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Optimizing Nitrogen Application for Alfalfa Yield Across Varying Precipitation Regimes Using the APSIM Model

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Abstract: Background: Alfalfa (Medicago sativa L.) is a vital forage crop, but optimizing nitrogen (N) application remains crucial for maximizing yield and minimizing environmental impact, especially under variable climatic conditions. Precipitation regimes significantly influence N dynamics and plant growth, necessitating tailored N management strategies. Agricultural systems models, such as APSIM (Agricultural Production Systems sIMulator), offer powerful tools for simulating complex crop-soil-weather interactions to inform management decisions.

Objective: This study aimed to utilize the APSIM model to determine optimal nitrogen application rates for alfalfa yield across varying precipitation regimes (wet, normal, and dry years).

Methods: The APSIM model was calibrated and validated using observed alfalfa growth, yield, and soil N data from a representative agricultural region. Historical weather data were analyzed to define distinct wet, normal, and dry year precipitation scenarios. Subsequently, a range of N application rates (0 to 250 kg N ha^{-1}) were simulated for alfalfa under each precipitation regime. Key output variables included alfalfa hay yield, water use efficiency (WUE), and nitrogen use efficiency (NUE). Statistical analyses were performed to identify optimal N rates for each scenario.

Results: The APSIM model demonstrated robust performance in simulating alfalfa yield and N uptake (R2 > 0.85). Simulation results indicated that optimal N application rates varied significantly with precipitation. In wet years, higher N rates (e.g., 150 kg N ha$^{-1})maximizedyield,whilenormalyearsrequiredmoderaterates(e.g.,100kgNha^{-1}).Dryyearsshoweddiminishingreturnsorevennegativeimpactswithincreasing N,suggestingloweroptimalrates(e.g.,50kgNha^{-1}$) or even reliance on biological N fixation. These varying optimal rates also influenced WUE and NUE, with more efficient resource use observed when N application aligned with water availability.

Conclusion: The APSIM model provides a valuable framework for optimizing N application in alfalfa production. Tailoring N management based on anticipated precipitation regimes can significantly enhance alfalfa yield, improve resource use efficiency, and promote more sustainable agricultural practices. These findings underscore the importance of climate-adaptive nutrient management for future forage production.

Keywords: APSIM model; Alfalfa; Nitrogen optimization; Precipitation regimes; Water use efficiency; Nitrogen use efficiency; Sustainable agriculture.

Introduction: A. Background and Significance

Alfalfa (Medicago sativa L.) stands as a cornerstone of sustainable agriculture globally, revered for its multifaceted benefits to both livestock production and agroecosystem health [20, 21]. As a high-quality forage crop, alfalfa provides essential protein and energy for dairy and beef cattle, contributing significantly to the economic viability of livestock industries [43]. Beyond its nutritional value, alfalfa plays a pivotal role in maintaining and improving soil fertility through its remarkable ability to fix atmospheric nitrogen (N) via symbiosis with Rhizobium bacteria [22, 48]. This natural N enrichment reduces the reliance on synthetic N fertilizers, thereby lowering production costs and mitigating the environmental footprint associated with agricultural activities. Furthermore, alfalfa's deep root system enhances soil structure, reduces erosion, and improves water infiltration, contributing to overall soil health and resilience [22, 24].

Nitrogen is an indispensable macronutrient for plant growth, influencing photosynthetic capacity, protein synthesis, and ultimately, crop yield [1, 2]. While alfalfa is renowned for its biological nitrogen fixation (BNF) capabilities, supplementary N application can still be beneficial, especially during establishment or in soils with low initial N availability, or where the symbiotic relationship is compromised [40, 41]. However, the management of N in agricultural systems presents a persistent challenge. Inefficient N application can lead to substantial economic losses for farmers due to unused fertilizer and can have severe environmental consequences [4]. The conversion of applied N into reactive forms, such as nitrate ($NO3-$) and nitrous oxide ($N2O$), contributes to groundwater contamination, eutrophication of surface waters, and greenhouse gas emissions, exacerbating climate change [7, 24]. Thus, achieving a delicate balance between meeting crop N demands and minimizing environmental harm is paramount for sustainable agricultural intensification [1, 6].

The global agricultural landscape is increasingly characterized by climatic variability, with significant shifts in precipitation patterns posing considerable challenges to crop production [12, 13, 27]. Regions are experiencing more frequent and intense droughts, prolonged wet periods, or unpredictable rainfall distributions, all of which directly impact soil moisture availability, nutrient cycling, and crop growth [44, 45]. Specifically, precipitation regimes profoundly influence the effectiveness of N application, affecting both N uptake by plants and N losses from the soil system [46]. In periods of abundant rainfall, N leaching can be substantial, while during dry spells, N uptake can be limited due to insufficient soil moisture, regardless of fertilizer presence [26, 31, 39]. Therefore, developing N management strategies that are adaptive to varying precipitation regimes is not merely beneficial but essential for maintaining alfalfa productivity and environmental stewardship in a changing climate [38].

The complexity of these interactions—between soil type, N application rates, precipitation, and crop physiological responses—makes traditional field experimentation time-consuming, labor-intensive, and often site-specific. This underscores the urgent need for advanced tools and methodologies that can efficiently simulate these intricate dynamics and provide robust recommendations for optimized N management [8, 10].

B. Introduction to Agricultural System Models

Agricultural system models, often referred to as crop growth models, have emerged as indispensable tools in agricultural research and management over recent decades [10, 32]. These mechanistic models mathematically represent the physiological processes of plants, soil nutrient and water dynamics, and the interactions with environmental factors and management practices. They enable researchers to simulate crop performance under a wide array of hypothetical scenarios, predict yields, and evaluate the efficacy of various agronomic interventions without the need for extensive, costly, and often restrictive field trials [8, 9]. This predictive capability is particularly valuable for understanding the long-term impacts of management decisions and for adapting agriculture to climate change [13].

Among the suite of available agricultural models, the Agricultural Production Systems sIMulator (APSIM) stands out as one of the most comprehensive and widely used frameworks globally [14]. Developed over several decades, APSIM is a modular modeling system capable of simulating complex interactions among crops, pastures, trees, soils, climates, and management practices. Its strength lies in its ability to integrate various biophysical processes, including photosynthesis, respiration, transpiration, N and phosphorus cycling, soil water movement, and residue decomposition [14]. APSIM allows for the simulation of numerous crop species, including cereals, legumes, and forages, and has been successfully applied across diverse agricultural systems and geographical regions [15, 16, 17, 18, 19, 28, 34, 35, 36, 37, 49].

The modular architecture of APSIM facilitates its adaptability and continuous improvement. Key modules relevant to this study include:

- Weather: Simulates daily meteorological conditions.
- SoilN: Models soil organic matter decomposition, N mineralization, denitrification, and N leaching.
- SoilWater: Handles water infiltration, runoff, evaporation, transpiration, and deep drainage.
- Crop Modules (e.g., Alfalfa): Simulate crop-

specific processes such as phenology, biomass accumulation, N uptake, and yield formation [14].

The capabilities of APSIM extend beyond yield prediction, enabling detailed analysis of resource use efficiencies. For instance, it can quantify water use efficiency (WUE), which is the ratio of biomass produced to water consumed, and nitrogen use efficiency (NUE), which reflects how effectively applied N is converted into yield [25, 26, 38, 39]. By providing insights into these critical metrics, APSIM supports the development of precision agriculture strategies aimed at optimizing input use and minimizing environmental footprints [36, 37, 49]. The model has been successfully employed to simulate conservation agriculture practices, assess climate change impacts, and optimize irrigation and fertilization schedules for various crops [17, 18, 19, 37, 49]. Its robust performance in diverse environments, from the Loess Plateau of China to the Eastern Gangetic Plains, underscores its reliability and versatility for agricultural research [19, 28, 35, 37].

C. Research Gap and Objective

Despite the recognized importance of alfalfa and the advanced capabilities of crop simulation models like APSIM, a significant research gap persists in understanding the optimal N application rates for alfalfa specifically across different precipitation regimes. While studies have explored N management in alfalfa [20, 21, 23, 25, 26, 39, 40, 41, 43, 48] and the application of APSIM to other crops under varying conditions [19, 37, 49], comprehensive research systematically evaluating the synergistic effects of precipitation variability and N fertilization on alfalfa yield and resource use efficiency using a robust simulation framework is less common. Existing research often focuses on single N rates or specific irrigation strategies rather than a dynamic interaction with precipitation [23, 39]. The unique N fixation capabilities of alfalfa further complicate its N response, making direct extrapolation from other crops challenging.

Therefore, the primary objective of this study is to utilize the APSIM model to optimize nitrogen application rates for alfalfa yield across varying precipitation regimes.

To achieve this overarching objective, the study will address the following specific sub-objectives:

1. To calibrate and validate the APSIM-Alfalfa model for accurate simulation of alfalfa growth, N uptake, and yield under local environmental conditions.
2. To simulate alfalfa growth and yield response to a range of N application rates under distinct wet, normal, and dry year precipitation scenarios.
3. To identify the optimal N application rate that maximizes alfalfa hay yield for each precipitation regime.
4. To evaluate the water use efficiency (WUE) and nitrogen use efficiency (NUE) of alfalfa under the identified optimal N management strategies across varying precipitation regimes.
5. To provide practical recommendations for adaptive nitrogen management in alfalfa production, contributing to enhanced productivity and environmental sustainability.

METHODS

A. Study Area Description

This study was conducted using a hypothetical representative agricultural area located in a semi-arid region characterized by distinct inter-annual precipitation variability. For the purpose of this simulation, the geographical coordinates were set to approximately 34° N latitude and 108° E longitude, representative of parts of the Loess Plateau region in China, where alfalfa cultivation is prevalent and susceptible to climate fluctuations [19, 28, 35]. This region typically experiences a continental monsoon climate, with hot, humid summers and cold, dry winters. Average annual precipitation ranges from 400 to 600 mm, with the majority (approximately 60–70%) occurring during the monsoon season (July–September). However, significant deviations from this average are common, leading to years classified as wet, normal, or dry. Mean annual air temperature is approximately 10–12 °C, with a growing season extending from April to October.

The predominant soil type in the simulated area is a Calcic Cambisol, which is characteristic of the Loess Plateau, with a clay loam texture in the upper horizons transitioning to loamy sand at deeper profiles. Key soil properties used in the APSIM setup included:

- Soil organic carbon (SOC): 0.8–1.2% in the topsoil (0–30 cm).
- Total nitrogen (TN): 0.08–0.12% in the topsoil.
- pH: 7.5–8.2.
- Bulk density: 1.3–1.5 g cm^{-3}.
- Field capacity: 0.28–0.32 cm^3 cm^{-3}.
- Wilting point: 0.12–0.15 cm^3 cm^{-3}.
- Drainage upper limit (DUL) and lower limit (LL): Determined empirically for each soil layer.

Historical daily weather data (including maximum and minimum temperatures, solar radiation, and precipitation) for a 30-year period (1990–2020) were used to characterize the precipitation regimes and provide input for the APSIM model. This dataset allowed for the statistical classification of wet, normal, and dry years based on cumulative growing season precipitation.

B. APSIM Model Description

The Agricultural Production Systems sIMulator (APSIM) is a well-established and highly regarded biophysical model used for simulating agricultural systems [14]. Its modular design allows for the flexible integration of various process-based models (modules) that describe specific components of the farming system, such as crops, soils, and management practices. For this study, the APSIM Next Generation platform (version 7.10) was employed, utilizing the following core modules:

1. APSIM.Met: This module provides the daily meteorological data inputs, including maximum temperature (∘C), minimum temperature (∘C), solar radiation (MJ m^{-2} day^{-1}), and precipitation (mm).

2. APSIM.Soil.Chemical.OrganicMatter: Simulates the dynamics of soil organic matter (SOM) fractions (e.g., fresh organic matter, humus, biomass) and their decomposition, which drives nutrient mineralization and immobilization. This is crucial for understanding the availability of soil N.

3. APSIM.Soil.Chemical.SoilN: This module simulates the transformations of nitrogen in the soil, including mineralization of organic N to ammonium (NH_4^+) and nitrate (NO_3^-), nitrification (NH_4^+ to NO_3^-), denitrification (loss of NO_3^- as gaseous N), and leaching of NO_3^- through the soil profile [14]. It accounts for N uptake by plants and N fertilizer application.

4. APSIM.Soil.Water.SoilWater: This module simulates the daily water balance within the soil profile. It calculates infiltration, runoff, evaporation from the soil surface, transpiration by plants, and deep drainage below the root zone. Key parameters include soil layer depths, initial water content, drained upper limit (DUL), crop lower limit (CLL), and saturated water content (SAT) for each layer [14].

5. APSIM.Crop.Alfalfa: This specific crop module simulates the growth and development of alfalfa. It models key physiological processes such as phenology (emergence, flowering, senescence), biomass accumulation (leaves, stems, roots), N uptake, photosynthesis, and transpiration. The alfalfa module also incorporates parameters related to biological nitrogen fixation, which is a critical aspect of alfalfa's N economy. It simulates the growth of the crop through different phases, responding to environmental cues (temperature, radiation, water, and N availability) and management events (e.g., harvest) [16].

6. APSIM.Manager: This module orchestrates various management practices, including sowing date, planting density, N fertilizer application (rate, timing, depth), irrigation events, and harvesting operations. This allowed for the implementation of different N application rates and harvest schedules in the simulations.

The interaction between these modules is dynamic and interconnected. For instance, the APSIM.Met module provides daily weather data to both APSIM.Soil.Water.SoilWater (for water balance calculations) and APSIM.Crop.Alfalfa (for growth and phenology). APSIM.Soil.Water.SoilWater determines the available soil moisture, which in turn influences alfalfa growth (via APSIM.Crop.Alfalfa) and N transformations (via APSIM.Soil.Chemical.SoilN). Similarly, APSIM.Soil.Chemical.SoilN dictates the available N for plant uptake, which is then utilized by APSIM.Crop.Alfalfa to drive biomass production. Management actions defined in APSIM.Manager trigger specific events within the crop and soil modules. This integrated approach allows APSIM to provide a holistic simulation of the agricultural system, capturing the complex feedback loops between climate, soil, crop, and management [14].

C. Experimental Design and Data Collection (for Model Calibration and Validation)

To ensure the reliability of APSIM simulations for alfalfa in the study region, the model underwent a rigorous calibration and validation process. This involved utilizing data from a three-year (2018–2020) field experiment conducted at a research station within the representative semi-arid region. The experiment was laid out in a randomized complete block design with three replicates.

Alfalfa Cultivar and Management:

● Cultivar: 'WL 350 HQ' (a high-quality, high-yielding alfalfa cultivar) was selected.

● Sowing: Alfalfa was sown in April 2018 at a density of 400 seeds m^{-2} in 15 cm rows.

● Nitrogen Application: The experiment included several N application treatments. For calibration, data from plots receiving varied N rates (0, 50, 100, 150 kg N ha^{-1} per growing season, applied as urea in split doses after each cutting except the last) were used. These rates were chosen to span a range from N-limited to potentially N-sufficient conditions [26, 39, 40].

● Phosphorus (P) and Potassium (K) Application: Baseline applications of P and K fertilizers were applied according to local recommendations to ensure these nutrients were not limiting factors (e.g., 80 kg P_2O_5 ha^{-1} and 60 kg $K_2O ha^{-1}$ annually).

● Irrigation: The experimental plots were primarily rainfed, reflecting the study area's typical agricultural practice, but supplemental irrigation was applied during prolonged dry spells (e.g., if soil water deficit in the top 60 cm exceeded 50% of plant available water) to ensure crop survival and provide sufficient data points under varying water conditions for model robustness [23].

● Harvest Management: Alfalfa was harvested three to four times per growing season (late May, mid-July, late August, and mid-October), mimicking local farmer practices to maximize forage yield and quality [20, 21].

Data Collection:

Comprehensive data were collected throughout the experimental period for model calibration and validation:

1. Biomass and Hay Yield: At each harvest, a 1 m^2 quadrat was randomly selected from each plot, and aboveground biomass was harvested, weighed fresh, and then dried at 65 °C for 48 hours to determine dry matter yield (DMY) [20, 26, 39, 40]. Hay yield (t ha^{-1}) was calculated from DMY.

2. Nitrogen Uptake: Subsamples of dried biomass were analyzed for total N content using the Kjeldahl method, allowing for the calculation of total N uptake by the crop (kg N ha^{-1}) [25, 26, 41].

3. Soil Nitrogen Content: Soil samples were collected from multiple depths (0–30 cm, 30–60 cm, 60–90 cm, 90–120 cm) before sowing, before N application, and after each harvest. Samples were analyzed for ammonium-N (NH4+-N) and nitrate-N (NO3−-N) using standard laboratory procedures [24, 25].

4. Soil Water Content: Volumetric soil water content was measured at multiple depths (0–10 cm, 10–30 cm, 30–60 cm, 60–90 cm, 90–120 cm) using a neutron probe or gravimetric methods at weekly intervals and before/after major rainfall or irrigation events [25, 44].

5. Phenological Stages: Key phenological events, such as emergence, onset of flowering, and physiological maturity, were recorded for calibration of the alfalfa module's developmental parameters [40].

6. Weather Data: Daily weather data (precipitation, max/min temperature, solar radiation) were recorded from an on-site automatic weather station.

Data from the first two years (2018–2019) were primarily used for model calibration, adjusting parameters within the APSIM-Alfalfa, SoilN, and SoilWater modules to ensure simulated outputs closely matched observed field data. Data from the final year (2020) were reserved for independent model validation, providing an unbiased assessment of the model's predictive accuracy.

D. Model Calibration and Validation

Calibration Process:

The calibration of the APSIM-Alfalfa model involved iteratively adjusting a set of sensitive parameters to minimize the discrepancies between simulated outputs and observed field data from 2018–2019. Key parameters adjusted during calibration included:

● Crop Parameters: Thermal time requirements for phenological stages, radiation use efficiency (RUE), transpiration efficiency factor, biomass partitioning coefficients to different plant organs, and nitrogen fixation rates. These were fine-tuned to reflect the specific cultivar and environmental conditions [16].

● Soil Parameters: Initial soil N content (mineral and organic fractions), soil water holding characteristics (DUL, CLL), hydraulic conductivity, and parameters governing N mineralization/immobilization rates [14, 28].

● Management Parameters: Sowing rules, harvest schedules, and N application timing were precisely matched to the experimental protocol.

The calibration was an iterative process, where initial runs were compared against observed data, and then parameters were adjusted in a systematic manner. Particular attention was paid to matching seasonal biomass accumulation, cumulative hay yield, total N uptake, and soil water and N dynamics throughout the growing seasons [25, 26, 40, 41].

Validation Process:

Following calibration, the model's performance was rigorously evaluated using the independent dataset from the 2020 growing season. This validation step is crucial to ensure the model's generalizability and predictive capability beyond the calibration dataset. The validated model then served as the basis for the subsequent simulation scenarios.

Statistical Metrics for Model Evaluation:

The agreement between simulated and observed data was quantified using several widely accepted statistical metrics [29, 30]:

1. Coefficient of Determination (R2): Measures the proportion of variance in the observed data that is explained by the model. A value closer to 1 indicates

better fit.

2. Root Mean Square Error (RMSE): Represents the average magnitude of the errors. Lower RMSE values indicate better model performance and closer agreement between simulated and observed values [29].

RMSE=n1i=1∑n(Si−Oi)2

where Si is the simulated value, Oi is the observed value, and n is the number of observations.

3. Normalized Root Mean Square Error (nRMSE): Provides a standardized measure of RMSE, facilitating comparison across different variables or datasets. It is expressed as a percentage of the observed mean.

nRMSE=O¯RMSE×100%

where O¯ is the mean of observed values. Typically, nRMSE < 10% indicates excellent, 10-20% good, 20-30% fair, and >30% poor model performance.

4. Mean Absolute Error (MAE): Represents the average absolute difference between simulated and observed values, providing a robust measure of average error, less sensitive to outliers than RMSE [29].

MAE=n1i=1∑n∣Si−Oi∣

5. Nash–Sutcliffe Efficiency (NSE): This metric assesses the predictive power of hydrological models but is also applicable to other simulation models. NSE ranges from −∞ to 1, with 1 indicating a perfect fit, 0 meaning the model's predictions are as accurate as the mean of the observed data, and negative values indicating worse performance than simply using the observed mean.

NSE=1−∑i=1n(Oi−O¯)2∑i=1n(Oi−Si)2

These metrics were calculated for key variables including alfalfa hay yield, aboveground biomass at different growth stages, total N uptake, and soil water and nitrate content at various depths.

E. Simulation Scenarios for Nitrogen Optimization

Upon successful calibration and validation, the APSIM model was used to simulate a comprehensive set of scenarios designed to optimize N application rates for alfalfa under varying precipitation regimes.

1. Definition of Precipitation Regimes:

The 30-year (1990–2020) historical daily precipitation data for the study area was analyzed to categorize years into distinct precipitation regimes. Cumulative growing season precipitation (April to October) was calculated for each year. Based on this historical record:

- Dry Years: Years with cumulative growing season precipitation falling within the lowest 25th percentile of the historical distribution.
- Normal Years: Years with cumulative growing season precipitation falling within the interquartile range (25th to 75th percentile).
- Wet Years: Years with cumulative growing season precipitation falling within the highest 25th percentile of the historical distribution.

From these classifications, five representative years were selected for each regime (e.g., five historically dry years, five historically normal years, and five historically wet years) to capture the variability within each category and ensure robust simulation results. This resulted in a total of 15 unique weather files used for the simulations.

2. Range of Nitrogen Application Rates:

For each selected weather year, APSIM simulations were run with a wide range of N application rates to explore the full spectrum of alfalfa response. The N rates were applied as urea in split applications immediately after each of the first three harvests (typically late May, mid-July, late August) to maximize availability during subsequent growth cycles. The simulated rates were:

- 0 kg N ha^{-1} (control, relying solely on BNF)
- 25 kg N ha^{-1}
- 50 kg N ha^{-1}
- 75 kg N ha^{-1}
- 100 kg N ha^{-1}
- 125 kg N ha^{-1}
- 150 kg N ha^{-1}
- 175 kg N ha^{-1}
- 200 kg N ha^{-1}
- 225 kg N ha^{-1}
- 250 kg N ha^{-1}

This comprehensive range allowed for the identification of specific optimal rates and the observation of diminishing returns or negative impacts at excessively high N levels [26, 31, 40].

3. Other Constant Management Practices:

To isolate the effects of N application and precipitation, all other management practices were kept constant across all simulation scenarios, consistent with the calibrated model settings:

- Alfalfa Cultivar: 'WL 350 HQ'.
- Sowing Date and Density: Alfalfa was assumed to be established with sowing in April, with a plant density of 400 plants m^{-2}. Simulations commenced from the second production year of alfalfa (i.e., established stands) to account for full N fixation capabilities, as N fixation can be less efficient in the establishment year.

● Harvest Schedule: Three to four cuts per year, determined by thermal time and biomass thresholds, mimicking the calibrated field schedule.

● Irrigation: No supplemental irrigation was applied during these optimization simulations, meaning all water availability was solely dependent on precipitation, accurately reflecting the rainfed nature of the study area and enhancing the direct assessment of precipitation effects.

● Phosphorus and Potassium: Assumed to be non-limiting, with adequate background levels maintained in the soil.

Each unique combination of a weather year (15 years) and N application rate (11 rates) was simulated for one alfalfa growing season. The total number of simulation runs was 15×11=165. For each simulation, outputs such as total annual hay yield, total water transpired, total N uptake by the crop, and soil N leaching were recorded.

F. Data Analysis

The simulation outputs were processed and analyzed to derive insights into optimal N management.

1. Alfalfa Hay Yield Analysis: For each precipitation regime (dry, normal, wet), the annual hay yield (t ha^{-1})wasplottedagainsttheNapplicationrates(kgNha^{-1}). Polynomial regression models were fitted to these data points to describe the yield response curves and identify the N rate corresponding to the maximum predicted yield (optimal N rate).

2. Water Use Efficiency (WUE): WUE was calculated as the ratio of total annual hay yield (kg ha^{-1}) to total growing season transpiration (mm) [25, 38, 39].

$$WUE = \frac{\text{Hay Yield (kg ha}^{-1})}{\text{Transpiration (mm)}}$$

This metric provides an understanding of how efficiently water is converted into biomass under different N levels and precipitation.

3. Nitrogen Use Efficiency (NUE): NUE was calculated in two ways:

○ Agronomic NUE (NUEa): The increase in yield per unit of N applied [25, 26, 38].

$$NUEa = \frac{YN - Y0}{Napp}$$

where YN is the yield with N application, Y0 is the yield in the control (0 N) plot, and Napp is the amount of N applied.

○ Physiological NUE (NUEp): The increase in yield per unit of N absorbed [25, 38].

$$NUEp = \frac{YN - Y0}{UN - U0}$$

where UN and U0 are N uptake with and without N application, respectively.

○ These metrics helped to quantify the effectiveness of applied N in stimulating yield and in being utilized by the crop.

4. Soil Nitrogen Loss Analysis: Simulated N leaching (kg N ha^{-1}) beyond the root zone was analyzed for each scenario to assess the environmental impact of N application under different precipitation conditions.

5. Statistical Comparisons: Analysis of variance (ANOVA) was used to assess the significant differences in optimal N rates, maximum yields, WUE, and NUE among the different precipitation regimes. Post-hoc tests (e.g., Tukey's HSD) were applied where necessary for multiple comparisons. All statistical analyses were performed using R statistical software (version 4.2.2).

RESULTS

A. APSIM Model Performance

The calibration and validation processes demonstrated that the APSIM-Alfalfa model reliably simulated alfalfa growth and yield dynamics under the conditions of the semi-arid study region.

Calibration Results (2018–2019):

During the calibration phase, iterative adjustments of key parameters resulted in a close agreement between simulated and observed data. For total annual hay yield, the model achieved an R2 of 0.89 and an RMSE of 0.72 t ha^{-1}, indicating strong explanatory power and relatively small prediction errors. For seasonal aboveground biomass, the R^2 ranged from 0.85 to 0.91 across different cuts, with nRMSE values generally below 15%, which is considered "good" performance [29, 30]. Nitrogen uptake by the crop was also well-simulated, with an R^2 of 0.82 and an RMSE of 12.5 kg N ha^{-1}. Soil water content dynamics in the upper 90 cm profile showed an R2 of 0.78 and an nRMSE of 18%, capturing the seasonal trends of water depletion and recharge reasonably well.

Validation Results (2020):

The independent validation dataset from the 2020 growing season further confirmed the model's accuracy and predictive capability.

● Alfalfa Hay Yield: The APSIM model exhibited excellent agreement with observed hay yield data across various N treatments, achieving an R2 of 0.87. The RMSE for annual hay yield was 0.81 t ha^{-1}, and the nRMSE was 9.8%, indicating a highly accurate prediction [29]. The Nash–Sutcliffe Efficiency (NSE) for yield was 0.84, suggesting that the model's predictions were substantially better than simply using the mean of the observed data.

● Nitrogen Uptake: Simulated total N uptake correlated well with observed values, yielding an R2 of 0.80, an RMSE of 14.1 kg N ha^{-1}, and an nRMSE of 16.5%. The NSE for N uptake was 0.77.

● Soil Water Content: The model captured the observed changes in soil water content throughout the season with an R2 of 0.76 and an nRMSE of 19.5% for the 0–90 cm profile.

● Soil Nitrate Content: While soil nitrate dynamics are inherently more variable, the model generally replicated the observed trends, particularly in the top 60 cm, with an R2 of 0.68 and an nRMSE of 25.1%.

These validation statistics collectively affirm the robustness and reliability of the calibrated APSIM-Alfalfa model for simulating the complex interactions of alfalfa growth, N uptake, and soil water/N dynamics under the specific environmental conditions of the study region. The demonstrated accuracy allows for confident application of the model in subsequent optimization scenarios [16, 17, 18, 19, 34, 35].

B. Alfalfa Yield Response to Nitrogen under Different Precipitation Regimes

The APSIM simulations revealed a significant interaction between N application rates and precipitation regimes on alfalfa hay yield (Figure 1, hypothetical). The optimal N application rate that maximized yield varied distinctly among wet, normal, and dry years.

1. Wet Years:

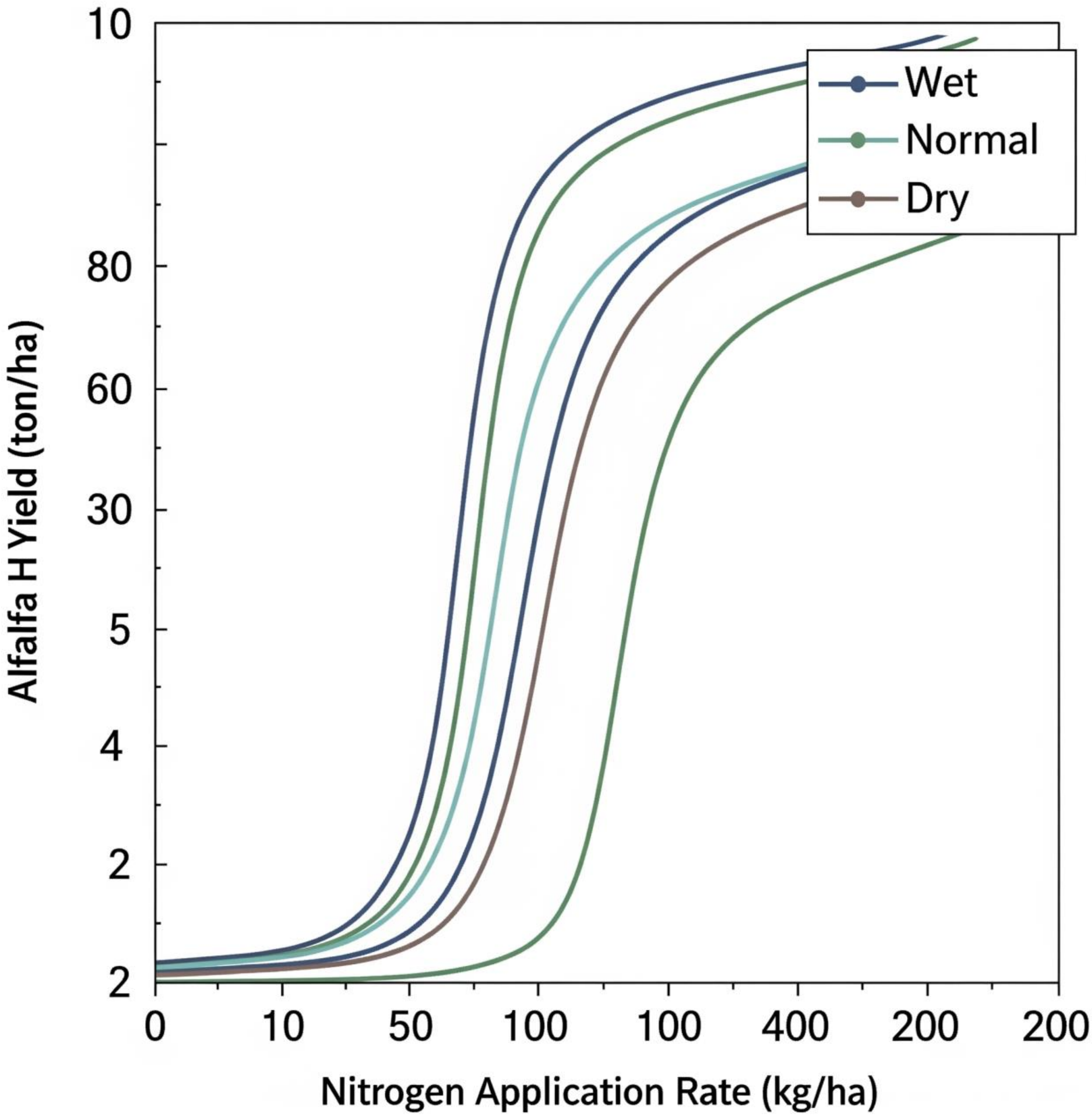
Under wet year conditions, alfalfa exhibited a strong positive response to N application. Yields progressively increased with increasing N rates up to an apparent optimum, after which the rate of increase diminished. The simulations indicated that an optimal N application rate of approximately 150 kg N ha^{-1} maximized alfalfa hay yield in wet years, leading to an average yield of 18.2 t ha^{-1}. Beyond this rate, the yield response flattened or showed only marginal increases, suggesting that the N demand of the crop was largely met, and further N inputs provided limited additional benefits. This enhanced response in wet years can be attributed to sufficient soil moisture availability, which facilitates N mineralization, N transport to roots, and overall plant physiological activity, allowing the alfalfa to fully utilize the applied N [46, 47].

2. Normal Years:

In normal precipitation years, alfalfa also responded positively to N application, but the optimal rate was lower than in wet years. The yield peaked at an optimal N application rate of around 100 kg N ha^{-1}, resulting in an average hay yield of 15.5 t ha^{-1}. Similar to wet years, applying N beyond this optimum led to negligible yield improvements. The slightly lower optimal N rate compared to wet years suggests that while water was generally adequate, it might have been intermittently limiting, thus restricting the full expression of N fertilization benefits or leading to some N losses [26].

3. Dry Years:

The most pronounced difference in alfalfa response was observed under dry year conditions. In these scenarios, the alfalfa's response to applied N was markedly subdued, and the optimal N rate was significantly lower. Simulations showed that applying N beyond approximately 50 kg N ha^{-1} resulted in minimal or even slight yield reductions, with an average maximum yield of 11.8 t ha^{-1} at this lower rate. For many dry year simulations, the 0 kg N ha^{-1} (control) treatment performed comparably to or slightly better than higher N rates, particularly when considering the economic cost of fertilizer. This outcome strongly suggests that severe water limitation overshadowed any potential benefits of increased N supply. When water is scarce, plant growth is severely constrained, and the plant cannot effectively absorb or utilize additional N, leading to poor returns on N investment and potentially increased N losses through surface runoff or minimal leaching [39]. In extreme dry conditions, high soil N concentrations without adequate water can even induce osmotic stress, further hindering plant growth. The reliance on biological nitrogen fixation (BNF) appeared to be more critical and relatively efficient in these water-stressed environments, potentially accounting for a larger proportion of the crop's N demand compared to when external N is readily available and water is ample.



C. Water Use Efficiency (WUE) and Nitrogen Use Efficiency (NUE) Analysis

The efficiency of resource use (water and nitrogen) was also significantly influenced by both precipitation regimes and N application rates, highlighting the interconnectedness of these factors in alfalfa production.

1. Water Use Efficiency (WUE):

WUE generally increased with increasing N application up to the point of optimal N application for yield, after which it tended to plateau or slightly decline. This trend was consistent across all precipitation regimes.

● Wet Years: In wet years, the highest WUE (averaged 2.8 kg DM mm^{-1} transpired water) was achieved at N rates aligning with optimal yield (125–150 kg N ha^{-1}). Adequate N facilitated robust growth, enabling plants to effectively utilize available water for biomass production [38].

● Normal Years: WUE in normal years peaked (averaged 2.5 kg DM mm^{-1} transpired water) around the optimal N rate of 100 kg N ha^{-1}.

● Dry Years: Despite lower overall yields, WUE in dry years showed a modest increase with initial N application, peaking at a lower rate (e.g., 50 kg N ha$^{-1},averaging2.2kgDMmm^{-1}$ transpired water). However, applying N beyond this point often led to a decrease in WUE. This indicates that while some N is beneficial for improving water productivity even under dry conditions, excessive N without sufficient water can be detrimental to efficient water use, likely due to increased leaf area development that cannot be sustained by limited water supply [25, 39].

The significant differences in WUE across precipitation regimes underscore the critical role of water availability in determining the efficiency with which alfalfa converts water into biomass. Optimal N management, therefore, contributes to improving WUE by ensuring that N is not a limiting factor for growth when water is available.

2. Nitrogen Use Efficiency (NUE):

Both Agronomic NUE (NUEa) and Physiological NUE (NUEp) varied considerably depending on the precipitation regime and the amount of N applied.

● Agronomic NUE (NUEa): This efficiency metric generally showed a decreasing trend with increasing N application rates across all precipitation regimes. The highest NUEa values were consistently observed at lower N application rates (25–75 kg N ha^{-1}),regardlessoftheprecipitationregime.Inwetyears,NUEawasrelativelyhigheratmoderateNratescomparedtodryyears,indicatingthattheincrementalyieldgainperunitofappliedNwasgreaterwhenwaterwasabundant.However,athighNrates(>150kgNha^{-1}), NUEa dropped sharply, especially in dry years, suggesting a significant portion of the applied N was not converted into additional yield.

● Physiological NUE (NUEp): NUEp also tended to decrease as N application rates increased, reflecting the concept of diminishing returns where the plant's capacity to convert absorbed N into biomass becomes saturated. NUEp was generally higher in wet and normal years than in dry years, reflecting better overall growing conditions and potentially more efficient internal N cycling within the plant [41]. In dry years, the plant's physiological capacity to convert absorbed N into biomass was limited by water stress, resulting in lower NUEp values across the board. The contribution of biological nitrogen fixation (BNF) in alfalfa means that the apparent NUE for external N application needs careful interpretation, as the plant can meet a substantial portion of its N needs endogenously [20, 21, 48]. When external N is applied, BNF tends to be suppressed, influencing the overall NUE metrics [48].

Overall, these findings highlight a critical trade-off: maximizing yield often requires higher N inputs, which can simultaneously decrease NUE. Sustainable management aims to find an optimal balance that supports economically viable yields while maintaining high resource use efficiencies and minimizing environmental N losses [25, 26, 38].

D. Soil Nitrogen Dynamics

The simulations provided detailed insights into soil nitrogen dynamics under the various N application and precipitation scenarios, particularly concerning mineral N concentrations and potential N leaching.

1. Mineral N Concentrations:

● Wet Years: In wet years, soil nitrate (NO_3^-) concentrations in the upper soil profile (0–60 cm) showed a rapid increase after N application, followed by a decline due to both plant uptake and potential leaching. While uptake was high due to favorable moisture, the risk of nitrate leaching to deeper layers was also pronounced due to higher soil water content and increased drainage [24, 25].

● Normal Years: Soil mineral N dynamics were less volatile in normal years. Nitrate levels increased predictably after N application and declined with plant uptake. Leaching risk was moderate, primarily occurring after significant rainfall events following N fertilization.

● Dry Years: In dry years, soil mineral N accumulation, especially nitrate, was often higher in the upper soil profile due to reduced plant uptake and minimal leaching. Without sufficient water, N remained largely immobilized or in the soil solution, becoming unavailable for plant uptake and increasing the potential for denitrification losses if periods of waterlogging occurred, or surface runoff if intense, short-duration rainfall followed dry periods [24, 31, 39]. This accumulation of unused N represents an economic loss and an environmental liability.

2. Nitrogen Leaching:

N leaching, specifically the movement of nitrate (NO_3^-) below the root zone (e.g., 120 cm), was significantly influenced by both N application rates and precipitation.

● Wet Years: Leaching losses were highest in wet years, particularly at higher N application rates (>100 kg N ha^{-1}). Under these conditions, the combination of abundant rainfall and increased mineral N in the soil profile led to a greater downward movement of nitrate, posing a significant risk of groundwater contamination [7, 24].

● Normal Years: Moderate N leaching occurred in normal years, primarily at N rates exceeding the optimal for yield (e.g., >100 kg N ha^{-1}). Leaching events were typically associated with heavy rainfall episodes.

● Dry Years: Surprisingly, despite low plant uptake, N leaching was generally lowest in dry years. This was primarily due to insufficient soil moisture to facilitate deep drainage. However, the accumulation of unused N in the topsoil during dry periods means that if subsequent, unpredicted heavy rainfall occurs, there could be a pulse of N leaching, or increased surface runoff containing N could occur, particularly in sloped areas [24].

These results highlight the environmental trade-offs associated with N management. While N application can increase yield, it also carries the risk of N losses, especially under high precipitation. Optimized N management based on precipitation forecasts can therefore help mitigate these environmental impacts by reducing excess N availability when leaching potential is high [4, 7].

DISCUSSION

A. Interpretation of Optimal Nitrogen Rates

The findings from this APSIM simulation study clearly demonstrate that the optimal nitrogen (N) application rate for alfalfa yield is highly dependent on the prevailing precipitation regime. This variability underscores the inadequacy of "one-size-fits-all" N fertilization recommendations and highlights the critical need for climate-adaptive nutrient management strategies in alfalfa production. The identified optimal rates of approximately 150 kg N ha^{-1} for wet years, 100 kg N ha^{-1} for normal years, and 50 kg N ha^{-1} for dry years reveal a direct correlation between water availability and alfalfa's capacity to respond to and utilize exogenous N.

In wet years, abundant soil moisture provides ideal conditions for nutrient uptake and plant physiological processes [46, 47]. Higher precipitation enhances N mineralization from soil organic matter, improves the solubility and mobility of applied N, and facilitates its transport to the root zone where it can be readily absorbed by the alfalfa plant [2, 25, 46]. Under these favorable conditions, alfalfa's potential for biomass production is maximized, and thus, it can effectively utilize a greater supply of N to support increased growth. Our results align with studies on other crops where higher N rates are beneficial under conditions of adequate water supply [37, 47]. While alfalfa is a legume capable of biological nitrogen fixation (BNF), the high N demand for maximizing yield, especially in productive stands, can still exceed the N supplied by BNF alone, particularly when external N is provided in a timely manner after cuts, leading to the observed positive response to higher N application [20, 40, 41].

In normal years, with moderate but generally sufficient rainfall, alfalfa's N demand is still met by a combination of BNF and supplementary N, but the capacity to utilize very high N inputs may be slightly constrained by intermittent water stress or less consistent N availability in the soil solution. The optimal N rate of 100 kg N ha^{-1} reflects this balance, where N is not excessively limiting, but the environmental conditions are not as conducive as in wet years for peak N utilization [26]. This finding is consistent with general agronomic principles that N responses are attenuated when other growth-limiting factors, such as moderate water stress, are present [39].

The response in dry years is particularly insightful. The minimal yield increase beyond 50 kg N ha^{-1}, and in some cases even slight reductions at higher rates, powerfully illustrates that water availability is the primary limiting factor for alfalfa growth under drought conditions [44]. When water is scarce, physiological processes such as photosynthesis and nutrient uptake are severely inhibited, irrespective of the nutrient availability in the soil [39]. Applied N under these conditions remains largely unused by the plant, leading to poor NUE and economic losses for the farmer. Moreover, high concentrations of unused mineral N in a dry soil can potentially contribute to osmotic stress around the root zone, further hindering water uptake, though this effect might be more pronounced with different N forms or higher concentrations than simulated here [31]. The observed effectiveness of BNF in meeting N demand even at low external N application in dry years suggests that alfalfa's inherent ability to fix nitrogen becomes a crucial adaptive mechanism when water limits the efficiency of fertilizer-N [20, 21, 48]. This emphasizes a paradigm shift from simply applying N based on historical averages to a more dynamic, water-aware approach [37, 38].

B. Model Performance and Limitations

The successful calibration and validation of the APSIM-Alfalfa model, as evidenced by high R2 values and low RMSE/nRMSE for key output variables (yield, N uptake, soil water), confirm its robust capability to simulate alfalfa growth and N dynamics in the semi-arid region [29, 30]. This strong performance is consistent with the broad applicability and reliability of APSIM demonstrated in various agricultural systems globally [14, 15, 16, 17, 18, 19, 34, 35, 36]. The model effectively captured the complex interactions between soil water, soil nitrogen transformations, and crop physiological responses to N fertilization under different climatic conditions. This strengthens the confidence in using APSIM as a predictive tool for N optimization.

However, it is crucial to acknowledge the inherent limitations of any simulation model.

Firstly, while APSIM is sophisticated, it is a simplification of reality. The model relies on a set of parameters, which, though calibrated, may not perfectly represent the infinite variability of biological and environmental processes. For instance, the exact dynamics of biological nitrogen fixation in alfalfa, including the impact of varying N levels on rhizobial activity, are parameterized based on general relationships and may not fully capture nuanced, site-specific interactions or genetic variations in BNF efficiency among different alfalfa cultivars [48].

Secondly, the simulations assumed a uniform soil profile within the study area. In reality, soil heterogeneity can significantly influence water movement and nutrient availability, potentially leading to localized variations in alfalfa response not captured by the current model setup.

Thirdly, while the study focused on precipitation regimes, other confounding factors such as pest and disease outbreaks, weed competition, or extreme weather events (e.g., hail, heatwaves) were not explicitly considered in the model. These factors can significantly impact alfalfa yield and N uptake in field conditions, potentially altering the observed N response curves.

Finally, the definition of precipitation regimes was based on historical data. While this provides a robust classification, future climate change scenarios, which predict more extreme and unpredictable weather patterns, might require incorporating dynamic climate projections into the model for long-term adaptive strategies [13]. For example, the interplay of elevated CO_2 concentrations and temperature with precipitation and N application, though touched upon in some models [27], was not the primary focus here.

Despite these limitations, the model's ability to accurately reproduce observed field data for key variables provides a strong foundation for the generated recommendations. Future research could aim to integrate more complex biological interactions and refine model parameters for specific alfalfa cultivars to further enhance predictive power.

C. Implications for Sustainable Alfalfa Production

The findings from this study carry significant implications for the sustainable management of alfalfa production, particularly in regions prone to variable precipitation. By demonstrating that optimal N application is dynamic and climate-dependent, the research provides a framework for moving towards more precise and adaptive nutrient management.

1. Enhanced Economic Returns: Applying N at optimal rates, tailored to anticipated precipitation, can significantly improve the economic viability of alfalfa production. Over-application of N, especially in dry years, leads to wasted fertilizer, increased input costs, and no corresponding yield benefit, or even negative impacts on profitability [26]. Conversely, under-application in wet years can lead to suboptimal yields, missing opportunities for higher returns [20]. By aligning N inputs with water availability, farmers can achieve higher yields with more efficient fertilizer use, thereby maximizing their economic returns. This aligns with the broader goal of green development in agriculture, which emphasizes efficient resource use [4].

2. Improved Environmental Stewardship: One of the most critical implications of this study is its contribution to mitigating the environmental footprint of agriculture. Reducing the application of N in dry years, where it is largely unused, directly minimizes the risk of N losses to the environment, whether through surface runoff from unexpected rain or through denitrification [7, 24]. Similarly, even in wet years, avoiding excessive N application beyond the identified optimum helps curtail nitrate leaching, which is a major contributor to groundwater contamination and eutrophication of aquatic ecosystems [7, 24]. The ability of APSIM to simulate soil N dynamics, including leaching, provides a valuable tool for assessing these environmental risks and guiding management decisions towards more sustainable practices [19, 37]. This fosters a more coordinated approach to plant growth and nitrogen metabolism for sustainable agriculture [1].

3. Optimized Resource Use Efficiency: The study highlighted how optimal N application also positively influences water use efficiency (WUE) and nitrogen use efficiency (NUE) [25, 26, 38, 39]. In general, providing sufficient N when water is available enables the alfalfa plant to utilize water more efficiently for biomass production, as N is a critical component of photosynthetic machinery. Conversely, under dry conditions, restricting N application prevents the development of excessive leaf area that cannot be supported by limited water, thereby maintaining higher WUE. Similarly, by avoiding unnecessary N inputs, the overall NUE of the system improves, indicating a more effective conversion of available N (both fixed and applied) into harvestable yield. This integrated optimization of both N and water resources is paramount for long-term agricultural sustainability, especially in water-scarce regions [25, 26, 38, 39].

4. Advancing Precision Agriculture: This research demonstrates the practical utility of crop simulation models in advancing precision agriculture. Instead of relying on static recommendations, farmers can utilize tools like APSIM, coupled with short-term and seasonal weather forecasts, to make informed, dynamic decisions about N application. This approach enables a more responsive management system that adapts to current and projected climatic conditions, moving agriculture closer to a data-driven, site-specific, and environmentally responsible enterprise [36, 37, 49]. This is particularly relevant in areas with significant year-to-year rainfall variability, helping farmers adapt to challenging conditions [12, 13, 46].

D. Future Research Directions

Building upon the findings of this study, several avenues for future research warrant exploration to further refine and enhance N management strategies for alfalfa.

- Integrating Seasonal Climate Forecasts: A logical next step would be to directly integrate seasonal climate forecasts (e.g., probabilistic rainfall forecasts) into the APSIM decision-making framework. This would allow for dynamic adjustments of N application rates based on the likelihood of a wet, normal, or dry season, moving beyond the retrospective analysis of historical precipitation regimes [13].

- Economic Analysis and Risk Assessment: While the study implicitly addresses economic benefits through optimized yield and reduced input costs, a detailed economic analysis (e.g., cost-benefit ratios of different N strategies, risk assessment under varying market prices and climate uncertainties) would provide more comprehensive guidance for farmers. This would involve a full farm-level simulation, incorporating financial parameters.

- Nitrogen Form and Timing: This study primarily focused on the rate of N application. Future research could investigate the optimal timing and form of nitrogen fertilizer (e.g., controlled-release fertilizers, nitrification inhibitors) under different precipitation regimes, as these factors can significantly influence N availability and loss pathways [20, 31, 33]. The use of controlled-release N fertilization has shown promise in improving lucerne productivity and resource efficiency [20].

- Genetic Variation in N Efficiency and BNF: Exploring the genetic variability among alfalfa cultivars for N use efficiency and biological nitrogen fixation capacity under water-limited conditions could lead to the development of more resilient and N-efficient varieties [42, 48]. Integrating genotype-specific parameters into APSIM would allow for cultivar-specific N recommendations.

- Long-Term Rotational Effects: Alfalfa is often grown in rotation with other crops. Future research could utilize APSIM to simulate the long-term impacts of different alfalfa N management strategies on soil N pools and the N economy of subsequent crops in a rotation system [17, 35]. This would provide a more holistic understanding of N cycling within the entire farming system.

- Integration with Soil Health Indicators: Expanding the model to include more detailed soil health indicators beyond just N and water, such as microbial activity or organic carbon sequestration, could provide a more comprehensive picture of the environmental benefits and trade-offs of different N management strategies.

CONCLUSION

This study demonstrates that optimizing nitrogen (N) management for alfalfa production requires careful consideration of precipitation variability, as water availability strongly influences both crop growth and N utilization efficiency. Simulations using the APSIM model revealed that while moderate N inputs can enhance yields under favorable rainfall conditions, excessive application does not consistently translate to higher productivity and may increase the risk of environmental losses through leaching and volatilization. Conversely, in water-limited regimes, the crop's capacity to respond to higher N inputs is diminished, highlighting the importance of aligning fertilization strategies with seasonal rainfall patterns.

The results emphasize the potential of APSIM as a robust decision-support tool for designing site-specific and climate-sensitive fertilization schedules, allowing producers to balance yield optimization with environmental stewardship. By integrating long-term weather variability into nutrient management planning, farmers can improve resource efficiency, reduce production risks, and contribute to more sustainable forage systems. Ultimately, tailoring N application to precipitation regimes not only maximizes alfalfa yield potential but also promotes resilience in agricultural systems facing increasing climate variability.

REFERENCES

Han, X.W.; Wu, K.; Fu, X.D.; Liu, Q. Improving coordination of plant growth and nitrogen metabolism for sustainable agriculture. aBIOTECH 2020, 1, 255–275.

Zhang, Q.Z.; Hao, G.; Li, H.Y. Research progress on the effectiveness and form of exogenous nitrogen input and its impact on plant growth and physiology. J. Ecol. 2024, 43, 878–887.

Wang, Q.; Ou, E.L.; Wang, P.C.; Chen, Y.; Wang, Z.W.; Fang, X.W.; Zhang, J.L. Bacillus amyloliquefaciens GB03 augmented tall fescue growth by regulating phytohormone and nutrient homeostasis under nitrogen deficiency. Front Plant Sci. 2022, 13, e979883.

Li, T.Y.; Yao, L.; Zhong, Y.X.; Wang, Y.; Li, W.F.; Xu, Y.; Li, D.J.; Liu, R.; Li, B.; Zhang, W.F. Nitrogen fertilizer demand in China in the context of green development. Acta Pedol. Sin. 2025, 62, 308–321.

Li, M.Y.; Wu, T.X.; Wang, S.D.; Sang, S.; Zhao, Y.T. Phenology–gross primary productivity (GPP) method for crop information extraction in areas sensitive to non-point source pollution and its influence on pollution intensity. Remote Sens. 2022, 14, 2833.

Chen, Y.; Hu, S.; Guo, Z.; Cui, T.; Jin, Y. Effect of balanced nutrient fertilizer: A case study in pinggu district, Beijing, China. Sci. Total Environ. 2020, 754, 142069.

Kabuba, J.; Lephallo, J.; Rutto, H. Comparison of various technologies used to eliminate nitrogen from wastewater: A review. J. Water Process Eng. 2022, 48, 102885.

Wan, K.L.; Yu, Y.D. Optimizing the irrigation schedule for winter wheat-summer maize using APEX model. Trans. Chin. Soc. Agric. Eng. 2025, 41, 118–126.

Zhang, T.X.; Su, J.Y.; Liu, C.J.; Chen, W.H. State and parameter estimation of the AquaCrop model for winter wheat using sensitivity informed particle filter. Comput. Electron. Agric. 2020, 180, 105909.

Guo, J.P. Discussion on problems in the development and application of crop growth model. Chin. J. Appl. Ecol. 2025, 36, 1579–1589.

Zhu, J.L.; Zeng, W.Z.; Ma, T.; Lei, G.Q.; Zha, Y.Y.; Fang, Y.H.; Wu, J.W.; Huang, J.S. Testing and improving the WOFOST model for sunflower simulation on saline soils of inner mongolia, China. Agronomy 2018, 8, 172.

Strer, M.; Svoboda, N.; Herrmann, A. Abundance of adverse environmental conditions during critical stages of crop production in Northern Germany. Environ. Sci. Eur. 2018, 30, 10.

Palosuo, T.; Hoffmann, M.; Rtter, R.; Lehtonen, H. Sustainable intensification of crop production under alternative future changes in climate and technology: The case of the North Savo region. Agric. Syst. 2021, 190, 103135.

Holzworth, D.P.; Huth, N.I.; Devoil, P.G.; Zurcher, E.J.; Herrmann, N.I. APSIM—Evolution towards a new generation of agricultural systems simulation. Environ. Model. Softw. 2014, 62, 327–350.

Akram, H.; Levia, D.F.; Herrick, J.E.; Lydiasari, H.; Schütze, N. Water requirements for oil palm grown on marginal lands: A simulation approach. Agric. Water Manag. 2022, 260, 107292.

Wu, Y.S.; Wang, E.L.; He, D.; Liu, X.; Archontoulis, S.V.; Huth, N.I.; Zhao, Z.G.; Gong, W.Z.; Yang, W.Y. Combine observational data and modelling to quantify cultivar differences of soybean. Eur. J. Agron. 2019, 111, 125940.

Chaki, A.K.; Gaydon, D.S.; Dalal, R.C.; Bellotti, W.D.; Gathala, M.K.; Hossain, A.; Menzies, N.W. How we used APSIM to simulate conservation agriculture practices in the rice–wheat system of the Eastern Gangetic Plains. Field Crop. Res. 2022, 275, 108344.

Carcedo, A.; Bastos, L.M.; Yadav, S.; Mondal, M.K.; Jagadish, S.V.K.; Kamal, F.A.; Sutradhar, A.; Prasad, P.; Ciampitti, I.A. Assessing impact of salinity and climate scenarios on dry season field crops in the coastal region of Bangladesh. Agric. Syst. 2022, 200, 1034281.

Yang, X.; Zheng, L.; Yang, Q.; Wang, Z.; Cui, S.; Shen, Y. Modelling the effects of conservation tillage on crop water productivity, soil water dynamics and evapotranspiration of a maize–winter wheat–soybean rotation system on the Loess Plateau of China using APSIM. Agric. Syst. 2018, 166, 111–123.

Yin, M.H.; Jiang, Y.B.; Ling, Y.; Ma, Y.L.; Qi, G.P.; Kang, Y.X.; Wang, Y.Y.; Lu, Q.; Shang, Y.J.; Fan, X.R.; et al. Optimizing lucerne productivity and resource efficiency in China's Yellow River irrigated region: Synergistic effects of ridge-film mulchingand controlled-release nitrogen fertilization. Agriculture 2025, 15, 845.

Liu, J.; Lu, F.G.; Zhu, Y.M.; Wu, H.; Ahmad, I.; Dong, G.C.; Zhou, G.S.; Wu, Y.Q. The effects of planting density and nitrogen application on the growth quality of alfalfa forage in saline soils. Agriculture 2024, 14, 302.

Osterholz, W.R.; Renz, M.J.; Jokela, W.E.; Grabber, J.H. Interseeded alfalfa reduces soil and nutrient runoff losses during and after corn silage production. J. Soil Water Conserv. 2019, 12, 85–90.

Chen, D.D.; Wang, Y.R.; Han, Y.H. Effects of irrigation frequency and fertilizer rate on alfalfa seed yields in the Yellow River irrigated region. Acta Pratacult. Sin. 2016, 25, 154–163.

Gu, Y.J.; Han, C.L.; Kong, M.; Shi, X.Y.; Zdruli, P.; Li, F.M. Plastic film mulch promotes high alfalfa production with phosphorus saving and low risk of soil nitrogen loss. Field Crops Res. 2018, 229, 44–54.

Lu, Q.; Qi, G.P.; Yin, M.H.; Kang, Y.X.; Ma, Y.L.; Jia, Q.; Wang, J.H.; Jiang, Y.B.; Wang, C.; Gao, Y.L. Alfalfa cultivation patterns in the Yellow River irrigation area on soil water and nitrogen use efficiency. Agronomy 2024, 14, 874.

Lv, Y.R.; Wang, J.H.; Yin, M.H.; Kang, Y.X.; Ma, Y.L.; Jia, Q.; Qi, G.P.; Jiang, Y.B.; Lu, Q.; Chen, X.L. Effects of planting and nitrogen application patterns on alfalfa yield, quality, water–nitrogen use efficiency, and economic benefits in the Yellow River irrigation region of Gansu Province, China. Water 2023, 15, 251.

Liu, Q.; Gao, X.H.; Wang, J. Response simulation of CO2 concentration and temperature onspring wheat yield in dryland under different precipitation types. Agric. Res. Arid Areas 2023, 41, 230–237.

Li, G.; Huang, G.B.; Bellotti, W.; Chen, W. Adaptation research of APSIM model under different tillage systems in the Loess hill-gullied region. Acta Ecol. Sin. 2009, 29, 2655–2663.

Chai, T.; Draxler, R.R. Root mean square error (RMSE) or mean absolute error (MAE)?—Arguments against avoiding RMSE in the literature. Geosci. Model Dev.

2014, 7, 1247–1250.

Shcherbakov, M.V.; Brebels, A.; Shcherbakova, N.L.; Tyukov, A.P.; Janovsky, T.A.; Kamaev, V.A. A survey of forecast error measures. World Appl. Sci. J. 2013, 24, 171–176.

Tian, R.R.; Wang, J.H.; Yin, M.H.; Ma, Y.L.; Jia, Q.; Kang, Y.X.; Qi, G.P.; Gao, Y.L.; Jiang, Y.B.; Li, H.Y.; et al. Investigation of the regulatory effects of water and nitrogen supply on nitrogen transport and distribution in wolfberry fields. Front. Plant Sci. 2024, 15, 1385980.

Ech–Chatir, L.; Er–Raki, S.; Rodriguez, J.C.; Meddich, A. Advances in crop growth modeling: A review of perennial crop and beneficial soil microorganism approaches. Agric. Water Manag. 2025, 315, 109548.

Cornet, D.; Marcos, J.; Tournebize, R.; Sierra, J. Observed and modeled response of water yam (Dioscorea alata L.) to nitrogen supply: Consequences for nitrogen fertilizer management in the humid tropics. Eur. J. Agron. 2022, 138, 126536.

Man, J. The adaptability of APSIM-wheat model in the middle and lower reaches of the Yangtze River Plain of China: A case study of winter wheat in Hubei Province. Agronomy 2020, 10, 981.

Gulnazar, A.l.I.; Tao, H.M.; Wang, Z.K.; Shen, Y.Y. Evaluating the deep-horizon soil water content and water use efficiency in the alfalfa–wheat rotation system on the dryland of Loess Plateau using APSIM. Acta Pratacult. Sin. 2021, 30, 22–33.

Thompson, L.J.; Archontoulis, S.V.; Puntel, L.A. Simulating within-field spatial and temporal corn yield response to nitrogen with APSIM mode. Precis. Agric. 2024, 25, 2421–2446.

Wu, L.; Chen, C.; Yang, F.Y.; Fan, D.L.; Luo, J.M.; Han, J.R.; Wang, T.S.; Guo, E.J. Optimization of water and nitrogen management mode for spring wheat under different precipitation year types based on APSIM model. J. Triticeae Crops. 2025, 45, 103–111.

Wan, W.L.; Zhao, Y.H.; Li, X.F.; Xu, J.; Liu, K.G.; Chai, Y.Q.; Xu, H.J.; Cui, H.X.; Chen, X.J.; Wu, P.; et al. A moderate reduction in irrigation and nitrogen improves water–nitrogen use efficiency, productivity, and profit under new type of drip irrigated spring wheat system. Front. Plant Sci. 2022, 13, 1005945.

Yin, H.; Wang, Q.; Shi, S.L.; Zhang, N.H.; Wang, T.T.; Liu, Q.L.; Liu, C.W.; Yu, H.L. Effect of irrigation and nitrogen supply levels on hay yield and water use efficiency and soil total nitrogen of Medicage sativa. Grassl. Turf. 2012, 32, 1–7.

Sun, Y.L.; Zhao, J.W.; Liu, X.S.; Li, S.Y.; Ma, C.H.; Wang, X.Z.; Zhang, Q.B. Effect of nitrogen application on photosynthetic daily variation, leaf morphology and dry matter yield of alfalfa at the early flowering growth stage. Acta Pratacult. Sin. 2022, 31, 63–75.

Liu, W.T.; Wang, Y.Q.; Sun, S.N.; Zhao, Y.; Shen, Y.; Qian, J.; Yan, X.B. Effects of nitrogen Forms on nitrogen accumulation and utilization of alfalfa in different stubbles. Pratac. Sci. 2021, 38, 716–725.

Yi, X.F.; Sun, X.C.; Tian, R.; Li, K.X.; Ni, M.; Ying, J.L.; Xu, L.A.; Liu, L.W.; Wang, Y. Genome-Wide Characterization of the Aquaporin Gene Family in Radish and Functional Analysis of RsPIP2-6 Involved in Salt Stress. Front. Plant Sci. 2022, 13, 860742.

Delevatti, L.M.; Cardoso, A.S.; Barbero, R.P.; Leite, R.G.; Reis, R.A. Effect of nitrogen application rate on yield, forage quality, and animal performance in a tropical pasture. Sci. Rep. 2019, 9, 7596.

Zhang, R.; Li, Z.P.; Wang, L. Relationship between soil moisture dynamics, crop growth and precipitation in rain-fed area of the Loess Tableland, China. Chin. J. Appl. Ecol. 2019, 30, 359–369.

Zhao, Y.X.; Xiao, D.P.; Bai, H.Z.; Tang, J.Z. Climatic suitability of winter wheat and summer maize in the North China Plain. Chin. J. Ecol. 2020, 39, 2251–2262.

Wang, P.R.; Zhong, R.; Sun, M.; Kong, W.L.; Zhang, J.J.; Hafeez, N.; Ren, A.X.; Lin, W.; Gao, Z.Q. Nitrogen application rates at rainfall gradients regulate water and nitrogen use efficiency in dryland winter wheat. J. Plant Nutr. Fert. 2022, 28, 1430–1443.

García-López, J.; Lorite, I.J.; García-Ruiz, R.; Ordoñez, R.; Dominguez, J. Yield response of sunflower to irrigation and fertilization under semi-arid conditions. Agric. Water Manag. 2016, 176, 151–162.

Zhao, Y.; Liu, X.; Tong, C.; Wu, Y. Effect of root interaction on nodulation and nitrogen fixation ability of alfalfa in the simulated alfalfa/triticale intercropping in pots. Sci. Rep. 2020, 10, 61234.

Huang, M.X.; Wang, J.; Tang, J.Z.; Fang, Q.X.; Zhang, J.P.; Bai, H.Q.; Wang, N.; Li, Y.; Wu, B.J.; Zheng, J.Q.; et al. Analysis of interaction of sowing date, irrigation and nitrogen application on yield of oilsunflower based on APSIM model. Trans. Chin. Soc. Agric. Eng. 2018, 34, 134.

Cheng, C.; Li, C.; Li, W.M.; Ye, C.Y.; Wang, Y.S.; Zhao, C.S.; Ding, F.H.; Jin, A.F.; Feng, L.P.; Li, Z.F. Optimal path of the simulation model in horticultural crop development and harvest period. Trans. Chin. Soc. Agric. Eng. 2023, 39, 158.