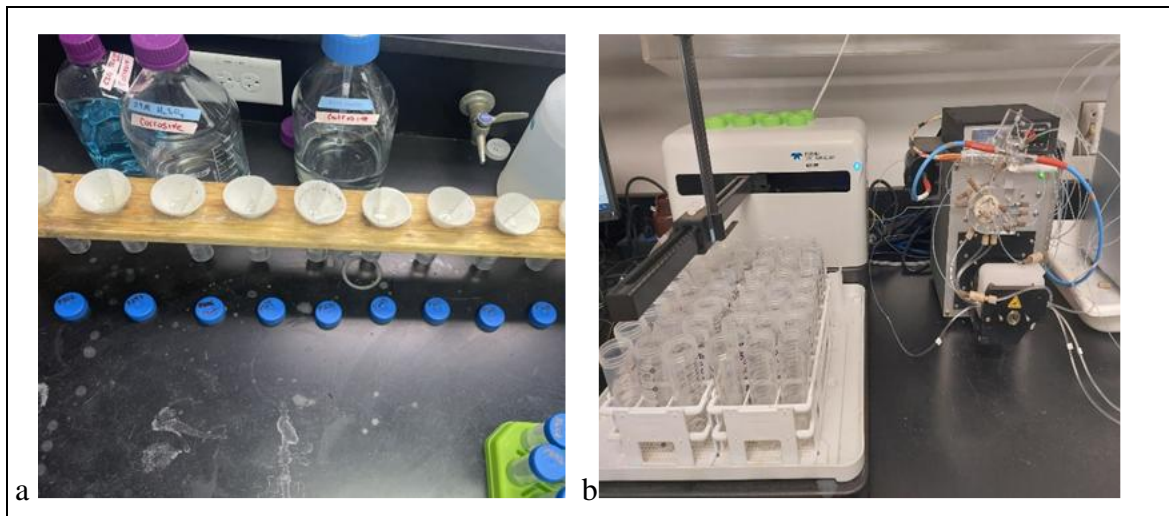
**Figure 3.6.2.** Sampling locations at Field F11



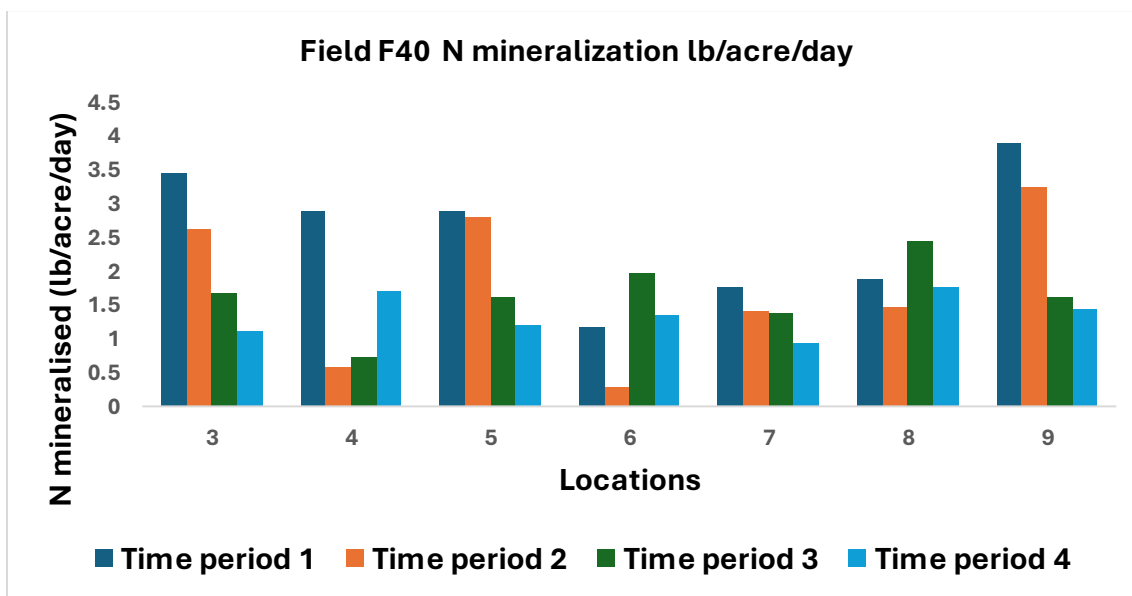
**Figure 3.6.3.** Sample collection a) soil sample collection near the row.



**Figure 3.6.4.** Sample incubation a) Measure same weight for uniform sample size for all the locations, b) packing and labeling soil in a whirl pak bag, and c) Sealing the bag and burying it parallel to the crop row.



**Figure 3.6.5.** Sample analysis a) KCl extraction of soil followed by filtration b) N analysis using flow injection analyzer



**Figure 3.6.6.** N mineralization during different time periods at Field F40.

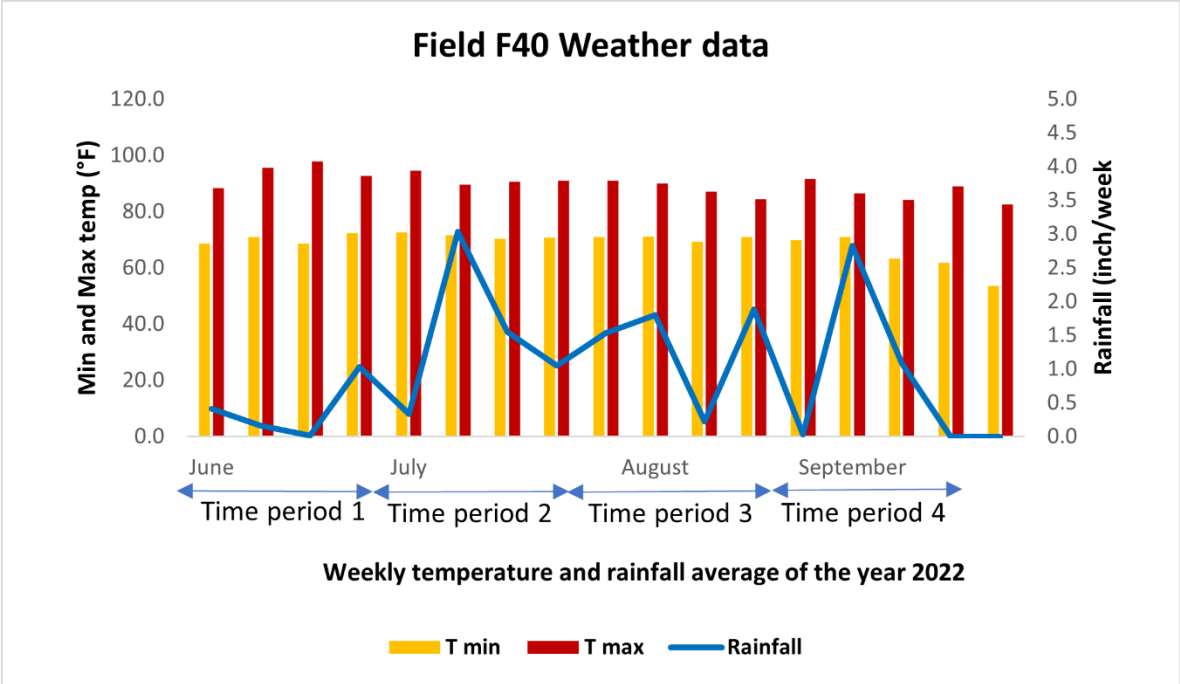


Figure 3.6.7. Weather data during the study period at Field F40.

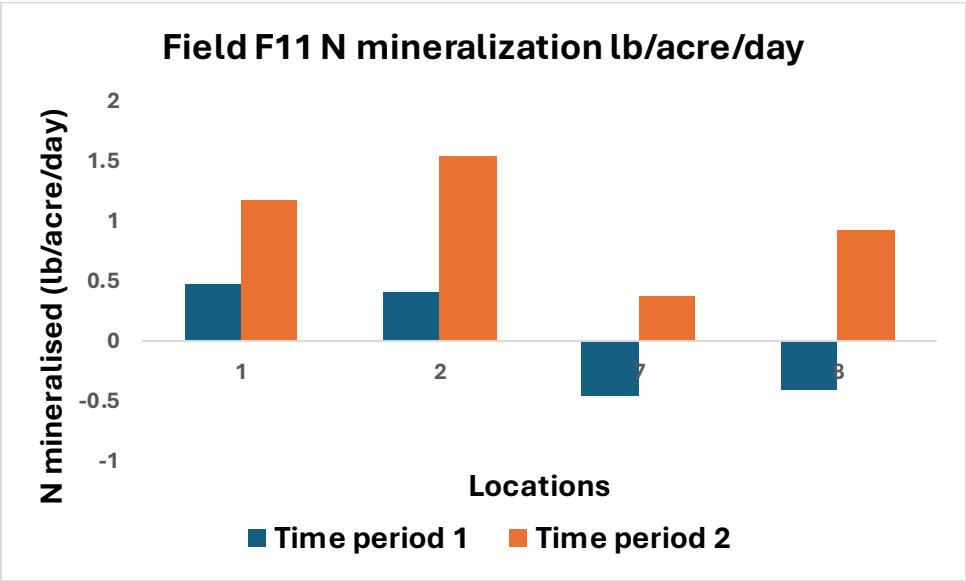


Figure 3.6.8. N mineralization during different time periods at Field F11.

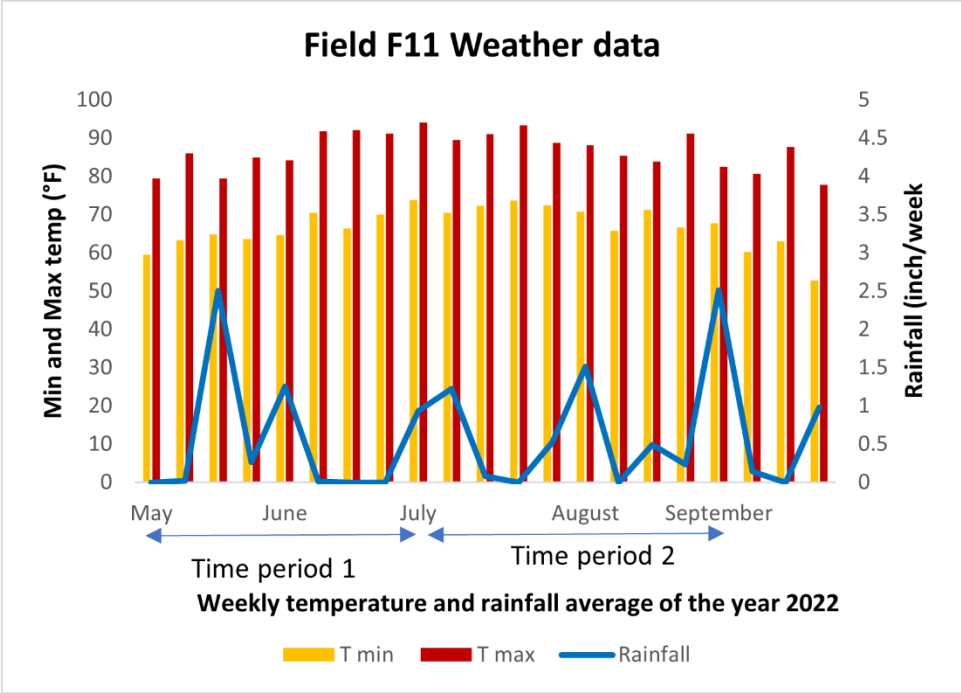


Figure 3.6.9. Weather data during the study period at Field F11.

## **Chapter 4. Understanding the impact of irrigation on nitrogen losses between high and low-yielding management zones in a commercial maize production system**

### **Abstract**

Understanding nitrogen (N) cycling at a large scale under real-world farming conditions presents logistical and technical challenges. Mechanistic models like DSSAT Cropping System Model provide a practical framework for simulating crop-soil-weather interactions and assessing N losses. This study calibrated and evaluated DSSAT CSM-CERES-Maize for maize production across distinct management zones (MZs), delineated based on historic yield data from a commercial farm. Nitrogen losses were quantified under wet, normal, and drought conditions using three irrigation scenarios. The model was parameterized using phenological and genetic data, achieving strong agreement between simulated and observed crop growth, yield components, and soil water content. Evaluation results confirmed reliable model performance, with RMSE and n-RMSE values within acceptable thresholds for phenology, leaf area index (LAI), soil moisture, and N uptake. Model simulations revealed distinct N loss pathways between zones. MZ1 (average yield of 14.5 Mg/ha), with greater soil water availability, exhibited higher N uptake but also greater leaching (16 kg/ha) and volatilization (54 kg/ha) losses. In contrast, MZ2 (average yield of 10 Mg/ha), retained more nitrate-N in the soil at harvest (62 kg/ha), indicating lower N use efficiency (NUE) and increased denitrification losses (6 kg/ha). Irrigation played a crucial role in yield stability, with MZ2 requiring 45% more irrigation to achieve yields comparable to MZ1. Rainfall during the growing season significantly influenced N losses: leaching and denitrification dominated in wet years, while volatilization was highest under drought. These results highlight the importance of zone-specific N and irrigation management in reducing N losses while optimizing

crop productivity. Soil properties, topography, and water availability were key drivers of NUE differences across zones. The study demonstrates DSSAT CSM-CERES-Maize as an effective decision-support tool for precision N management, offering insights into sustainable agricultural practices under variable environmental conditions.

Keywords: DSSAT, CSM-CERES-Maize, Nitrogen cycling, Nitrogen use efficiency, Volatilization, Leaching, Denitrification

#### 4.1. Introduction

Nitrogen is the most widely used nutrient in agriculture, contributing to more than 50% of global food production (Zhang et al., 2015). However, its intensive and imbalanced use results in low recovery and higher investment costs (Bindraban et al., 2020). On average, only 48% of applied N to crops is recovered globally (Quan et al., 2021), whereas in the United States, the mean average recovery of N fertilizers is about 66% (van Grinsven et al., 2015). The remaining N is lost via various pathways (e.g., leaching, denitrification, volatilization), leading to significant inefficiencies in the production system (Bernhard, 2010). These inefficiencies reduce the effectiveness of N fertilizers in supporting crop growth and result in various environmental implications (Dimkpa et al., 2020). Nitrogen loss via surface and subsurface loss leads to water contamination and eutrophication, whereas gaseous losses lead to greenhouse gas emissions (Martin & Sprunger et al., 2021; Ashitha et al., 2021; Rashmi et al., 2020; Coskun et al., 2017).

Addressing these N losses is critical for sustainable agricultural systems, especially in cereal crops like maize, as they are heavy N feeders. Maize is a widely grown crop globally, serving as a food staple, feed, and biofuel. The United States is the world's largest maize producer and exporter, producing about 30-35% of the global maize export (NASS, USDA, 2023). On average, around 12 million tons of N fertilizers are used yearly in maize production (USDA-ERS 2018). Nafziger (2023) summarized several studies using the  $^{15}\text{N}$  method to quantify the proportion of fertilizer N taken up by the crop. The author reported that an average of 28% of the total N in the maize plant came from fertilizer. In addition, Blesh and Drinkwater (2013) reported that in Midwest farming systems that follow alternating monoculture of maize and soybean are the “leakiest” or most prone to N losses compared to other cropping systems. Due to the low recovery rate of N, which is

approximately 50% in maize (Davies et al., 2020), there are significant N losses from the maize production system. Thus, there are increasing concerns about the high N usage in maize production in the USA and its potential negative impacts. In addition to economic and environmental concerns, N losses lead to serious health issues due to poor air quality especially near farm lands and contaminated fresh water streams (Zhang et al., 2015). Elevated levels of nitrate above safe limits of 50 mg/L are estimated to cause 2,300 to 12,594 cancer cases in the United States (Temkin et al., 2019). Maize production also leads to increased atmospheric concentrations of PM<sub>2.5</sub> due to airborne NH<sub>3</sub>, which is harmful to human health, causing an estimated 4,300 premature deaths annually (Zivin et al., 2018; Hill et al., 2019). The higher levels of NH<sub>3</sub> in the air result from lower yields in high N-use regions and higher use of animal manure as fertilizers (Hill et al., 2019).

In recent years, maize production in Alabama has experienced significant growth. In 2023, approximately 145,687 ha were planted with maize, marking a 20% increase from 121,406 ha in 2022. This upward trend is even more pronounced when compared to earlier years; for instance, in 2019, about 117,359 ha were planted with corn (NASS, USDA, 2023). Unpredictable weather patterns such as droughts or excessive rains significantly impact N management in Alabama. High intensity or prolonged rainfall events lead to surface runoff or leaching losses, while drought leads to insufficient N uptake by crops, thus leading to susceptibility of N to volatilization losses (Isasmendi et al., 2013). It is crucial to adopt resilient N management practices to address these challenges. It is also necessary to understand N cycling in maize on farmers' fields to understand the pathways through which N is lost and find suitable practices to improve both N recovery and loss. The understanding and determination of the N cycle is further complicated due to spatial and temporal variability within fields (Sharma et al., 2023).

However, estimating on-farm gaseous losses of N is expensive. Thus, associating field experiments with simulation models can increase the understanding of various processes and help evaluate the sustainability of N management practices (Re et al., 2020). The Decision Support System of Agrotechnology Transfer (DSSAT) model is a valuable tool for understanding N mass balance (Hoogenboom et al., 2019; Jones et al., 2003). Re et al., (2003) simulated interaction of water and N balance in a maize-peanut crop rotation under Florida's humid climate conditions. The study reported a significant interaction between water and N leaching. Owing to regions' frequent rainfall, the N leaching and denitrification were prominent losses, particularly under maize with high N fertilizer demands. Another study conducted in Ontario, Canada, simulated long-term crop yield and N cycle under continuous maize production. The research demonstrated that the model effectively simulated the complexities of N cycle but consistently over simulated soil nitrate losses (Liu et al., 2011). Kumar et al. 2024, simulated growth and N dynamics of maize under long term maize-wheat rotation. The study found that reduced tillage along with optimized fertilizer N application rates and timing led to reduced losses of N through volatilization and leaching while improving crop N uptake. The research concluded that using DSSAT crop model provides a detailed understanding of interactions between crop, soil, and weather systems, and helps assess water dynamics and N transformations, offering a comprehensive overview of N response within a system. By modelling interactions between soil-crop-atmosphere, the DSSAT model can help to identify N losses, predict N availability, and optimize N use efficiency (Thorp et al., 2007; Malik et al., 2019; Yang et al., 2023).

Despite advancements in agronomic practices and modeling tools, there is a significant knowledge gap in understanding N dynamics in commercial maize production and in evaluating the DSSAT-CSM model's ability to assess N losses across different yield management zones. By calibrating

and evaluating the DSSAT CSM-CERES-Maize model using management zone-specific data, we can enhance our understanding of site-specific N dynamics in a maize production system. This will facilitate the development of more efficient, site-tailored N management strategies, ultimately reducing environmental impacts.

In addition to exploring N dynamics within distinct management zones, it is crucial to investigate how weather influences these dynamics and how management practices under varying weather conditions affect N losses. Irrigation timing plays a crucial role in N cycling by impacting processes such as leaching, volatilization, and denitrification (Barakat et al., 2016). Weather conditions further compound these effects; for example, wet years can increase leaching, while drought years may trigger greater volatilization losses and reduce N availability to plants (Shi et al., 2024; Hu et al., 2023). By categorizing historical weather data into wet, normal, and drought years, we can evaluate how different weather patterns influence N dynamics under irrigated conditions. This approach will help identify trends and vulnerabilities in N management across varying climate conditions, which is essential for predicting how different weather scenarios impact N availability and soil N loss (Congreves et al., 2016). Using decision support tools such as DSSAT will be greatly helpful to researchers, policy makers and stake holders, particularly important in regions like Alabama that experience highly variable weather patterns. This study has two aims: to calibrate and evaluate maize growth, yields and soil water balance to assess the accuracy of CSM-CERES-Maize in simulating maize growth, yield, soil water and N balance; and to simulate N dynamics using long-term (40 years) weather data to quantify N losses in distinct management zones under three irrigation scenarios (50% deficit, 30% deficit, and no irrigation).

## 4.2. Materials and Methods

### 4.2.1. Study site

The study was conducted on a commercial farm located in North Alabama, Alabama, located at 34° 43' 6.67" N, 87° 23' 13.52" W, and 181 meters above sea level. The farm grows maize, soybean, and wheat as the main cash crops in rotation. The site is in a humid subtropical region (Peel et al., 2007). The historic maximum temperature ( $T_{\max}$ ) and minimum temperature ( $T_{\min}$ ) at the study site are 33.0 °C, 10.5 °C, respectively, and it has an average annual rainfall of 120.5 cm (Figure 4.6.1.1). This study involves observations taken from a maize field during the years 2022 and 2019. In the year 2022, a total of 118 cm (annual) of rain was received, with more events occurring in winter and spring months, whereas the 2019 rainfall was 159 cm and spread throughout the year. Of the 190-hectare field, 125 hectares are irrigated using a center pivot system. The field's soil type varied from Abernathy-Emory Clay loam to Decatur silty clay loam, with slopes ranging from 2 to 12 % and elevations ranging between 169 and 180 meters above sea level. For data collection, the field was divided into two distinct management zones (Figure 4.6.2), MZ1 (stable high yield) and MZ2 (stable low yield). These zones were delineated using six years of historic maize crop yield data (2010, 2012, 2014, 2018, 2019, and 2020) with ArcGIS software (version 10.8). Two algorithms—standard deviation algorithm and the two-way outlier algorithms—were used to define the yield stability of each zone (Maestrini & Basso 2021). Further, previous studies by Morata et al., 2020 and Kumar et al., 2022 incorporated topographic indices like elevation, slope, topographic position index (TPI), and topographic wetness index (TWI) to evaluate the stability of the yield management zones. The main differences between the two management zones under study were attributed to slope and elevation variations. MZ1 exhibited a slope of 0–2%, characterized by low TPI values, indicating its position in lower-lying areas or

depressions, and high TWI values, reflecting higher water accumulation potential and moisture availability. Conversely, MZ2 had a 6–10% slope, with higher TPI values indicating its elevated position on ridges or slopes and low TWI values, suggesting reduced moisture retention and greater drainage rate. The soil's physical and chemical characteristics are given in Tables 4.6.1 and 4.6.2.

#### **4.2.2. Model operation**

The CSM-CERES-Maize model requires comprehensive inputs such as crop genetic coefficients, weather data, soil characteristics, and crop management practices to simulate growth, and soil water and N dynamics on a daily time step. All the input data used in the model are described in the section below.

##### **4.2.2.1. Soil input data**

The soil cores (121 cm deep) were collected from different locations within the field prior to planting using a tractor-mounted deep soil coring rig (i.e., Keeney & Nelson, 1982). Each soil core was sectioned by depth at 0–5, 5–15, 15–23, 23–30, 30–46, 46–61, 61–91, 91–106, and 106–121 cm intervals. Different sections of the soil cores were used to determine pH, soil texture, bulk density, volumetric water content, organic carbon, total nitrogen (TN), and mineral nitrogen (N) input (Table 4.6.1 & 4.6.2).

Bulk density was determined using the mass-to-volume ratio of oven-dried soil samples (105°C for 48–72 hours) following the method described by Schepers et al. (1989). Mineral N ( $\text{NO}_3^-$ -N and  $\text{NH}_4^+$ -N) was extracted using a 1:5 soil-to-2 M KCl solution, following the Keeney & Nelson (1982) protocol, and analyzed using the FIAlyzer-1000 Flow Injection Analyzer (FIALab Instruments Inc.) according to EPA Method 353.2. Total nitrogen (TN) was measured using a LECO C/N Analyzer, and organic nitrogen (Organic N) was calculated as TN minus inorganic N

( $\text{NO}_3^-$ -N +  $\text{NH}_4^+$ -N) (Hood et al., 2010; Bly et al., 2024). The drainage rate and runoff curve number were estimated using the USDA-NRCS SSURGO database. Soil moisture data was recorded continuously throughout the crop period using an Acclima soil moisture sensor (Meridian, Idaho, USA), installed at 15, 45, and 60 cm depths at each sampling location.

#### **4.2.2.2. Weather data**

The weather data for the study year 2019 and 2022 was obtained from an automated weather station installed outside the field. The weather station recorded data at 15 minutes interval for maximum and minimum temperature ( $^{\circ}\text{C}$ ), precipitation (mm), solar radiation ( $\text{MJ}/\text{m}^2$ ), and humidity (%).

#### **4.2.2.3. Crop input data**

The maize growth stages were recorded throughout the crop period. The leaf area index (LAI) was obtained using a Li-Cor-LAI 2200 instrument (LICOR, Lincoln, NE, USA) and plant samples were collected in six replicates (1 meter-rows) from each location to determine above-ground biomass. The sampling was done at V7 (26 DAP), R1 (40 DAP), and R8 (128 DAP), growth stages. The plant samples were partitioned into leaves, stems, husk, and cob based on respective growth stages; oven dried at  $70^{\circ}\text{C}$  until they reached constant mass; and composite dry samples for each plant part were recorded and analyzed for tissue N concentration.

Subsamples of the grains were also analyzed to determine the number per ear, unit grain weight, and kernel moisture. Based on the latter, the yield was adjusted to dry weight (0% moisture).

#### **4.2.2.4. Management information**

All management practices were chosen and executed by the farmer. In 2019, the field was planted with the maize hybrid Dekalb® DKC 66-97 of 116 days relative maturity, while in 2022, Dekalb®

DKC 169-16 was planted with a similar relative maturity. The maize was planted at 0.76 m row spacing and a plant population of 32,000 seeds per acre. Agronomic practices such as planting dates, fertilization, irrigation events, and harvest are provided in Table 4.6.3.

#### **4.2.3. Model calibration**

Data collected for maize in 2022 from a potential yield location under MZ1 (Figure 4.6.2, location1) was used to calibrate the model. For model evaluation, a low yield location under MZ2 was used (Figure 4.6.2, location 5), and further evaluation was done using maize growth and yield data from 2019 (Morata et al., 2020). The model was calibrated using DSSAT model 4.8.5. (Hoogenboom et al. 2024) to simulate maize growth and yield. The Century Parton model (Parton et al., 1987) was used to simulate soil organic matter dynamics, while the Ritchie method (Ritchie, 1972) was applied to simulate infiltration and hydrology.

The CSM-CERES-Maize uses six cultivar coefficients to calibrate growth and development of crops under certain environmental conditions (Table 4.6.4. P1, P2, and P3 represent early growth, G2, and G3 represent grain filling, and PHINT represents the phyllochron interval between successive leaf tips). The genetic coefficients of the cultivar (Dekalb® DKC 69-16) were determined using the Generalized Likelihood Uncertainty Estimation (GLUE) tool. The genetic coefficients of maize hybrid DKB 66-97 were used as the starting point for cultivar coefficient calibration (Morata et al., 2020). After the GLUE runs, sensitivity analysis was performed to minimize errors between simulated and observed values of phenology data. The anthesis (P1) and maturity date (P5) genetic coefficients were adjusted to match the field observed data. After obtaining a good agreement between simulated and observed values for P1 and P5, other genetic coefficients G2, G3 and PHINT were adjusted to align simulated and observed grain yield, grain unit weight, LAI, and tops weight.

#### **4.2.3.1. Soil water and nitrogen balance**

The management and soil modules in the DSSAT shell calibrate soil water and N balances using similar soil properties and management practices. The daily soil moisture data collected using an Acclima soil moisture sensor installed at 15 (soil layer 2), 45 (soil layer 4), and 60 cm (soil layer 6) depth at the potential yield zone (MZ1) was used to calibrate the soil-crop water balance. The soil parameters considered for calibration of water balance and N movement in the soil profile included the following: lower limit (LL,  $\text{cm}^3 \text{cm}^{-3}$ ), drained upper limit or field capacity (DUL,  $\text{cm}^3 \text{cm}^{-3}$ ), saturated water content (SAT,  $\text{cm}^3 \text{cm}^{-3}$ ), saturated hydraulic conductivity (KSAT,  $\text{cm h}^{-1}$ ), bulk density ( $\text{g cm}^{-3}$ ), and root growth factor (Table 4.6.5). The measured values of soil texture, bulk density, and soil water content were used as inputs to the DSSAT soil module, and initial values for DUL, LL, hydraulic conductivity, and root growth factors were determined using the SBuild program of DSSAT v 4.8.5. (Hoogenboom et al. 2024) To calibrate the soil water balance, it was necessary to minimize the root mean square error by matching the simulated and observed moisture data. Thus, the SAT, LL, and DUL were adjusted for each soil layer to improve the fitness of the model. The KSAT and root growth factor (generated by DSSAT) and the values for the runoff curve number (75), soil drainage factor (0.35), and soil albedo (0.14) obtained from USDA-NRCS SSURGO database were not changed during the calibration process. The calibration of the N balance in DSSAT is highly dependent on the calibration of the soil water balance. This interdependence arises because soil water dynamics directly influence N processes such as leaching, denitrification, mineralization, and plant uptake. According to Tsuji et al. (1998) and He et al. (2016), a properly calibrated soil water balance provides an accurate representation of soil moisture dynamics, which serves as a foundation for N mass balance calculations.

#### 4.2.4. Model performance statistics

The crop model performance was evaluated by comparing the simulated and observed LAI, crop biomass, soil water content, crop N uptake, soil nitrate, grain yield, and TN uptake at harvest. Root means square error (*RMSE*) and normalized root means square error (*n-RMSE*) indices were used to evaluate the model performance. The *RMSE* was calculated as the square root of the variance of the differences between the predicted and observed values, whereas *n-RMSE* is a non-dimensional statistic that facilitates comparison between different datasets; if *n-RMSE* < 15%, the model is a good fit, *n-RMSE* >15% and < 30% is moderate fit and > 30% is poor fit.

$$\blacksquare \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad Eq\ 1$$

$$\blacksquare \quad nRMSE = \frac{RMSE}{Mean(observed)} \times 100 \quad Eq2$$

- Where n is the number of observations,
- $P_i$  is the predicted value for the  $i$ th observation,
- $O_i$  is the observed value for the  $i$ th observation,
- $P_i - O_i$  is the difference (error) between predicted and observed values for the  $i$ -th observation.

#### 4.2.5. Climate variability

We used historical weather data from 1984 until 2022 (historical data was retrieved from global historical climatology network-daily [GHCN-Daily] from NOAA) for the maize growing period and categorized each year into wet, normal, and drought years using the Standardized Precipitation Index (SPI) to understand the effect of weather on N dynamics. The SPI was calculated to characterize meteorological drought on the weather range specified (Keyantash et al., 2023).

$$\text{SPI} = (P - P^*) / \sigma_p$$

*Eq 3*

where P = precipitation

P\* = mean precipitation

$\sigma_p$  = standard deviation of precipitation

The calculated SPI Thresholds used to classify years into drought, normal, and wet years were:

SPI  $\leq$  -1.0: Drought

-1.0 < SPI  $\leq$  1.0: Normal

SPI > 1.0: Wet

The seasonal analysis was conducted using DSSAT v4.8.5. (Hoogenboom et al. 2024) for the years 1984 to 2022. Simulations were performed under three irrigation scenarios: (1) fixed irrigation with a 30% deficit (% deficit refers to applying irrigation when 30% of the available soil water holding capacity has been depleted), (2) fixed irrigation with a 50% deficit, and (3) no irrigation (rainfed condition). The daily irrigation amount was set at 15.22 mm, reflecting the common irrigation practice among farmers in North Alabama. All other management practices remained consistent with those used for model calibration and evaluation. Following the simulations, the treatments were analyzed for yield, N uptake, N use efficiency (NUE), and N losses through volatilization, denitrification, and leaching. Additionally, cumulative effective irrigation, as well as residual soil N at harvest, were assessed to evaluate N dynamics across the three irrigation schedules and water years.

#### **4.2.6. Data statistics**

To evaluate the effects of irrigation scenarios on crop yield, N dynamics, and water use efficiency, both descriptive and inferential statistical analyses were performed using SAS 9.4 (SAS Institute, 2013). A generalized linear mixed model was implemented via the PROC GLIMMIX procedure to assess the impact of irrigation treatments on response variables. The classification for rainfall years, i.e. wet, normal, and drought, were included as a random effect to account for inter-annual variability. Given the unequal distribution of years across these categories, the PROC UNIVARIATE procedure was used prior to the mixed model analysis to assess data normality, ensuring that the assumptions of the statistical model were followed.

### **4.3. Results and Discussion**

#### **4.3.1. Model calibration**

Calibration of crop phenology plays an important role in determining canopy development and biomass accumulation. By ensuring accurate calibration of phenology, the DSSAT-CSM-CERES maize can provide reliable predictions of yield and N dynamics, supporting better decision-making in crop management (Jones et al., 2003). A comparison between simulated and observed values for the growth parameters of maize hybrid Dekalb® DKC 69-16 is provided in Table 4.6.5. The emergence occurred 1 day earlier in the simulation (7 DAP) compared to the observed 8 DAP. The anthesis was simulated at 69 DAP and physiological maturity at 120 DAP. The maximum leaf area index (4.7) was slightly overestimated compared to the (4.4) measured LAI. The simulated yield and yield components closely aligned with the measured data. Overall, the model demonstrated strong performance in calibrating crop growth, phenology, and N dynamics, as evidenced by the close alignment between measured and simulated values across most parameters. These results

indicate that the model was well calibrated for maize hybrid under the management and environmental conditions of the study site.

### **4.3.2. Model outputs and performance**

#### **4.3.2.1. Soil water balance**

The calibration for soil water content for maize in MZ1 and MZ2 2022 was performed by adjusting DUL, LL, and SAT. Table 4.6.5 represents the variables calibrated for each depth in the soil profile. Model performance was evaluated by comparing simulated daily soil water content to sensor-based observations at 15, 45, and 60 cm depths. Model performance was evaluated by comparing simulated daily soil water content to sensor-based observations at 15, 45, and 60 cm depths. The accuracy of simulations was assessed using normalized root mean square error (n-RMSE). Figures 4.6.3.1 and 4.6.3.2 illustrate the temporal dynamics of simulated and observed soil moisture for MZ1 and MZ2, respectively. The model effectively captured the temporal variation in soil moisture. For MZ1, n-RMSE values were 7% at 15 cm, 6% at 45 cm, and 7% at 60 cm. For MZ2, n-RMSE values were 13%, 9%, and 6% at the respective depths (Figure 4.6.3.2). All values fall within the commonly accepted threshold of 15% for reliable model performance.

These results are consistent with previous studies that reported strong agreement between simulated and observed soil water content using DSSAT, including researchers in Ontario used DSSAT v 4.8.5 to simulate maize and soybean yields, near-surface soil water content, and cumulative nitrate-N losses under different drainage systems. The model showed good agreement with observed data, achieving normalized root mean square error (n-RMSE) values ranging from 9.9% to 14.8% for soil water content (Liu et al. 2011). Low RMSE and n-RMSE values suggest the model successfully represented the effects of rainfall, evapotranspiration, and root uptake on soil moisture variability throughout the profile.

Minor discrepancies between simulated and observed data can be attributed to environmental variability, sensor measurement errors, or micro-site heterogeneity. Similar slight overestimations in soil water content have also been documented in DSSAT evaluations (Mehrabi et al., 2020; Re et al., 2020), often due to the model's generalization of field-scale soil properties.

#### **4.3.2.2. Leaf area index (LAI)**

The leaf area index (LAI) is a crucial indicator of the canopy structure and photosynthetic capacity of the crop. Accurate simulation of LAI is essential for ensuring that the model can predict the extent of the assimilatory system, which drives dry matter accumulation and partitioning (Kumar et al., 2024; Wang et al., 2021). In this study, the simulated maximum LAI at MZ1 (4.8) was marginally higher than the observed value (4.4). The model yielded a slight over simulation of LAI (Figure 4.6.4) with RMSE of 29.1 and n-RMSE of 8.5%. Kumar et al., 2024, reported 10% n-RMSE for LAI predictions, indicating good overall accuracy but with some overestimation tendencies.

#### **4.3.2.3. Crop Yield and Nitrogen uptake**

Accurate yield simulation is crucial for understanding N dynamics of a crop as yield directly influences how N is utilized and cycled within crop-soil system (Thompson et al., 2024). During the 2022 growing season, the DSSAT model effectively simulated grain yield for MZ1 with predicted yield of 13583 kg/ha compared to observed yield (14236 kg/ha). This resulted in RMSE of 1857 kg/ha and n-RMSE of 12%, indicating reasonable accuracy for tops yield (Figure 4.6.5). The corresponding N uptake for MZ1 was also simulated accurately (Figure 4.6.6) with RMSE of 24 kg/ha and n-RMSE of 14 %. These results are consistent with Thorp et al., 2007 and Re et al. 2020, who reported n-RMSE values below 10% for crop yields and N uptake under irrigated maize conditions, highlighting the model's reliability in simulating these variables.

#### **4.3.2.4. Soil mineral Nitrogen**

The model effectively captured both surface nitrate ( $\text{NO}_3^-$ ) and ammonium ( $\text{NH}_4^+$ ) dynamics throughout the season. The simulated peaks are aligned with the N fertilizer application (Figure 4.6.7). The simulated and observed soil nitrate ( $\text{NO}_3^-$ ) showed a strong agreement with RMSE of 7.2 kg/ha and n-RMSE of 14% (Figure 4.6.7 A). However, the model failed to predict  $\text{NH}_4^+$  concentration in soil. The prediction showed a faster decline in ammonium concentrations which indicated overestimation of nitrification process (Figure 4.6.7 B). These discrepancies in inorganic N estimations can be attributed to several factors, including model's handling of soil N dynamics, as it may not always accurately capture the complexity of soil processes (Boote, 2020; Liu et al., 2011).

#### **4.3.3. Model evaluation**

The DSSAT-CERES-Maize model was evaluated using observed data from two independent site-years: MZ2 in 2022 and MZ1 in 2019. Genetic coefficients calibrated for MZ1 in 2022 were applied to both datasets to assess the model's ability to simulate crop growth, development, and yield under varying environmental and management conditions. The evaluation results indicated a strong alignment between simulated and observed values for key phenological stages and yield components (Table 4.6.6).

For MZ2 (2022), the model accurately simulated both emergence and physiological maturity dates. The simulated LAI (3.2) was overestimated compared to observed value (2.8), with n-RMSE of 15%. However, the model evaluation for MZ2 yield in 2022 showed slightly higher errors, with an RMSE of 1940 kg/ha and n-RMSE of 8% for yield (Figure 4.6.5). Nitrogen uptake simulation for MZ2 showed reasonable agreement with observed values, with an RMSE of 27 kg/ha and an n-RMSE of 19%. These deviations may be due to unaccounted spatial heterogeneity in soil

properties or microclimatic variation within the management zone, such as localized differences in infiltration, root distribution, or organic matter content, which were not explicitly captured in the model inputs.

The DSSAT evaluation using independent dataset from the year 2019 for MZ1, the simulated and observed LAI values were in close agreement (n-RMSE of 10%). The grain yield (12,099 kg/ha) closely matched the observed yield (12,038 kg/ha) with n-RMSE of 5%, whereas the total biomass prediction reported n-RMSE of 11%. However, the model slightly overestimated the anthesis and physiological maturity dates in MZ1, which contributed to a modest underestimation of both grain and total aboveground biomass. The simulated total biomass in MZ1 was approximately 11% lower than the observed value.

This degree of deviation is considered acceptable in crop model evaluation. Previous studies have demonstrated that prediction errors within  $\pm 15\%$  are indicative of good model performance for yield and biomass (Rani et al., 2018; Kipkulei et al., 2022; Wang et al., 2021). For instance, Rani et al. (2018) reported normalized RMSE values below 20% for yield simulations across variable nitrogen and planting densities, while Kipkulei et al. (2022) found RMSE values between 5.1% and 8.1% for two maize hybrids in Kenya. Such benchmarks support the interpretation that the model's performance in this study was well within acceptable limits.

The minor discrepancies observed between simulated and observed values for 2019 MZ1 evaluation are likely due to hybrid-specific differences in physiological traits or year-to-year weather variability between calibration and evaluation datasets. As Wang et al. (2021) noted, the accuracy of DSSAT simulations is highly sensitive to cultivar-specific genetic coefficients, particularly under stress conditions such as irrigation and fertilizer constraints.

Overall, the model demonstrated a good fit for the calibrated parameters (MZ1–2022) and moderate agreement for the independent evaluation datasets. These results are consistent with previous DSSAT studies that report higher uncertainty when evaluating model performance across years or spatially generalized conditions without site-specific calibration.

#### 4.3.4. Nitrogen balance

The nitrogen mass balance in the two management zones revealed distinct differences influenced by their topography and soil characteristics. In the year 2022, MZ1 showed greater N uptake (305 kg/ha) compared to MZ2 (246 kg/ha), reflecting MZ1's better soil water and nutrient availability. However, MZ1 also exhibited greater N losses through leaching (16 kg/ha) and volatilization (34 kg/ha), while the denitrification losses were minimal (2 kg/ha). In contrast, MZ2 retained significantly more  $\text{NO}_3^-$  in the soil at the end of the growing season (60 kg/ha compared to 10 kg/ha at MZ1). Higher nitrate retention in the soil profile at harvest indicates reduced N use efficiency in this zone, potentially due to low water retention capacity. This left over N in the soil at harvest can be potentially lost after harvest during rainfall events (Table 4.6.8). The leaching and volatilization losses in the two zones were similar, while the MZ2 exhibited higher denitrification loss (6 kg/ha). The higher denitrification losses from MZ2 can be attributed to its low pH and high clay content, which might have created localized anaerobic pockets favoring denitrification (Liu et al., 2011).

#### 4.3.5. Growing Season Rainfall Categories

The Standardized Precipitation Index (SPI) serves as a critical tool for assessing precipitation anomalies by quantifying deviations from long-term climatological norms. The analysis of SPI over a 40-year maize crop period (1984–2022) revealed significant climate variability (Figure

4.6.1.2). Among the analyzed years, three distinct classifications emerged: wet, drought, and normal. Wet years ( $SPI \geq +1$ ) notably included years 1989, 1991, 1997, 2020, and 2021, indicated by positive SPI values (blue bars on Figure 4.6.1.2) significantly above the upper threshold (+1). Conversely, drought years ( $SPI \leq -1$ ) were clearly identified in 1987, 1988, 2000, 2006, and 2007, characterized by negative SPI values (red bars on Figure 4.6.1.2) surpassing the drought threshold (-1). The remaining years were classified as normal, demonstrating moderate fluctuations around the mean SPI value

### **4.3.6. Long-term N dynamics in distinct management zones, irrigation scenarios, and weather conditions**

#### **4.3.5.1. Yield and Nitrogen Use Efficiency (NUE)**

Maize yield varied significantly across management zones, irrigation scenarios, and Growing Season Rainfall Categories (GSRCs). MZ1 consistently produced higher yields than MZ2 across all conditions and irrigation treatments (Table 4.6.9). The highest yield was observed in MZ1 under wet conditions with a 30% irrigation deficit ( $21,800 \text{ kg ha}^{-1}$ ), closely followed by a 50% deficit ( $21,516 \text{ kg ha}^{-1}$ ). Under normal GSRC, yields in MZ1 remained relatively stable, with values of  $20,893 \text{ kg ha}^{-1}$  (30%) and  $20,723 \text{ kg ha}^{-1}$  (50%). The impact of irrigation deficits (30% and 50%) across both MZ1 and MZ2 was not statistically significant, likely due to the model's fixed irrigation simulation, which applied water whenever a deficit was detected, thereby ensuring that crop water needs were met.

However, non-irrigated treatments led to significant yield reductions, particularly under drought conditions, where the lowest yield ( $6,129 \text{ kg ha}^{-1}$ ) was observed in MZ2, a stark contrast to irrigated treatments. The yield gap between MZ1 and MZ2 widened under water-limited conditions, highlighting differences in water-use efficiency. Under normal conditions, MZ2 with

30% and 50% deficits produced lower yields than MZ1 under the same conditions, confirming the zone-specific yield potential. These findings align with Van Donk et al. (2011), who observed that deficit irrigation (158 mm post-tasseling) resulted in near-optimal maize yields (10.9 Mg ha<sup>-1</sup>), only 0.6 Mg ha<sup>-1</sup> lower than full irrigation treatments, suggesting the effectiveness of strategic irrigation in water-limited environments.

The NUE was significantly influenced by MZs (Figure 4.6.8.2B; Table 4.6.9), irrigation deficits, and water conditions. Overall, MZ1 exhibited a higher average NUE (64.6%) compared to MZ2 (60.3%). Under a 30% irrigation deficit, MZ2 achieved slightly higher NUEs across wet (69%), normal (68%), and drought (63%) years compared to MZ1. Similarly, under a 50% deficit, NUE remained relatively stable in both zones. However, under drought conditions without irrigation, NUE declined significantly—down to 21% in MZ2 and 45% in MZ1—highlighting the adverse impact of water stress on nitrogen uptake efficiency.

These results are supported by previous findings. Peralta et al. (2015) reported significant NUE differences across management zones in wheat. Kumar et al. (2022) highlighted that within-field N variability significantly affects uptake, with higher availability in high-yield zones. Hatfield et al. (2015) confirmed that drought stress decreases NUE across crops, while Ransom et al. (2020) and Govindasamy et al. (2023) emphasized that both excess rainfall and moisture deficits can impair NUE through increased leaching or volatilization, respectively.

#### **4.3.5.2. Irrigation requirement**

The model simulations revealed that irrigation was essential in bridging the inherent yield gap between MZ1 and MZ2 (Figure 4.6.8.1 A&B, Table 4.6.9). By irrigating MZ2 more frequently (21 times compared to 15 times for MZ1) and using 45% more total irrigation water (270 mm versus 186 mm for MZ1), the yield gap between MZ1 and MZ2 was effectively closed. The

increased irrigation frequency and higher water input highlights the greater need for water management in MZ2 to sustain crop growth under similar conditions. Across GSRC, drought required the highest irrigation input (21 events, 249 mm), followed by normal (17 events, 225 mm) and wet conditions (17 events, 210 mm), reflecting the increased irrigation demand under moisture stress. Similarly, deficit levels influenced irrigation needs, with 30 deficit treatments requiring 28% more irrigation events and 19% more total irrigation water, reinforcing the need for additional irrigation as moisture stress intensified. These results align with previous findings emphasizing that crops under water stress require increased irrigation to maintain productivity, particularly in soils with lower water-holding capacity (Sadras & Rodriguez, 2010). Despite MZ2's naturally lower yield potential, higher irrigation frequency and greater water inputs allowed it to achieve yields comparable to MZ1. The model's fixed irrigation strategy effectively compensated for MZ2's limitations, particularly under drought and normal conditions, where additional water applications were crucial in maintaining plant productivity. Previous research on variable rate irrigation (VRI) has shown that adjusting irrigation application to match spatial water demand can optimize crop response and reduce water use inefficiencies (O'Shaughnessy et al., 2016; Ko et al., 2022). These simulation results emphasize the importance of zone-specific irrigation management, demonstrating that precise control over both irrigation frequency and total water applied. It might also help mitigate the effects of weather variability and overcome yield limitations due to topographical and soil characteristics in naturally lower-yielding environments while optimizing water use efficiency.

#### 4.3.5.3. Nitrogen losses and soil nitrogen retention

Nitrogen losses through volatilization, leaching, and denitrification were strongly influenced by irrigation level, rainfall category, and management zone (Tables 4.6.9, 4.6.10). Volatilization was

the dominant loss pathway, with MZ1 exhibiting 61% higher losses (average 61 kg ha<sup>-1</sup>) than MZ2 (49 kg ha<sup>-1</sup>), suggesting more favorable conditions for ammonia loss in MZ1—possibly due to surface-applied urea and lower soil moisture retention. Across GSRCs, drought years had the highest average volatilization losses (70.5 kg ha<sup>-1</sup>), followed by normal (56 kg ha<sup>-1</sup>) and wet (47 kg ha<sup>-1</sup>). Deficit irrigation treatments of 50% (57 kg ha<sup>-1</sup>) and no irrigation (64 kg ha<sup>-1</sup>) led to greater volatilization than 30% deficit (49 kg ha<sup>-1</sup>), indicating that lower soil moisture intensified ammonia volatilization.

These trends are supported by Wan et al. (2021), who reported rapid ammonia emissions within days of urea application under rainfed conditions, with losses up to 66 kg ha<sup>-1</sup>. Afshar et al. (2018) and Santos et al. (2020) also observed high volatilization with conventional urea, which could be reduced by using coated urea. Drought-induced moisture deficits and higher soil surface temperatures have been shown to elevate volatilization risks (Govindasamy et al., 2023).

In contrast, nitrate leaching was most pronounced in wet years (average 25 kg ha<sup>-1</sup>), more than double the losses during normal (9.3 kg ha<sup>-1</sup>) and drought conditions (6.2 kg ha<sup>-1</sup>). Leaching was significantly higher under non-irrigated treatments (33 kg ha<sup>-1</sup>), whereas 30% (13 kg ha<sup>-1</sup>) and 50% deficit treatments (8 kg ha<sup>-1</sup>) showed reduced leaching. These results indicate that moderate irrigation helps maintain N within the root zone and minimizes percolation-related losses. Jabloun et al. (2015), Hu et al. (2023), and Kome et al. (2019) reported similar patterns, linking excessive rainfall and poorly timed irrigation with higher nitrate leaching. Carlton et al. (2016) further emphasized that deficit irrigation can reduce leaching by maintaining moderate soil moisture.

Denitrification patterns contrasted with volatilization: wet years exhibited the highest losses (8.2 kg ha<sup>-1</sup>), followed by normal (5.5 kg ha<sup>-1</sup>) and drought (4.1 kg ha<sup>-1</sup>). Denitrification was nearly three times higher in MZ2 (10.2 kg ha<sup>-1</sup>) than in MZ1 (2.0 kg ha<sup>-1</sup>), reflecting greater residual N

and irrigation frequency. Non-irrigated treatments showed the highest denitrification ( $11.5 \text{ kg ha}^{-1}$ ), whereas deficit-irrigated plots had significantly lower losses ( $\sim 4 \text{ kg ha}^{-1}$ ), due to limited anaerobic microbial activity under drier soil conditions.

Zebarth et al. (2019) noted increased denitrification in lower-yielding zones with high moisture and N availability. Studies from Kansas State University (2016) showed enhanced denitrification in waterlogged soils with restricted oxygen, matching the patterns observed in MZ2.

Nitrogen retention at harvest was also zone-dependent. MZ2 retained significantly more soil N (average  $94 \text{ kg ha}^{-1}$ ) than MZ1 (average  $27 \text{ kg ha}^{-1}$ ). This retention reduced volatilization but contributed to higher denitrification, especially under irrigated conditions. Meanwhile, MZ1's lower retention was associated with greater volatilization losses. Despite these differences, leaching was similar across zones, likely due to consistent infiltration patterns under the fixed irrigation regime.

Deficit irrigation consistently reduced N losses from all pathways. Deng et al. (2021) showed that drought increases mineral N accumulation in soil while reducing nitrification and mineralization rates. These findings support the need for precise water management strategies to minimize N losses and enhance N retention in cropping systems.

#### **4.4. Conclusions**

The DSSAT-CSM-CERES-Maize model effectively simulated crop growth, yield, and nitrogen dynamics across MZs and GSRC. Model performance metrics for yield, nitrogen uptake, and soil moisture were within acceptable limits, though minor discrepancies were noted in post-harvest soil mineral nitrogen. Nitrogen balance analysis revealed clear zone-specific differences. MZ1 experienced higher leaching ( $16 \text{ kg/ha}$ ) and volatilization ( $54 \text{ kg/ha}$ ), linked to better water

availability, while MZ2 showed greater residual nitrate (62 kg/ha) and denitrification losses (6 kg/ha), indicating lower NUE. These results underscore the need for zone-specific nitrogen strategies.

Although GSRC classifications were expected to drive variability, the model's adaptive irrigation strategy reduced differences across climate categories. MZ2 required 45% more irrigation than MZ1 to achieve similar yields, highlighting water availability as the key limiting factor. Frequent irrigation in MZ2, triggered by a 50% soil moisture depletion threshold, stabilized yields and reduced losses.

Irrigation strategy significantly shaped nitrogen loss pathways. High moisture deficits increased volatilization, while moderate deficit irrigation minimized total losses and maintained favorable soil moisture for nitrogen uptake. In contrast, non-irrigated conditions promoted leaching due to erratic rainfall patterns. Overall, the findings highlight the trade-offs between irrigation, nitrogen management, and environmental outcomes. A moderate deficit irrigation strategy offers a balanced approach, and future work will focus on refining these strategies to improve NUE and resilience under climate variability.

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#### 4.6. Tables and Figures

**Table 4.6.1.** Soil physical and chemical characteristics of MZ1 (high yield zone)

Soil depth (cm)	Clay (%)	Silt (%)	pH	Bulk Density g/cm <sup>3</sup>	Organic Carbon (%)	Total Nitrogen (%)
0 – 5	23	54	5.9	1.4	1.42	0.14
5–15	32	46	6.1	1.3	0.79	0.08
15–25	32	50	6.1	1.4	0.54	0.06
25–30	30	54	5.8	1.4	0.54	0.06
30–45	28	42	5.9	1.6	0.4	0.04
45–60	32	36	5.9	1.6	0.4	0.04
60–75	34	36	5.9	1.7	0.4	0.04
75–90	34	40	5.9	1.6	0.4	0.02
90–105	38	40	5.9	1.6	0.2	0.02

**Table 4.6.2.** Soil physical and chemical characteristics of MZ2 (low yield zone)

Soil depth	Clay (%)	Silt (%)	pH	Bulk Density g/cm <sup>3</sup>	Organic Carbon (%)	Total Nitrogen (%)
0 – 5	28	42	5.7	1.5	1.63	0.16
5–15	38	34	5.3	1.6	0.69	0.08
15–25	48	36	4.8	1.7	0.23	0.04
25–30	46	34	4.8	1.6	0.17	0.03
30–45	46	32	5.0	1.7	0.16	0.03
45–60	48	30	5.0	1.7	0.14	0.03
60–75	44	30	4.6	1.7	0.14	0.03
75–90	46	30	5.2	1.7	0.14	0.02
90–105	46	28	5.0	1.6	0.12	0.02

**Table 4.6.3.** Crop Management details for all three crops (2019 & 2022)

<b>Year</b>	<b>2019</b>	<b>2022</b>
<b>Cultivar</b>	Dekalb® DKC 66-97	Dekalb® DKC 69-16
<b>Planting</b>	03/26/2019	4/21/2022
<b>Fertilization</b>	Split application 67 kg N/ha at planting and 201 kg N/ha on May 05, 2019	4.4 Mg/ha Poultry manure on March 28, 2022, and 220 N kg/ha on May 13, 2024
<b>Irrigation</b>	May 31 (15.2 mm), June 13 (25.4 mm), Jun 29 (25.4mm)	June 16 (17.8 mm), June 19 (17.8 mm), June 22 (17.8 mm), June 28 (15.2 mm), July 1 (15.2 mm), July 4 (15.2 mm), July 20 (15.2 mm),
<b>Harvest</b>	08/29/2019	08/25/2022

**Table 4.6.4.** Cultivar coefficients of the maize hybrid Dekalb® DKC 69-16 used in the CERES-Maize model.

<b>Legend</b>	<b>Cultivar coefficients</b>	<b>Unit</b>	<b>Value</b>
P1	Thermal time from emergence to end of Juvenile	Degree days	245.6
P2	Photoperiod sensitivity coefficient	Days	0.450
P5	Thermal time from silking to physiological maturity	Degree days	967.9
G1	Maximum possible kernels per plant	Unit less	940.7
G2	Kernel filling rate during linear grain filling	mg d <sup>-1</sup>	10.4
PHINT	Phyllochron Interval (leaf tip to emergence)	Degree days	53.2

**Table 4.6.5.** Soil hydrological properties calibrated for high yield zone (MZ1) and low yield zone (MZ2).

Soil depth (cm)	DLL <sup>1</sup> (cm <sup>3</sup> cm <sup>-3</sup> )		DUL <sup>2</sup> (cm <sup>3</sup> cm <sup>-3</sup> )		KSAT <sup>3</sup> (cm h <sup>-1</sup> )		RGWF <sup>4</sup>	
	MZ1	MZ2	MZ1	MZ2	MZ1	MZ2	MZ1	MZ2
0 – 5	0.125	0.195	0.299	0.301	0.68	0.55	1	1
5–15	0.149	0.221	0.311	0.308	0.65	0.48	1	1
15–25	0.253	0.282	0.328	0.315	0.35	0.38	1	1
25–30	0.251	0.294	0.335	0.320	0.15	0.25	0.81	0.93
30–45	0.242	0.318	0.331	0.352	0.15	0.25	0.74	0.74
45–60	0.251	0.323	0.354	0.356	0.15	0.25	0.52	0.54
60–75	0.265	0.327	0.392	0.355	0.15	0.25	0.45	0.45
75–90	0.282	0.328	0.424	0.365	0.1	0.25	0.21	0.18
90–105	0.310	0.332	0.420	0.369	0.09	0.25	0.10	0

<sup>1</sup>Drained lower limit; <sup>2</sup>Drained upper limit; <sup>3</sup>Saturated hydraulic conductivity; <sup>4</sup>Root growth weighting factor

**Table 4.6.6.** A comparison of simulated and measured values for maize growth and development parameters for management zone 1 during the year 2022.

Growth and Development Variables (MZ1)		
VARIABLE	SIMULATED	OBSERVED
Emergence day (dap)	7	8
Anthesis day (dap)	69	68
Physiological maturity day (dap)	120	121
Yield at harvest maturity (kg [dm]/ha)	14,054	14,236
Unit wt. at maturity (g [dm]/unit)	0.31	0.32
Tops weight at maturity (kg [dm]/ha)	24,681	25,962
By product at maturity (kg [dm]/ha)	10,706	10,476
Maximum leaf area index	4.7	4.4
Grain N at maturity (kg/ha)	220	216
Tops N at maturity (kg/ha)	266	254
Total N uptake (kg/ha)	305	303

**Table 4.6.7.** Simulated vs measured growth and development variables for management zone 2 (2022) and management zone 1 (2019)

Growth and Development Variables	2022 MZ 2		2019 MZ 1	
VARIABLE	simulated	observed	simulated	observed
Emergence day (dap)	8	8	9	8
Anthesis day (dap)	70	68	80	78
Physiological maturity day (dap)	122	121	134	131
Yield at harvest (kg [dm]/ha)	10281	10367	12099	12038
Number at maturity (no/m <sup>2</sup> )	3792	4173	4076	4537
Unit wt at maturity (g [dm]/unit)	0.27	0.27	0.30	0.33
Tops weight at maturity (kg [dm]/ha)	17093	17870	21360	24232
Maximum leaf area index	2.7	3.4	4.1	4.1

**Table 4.6.8.** Model simulated nitrogen mass balance for two management zones (MZ1 and MZ2) for 2022.

<b>MZ1</b>		<b>MZ2</b>	
N additions (kg/ha)	N subtractions (kg/ha)	N additions (kg/ha)	N subtractions (kg/ha)
Soil Initial N	Soil Final N	Soil Initial N	Soil Final N
NH <sub>4</sub> – 57	NH <sub>4</sub> – 0.3	NH <sub>4</sub> – 56	NH <sub>4</sub> – 1
NO <sub>3</sub> – 8	NO <sub>3</sub> – 10	NO <sub>3</sub> – 8	NO <sub>3</sub> – 60
Inorganic N – 220	N uptake – 305	Inorganic N – 220	N uptake – 246
Mineralized N – 96	N immobilized – 15	Mineralized N – 89	N immobilized – 17
	N leached – 16		N leached – 13
	N volatilized – 33		N volatilized – 30
	N Denitrified – 2		N Denitrified – 5
N balance = 382	382	N balance = 372	372

**Table 4.6.9.** Long-term nitrogen dynamics under water deficits for different growing season rainfall categories in MZ1 and MZ2

Irrigation Deficits		Wet		Normal		Drought	
		MZ1	MZ2	MZ1	MZ2	MZ1	MZ2
30	Yield (kg/ha)	21800±618	19658±959	20893±1471	19863±1542	20401±1182	18942±741
	NUE (%)	65±5	69±4	65±4	68±6	60±3	63±2
	Volatilization	49±7	37±14	57±12	44±18	61±13	56±7
	Leaching	23±6	13±5	7±6	10±5	12±1	15±1
	Denitrification	2±2	7±2	2±1	6±3	2±1	6±2
	Soil N harvest	23±5	40±6	21±4	47±20	38±4	59±1
	Irrigation (mm)	202±29	288±8	195±57	292±47	217±26	313±21
	Irrigation no.	15±2	22±2	15±4	23±3	21±4	27±2
50	Yield (kg/ha)	21516±797	18169±643	20723±1591	18622±1862	20407±991	18812±1385
	NUE	64±11	67±11	62±5	66±7	63±9	59±4
	Volatilization	58±21	44±28	61±21	47±26	73±21	60±14
	Leaching	18±12	14±7	7±9	8±6	0±1	3±1
	Denitrification	2±2	6±2	1±1	5±3	2±1	4±1
	Soil N harvest	20±5	39±9	22±4	41±7	44±3	62±16
	Irrigation (mm)	154±31	222±19	165±44	241±41	204±44	260±31
	Irrigation no.	11±2	18±3	5±3	13±4	15±5	20±1
Not irrigated	Yield (kg/ha)	19547±1414	11129±1754	19957±2852	11052±3713	12064±2962	6129±2192
	NUE	56±2	41±8	61±7	42±15	45±8	21±6
	Volatilization	68±13	50±26	69±23	55±41	79±19	64±24
	Leaching	75±19	58±21	28±13	24±8	6±14	9±7
	Denitrification	12±8	29±15	5±3	13±4	2±2	8±3
	Soil N harvest	11±6	122±55	24±24	139±73	99±32	239±27

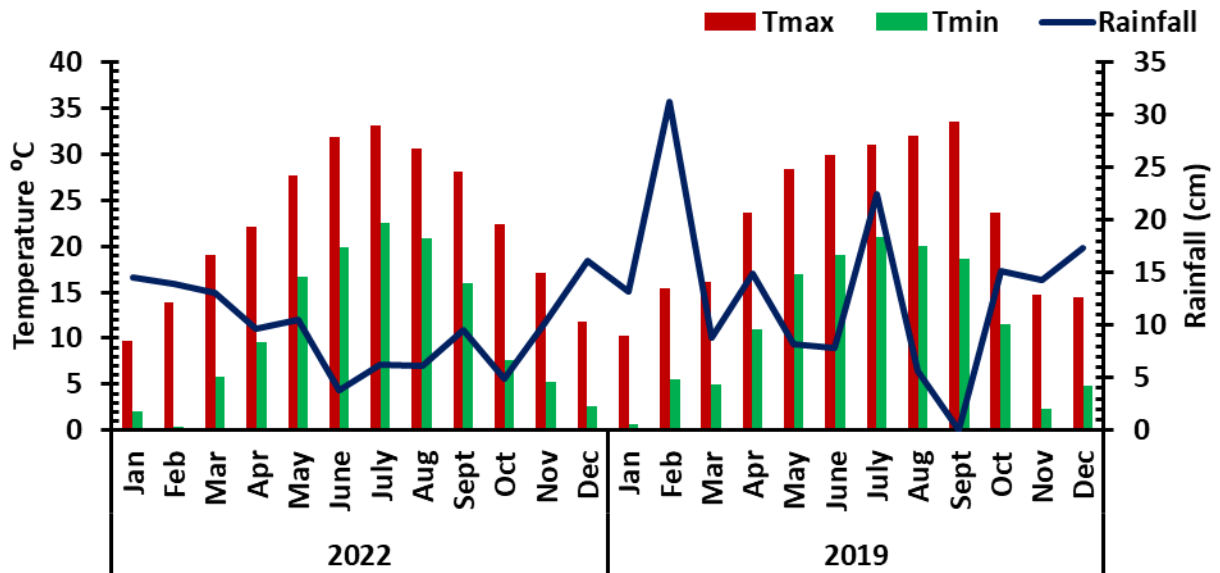
\*The data corresponding to each variable represents are means followed by standard deviations.

\* All values are expressed in kg ha<sup>-1</sup>, except for irrigation, which is reported in millimeters (mm).

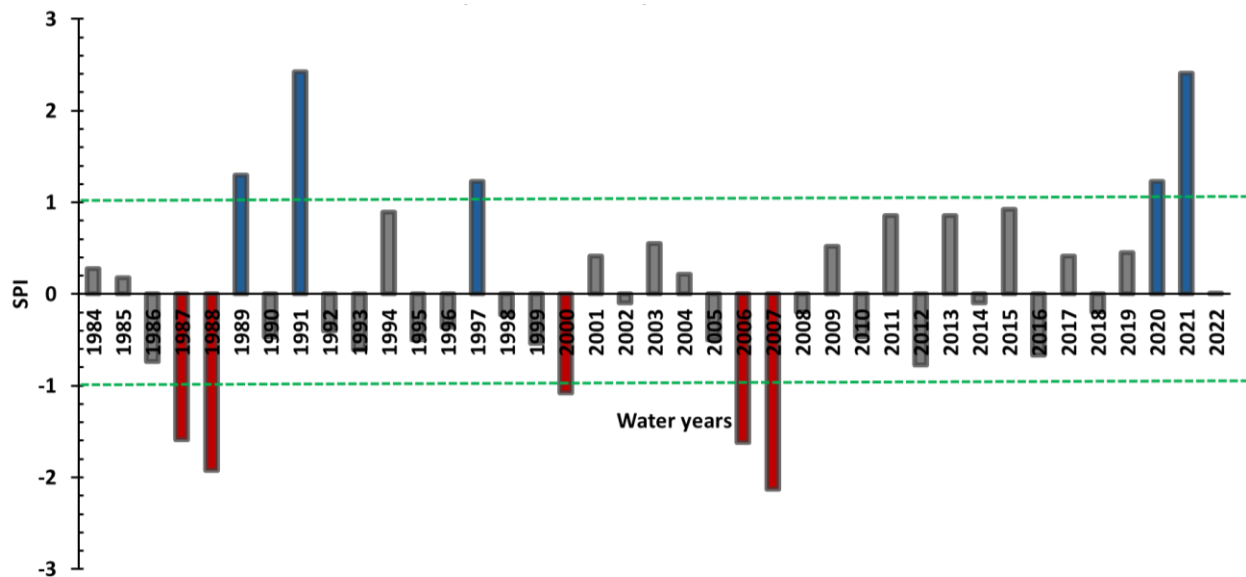
**Table 4.6.10.** P-value summary of fixed effects and interactions in crop response and nitrogen dynamics

	ID	MZ	WY	MZ*ID	WY*ID	MZ*WY	MZ*WY*ID
Yield	<0.0001	<0.0001	0.003	0.009	0.156	0.41	0.78
NUE	<0.0001	0.0003	<0.0001	<0.0001	0.0003	0.3497	0.7727
Volatilization	<0.0001	<0.0001	0.0021	<0.0001	0.0924	0.4148	0.6793
Leaching	<0.0001	0.0001	<0.0001	<0.0001	0.0006	0.3622	0.8519
Denitrification	<0.0001	<0.0001	0.0008	0.0039	0.1583	0.6089	0.8991
Soil N	<0.0001	<0.0001	0.0052	<0.0001	0.2314	0.4973	0.9121
Irrigation	<0.0001	<0.0001	0.0002	0.0144	0.8556	0.7388	0.6637
Irrigation no.	<0.0001	<0.0001	0.0002	0.0144	0.8556	0.7388	0.6637

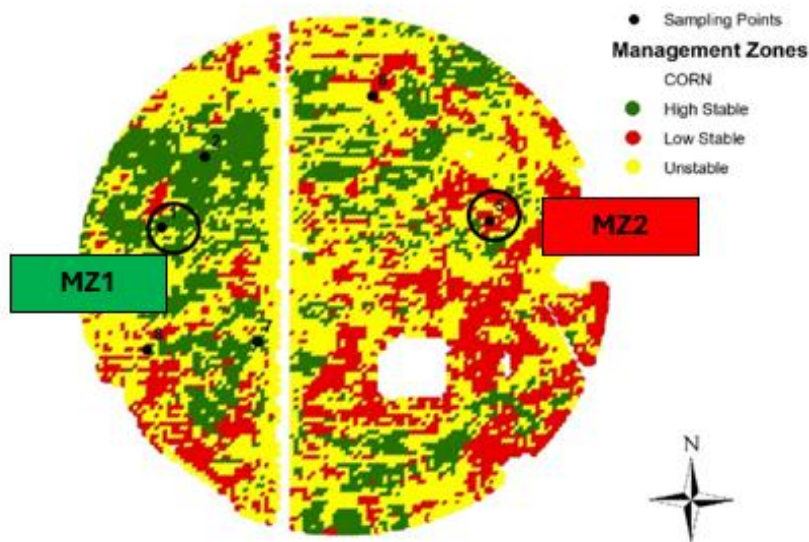
\*MZ = management zones; ID = irrigation deficits; GSRC = growing season rainfall categories



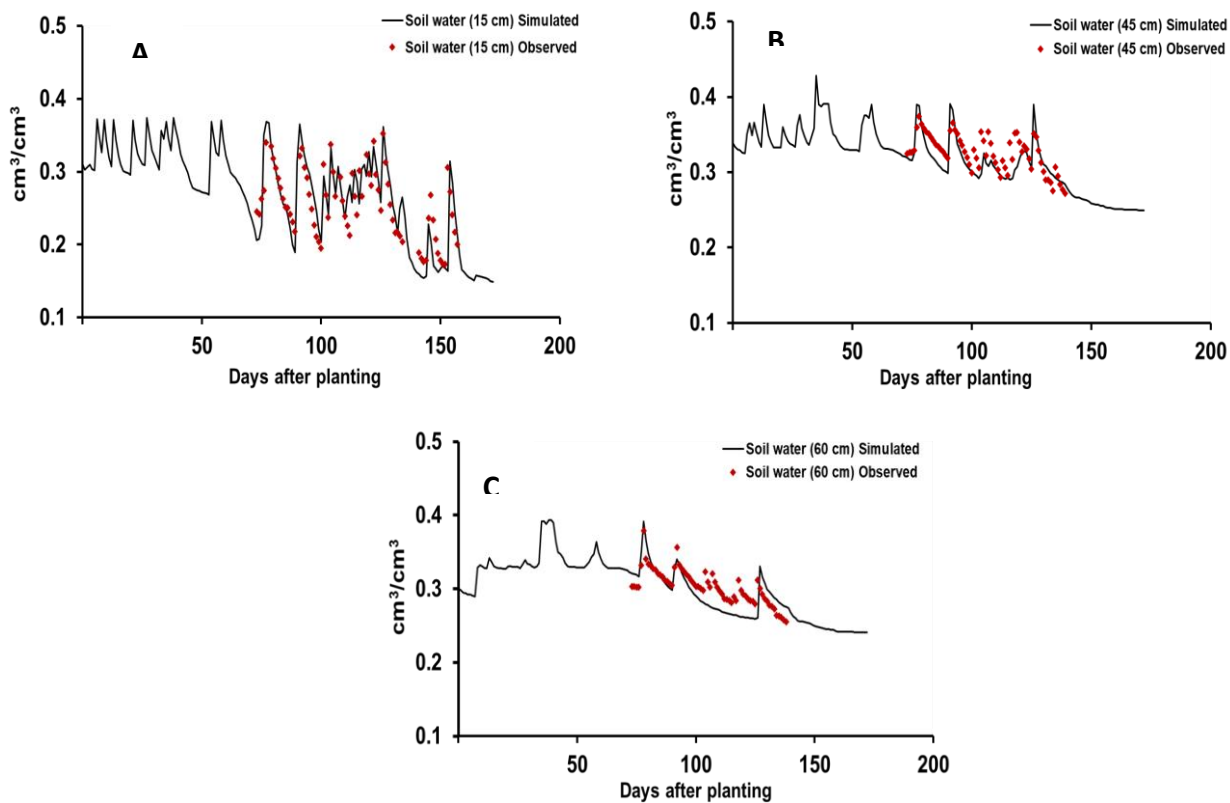
**Figure 4.6.1.1.** Maximum, minimum temperature and rainfall distribution at study site for the year 2019 and 2022.



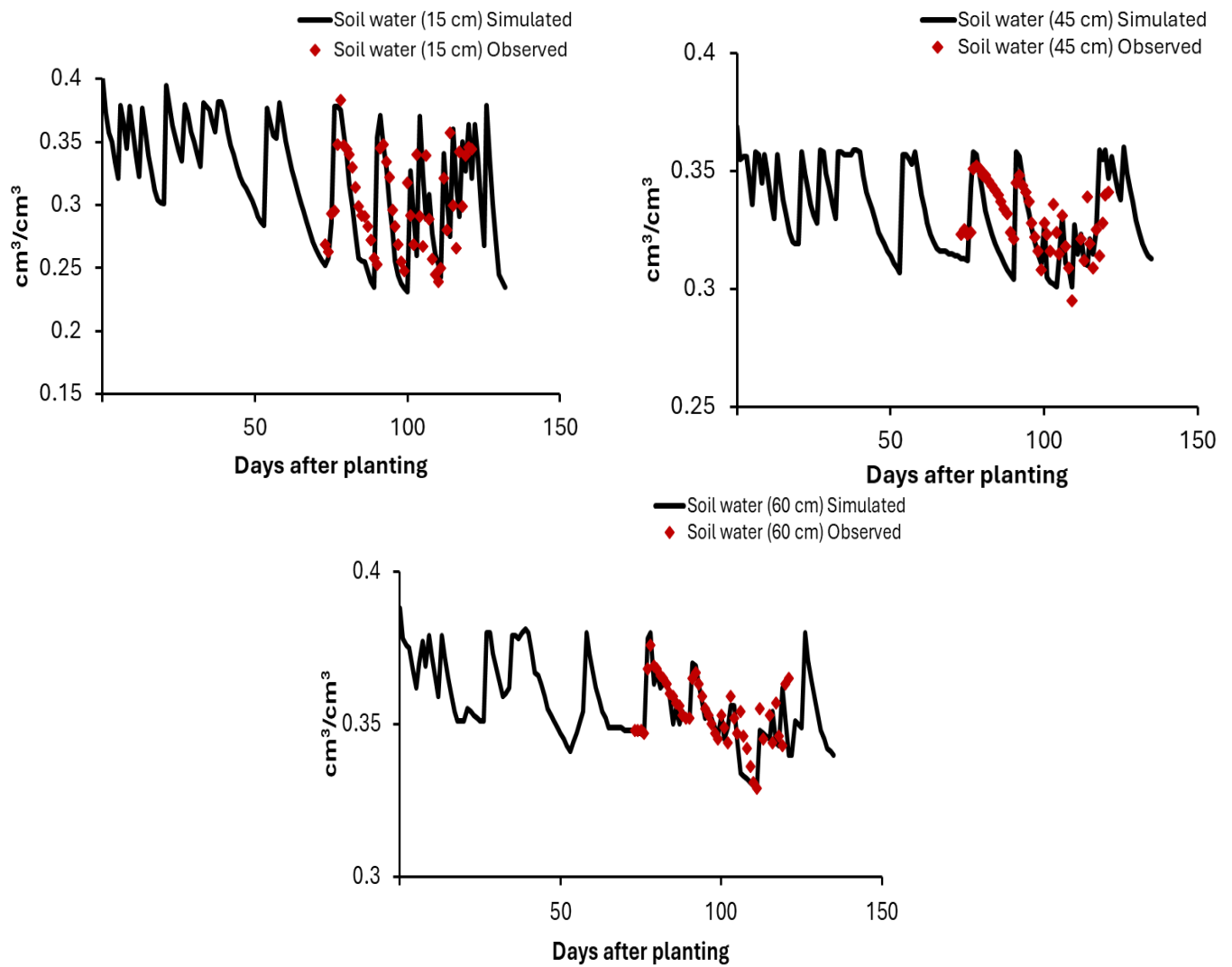
**Figure 4.6.1.2.** Standardized Precipitation Index to characterize meteorological drought for years 1984 – 2022. The red bars represent drought years, blue bars represent wet years, and grey bars represent normal years.



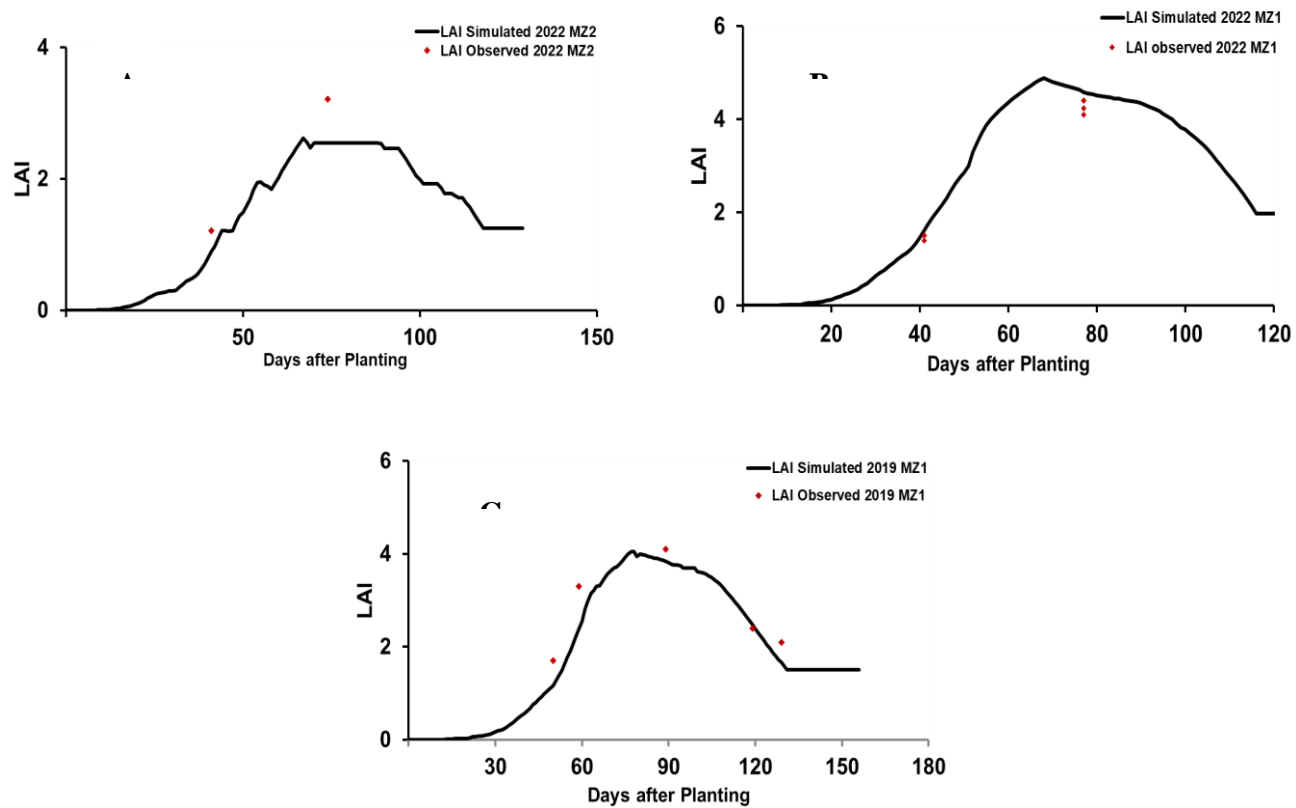
**Figure 4.6.2.** Maize crop management zones delineated based on historical crop yields and topographic characteristics.



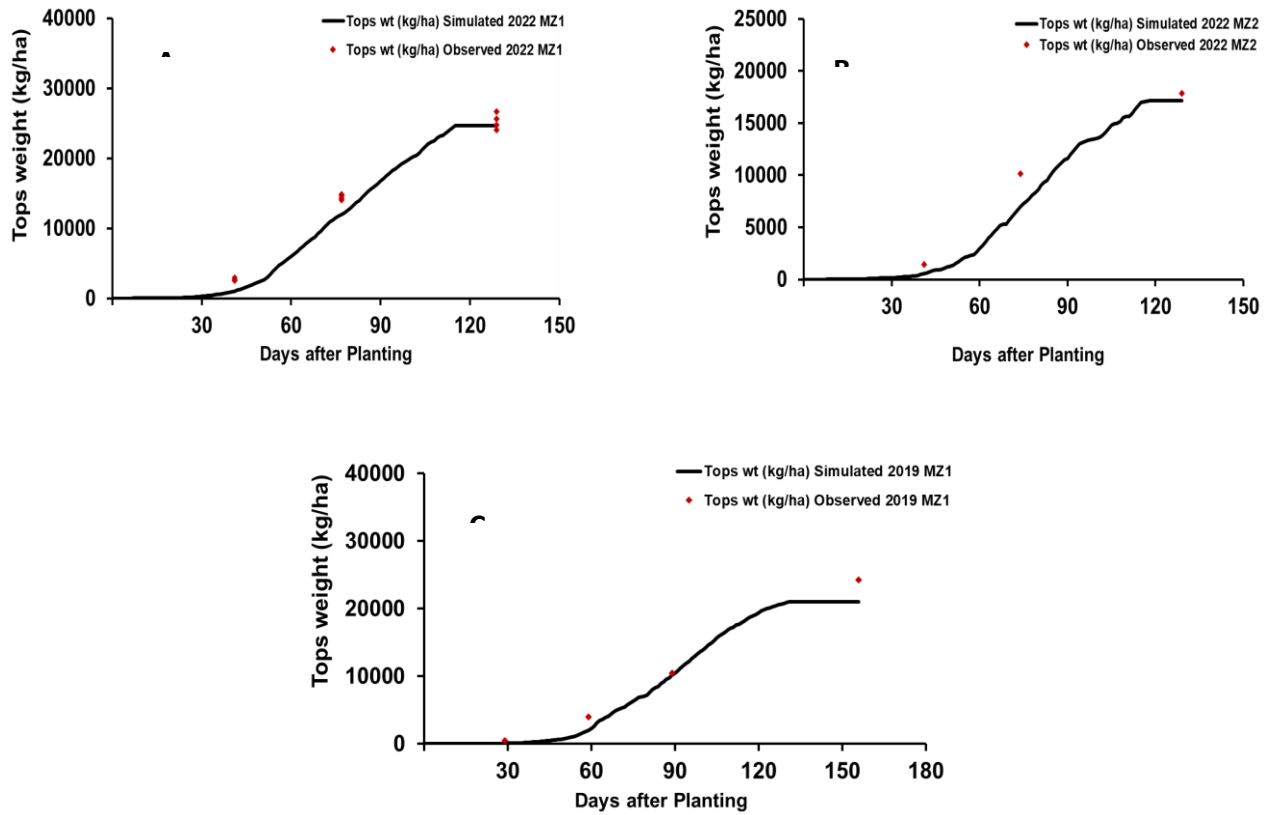
**Figure 4.6.3.1.** A comparison of simulated and observed volumetric soil water content for high yield zone (MZ1 – 2022) at depth 15 (A), 45 (B), and 60 (C) cm.



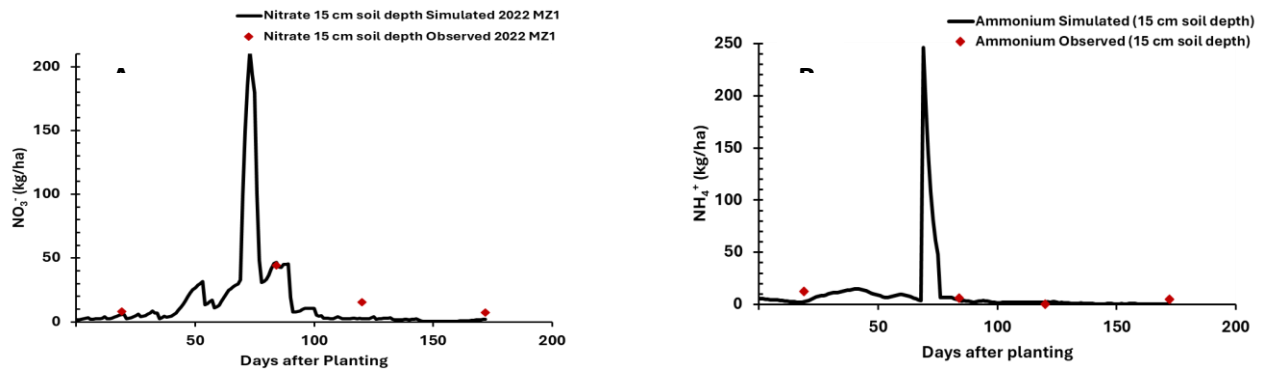
**Figure 4.6.3.2.** A comparison of simulated and observed volumetric soil water content for low yield zone (MZ2 – 2022) at depth 15 (A), 45 (B), and 60 (C) cm.



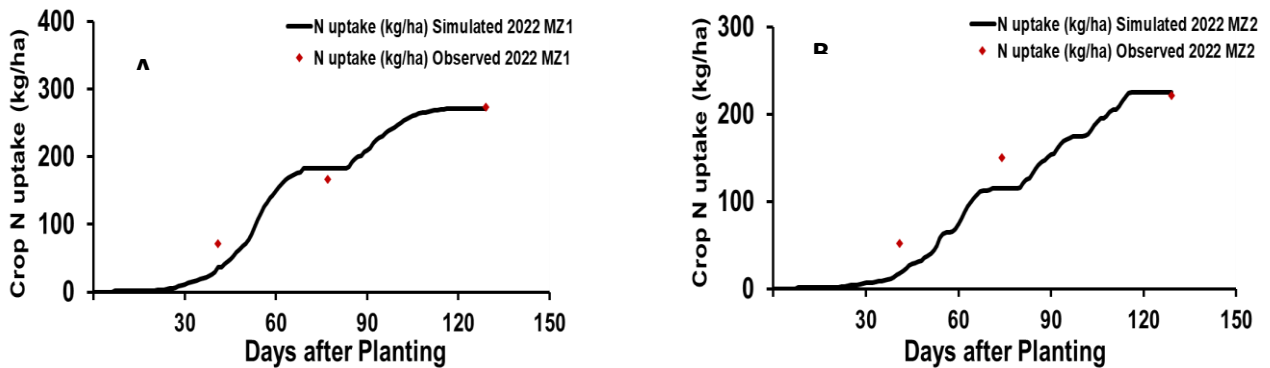
**Figure 4.6.4.** A comparison of simulated and observed leaf area index of high yield zone (MZ1 – 2022).



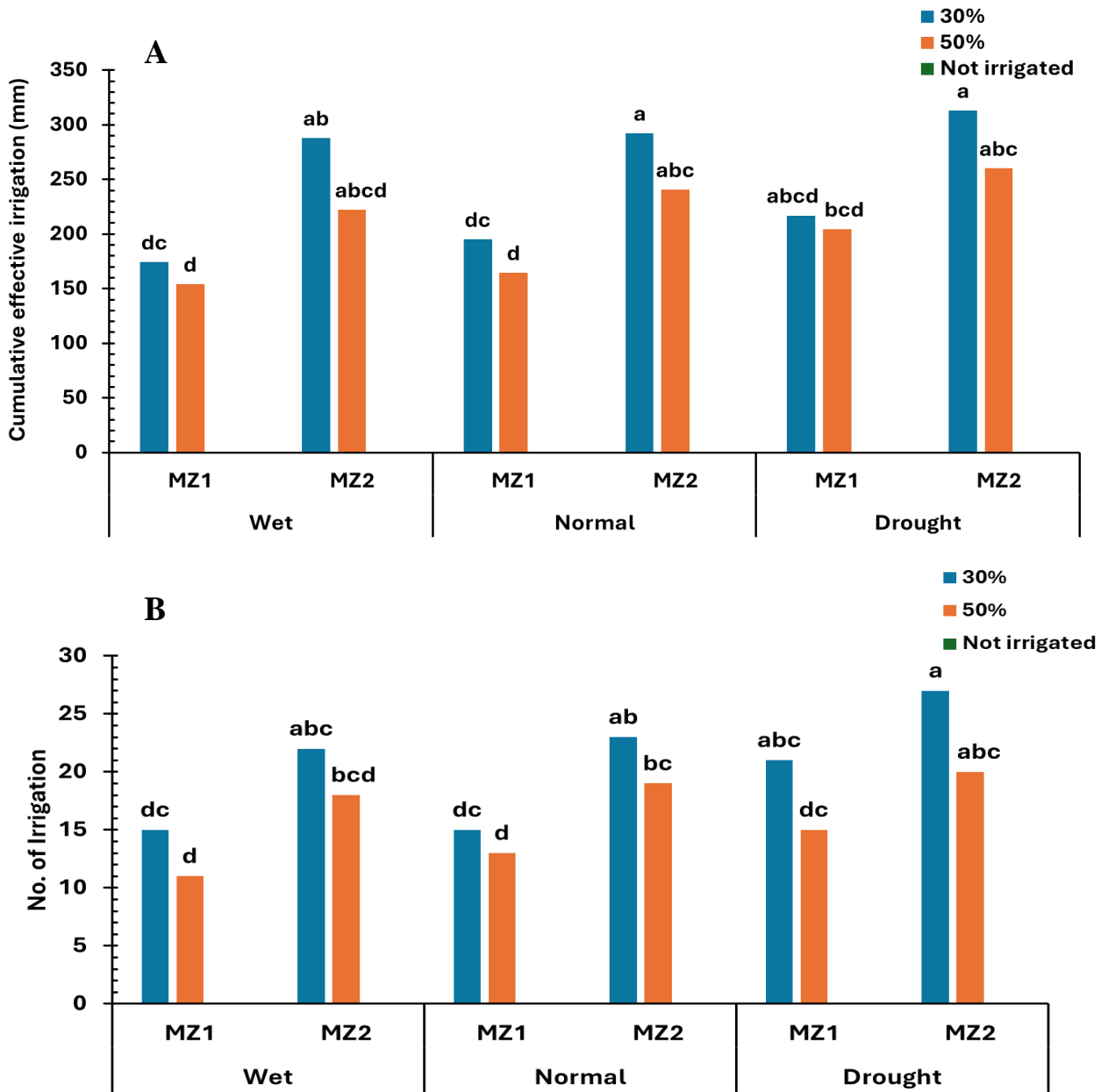
**Figure 4.6.5.** A comparison of simulated and observed tops weight for A) high yield zone (MZ1, year 2022) (B) Low yield zone (MZ2, year 2022), and C) high yield zone (MZ1, year 2019).



**Figure 4.6.6.** A comparison of simulated and observed soil N at maize harvest for A) nitrate- high yield zone (MZ1, year 2022) (B) and ammonium- high yield zone (MZ1, year 2022).

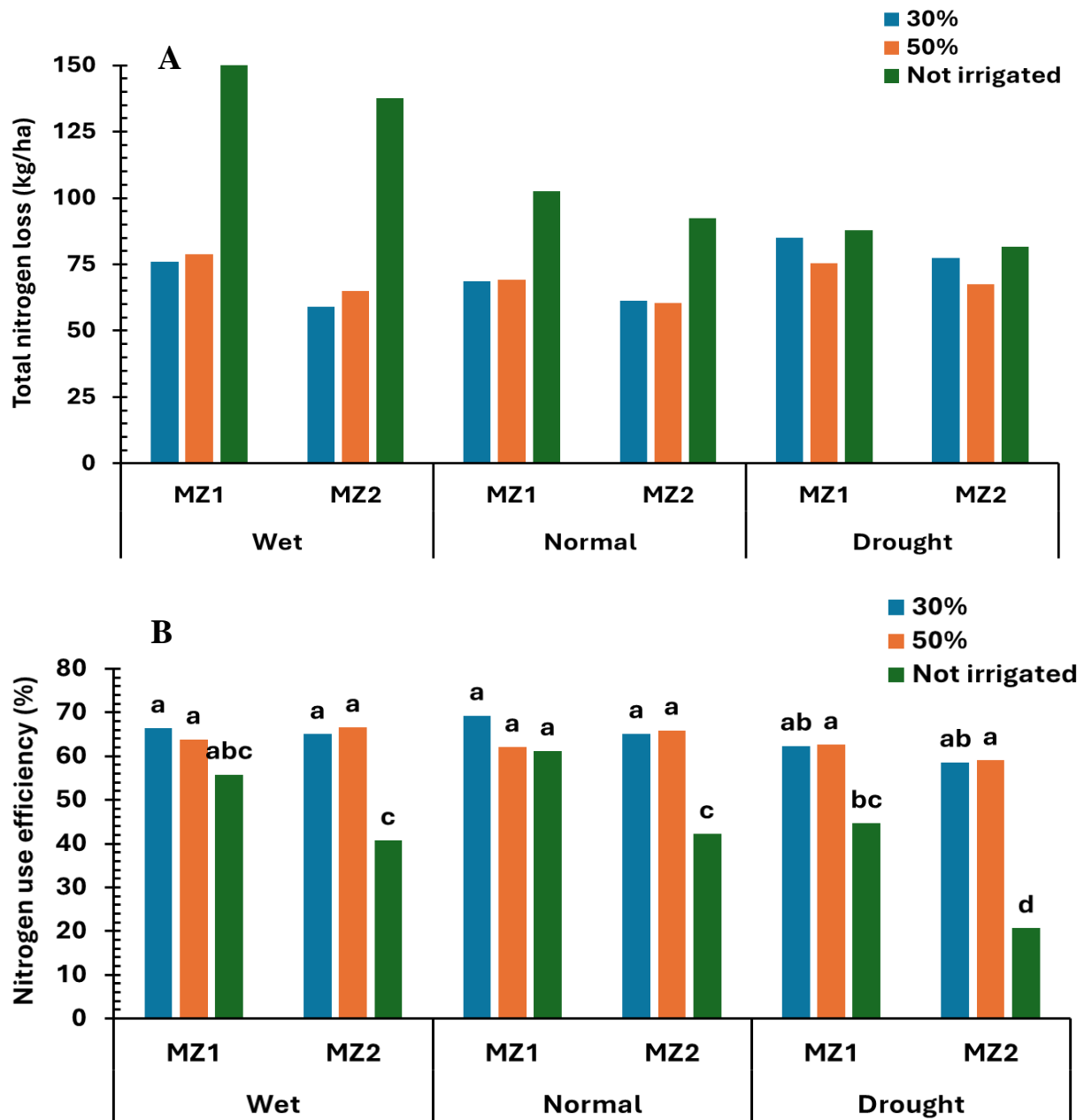


**Figure 4.6.7.** A comparison of simulated and observed nitrogen uptake for MZ1, year 2022 (A) and nitrogen uptake for MZ2, year 2022 (B).



**Figure 4.6.8.1** Long term cumulative effective irrigation (A), and no. of irrigation (B) under different water deficits for different growing season rainfall conditions in MZ1 and MZ2.

The letters on the graph indicate significant difference among treatments ( $P < 0.05$ ), based on Tukey's test.



**Figure 4.6.8.2.** Long term cumulative nitrogen losses (A), and nitrogen use efficiency (B) under different water deficits for different growing season rainfall conditions in MZ1 and MZ2.

The letters on the graph indicate significant difference among treatments ( $P < 0.05$ ), based on Tukey's test.

## **Chapter 5. DSSAT-Based Evaluation of Nitrogen Rate and Timing Under Variable Irrigation Scenarios Across Contrasting Management Zones in Maize**

### **Abstract**

Understanding nitrogen (N) cycling at field scales under real-world farming conditions presents logistical and technical challenges. This study employed the DSSAT-CSM-CERES-Maize model to evaluate N management strategies under varying irrigation deficits across contrasting management zones (MZs) in a commercial maize field in Alabama. Simulations conducted over 40 years of weather variability examined the effects of four N rates (120, 160, 220, and 280 kg ha<sup>-1</sup>) and three irrigation regimes (no irrigation, 50%, and 30% deficit). Results showed that MZ1 consistently outperformed MZ2, with 25% higher grain yield (10.1 vs. 8.1 Mg ha<sup>-1</sup>) and 24% greater N uptake. Seasonal rainfall strongly influenced outcomes—drought years reduced yield and uptake by 15% and 10%, respectively, while wet years increased nitrate leaching by 82% over drought years. Volatilization was highest in MZ1 (49.4 kg ha<sup>-1</sup>), while denitrification was dominant in MZ2 (6.7 kg ha<sup>-1</sup>). Leaching peaked during wet years (18.3 kg ha<sup>-1</sup>), particularly under higher N rates combined with reduced irrigation. Reducing N input to 160 kg ha<sup>-1</sup> under 30–50% deficit irrigation sustained yields within 5% of baseline levels (220 kg ha<sup>-1</sup>) while minimizing N losses.

Key words: nitrogen dynamics; nitrogen rate; deficit irrigation; climate variability; management zone; DSSAT

## 5.1. Introduction

Nitrogen (N) is a critical macronutrient required for crop growth and productivity. However, inefficient N management in agricultural systems often leads to significant agronomic and environmental challenges. Excessive or poorly timed N applications result in substantial N losses through leaching, denitrification, and volatilization, contributing to groundwater contamination and greenhouse gas emissions (Robertson & Vitousek, 2009). These losses not only reduce nitrogen use efficiency (NUE) but also increase production costs for farmers while exacerbating environmental concerns. Given the complexity of N cycling and its interactions with soil, climate, and management practices, optimizing N management strategies is essential to find strategies to improve NUE along with sustaining high yields while minimizing negative environmental impacts (Ali et al., 2025; Congreves et al., 2021). Cameron et al. (2013) conducted a comprehensive review of N losses across different cropping systems and soil types and concluded that optimizing and consciously implementing N management practices such as crop need-based fertilizer rate and timing can substantially reduce leaching and denitrification losses.

Irrigation plays a crucial role in regulating N availability and movement in the soil. Water availability directly influences N uptake, soil moisture retention, and the risk of N losses via leaching and denitrification (Drobnitch et al., 2024; Attia et al., 2015). In water-limited environments, irrigation strategies must be carefully aligned with the N application rate to enhance NUE and minimize environmental losses. However, the effects of irrigation on N dynamics vary across different landscape positions and soil types. Fields with spatial heterogeneity in soil properties often exhibit yield stability differences, leading to the delineation of management zones (MZs) based on historical productivity patterns (Flowers et al., 2005; Gozdowski et al., 2014).

High-yield stability zones, typically found in lower landscape positions with finer-textured soils, tend to retain more water and nutrients, resulting in reduced N losses. Leuthold et al. (2023) observed that low-yield stability zones on sloped terrains were more prone to nutrient losses due to rapid drainage and limited water retention, while high-stability zones in depressions retained more water and nutrients, reducing N loss potential. Zhao et al. (2020) supported these findings in a study across diverse agroecological zones in China, concluding that understanding topographic and soil heterogeneity is vital for developing sustainable N management strategies. Several studies have investigated the impact of N rate and timing on yield and N losses under varying irrigation conditions.

Several studies have demonstrated that reducing N rates without compromising yield can enhance NUE while mitigating environmental risks. Dabney et al. (2010) reported that reduced N rates did not compromise maize yield but significantly improved NUE and decreased leaching losses. Morris et al. (2018) tested different N application rates and found that optimal N strategies could be tailored without yield penalties, provided they accounted for site-specific soil characteristics. Feng et al. (2023) further confirmed these results in maize systems, emphasizing the role of phenology-aligned N applications under variable irrigation. In addition, adjusting the timing of N applications, such as split applications at critical crop growth stages, has been shown to improve N retention and uptake efficiency (Di Paola et al., 2020). However, the effectiveness of these strategies is highly dependent on irrigation scheduling, as excessive or untimely irrigation can lead to increased leaching and denitrification, particularly in sandy or well-drained soils (Sturgul et al., 2020). These findings highlight the need for an integrated approach that considers both N application rate and timing in conjunction with irrigation management to optimize crop productivity and minimize N losses.

The Decision Support System for Agrotechnology Transfer (DSSAT) is a widely used modeling platform that integrates soil, crop, weather, and management inputs to simulate crop growth, soil-N transformations, and environmental N losses under different production scenarios (Jones et al., 2003 and 1998). Kipkulei et al. (2022) highlighted DSSAT's utility in assessing sustainable N management strategies using long-term simulations over decades. He emphasized short-term field trials may not capture the full range of weather fluctuations, but long-term simulations using process-based crop models allow for a more comprehensive evaluation of crop management practices. DSSAT's ability to assess what-if scenarios makes it a powerful tool for evaluating the long-term effects of N rate, timing, and irrigation on maize production, helping to inform sustainable management decisions (Gobezie et al., 2025).

Building on chapter 2 and 4, this study employs DSSAT-based simulations to further investigate optimal N management strategies under different irrigation regimes in two contrasting MZ of a commercial farm. By integrating long-term weather data with DSSAT simulations, this study aims to generate data-driven recommendations for precision N management that enhance NUE and reduce environmental losses under site-specific irrigation regimes. The findings will contribute to the development of sustainable agronomic practices tailored to spatially heterogeneous fields, supporting decision-making for improved maize production efficiency and environmental stewardship. The objectives of this study are a) to determine the long-term weather effects of N rate and application timing on maize yield and N losses across different irrigation scenarios in MZ1 and MZ2 and b) to identify the optimal N and irrigation management strategies required to minimize N losses while closing the yield gap between high-yield and low-yield MZ.

## 5.2. Materials and Methods

### 5.2.1. Study Site and Experimental Setup

The study was conducted on a commercial maize farm in Town Creek, Alabama (34° 43' 6.67" N, 87° 23' 13.52" W; 181 m above mean sea level). The site falls within a humid subtropical region (Peel et al., 2007) and supports a maize–soybean–wheat rotation. Historical weather data indicate  $T_{\max}$  of 33.0°C,  $T_{\min}$  of 10.5°C, and an annual rainfall of 120.5 cm. Rainfall was 118 cm in 2022, concentrated in winter and spring, and 159 cm in 2019, evenly distributed. The field spans 190 ha, with 125 ha under center pivot irrigation. Soils vary from Abernathy-Emory clay loam to Decatur silty clay loam, with slopes of 2–12% and elevations ranging from 169 to 180 m.

### 5.2.2. Management Zone Delineation

The field was classified into two management zones (MZ1: high yield stability; MZ2: low yield stability) using six years (2010–2020) of maize yield data in ArcGIS 10.8. Yield stability was defined using a standard deviation and two-way outlier algorithm (Maestrini & Basso, 2021). Additional classification incorporated topographic indices (slope, topographic position index (TPI), topographic wetness index (TWI), and elevation)) (Morata et al., 2020; Kumar et al., 2022). MZ1 (0–2% slope) was characterized by lower TPI, higher TWI, and greater moisture retention, whereas MZ2 (6–10% slope) exhibited higher TPI, lower TWI, and greater drainage (Figure 5.6.1).

MZ1 with a slope of 0-2%, has relatively flat terrain, which generally leads to more uniform water distribution and lower risk of surface runoff. The slower water movement in the Abernathy-Emory clay loam in this area means it can hold more water but may also be prone to waterlogging if over-irrigated. In contrast, MZ2 with a steeper slope of 6-10%, has more uneven water flow, increasing the risk of runoff and soil erosion, particularly under high rainfall or heavy irrigation. These slope

differences highlight the need for tailored irrigation strategies to avoid over-watering (MZ1) and to reduce runoff and prevent nutrient loss (MZ2).

Additionally, N management needs to be adjusted based on both soil and topography. In the flatter MZ1, N is likely to volatilize or leach due to good drainage compared to MZ2 where it may become less available to crops due to its strong retention in the clay prominent soil profile. Here, split applications of fertilizers can ensure a steady supply of N throughout the growing season.

### **5.2.3. Experimental details**

Given the distinct soil properties and topographic differences between MZ1 and MZ2, the long-term experiment design for irrigation scenarios was tailored to explore how varying levels of water availability impact crop growth under these conditions (Chapter 2). The three irrigation scenarios considered—50% irrigation deficit, 30% irrigation deficit, and a non-irrigated condition without supplemental irrigation—were chosen to assess how each MZ responds to different irrigation and N management strategies. For MZ1, with its flat terrain and slower water movement, the 50% and 30% irrigation deficits provide insight into how reduced irrigation affects soil moisture retention and crop productivity in Abernathy-Emory clay loam. Meanwhile, for MZ2, with its steeper slope and high clay content, these same irrigation deficits help us understand how water management efforts would affect crop yield and N losses. The non-irrigated conditions at both sites will further highlight the resilience of each soil type under natural precipitation, revealing the role of soil texture and slope in water retention and crop performance without supplemental irrigation. This experimental approach allows for a comprehensive evaluation of irrigation strategies tailored to the unique characteristics of each site.

Building on the irrigation scenarios optimized in chapter 4, we wanted to further investigate the interaction of the irrigation scenarios with N application rates and timing on crop performance and N losses under different growing season rainfall conditions (GSRC). Four N application rates were tested: baseline N (220 kg N ha<sup>-1</sup>), increased N (280 kg N ha<sup>-1</sup>), reduced N rate @ 160 kg N ha<sup>-1</sup>, and 120 kg N ha<sup>-1</sup>, to evaluate how varying N inputs influence maize yields and N uptake at both MZ's. The timing of N application was split N dose with 1/3<sup>rd</sup> urea at planting and 2/3<sup>rd</sup> UAN at the V7 growth stage of maize. The split-application strategy was designed to reflect common nitrogen management practices among Alabama maize growers.

#### **5.2.4. DSSAT Model Operation**

DSSAT requires comprehensive inputs such as crop genetic coefficients, weather data, soil characteristics, and crop management practices to simulate growth, soil water, and nitrogen dynamics on a daily time step. All the input data used in the model are described below:

##### **5.2.4.1. Soil input data**

The soil cores (121 cm deep) were collected from different locations within the field prior to planting using a tractor-mounted deep soil coring rig (as described in Keeney & Nelson, 1982). Each soil core was sectioned by depth at 0–5, 5–15, 15–23, 23–30, 30–46, 46–61, 61–91, 91–106, and 106–121 cm intervals. Different sections of the soil cores were used to determine pH, soil texture, bulk density, volumetric water content, organic carbon, total nitrogen (TN), and mineral nitrogen (N) input.

Bulk density was determined using the mass-to-volume ratio of oven-dried soil samples (105°C for 48–72 hours) following the method described by Schepers et al. (1989). Mineral N (NO<sub>3</sub><sup>-</sup>-N and NH<sub>4</sub><sup>+</sup>-N) was extracted using a 1:5 soil-to-2 M KCl solution, following the Keeney & Nelson

(1982) protocol, and analyzed using the FIAlyzer-1000 Flow Injection Analyzer (FIALab Instruments Inc.) according to EPA Method 353.2. Total nitrogen (TN) was measured using a LECO C/N Analyzer, and organic nitrogen (Organic N) was calculated as TN minus inorganic N ( $\text{NO}_3^-$ -N +  $\text{NH}_4^+$ -N) (Hood et al., 2010; Bly et al., 2024). The drainage rate and runoff curve number were estimated using the USDA-NRCS SSURGO database. Soil moisture data was recorded continuously throughout the crop period using an Acclima soil moisture sensor (Meridian, Idaho, USA), installed at 15, 45, and 60 cm depths at each sampling location.

#### **5.2.4.2. Weather data**

The weather data for the study years 2019 and 2022 was obtained from an automated weather station installed outside the field. The weather station recorded data at 15 minutes interval for maximum and minimum temperature ( $^{\circ}\text{C}$ ), precipitation (mm), solar radiation ( $\text{MJ}/\text{m}^2$ ), and humidity (%).

For long term simulation experiment, forty years of historical weather data from 1984 till 2022 (retrieved from Global Historical Climatology Network-daily (GHCN-Daily) from NOAA) for the maize growing period was categorized each year into wet, normal, and drought years using the Standardized Precipitation Index (SPI) to understand the effect of weather on N dynamics. The SPI was calculated to characterize meteorological drought in the specified weather range (McKee et al., 1993). The calculation was done using the standard deviation method, which involves comparing observed precipitation to the long-term average for a given period. Specifically, SPI is computed by subtracting the mean precipitation from the observed value and dividing the result by the standard deviation (Eq 1). This standardization allows precipitation anomalies to be expressed in terms of standard deviations from the mean, facilitating consistent interpretation of wet and dry conditions across different timescales and regions.

$$\text{SPI} = (P - P^*) / \sigma_p \quad \text{Eq 1}$$

where P = precipitation

P\* = mean precipitation

$\sigma_p$  = standard deviation of precipitation

The calculated SPI values were used to categorize the study years into three GSRC types: drought, normal, and wet, with the following classification thresholds:

SPI  $\leq$  -1.0: Drought ( $\leq$ 520 mm)

-1.0 < SPI  $\leq$  1.0: Normal (between 520-835 mm)

SPI > 1.0: Wet (>835 mm)

#### **5.2.3.4. Crop input data**

The maize growth stages were recorded throughout the crop period. The leaf area index (LAI) was obtained using a Li-Cor-LAI 2200 instrument (LICOR, Lincoln, NE, USA) and plant samples were collected in six replicates (1 meter-rows) from each location to determine above-ground biomass. The sampling was done at V7 (26 DAP), R1 (40 DAP), and R8 (128 DAP), growth stages. The plant samples were partitioned into leaves, stems, husk and cob based on respective growth stages, oven dried at 70°C until they reached constant mass, and composite dry samples for each plant part were recorded and analyzed for tissue N concentration to determine N uptake.

The grains subsamples were analyzed to determine the number of grains per ear, unit grain weight, and kernel moisture. Following by kernel moisture determination, the yield was adjusted to dry weight (0% moisture).

### **5.2.3.5. Management information**

All the management practices were decided and executed by the farmer. In 2019, the field was planted with the maize hybrid Dekalb® DKC 66-97 of 116 days relative maturity, while in 2022, Dekalb® DKC 169-16 was planted with a similar relative maturity. The maize was planted at a 0.76 m row spacing and a plant population of 79,073 seeds per ha. Agronomic practices such as planting dates, fertilization, irrigation events, and harvest are given in Table 5.6.1.

### **5.2.3.6. Model calibration and evaluation**

Data collected for maize in 2022 from a potential yield location under MZ1 (Figure 5.6.1, location 1) was used to calibrate the model. For model evaluation, a low yield location under MZ2 in 2022 was used (Figure 5.6.1, location 5), and further evaluation was done using maize growth and yield data from MZ1 in 2019 (Morata et al., 2020). The model was calibrated using DSSAT model 4.8.5. (Hoogenboom et al. 2024) to simulate maize growth and yield. The Century Parton model (Parton et al., 1987) was used to simulate soil organic matter dynamics, while the Ritchie method (Ritchie, 1972) was applied to simulate infiltration and hydrology.

The DSSAT-CSM-CERES maize uses six cultivar coefficients to calibrate growth and development of crops under certain environmental conditions (Table 5.6.2. P1, P2, and P3 represent early growth, G2, and G3 represent grain filling, and PHINT represents the phyllochron interval between successive leaf tips. The genetic coefficients of the cultivar (Dekalb® DKC 69-16) were determined using the Generalized Likelihood Uncertainty Estimation (GLUE) tool was used for cultivar coefficient estimation with a total of 50,000 runs. After running GLUE, the sensitivity analyses tool was used to estimate the cultivar coefficients value that minimized the error between simulated and measured values of phenology data (Table 5.6.2). The anthesis (P1) and maturity date (P5) genetic coefficients to match the field observed crop development. After

getting a good agreement between simulated and observed values for P1 and P5, other genetic coefficients G2, G3 and PHINT were adjusted to align simulated and observed grain yield, grain unit weight, LAI, and tops weight.

After model calibration, the DSSAT model was evaluated using an independent dataset from maize planted in 2019 in Management Zone 1 (MZ1). To further assess model performance, additional evaluation was conducted using data from Management Zone 2 (MZ2), a low-yielding zone, also from the 2022 season (calibration year). While the genetic coefficients remained unchanged, zone-specific soil properties were used to reflect the distinct soil conditions of each management zone.

### 5.2.5. Statistical Analysis

The crop model performance was evaluated by comparing the simulated and observed LAI, crop biomass, soil water content, crop N uptake, soil nitrate, grain yield, and total nitrogen uptake at harvest. The coefficient of determination ( $R^2$ ), and the index of agreement (d-stat) were used to evaluate the model performance. The coefficient of determination ( $R^2$ ) was used to measure the proportion of variance in the observed data that is explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad \text{Eq1.}$$

$$d - stat = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (|S_i - \bar{S}| + |O_i - \bar{O}|)^2} \quad \text{Eq. 2}$$

Where,

- n is the number of observations,
- $P_i$  is the predicted value for the  $i$ th observation,
- $O_i$  is the observed value for the  $i$ th observation,
- $O_i - P_i$  is the difference (error) between predicted and observed values for the  $i$ -th observation.
- $S_i$ : Simulated value at observation  $\mathbf{I}$ ,
- $\bar{O}$ : Mean of the observed values,

Statistical analyses were performed using SAS 9.4 (SAS Institute, 2013). A mixed-model approach (Proc GLIMMIX) was used to account for the hierarchical split-plot design and repeated measures across conditions. Conditions categorized as wet, normal, or drought—based on precipitation patterns for maize cropping season, were treated as replicates to capture interannual climatic variability. A factorial ANOVA was conducted to assess the effects of four nitrogen rates combined with three irrigation deficits, management zone (MZ), growing season rainfall categories (GSRC), and their interactions. The model included 12 treatment combinations, enabling direct comparisons between application strategies across varying irrigation levels and nitrogen rates. Fixed effects included management zone, GSRC, treatment (rate or timing), and their interactions. Replication and the interaction between crop and replication were included as random effects to account for variability across blocks and repeated measures. Degrees of freedom were adjusted using the Kenward-Roger method to provide more accurate estimates under unequal replication of wet, normal, and drought years. Type III tests of fixed effects were used to determine the significance of main effects and interactions ( $P < 0.05$ ), and Tukey's HSD test was applied for mean separation when significant differences were found. Assumptions of normality and homogeneity of variance were verified through diagnostic checks. Normality of residuals was assessed using the Shapiro-Wilk test and Q-Q plots, while homogeneity of variance was evaluated using Levene's test. Residual plots were also visually inspected to confirm model assumptions.

### **5.3. Results and Discussion**

#### **5.3.1. Growing Season Rainfall Conditions**

The Standardized Precipitation Index (SPI) serves as a critical tool for assessing precipitation anomalies by quantifying deviations from long-term climatological norms. The analysis of SPI over a 40-year maize crop period (1984–2022) revealed significant climate variability (Figure

5.6.2). Based on predefined SPI thresholds, years were categorized into three classifications: wet, normal, and drought conditions, we are broadly calling these categories as growing season rainfall conditions. Wet years ( $SPI \geq +1$ ) notably included years 1989, 1991, 1997, 2020, and 2021, indicated by positive SPI values (blue bars in Figure 5.6.2) significantly above the upper threshold (+1). Conversely, drought years ( $SPI \leq -1$ ) were clearly identified in 1987, 1988, 2000, 2006, and 2007, characterized by negative SPI values (red bars in Figure 5.6.2) surpassing the drought threshold (-1). The remaining years were classified as normal, demonstrating moderate fluctuations around the mean SPI value.

Categorizing precipitation data based on SPI is highly relevant for studying the long-term efficiency of different N management approaches. In wet years, higher precipitation amounts can significantly increase N losses through leaching and denitrification processes. Conversely, drought years with reduced water availability may limit crop N uptake, increasing risks of N accumulation in soil and volatilization or immobilization losses of N. In contrast, wet years often resulted in higher yields but substantial N losses through runoff and leaching, decreasing N availability. Near-normal years provided a more stable yield and uptake responses. Together, these studies emphasize the strong connection between precipitation patterns, crop productivity, and nitrogen dynamics, highlighting the importance of weather-responsive N management strategies to sustain yield and NUE.

### **5.3.2. Model calibration and evaluation**

Accurate calibration of crop phenology is essential for simulating canopy development, biomass accumulation, and nitrogen dynamics. In this study, the DSSAT CSM-CERES-Maize model was calibrated using field data from Management Zone 1 (MZ1) in 2022 for the maize hybrid Dekalb®

DKC 69-16. Calibration focused on adjusting simulated and observed values for key growth and development parameters (Table 5.6.4, Figure 5.6.3).

The model slightly advanced crop emergence by one day (7 DAP simulated vs. 8 DAP observed) and predicted anthesis and physiological maturity at 69 and 120 DAP, closely matching the observed 68 and 121 DAP, respectively. The simulated maximum leaf area index (LAI) was marginally overestimated at 4.7 compared to the observed 4.4. The simulated yield and yield components closely aligned with the measured data. Overall, the model demonstrated strong performance in calibrating crop growth, phenology, and nitrogen dynamics, as evidenced by the close alignment between measured and simulated values across most parameters. These results indicate that the model was well calibrated for maize hybrid under the management and environmental conditions of the study site.

Overall, the model performed well across phenology, yield, and nitrogen dynamics, demonstrating its ability to replicate crop response under the specific management and environmental conditions of the site. The high degree of alignment between simulated and observed data confirms that the model was effectively calibrated and is suitable for further simulations involving nitrogen and irrigation strategies.

After successful calibration of the model, evaluation was carried out using independent datasets from Management Zone 2 (MZ2) in 2022 and Management Zone 1 (MZ1) in 2019. The genetic coefficients calibrated using MZ1 data from 2022 were applied during this evaluation. The model showed strong agreement between simulated and observed values for key growth and development parameters in both zones (Table 5.6.5, Figure 5.6.4).

For MZ2 in 2022, simulated phenological stages—emergence and physiological maturity—closely matched observed dates, and grain yield was slightly underestimated (10,293 vs. 10,367 kg ha<sup>-1</sup>).

In MZ1 for the 2019 season, the model also accurately reproduced growth trends, though minor deviations were noted. The simulated and observed grain yield were closely aligned (12,099 vs. 12,038 kg ha<sup>-1</sup>), and top biomass was underpredicted by approximately 11%. This degree of deviation is considered acceptable in crop model evaluation. Previous studies have demonstrated that prediction errors within  $\pm 15\%$  are indicative of good model performance for yield and biomass (Rani et al., 2018; Kipkulei et al., 2022; Wang et al., 2021). For instance, Rani et al. (2018) reported normalized RMSE values below 20% for yield simulations across variable nitrogen and planting densities, while Kipkulei et al. (2022) found RMSE values between 5.1% and 8.1% for two maize hybrids in Kenya. Such benchmarks support the interpretation that the model's performance in this study was well within acceptable limits.

The minor discrepancies observed between simulated and observed values for 2019 MZ1 evaluation are likely due to hybrid-specific differences in physiological traits or year-to-year weather variability between calibration and evaluation datasets. As Wang et al. (2021) noted, the accuracy of DSSAT simulations is highly sensitive to cultivar-specific genetic coefficients, particularly under stress conditions such as irrigation and fertilizer constraints.

Overall, the model demonstrated a good fit for the calibrated parameters (MZ1–2022) and moderate agreement for the independent evaluation datasets. These results are consistent with previous DSSAT studies that report higher uncertainty when evaluating model performance across years or spatially generalized conditions.

### **5.3.3. Effect of split nitrogen rate and irrigation deficit treatments**

#### **5.3.3.1. Crop yields and Nitrogen uptake**

Analysis of DSSAT-simulated maize yields and nitrogen uptake (Figure 5.6.4) revealed significant effects of MZ (Table 5.6.6), seasonal rainfall condition (drought, normal, wet year), fertilizer treatments, and their two-way interactions with treatments ( $P < 0.0001$ ). In contrast, the interactions between MZ and seasonal condition, as well as  $MZ \times \text{seasonal condition} \times \text{treatment}$ , were not significant ( $< 0.0001$ ), indicating that treatment responses and the relative advantage of MZ1 over MZ2 remained stable across years.

Among all factors, the management zone exerted the strongest influence. Averaged across treatments and water years, MZ1 produced approximately 25% higher yields (10.1 vs. 8.1 Mg ha<sup>-1</sup>) and 24% higher nitrogen uptake (229.79 vs. 185.52 kg ha<sup>-1</sup>) compared to MZ2. This spatial productivity gap reflects inherent soil and resource variability across zones and validates the yield-based management zone delineations. Similar findings were reported by Brock et al. (2005), who noted consistently higher yields in stable high-yielding zones derived from historical clustering of maize and soybean production. Spatial variability in yield potential highlights the necessity for site-specific management strategies.

Seasonal rainfall also significantly affected yield and nitrogen uptake. Yields averaged 9.73 Mg ha<sup>-1</sup> in wet years, 9.15 Mg ha<sup>-1</sup> in normal years, and 8.41 Mg ha<sup>-1</sup> under drought, corresponding to a 15% yield reduction under drought relative to wet years. Similarly, nitrogen uptake declined approximately 10% under drought compared to wet conditions (216.35 vs. 195.08 kg ha<sup>-1</sup>). These results align with previous findings (Sperry et al., 2002; Xu et al., 2018), emphasizing the crucial role of soil moisture in supporting biomass accumulation and nutrient transport, especially during critical reproductive stages.

Fertilizer treatment effects were highly significant ( $< 0.0001$ ) for both yield and nitrogen uptake. Yield and uptake increased sharply from the lowest nitrogen rate (120 kg ha<sup>-1</sup>) to the baseline (220

kg ha<sup>-1</sup>), with little additional benefit at the increased rate (280 kg ha<sup>-1</sup>). Treatments T1 and T2 (220 and 280 kg ha<sup>-1</sup> under 30% deficit) achieved the highest yields (12.11 and 12.39 Mg ha<sup>-1</sup>, respectively) and highest nitrogen uptake levels, with only a 2% gain from increasing N beyond baseline. Moderate nitrogen reductions (T3 and T7; 160 kg ha<sup>-1</sup>) under 30% and 50% deficits maintained yields and uptake comparable to baseline treatments, suggesting that maize systems managed with strategic deficit irrigation can tolerate moderate nitrogen reductions without significant yield or nutrient uptake penalties (Tian et al., 2023; Khan et al., 2023).

Under severe N reductions (120 kg ha<sup>-1</sup>) and higher irrigation deficits or no irrigation (T4, T8, T12), sharp declines in both yield and uptake were observed. In rainfed treatments, yields fell below 8 Mg ha<sup>-1</sup> and nitrogen uptake dropped significantly, representing a 35% reduction relative to baseline deficit treatments. This highlights the compounded impact of simultaneous water and nitrogen limitations on maize productivity and nutrient acquisition.

Zone-specific trends revealed that MZ1 maintained relatively high yield and uptake across both 30% and 50% irrigation deficits, demonstrating greater resilience to moisture and nutrient stress. Conversely, MZ2 displayed higher sensitivity, performing significantly better under 30% irrigation deficit compared to 50%, particularly under moderate nitrogen rates. However, the absence of significant MZ × seasonal condition interactions suggests that integrated management strategies developed here can be broadly applied across spatial zones.

Interestingly, yields and nitrogen uptake under 30% and 50% irrigation deficits were relatively stable across wet, normal, and drought years. This stability reflects DSSAT's soil moisture-triggered irrigation scheduling, where supplemental water was applied whenever soil moisture dropped below a set threshold, buffering maize against seasonal drought stress. As a result, even during drought years, yields and nitrogen uptake under deficit irrigation treatments remained

comparable to those in wetter years. These findings are consistent with Si et al. (2021), who showed that deficit irrigation targeting critical growth stages using DSSAT modeling can sustain maize yields near full irrigation levels by optimizing water use based on soil moisture dynamics.

### **5.3.3.2. Soil inorganic nitrogen at harvest**

DSSAT-simulated soil inorganic N at harvest showed significant effects (Table 5.6.6) of MZ, seasonal rainfall condition (drought, normal, wet year), fertilizer treatment, and their two-way interactions with treatments ( $< 0.0001$ ; Table 5.6.6). However,  $MZ \times \text{Condition}$  and  $MZ \times \text{Condition} \times \text{Treatment}$  interactions were not significant ( $< 0.0001$ ), suggesting that while treatment and seasonal differences affected soil N retention, these patterns were consistent across zones.

Residual soil inorganic nitrogen at harvest varied significantly between management zones. Across all treatments and years, MZ2 (Figure 5.6.5) retained substantially more inorganic N than MZ1 (70.4 vs. 28.6 kg ha<sup>-1</sup>). This spatial disparity likely reflects differences in soil properties: MZ2's higher clay content (up to 52% in deeper layers) may enhance ammonium retention within clay minerals (Vogel et al., 2015). High clay content has been reported to stabilize soil organic matter (OM), slow OM decomposition, and reduce N mineralization rates, thereby limiting N losses through leaching or volatilization. However, this can also restrict N availability during periods of high crop demand (Huang et al., 2025; Macduff & White, 1985). In contrast, MZ1 exhibited consistently lower residual N, suggesting greater N uptake by crops and/or greater N loss potential through volatilization or leaching, particularly given its lighter soil texture.

Seasonal rainfall patterns also influenced residual soil N. Drought years resulted in significantly greater inorganic N retention compared to wet years (55.4 vs. 42.9 kg ha<sup>-1</sup>), likely due to reduced

water movement and N leaching. Similar findings have been reported by Bahrami et al. (2022), who noted that under water-limited conditions, nitrogen losses are minimized but nutrient use efficiency can decline if plant uptake is also constrained.

In contrast, treatments applying reduced nitrogen rates (T4, T8, T12) under no irrigation conditions exhibited the lowest residual soil N levels ( $<12 \text{ kg ha}^{-1}$ ). Under these severely water-limited conditions, both crop growth and nitrogen uptake were constrained; however, lower fertilizer inputs helped avoid excessive nitrogen surplus in the soil profile. Reduced N applications were better aligned with the limited biomass production potential under drought stress, leading to improved synchronization between nitrogen supply and crop demand. Consequently, minimal nitrogen remained unused at harvest, reducing the risk of post-harvest nitrogen losses through leaching following rainfall events or volatilization during soil rewetting. These findings are consistent with observations by Chen et al. (2018), who reported that lower N application rates under rainfed conditions minimized residual soil nitrogen and reduced the potential for environmental nitrogen losses in maize cropping systems.

### **5.3.3. Nitrogen losses**

#### **Denitrification Losses**

Management zone (MZ), seasonal rainfall conditions, and fertilizer treatment significantly influenced denitrification outcomes ( $P < 0.0001$ ; Table 5.6.6), whereas interactions between MZ  $\times$  Condition and the three-way interaction were not significant ( $P = 0.7517$ ,  $P = 1.000$ , respectively) (Table 5.6.6).

Across all conditions, MZ2 exhibited markedly greater denitrification than MZ1. Averaged across treatments and rainfall years, denitrification in MZ2 reached  $6.68 \text{ kg N ha}^{-1}$ , compared to only

2.89 kg N ha<sup>-1</sup> in MZ1 (Figure 5.6.6). This trend can be attributed to the inherent soil characteristics of MZ2, which includes high clay content and lower pH values. These properties may lead to reduced drainage and the formation of anaerobic microsites within the soil profile, promoting conditions favorable to denitrifying microbial communities (Castaldelli et al., 2019).

Additionally, growing season rainfall also significantly affected denitrification. Denitrification losses were highest under wet conditions (6.10 kg N ha<sup>-1</sup>), significantly greater than under normal (3.96 kg N ha<sup>-1</sup>) or drought (4.30 kg N ha<sup>-1</sup>) years. Increased precipitation or irrigation elevates soil water content, which not only enhances microbial activity but also induces anaerobic conditions that accelerate the microbial reduction of nitrate (NO<sub>3</sub><sup>-</sup>) to gaseous forms such as N<sub>2</sub> and N<sub>2</sub>O. Moreover, wetter soils promote increased mineralization and nitrification, resulting in greater nitrate availability, which further supports denitrification processes (Iqbal et al., 2018; Vaccare et al., 2019; He et al., 2025).

Although the overall R-I treatment (fertilizer × irrigation) effects were statistically significant ( $P < 0.0001$ ), irrigation scenario trends were more pronounced. Treatments under no irrigation exhibited the lowest denitrification, supporting the idea that limited soil water content suppresses denitrification activity. Conversely, deficit irrigated treatments (especially at 30% and 50% thresholds) showed progressively greater denitrification losses, with wetting events intermittently creating anaerobic microsites conducive to denitrification.

Together, these results highlight that denitrification is primarily driven by soil water status, soil physical properties, and nitrate availability. Management practices that moderate soil moisture, especially in high-clay zones like MZ2, are crucial for minimizing gaseous N losses and improving nitrogen use efficiency.

## Volatilization Losses

DSSAT-simulated volatilization losses (Figure 5.6.7, Table 5.6.6) showed highly significant effects of MZ, growing season rainfall condition (GSRC: drought, normal, wet), fertilizer treatment, and their two-way interactions with treatment ( $P < 0.0001$ ; Table 5.6.6). However, MZ  $\times$  GSRC interaction was non-significant ( $P = 0.0673$ ), and the three-way interaction (MZ  $\times$  GSRC  $\times$  Treatment) was also not significant ( $P = 0.9877$ ), indicating that treatment effects on volatilization were largely consistent across zones and rainfall conditions.

Volatilization losses followed a distinct spatial trend, with MZ1 exhibiting substantially higher losses compared to MZ2. Averaged across treatments and growing seasons, MZ1 volatilization was  $49.4 \text{ kg ha}^{-1}$ , nearly 38% higher than MZ2 ( $35.7 \text{ kg ha}^{-1}$ ) (Figure 5.6.7). This pattern likely reflects the better aeration and drainage of silty clay loam soils in MZ1, which enhance urea hydrolysis and ammonia release under high temperatures (Tian et al., 2001). In contrast, the heavier clay soils in MZ2 retained more surface moisture and ammonium ions, limiting potential volatilization.

Growing season rainfall conditions had a strong influence on volatilization losses. Losses were lowest during wet growing seasons, where frequent rainfall likely enhanced fertilizer dissolution and reduced surface exposure of urea-derived ammonium, limiting ammonia volatilization (Watson and Miller, 1996). Conversely, normal and drought-growing seasons exhibited higher volatilization, driven by increased soil drying, elevated surface temperatures, and delayed fertilizer incorporation.

Nitrogen fertilizer rates had a significant effect on simulated volatilization losses (Table 5.6.6;  $P < 0.0001$ ). Treatments with reduced nitrogen rates ( $160 \text{ kg N ha}^{-1}$ ; T3, T7, T11) and low N rates

(120 kg N ha<sup>-1</sup>; T4, T8, T12) exhibited substantially lower volatilization compared to baseline (220 kg N ha<sup>-1</sup>) and increased (280 kg N ha<sup>-1</sup>) N treatments. This trend reflects the reduced availability of ammonium substrate for volatilization processes when lower quantities of urea-based fertilizers are applied to the soil surface (Pan et al., 2016). However, beyond baseline rates, volatilization losses tended to plateau. Treatments with baseline and increased N rates showed similar volatilization magnitudes across most irrigation scenarios, consistent with findings by Minato et al. (2019), who observed that ammonia volatilization tends to saturate beyond moderate N application rates in maize systems.

Irrigation timing also moderated volatilization losses. Under irrigated scenarios (30% and 50% deficit), supplemental water following fertilizer applications likely promoted better fertilizer incorporation, reducing volatilization relative to non-irrigated conditions. This aligns with studies highlighting the role of timely rainfall or irrigation in minimizing volatilization from surface-applied fertilizers (Zaman et al., 2009; Liu et al., 2019; Quemada et al., 2024).

Overall, these results demonstrate that volatilization is jointly governed by N application rates, fertilizer form, surface moisture conditions, and soil texture. Strategies to mitigate volatilization should emphasize applying lower or optimized nitrogen rates, using appropriate fertilizer types, and synchronizing applications with rainfall or irrigation events.

### **Leaching Losses**

Leaching losses (Figure 5.6.8, Table 5.6.6) varied significantly across growing season rainfall conditions ( $P < 0.0001$ ), but not between management zones (MZ). Although MZ1 had slightly higher average leaching (15.0 kg N ha<sup>-1</sup>) than MZ2 (9.7 kg N ha<sup>-1</sup>), the spatial difference, while statistically significant, was much less pronounced compared to rainfall-driven variability.

Growing season rainfall emerged as the dominant driver. Leaching was 89% greater during wet years (18.30 kg N ha<sup>-1</sup>) compared to drought years (10.07 kg N ha<sup>-1</sup>), with normal years showing the lowest leaching (8.68 kg N ha<sup>-1</sup>). These findings highlight the critical role of water movement in transporting nitrate below the root zone. Elevated precipitation likely facilitated greater nitrate mobility, increasing losses beyond the crop's uptake capacity (Aparicio et al., 2008; Govindasamy et al., 2023).

Treatment effects were marginally significant ( $P = 0.0514$ ). Across treatments, higher fertilizer N rates and reduced irrigation deficit (30% deficit and no irrigation) resulted in greater nitrate leaching than lower N rate treatments. Specifically, T2 (increased N) and T1 (baseline N) reported the highest leaching values, whereas T12 (reduced N, no irrigation) showed the lowest.

Interestingly, non-irrigated treatments exhibited both high residual soil N and higher leaching losses after rainfall events. This suggests a mismatch between fertilizer application and crop N demand under rainfed conditions: when water limits crop growth, surplus N remains vulnerable to leaching following heavy rain (del Pilar Muschietti et al., 2018; Govindasamy et al., 2023). Further, the DSSAT fixed-date fertilizer application approach may exacerbate leaching risk when fertilizer applications coincide with rainfall events, enhancing nitrate movement down the profile.

#### **5.4. Conclusion**

This study demonstrated how soil properties, seasonal rainfall variability, and nitrogen management strategies interact to shape maize productivity and nitrogen fate across irrigated systems in Alabama. Management zones exerted the strongest influence: MZ1, characterized by lighter soils, consistently outperformed MZ2, producing 25% higher yields and 24% greater nitrogen uptake. In contrast, MZ2's heavier clay soils, while supporting higher soil inorganic N

retention, also favored denitrification, leading to over twice the gaseous nitrogen losses compared to MZ1. Seasonal rainfall patterns further amplified these spatial differences. Wet years enhanced crop yields and nitrogen uptake but at the cost of increased leaching, which rose by 89% compared to drought years. Meanwhile, drought years, despite reducing yields by 15%, minimized nitrogen losses by limiting leaching and denitrification pathways.

Fertilizer management significantly modified system responses. Increasing nitrogen rates from 120 to 220 kg N ha<sup>-1</sup> sharply improved yields and uptake but further increases to 280 kg N ha<sup>-1</sup> offered minimal additional benefit (<2%). Moderate nitrogen reductions (160 kg N ha<sup>-1</sup>) under strategic 30% and 50% irrigation deficits sustained yields within 5% of baseline treatments while reducing residual soil nitrogen, volatilization, and leaching losses. Among nitrogen loss pathways, volatilization was most pronounced in MZ1, increasing by 38% relative to MZ2, whereas denitrification dominated in MZ2. Leaching losses were primarily rainfall-driven, especially in scenarios where fertilizer applications were poorly synchronized with crop demand under non-irrigated conditions.

The research findings emphasize the need for integrated, zone-specific nitrogen and water management strategies that align fertilizer rates, application timing, and irrigation decisions with soil properties and climatic variability. By leveraging deficit irrigation and moderate nitrogen reductions, it is possible to sustain maize yields while minimizing environmental nitrogen losses, promoting more resilient and sustainable maize production systems.

## 5.5. References

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## 5.6. Tables and Figures

**Table 5.6.1.** Summary of corn crop management practices for the 2019 and 2022 seasons, including cultivar, planting population, fertilization, irrigation, and harvest dates used in DSSAT model calibration and evaluation.

<b>Year</b>	<b>2019</b>	<b>2022</b>
<b>Cultivar</b>	Dekalb® DKC 66-97	Dekalb® DKC 69-16
<b>Planting population</b>	84,000 plants/ha	80,000 plants/ha
<b>Planting</b>	03/26/2019	4/21/2022
<b>Fertilization</b>	Split application 67 kg N/ha at planting and 201 kg N/ha on May 05, 2019	4.4 Mg/ha Poultry manure on March 28, 2022, and 220 N kg/ha on May 13, 2024
<b>Irrigation</b>	May 31 (15.2 mm), June 13 (25.4 mm), Jun 29 (25.4mm)	June 16 (17.8 mm), June 19 (17.8 mm), June 22 (17.8 mm), June 28 (15.2 mm), July 1 (15.2 mm), July 4 (15.2 mm), July 20 (15.2 mm),
<b>Harvest</b>	08/29/2019	08/25/2022

**Table 5.6.2.** Genetic coefficients used to calibrate the DSSAT CSM-CERES-Maize model for the Dekalb® DKC 69-16 corn hybrid. Coefficients were estimated using the GLUE approach based on 2022 field observations from Management Zone 1.

<b>Legend</b>	<b>Cultivar coefficients</b>	<b>Unit</b>	<b>Value</b>
P1	Thermal time from emergence to end of Juvenile	Degree days	245.6
P2	Photoperiod sensitivity coefficient	Days	0.450
P5	Thermal time from silking to physiological maturity	Degree days	967.9
G1	Maximum possible kernels per plant	Unit less	940.7
G2	Kernel filling rate during linear grain filling	mg d <sup>-1</sup>	10.4
PHINT	Phyllochron Interval (leaf tip to emergence)	Degree days	53.2

**Table 5.6.3.** Nitrogen rate and irrigation deficit treatment combinations used in the simulations for maize production.

<b>Treatments</b>	<b>Nitrogen Level</b>	<b>Irrigation Scenario</b>
T1	Baseline N (220kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	30% Irrigation Deficit
T2	Increased N (280 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	30% Irrigation Deficit
T3	Reduced N (160 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	30% Irrigation Deficit
T4	Reduced N (120 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	30% Irrigation Deficit
T5	Baseline N (220kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	50% Irrigation Deficit
T6	Increased N (280 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	50% Irrigation Deficit
T7	Reduced N (160 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	50% Irrigation Deficit
T8	Reduced N (120 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	50% Irrigation Deficit
T9	Baseline N (220kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	No Irrigation
T10	Increased N (280 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	No Irrigation
T11	Reduced N (160 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	No Irrigation
T12	Reduced N (120 kg/ha) (1/3 <sup>rd</sup> at planting and 2/3 <sup>rd</sup> at V7)	No Irrigation

**Table 5.5.4.** Comparison of simulated and observed crop growth and development parameters for corn in Management Zone 1 during the DSSAT-CSM-CERES calibration phase in 2022.

Growth and Development Variables (MZ1)		
VARIABLE	SIMULATED	OBSERVED
Emergence day (dap)	7	8
Anthesis day (dap)	69	68
Physiological maturity day (dap)	120	121
Yield at harvest maturity (kg [dm]/ha)	14,054	14,236
Unit wt. at maturity (g [dm]/unit)	0.31	0.32
Tops weight at maturity (kg [dm]/ha)	24,681	25,962
By product at maturity (kg [dm]/ha)	10,706	10,476
Maximum leaf area index	4.7	4.4
Grain N at maturity (kg/ha)	220	216
Tops N at maturity (kg/ha)	266	254
Total N uptake (kg/ha)	305	303

**Table 5.6.5.** Comparison of simulated and observed values for corn growth and development parameters in Management Zone 2 (2022) and Management Zone 1 (2019) during the DSSAT-CESM-CERES model evaluation.

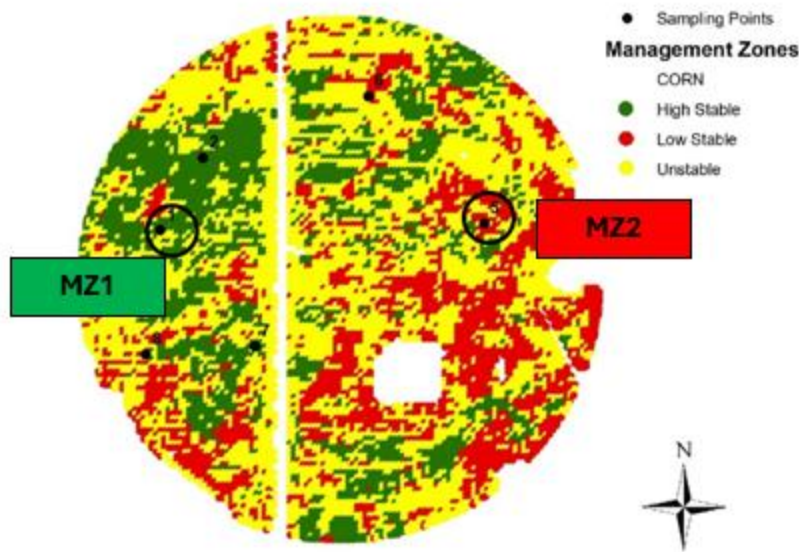
Growth and Development Variables VARIABLE	2022 MZ 2		2019 MZ 1	
	simulated	observed	simulated	observed
Emergence day (dap)	8	8	9	8
Anthesis day (dap)	70	68	80	78
Physiological maturity day (dap)	122	121	134	131
Yield at harvest (kg [dm]/ha)	10,281	10,367	12,099	12,038
Number at maturity (no/m <sup>2</sup> )	3,792	4,173	4,076	4,537
Unit wt at maturity (g [dm]/unit)	0.27	0.27	0.30	0.33
Tops weight at maturity (kg [dm]/ha)	17,093	17,870	21,360	24,232
Maximum leaf area index	2.7	3.4	4.1	4.1

**Table 5.6.6.** Analysis of variance (P-values) for the effects of nitrogen rate (R-I), split timing (RT-I), management zone (MZ), and Growing season rainfall conditions (GSRC) on maize yield, nitrogen uptake, soil residual nitrogen, and nitrogen loss pathways (denitrification, volatilization, and leaching).

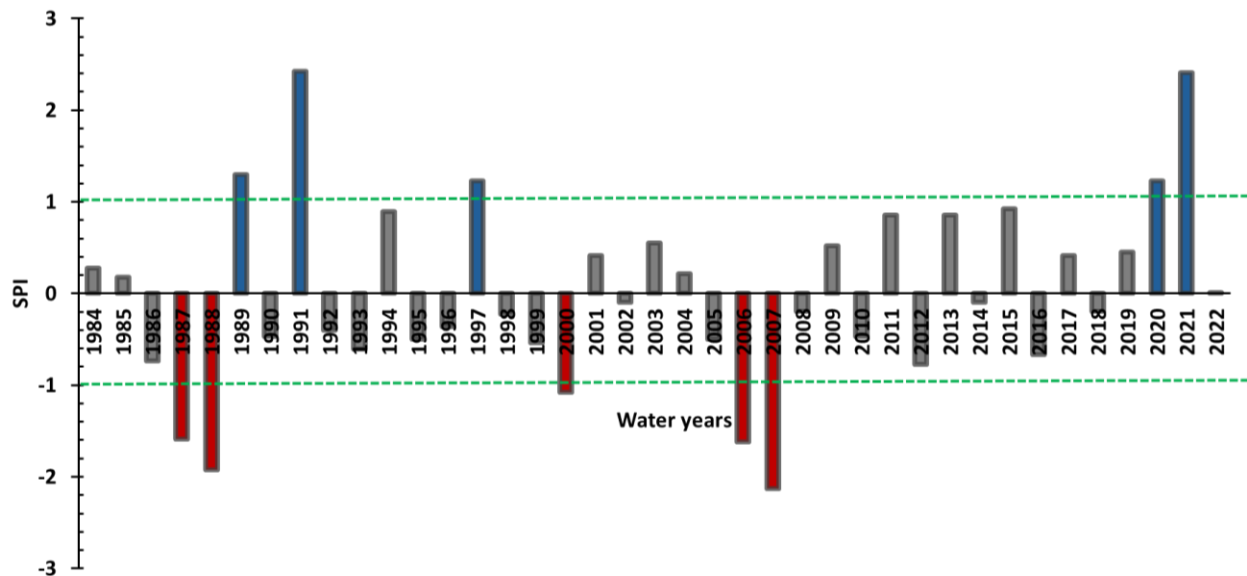
<b>Effect</b>	<b>Yield</b>	<b>N Uptake</b>	<b>Soil N</b>	<b>Denitrification</b>	<b>Volatilization</b>	<b>Leaching</b>
MZ	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Condition	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
RT-I	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0514
MZ*Condition	0.4328	0.4553	0.2893	0.7517	0.0673	< 0.0001
MZ* RT-I	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0249	0.9980
Condition* RT-I	< 0.0001	< 0.0001	< 0.0425	0.1713	0.2513	< 0.0001
MZ*Condition*	1.000	0.9797	0.9703	1.000	0.9877	1.000
RT-I						

\* RT-I= N rate (baseline, increased and reduced N) split into two doses and irrigation deficits (30 %, 50% deficit, no irrigation).

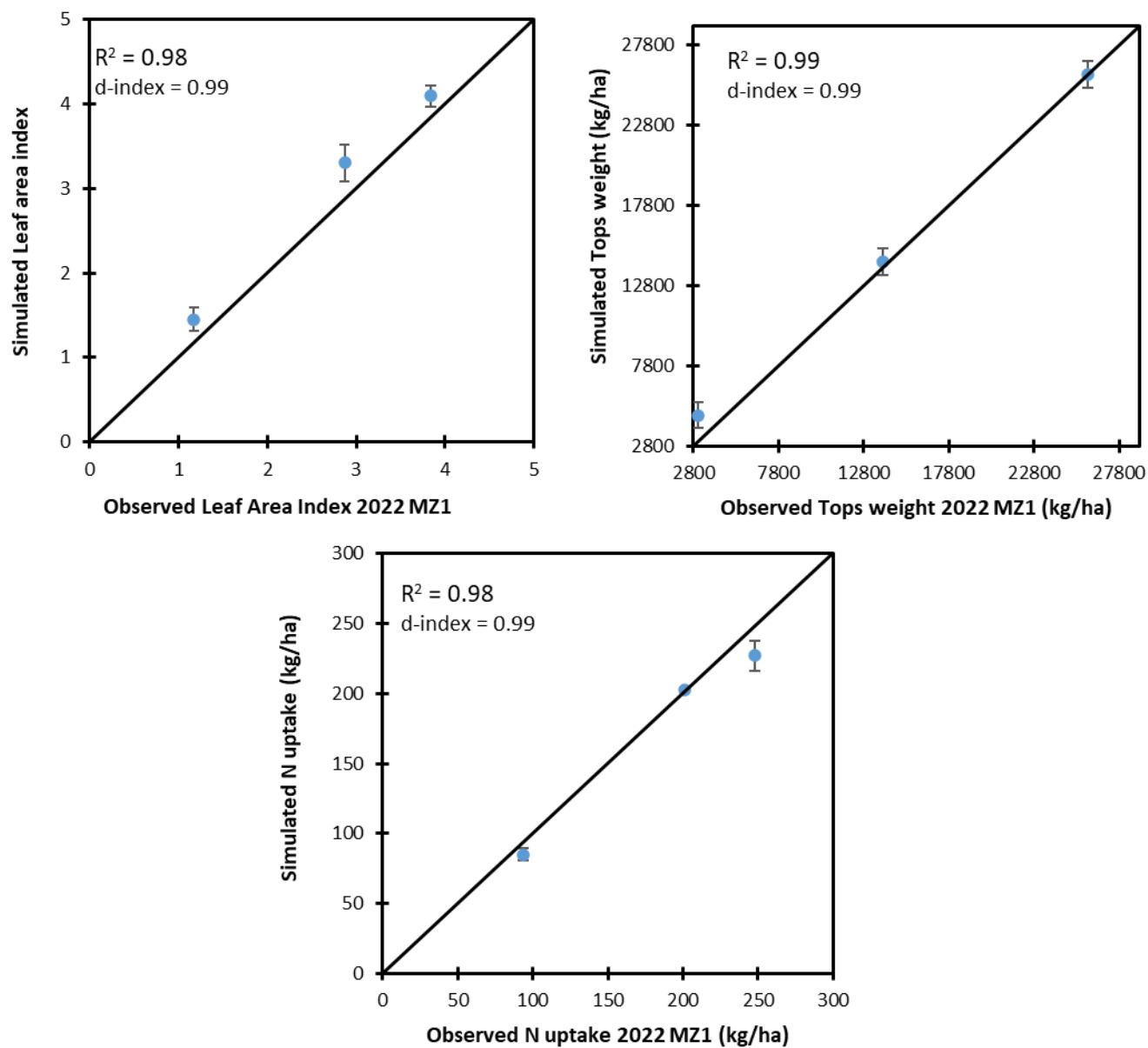
MZ=Management Zone; Condition= Water Year (Drought, Normal, Wet).



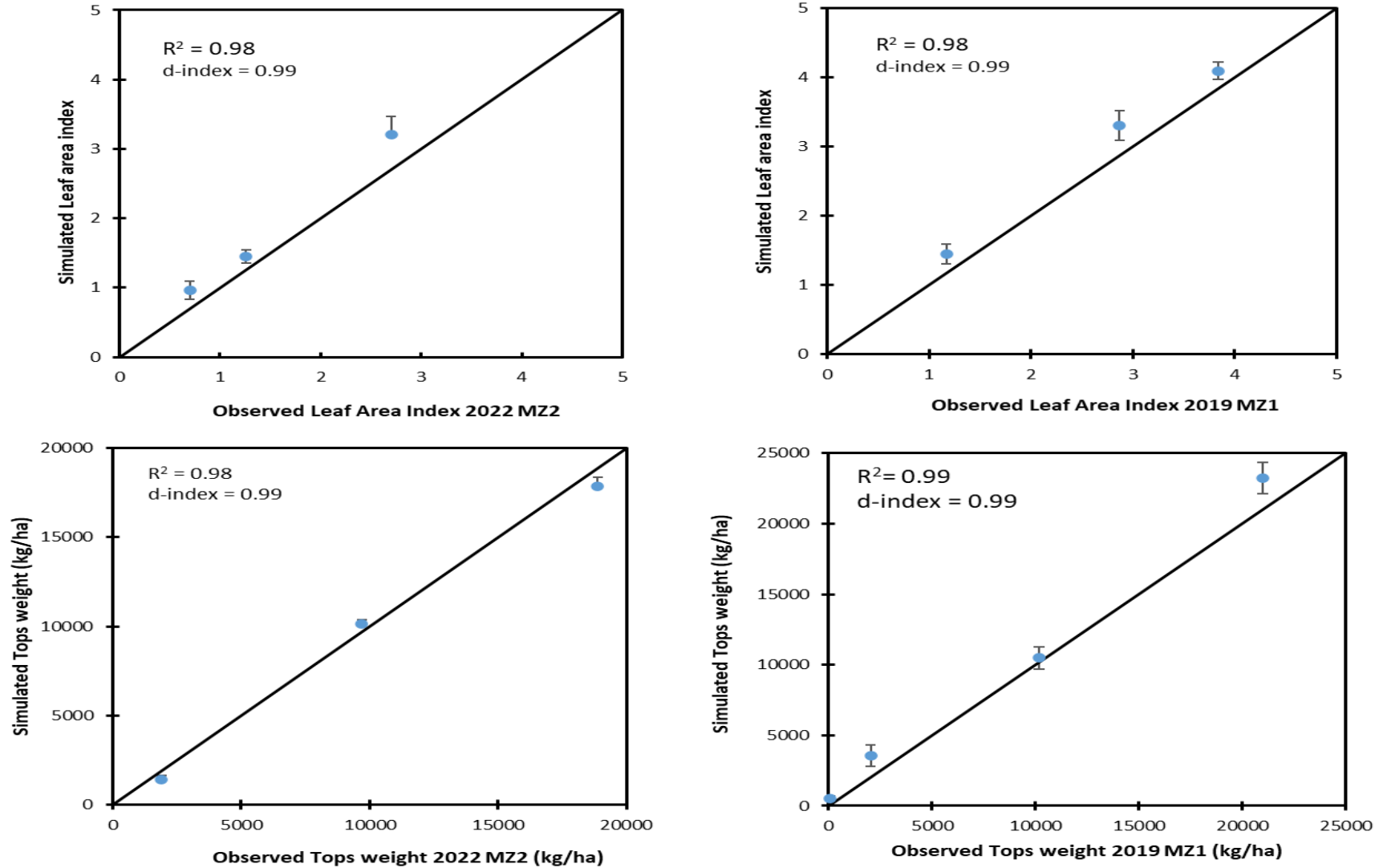
**Figure 5.6.1.** Corn crop management zones delineated based on historical crop yields and topographic characteristics.



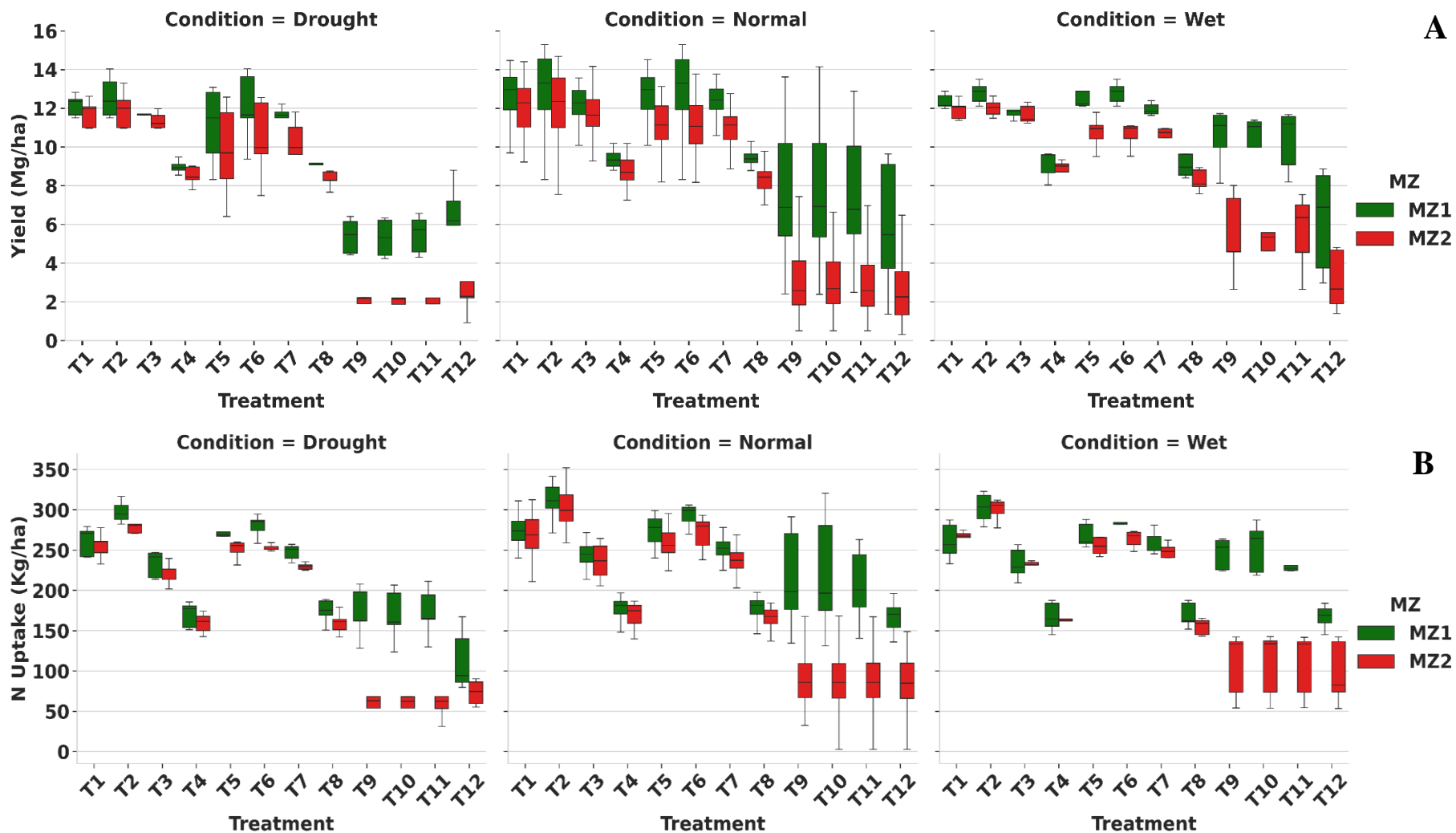
**Figure 5.6.2.** Standardized Precipitation Index (SPI) for the corn growing season from 1984 to 2022, used to classify Growing season rainfall conditions (GSRC) as drought ( $SPI \leq -1$ , red), normal ( $-1 < SPI \leq 1$ , gray), and wet ( $SPI > 1$ , blue). This classification was used to group years for long-term DSSAT simulations evaluating nitrogen and irrigation strategies.



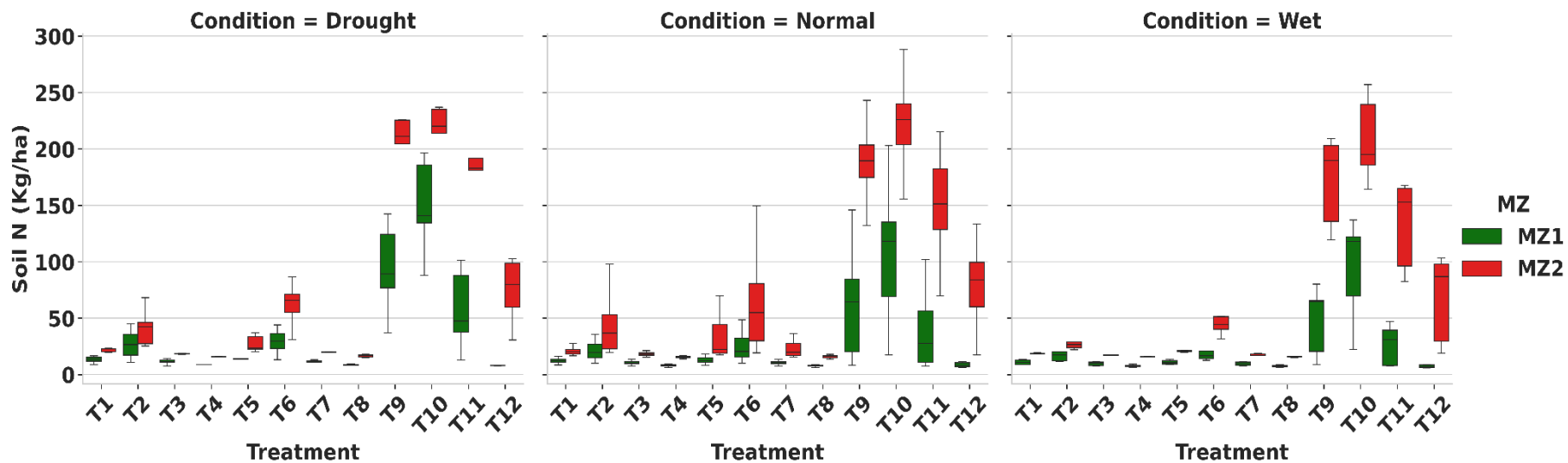
**Figure 5.6.3.1.** Calibration of DSSAT-CSM-CERES-Maize model performance using independent field data from Management Zone 1, 2022. The figure compares observed and simulated values leaf area index, tops weight, and nitrogen uptake to assess model accuracy.



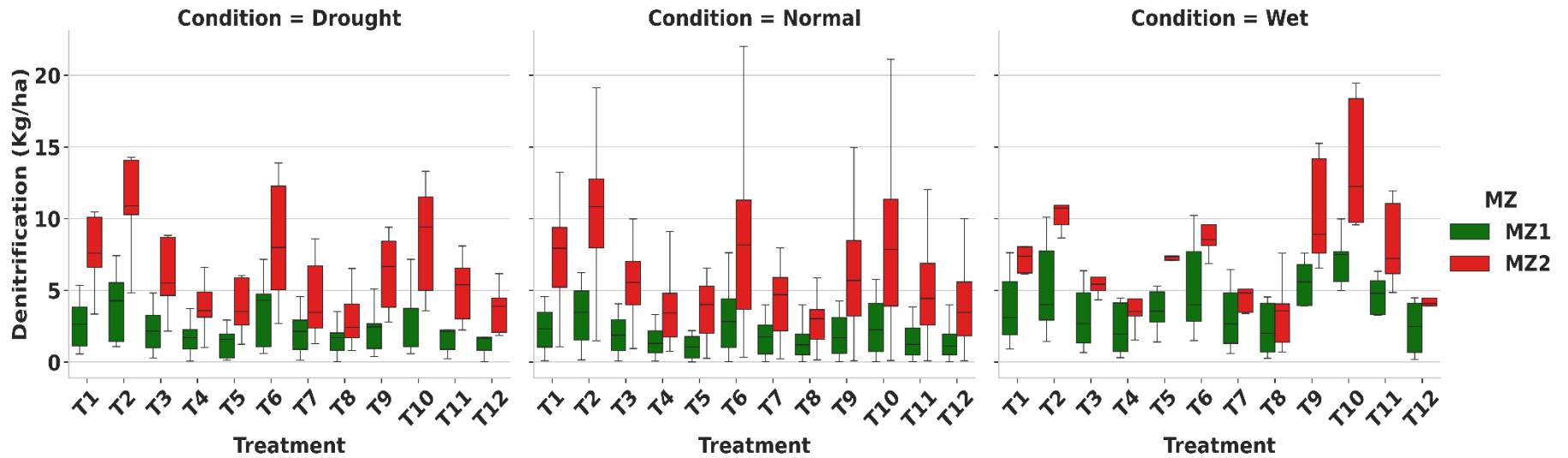
**Figure 5.6.3.2.** Evaluation of DSSAT-CSM-CERES-Maize model performance using independent field data from Management Zone 2 (MZ2, 2022) and Management Zone 1 (MZ1, 2019). The figure compares observed and simulated values leaf area index, and tops weight to assess model accuracy across zones and hybrids.



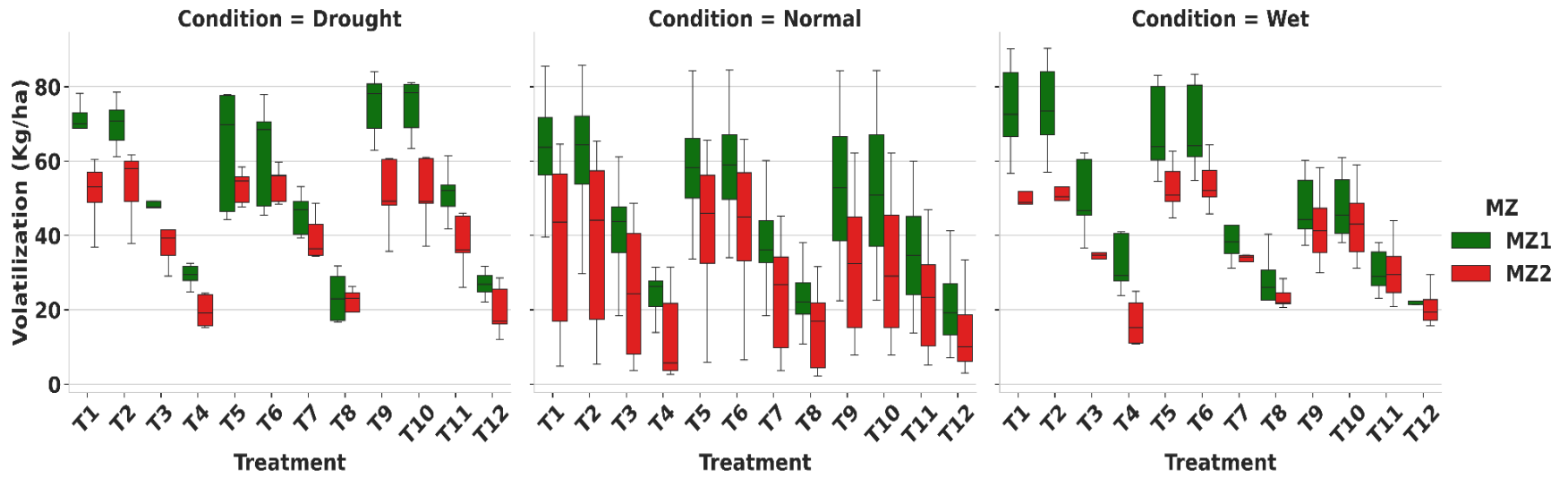
**Figure 5.6.4.** Simulated maize (A) grain yield and (B) nitrogen uptake under nitrogen rate  $\times$  irrigation deficit (R-I) treatments across management zones (MZ1 and MZ2) and GSRCs (wet, normal, drought). Bars represent treatment means, and different letters indicate significant differences at  $P < 0.05$  based on Tukey's HSD test.



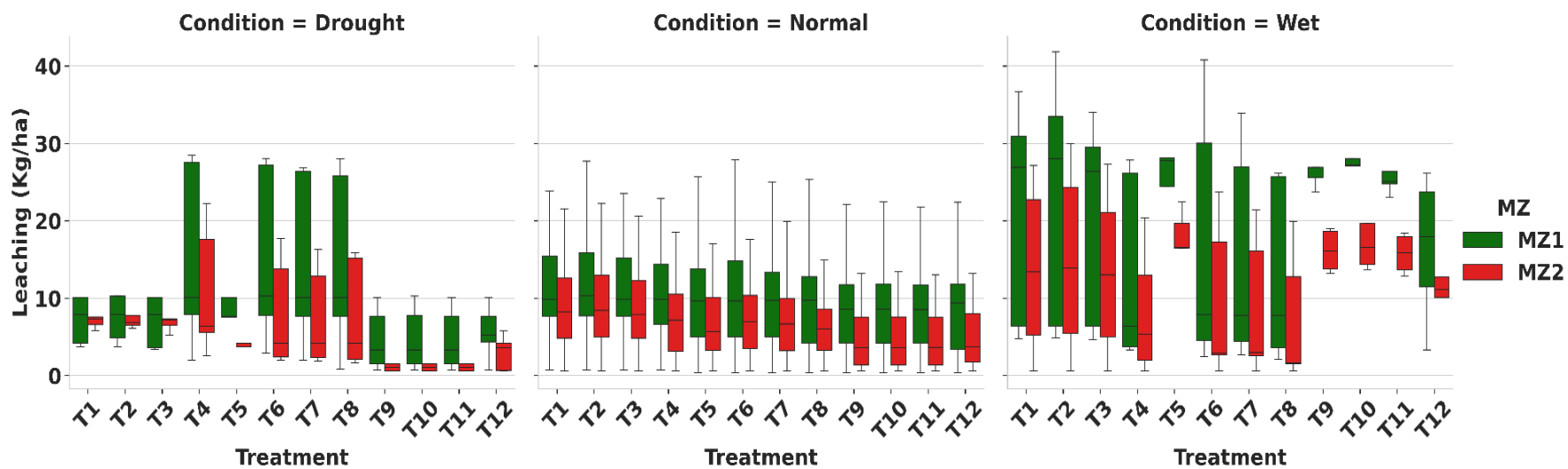
**Figure 5.6.5.** Soil residual nitrogen at corn harvest as influenced by nitrogen rate X irrigation deficit, management zones, and GSRCs. Bars with different letters are significantly different at  $P < 0.05$  according to Tukey's Honestly Significant Difference (HSD) test.



**Figure 5.6.6.** Simulated nitrogen denitrification under nitrogen rate  $\times$  irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments ( $P < 0.05$ ) based on Tukey's HSD test.



**Figure 5.6.7.** Simulated nitrogen volatilization under nitrogen rate  $\times$  irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments ( $P < 0.05$ ) based on Tukey's HSD test.



**Figure 5.6.8.** Simulated nitrogen leaching under nitrogen rate  $\times$  irrigation deficit (R-I) treatments across management zones and GSRCs. Letters indicate significant differences among treatments ( $P < 0.05$ ) based on Tukey's HSD test.

## Chapter 6. Summary

Improving nitrogen use efficiency in row crop systems has long been a challenge, particularly in spatially variable and climate-sensitive regions like the southeastern United States. This dissertation was driven by a central research question: what underlying factors cause nitrogen dynamics to vary significantly within the same agricultural field, and how can we manage it more efficiently to support both crop productivity and environmental sustainability? What began as a study of nutrient imbalances across yield zones evolved into a broader exploration of nitrogen dynamics, soil biology, irrigation strategy, and long-term crop performances and N dynamics under spatial and temporal variability. It led to optimization of N and irrigation; management strategies that fit each zone and help reduce yield gaps between the high and low yielding zones along with reducing N losses. Each phase of the research built upon the last, forming a story of how complex field conditions require equally nuanced, site-specific solutions.

The investigation began with a field-scale nitrogen budget analysis across three yield stability zones—MZ1 (stable high yield), MZ2 (stable low yield), and MZ3 (unstable yield)—on a 190-hectare farm growing corn, soybean, and wheat in rotation. Despite receiving comparable nitrogen inputs, substantial differences emerged in nitrogen uptake and loss among the zones. Corn received the highest nitrogen inputs—up to  $451 \pm 12$  kg/ha—and had the largest unaccounted-for nitrogen losses in low-performing zones:  $157 \pm 19$  kg/ha in MZ2 and  $114 \pm 18$  kg/ha in MZ3. Soybean fields, by contrast, exhibited negative nitrogen balances, especially in MZ1 ( $-15 \pm 1$  kg/ha), suggesting that the crop was adding N to soil as soybean is a N fixer. Wheat fields showed the highest average nitrogen losses, up to  $172 \pm 9$  kg/ha, likely due to poor synchrony between fertilizer application and

crop demand. Edge-of-field monitoring revealed that runoff losses were greatest in MZ3, where steeper slopes and rainfall during the fallow and wheat periods resulted in cumulative nitrogen runoff losses of 6 kg/ha compared to only 1 kg/ha in flatter topography of MZ1. These findings underscored that despite similar inputs, each zone behaved differently in terms of nitrogen retention and crop uptake, pointing to the urgent need for site-specific nutrient management.

To explore the biological dimension of nitrogen availability, the research next examined the spatial variability of potential nitrogen mineralization (PMN) across several commercial fields in Alabama, including the original study site. Substantial variability in PMN was observed both within and across farms, ranging from 22 to 67 kg N/ha. Farms with cover crops and residue retention had significantly higher mineralization potential, confirming the role of conservation practices in supporting soil biological activity and enhancing natural nitrogen cycling. At the study site, zones with historically higher yields and better soil organic matter levels also demonstrated higher PMN, reinforcing the idea that the soil's ability to release plant-available nitrogen depends not only on its chemical content but also on its biological condition and past management.

Given the difficulty of directly quantifying different components of N cycle especially mineralization, leaching and gaseous emissions, the study leveraged the DSSAT CSM-CERES-Maize model to understand N dynamics by simulating N mass balance. The study included simulating long-term nitrogen dynamics under various irrigation and climate scenarios. Model calibration with field data showed strong agreement for crop growth and nitrogen uptake, validating DSSAT's use for scenario testing. Simulations revealed that nitrogen loss pathways were strongly influenced by both yield zone and water availability. In MZ1, higher productivity led to increased nitrogen uptake, but also higher volatilization and leaching, particularly under full irrigation. In MZ2, the lower uptake and waterlogging-prone soils increased the risk of

denitrification. Weather variability also played a critical role. In drought years, nitrogen tended to accumulate in the soil, while in wet years, losses through leaching and runoff were amplified. These simulations confirmed that both spatial and temporal variability must be accounted for in nitrogen and irrigation planning.

The modeling work continued with a more targeted evaluation of nitrogen rate and timing strategies under varying irrigation levels. Sixty management scenarios were tested across MZ1 and MZ2 using 40 years of historical weather data. Results demonstrated that MZ1 consistently outperformed MZ2, with 25% higher yields and 24% greater nitrogen uptake. In contrast, MZ2's heavier clay soils, while promoting greater soil inorganic nitrogen retention, also facilitated denitrification, resulting in more than twice the gaseous nitrogen losses compared to MZ1. These spatial differences were further amplified by seasonal rainfall variability. Wet years increased crop yields and nitrogen uptake but also led to an 89% rise in leaching losses relative to drought years. Drought conditions, although reducing yields by 15%, limited nitrogen losses by constraining leaching and denitrification. Fertilizer management played a pivotal role in shaping system performance. Raising nitrogen application from 120 to 220 kg N ha<sup>-1</sup> markedly enhanced yields and uptake; however, increasing rates beyond 220 kg N ha<sup>-1</sup> offered limited additional benefit (<2%). Moderate nitrogen reductions (160 kg N ha<sup>-1</sup>), when paired with 30% and 50% irrigation deficits, maintained yields within 5% of baseline treatments while effectively lowering residual soil nitrogen, volatilization, and leaching losses. Among the nitrogen loss pathways, volatilization was most prominent in MZ1, increasing by 38% relative to MZ2, whereas denitrification was the dominant loss mechanism in MZ2. Leaching losses were largely governed by rainfall intensity, particularly when fertilizer applications were misaligned with crop nitrogen demand under rainfed conditions.

Altogether, this body of work demonstrates that achieving efficient nitrogen use in row crop systems requires more than simply adjusting fertilizer rates. It demands a systems-based approach that considers spatial variability in yield potential and soil function, incorporates biological contributions such as mineralization, and tailored management to seasonal weather and irrigation conditions. From mass balance diagnostics to simulation modeling and field-level validation, each chapter built upon the last to create a detailed picture of how nitrogen moves through a complex and variable farming system.

These findings offer practical guidance for farmers and land managers looking to reduce nitrogen losses, enhance nutrient efficiency, and build resilience in cropping systems. Zone-specific nitrogen management, combined with moderate irrigation and precise application timing, can not only sustain yields but also curb environmental losses. Conservation practices like cover cropping further support this goal by improving soil health and boosting natural nitrogen cycling. As climate variability increases and fertilizer costs remain high, the integration of data-driven strategies with adaptive management will be key to maintaining crop yields while protecting environmental resources.