Biologically Grounded Tabular Foundation Models for In-Season Maize Nitrogen Status Prediction

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Abstract.

Precision nitrogen (N) management needs timely information on maize (Zea mays L.) N status, including aboveground biomass (AGB), plant N concentration (PNC), plant N uptake (PNU), and the N nutrition index (NNI). In practice, these variables are still mostly obtained from destructive plant sampling. Crop models can represent the physiological links among them, but their use often depends on site-specific calibration. Remote sensing and machine learning are easier to scale across fields. However, predictions made for each target separately can still disagree with the biological relationships that define crop N status. This study evaluated Tabular Prior-data Fitted Network (TabPFN)+FixNet, a constrained tabular foundation-model framework that uses TabPFN v2.5 for initial prediction, followed by a neural refinement layer, physiological loss terms, and inference-time projection to agronomic constraints. Data were gathered from a split-plot maize experiment at Becker and Westport, Minnesota, from 2021 to 2024, with six N rates and four irrigation regimes. Models were tested using feature sets that combined PlanetScope imagery with environmental, hybrid, and management information. Evaluation used grouped out-of-fold cross-validation for 2021-2023 and a separate 2024 temporal holdout. On the full feature set in 2024, TabPFN+FixNet reached a mean R^2 of 0.91, an nRMSE of 6.27%, and 99.46% physiological constraint compliance. Compliance increased by 5.77 percentage points relative to the unconstrained TabPFN baseline, with little loss in accuracy. The predictions also followed the observed N-rate response across treatments. For water-sufficient observations, predicted NNI separated three N-status classes with 84.5% accuracy and a Cohen's κ of 0.72. These results support the use of satellite remote sensing, tabular foundation models, and physiological constraints for more consistent in-season maize N diagnosis and variable-rate N decision support.

Keywords.
maize nitrogen status, nitrogen nutrition index, critical nitrogen dilution, tabular foundation models, physiological constraint enforcement, precision nitrogen management.

Introduction

Food demand is expected to increase sharply by 2050, with recent estimates ranging from 35%

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to 56% between 2010 and 2050, and up to 62% when climate change is included (van Dijk et al., 2021). Meeting this demand will require higher crop productivity without adding unnecessary pressure on natural resources or food-system-related planetary boundaries (Kroll et al., 2019; Richardson et al., 2023; te Wierik et al., 2025). Climate change makes this task more difficult because crops are likely to face more frequent environmental stress, with possible effects on yield and grain quality (Jägermeyr et al., 2021; Miao et al., 2011). In maize (Zea mays L.) production, nitrogen (N) management is one of the main places where yield, profitability, N surplus, and N use efficiency meet (Wang et al., 2019). Knowledge-based N management seeks to better match crop N demand with N supply, and synthesis work has shown that these practices can increase staple crop yield while reducing greenhouse gas emissions, N leaching, and runoff (L. Xia et al., 2017).

At the field scale, N decisions need to account for crop demand, yield potential, soil and weather conditions, and management history. Uniform N rates are often too simple for this purpose because crop N uptake, biomass accumulation, and fertilizer N losses vary across space and through the season (Ata-Ul-Karim et al., 2020; Ladha et al., 2016; Maltese et al., 2023; Quan et al., 2021). More fertilizer also does not guarantee higher economic return. Any added yield has to be weighed against fertilizer cost and possible losses through nitrate leaching and nitrous oxide emissions (Epule et al., 2023; Mueller et al., 2012; Smerald et al., 2022). A useful N recommendation, therefore, needs two pieces of information: the crop growth that can be supported under the current conditions and the minimum N supply required to sustain that growth. This is the basis for physiological indicators such as the nitrogen nutrition index (NNI), which uses the critical nitrogen dilution curve (CNDC) to diagnose crop N status during the growing season (Ciampitti et al., 2022; Plénet & Lemaire, 1999; Shao et al., 2023).

NNI is a useful diagnostic index, but it is not easy to use directly at field scale. Its calculation requires destructive measurement of aboveground biomass (AGB) and laboratory analysis of plant N concentration (PNC). The same two variables are also needed to calculate plant N uptake (PNU), through the plant N mass-balance relationship (Lemaire et al., 2008; Li et al., 2022a). For this reason, AGB, PNC, PNU, and NNI should not be treated as unrelated targets. A prediction system for crop N diagnosis needs accurate estimates, but it also needs the estimates to agree with the physiological relationships among the variables.

Multispectral remote sensing offers a non-destructive way to estimate crop N status because canopy reflectance is linked with chlorophyll content, canopy structure, green area index, and biomass (Berger et al., 2022; Weiss et al., 2020). In maize, red-edge and chlorophyll-sensitive vegetation indices have often improved estimation of PNC, PNU, and NNI compared with broader red and near-infrared indices. Their performance, however, can change with growth stage, canopy density, biomass saturation, and site-year conditions (F. Li et al., 2014; T. Xia et al., 2016). Spectral signals can also reflect water stress, phenology, genotype, and structural development, not only N stress, which is a particular issue when N and water limitations occur together (Becker et al., 2020). Recent studies have therefore moved beyond individual vegetation indices and used integrated predictors that combine spectral, structural, thermal, satellite, UAV, radiative-transfer models, genetic, environmental, and management information to estimate NNI or canopy N across hybrids, growth stages, and water and N treatments (J. Li et al., 2024; Liang et al., 2023; Lu et al., 2025; Yan et al., 2025; Yu et al., 2024).

Machine learning (ML) has become a common tool for crop N-status prediction because it can use high-dimensional sensing data and model nonlinear responses (Chlingaryan et al., 2018). For structured tabular data, common baselines include tree-based ensembles such as Random Forest (RF), Extremely Randomized Trees (ExtraTrees), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost), along with neural tabular models and tabular foundation models (Bentéjac et al., 2021; Geurts et al., 2006; Erickson et al., 2025). Recent benchmarks suggest that foundation models can perform well on small tabular datasets, while gradient-boosted trees remain strong practical baselines and neural tabular models may become competitive when larger tuning or ensembling budgets are available

(Barkov et al., 2025; Borisov et al., 2024; Grinsztajn et al., 2025). This small-data setting is common in crop N studies because destructive plant measurements limit the number of labeled observations. The targets also have known links: NNI is calculated from PNC, and the critical N concentration is estimated from AGB, while PNU is calculated from AGB and PNC. Accuracy alone is therefore not enough, the predicted variables should also satisfy these relationships.

Tabular Prior-Data Fitted Network (TabPFN) is useful in this setting because it provides a statistical prior for small tabular datasets through synthetic-data pretraining and in-context learning (Hollmann et al., 2025). Physics-informed machine learning offers a related way to include known mathematical or physical relationships in data-driven models (Karniadakis et al., 2021). For maize N diagnosis, these two ideas can be combined: a flexible tabular model can learn from remote sensing and management data, while physiological constraints keep the outputs within agronomically meaningful relationships.

This study developed and evaluated a biologically constrained tabular foundation-model framework for non-destructive maize N-status diagnosis. The framework, TabPFN+FixNet, combines TabPFN-based prediction with a constrained neural refinement module and inference-time algebraic closure to improve agreement among AGB, PNC, PNU, and NNI. The objectives were to: (1) evaluate the added value of PlanetScope remote sensing, environmental, genotypic, and management variables; (2) compare TabPFN+FixNet with linear, kernel-based, tree-ensemble, tabular deep learning, and foundation-model baselines using grouped cross-validation and a strict 2024 temporal holdout; (3) test whether constrained refinement improves physiological compliance while maintaining prediction accuracy; and (4) examine whether the predictions preserve treatment-level N-response patterns and support three-class NNI diagnosis under water-sufficient conditions.

Materials and Methods

Study sites and experimental design

Field experiments were conducted from 2021 to 2024 at two University of Minnesota research farms in Minnesota, USA: the Sand Plain Research Farm near Becker and the Rosholt Research Farm near Westport. Both sites have coarse-textured soils with relatively low water-holding capacity, which is useful for evaluating maize response to N and irrigation management. Weather data from nearby North Dakota Agricultural Weather Network stations were used to summarize growing-season precipitation and thermal time.

A split-plot design with four replications was used at each site-year. Irrigation was assigned to main plots, and N fertilizer rate was assigned to subplots. From 2021 to 2023, the irrigation treatments were full irrigation, 75% full irrigation, 50% full irrigation, and a zero-irrigation target. In 2024, the treatments were changed to 125%, 100%, 65%, and 0% full irrigation targets. The six N rates were 0, 78, 157, 235, 314, and 392 kg N ha^{-1} in all years. Each irrigation-by-N combination occurred once in each replication, giving 96 plots per site-year.

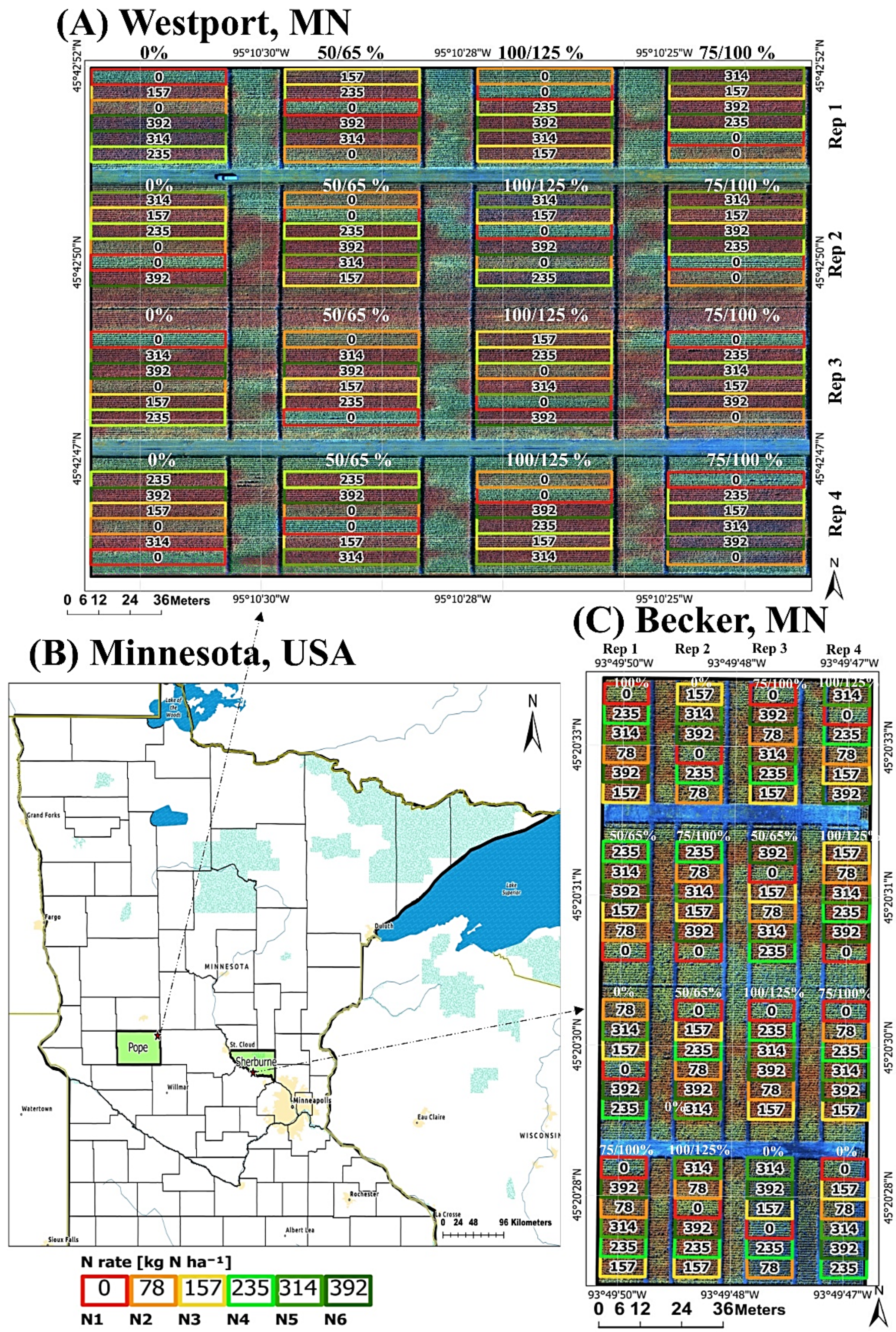

Figure 1. Study locations and split-plot experimental layout at Becker and Westport, Minnesota. Irrigation treatments were assigned to main plots, and nitrogen-rate treatments were assigned to subplots.

Crop management and plant sampling

Maize was planted from late April to late May, depending on field conditions. Becker was planted with DKC51-38RIB from 2021 to 2023 and NK0440-AT in 2024, while Westport used DKC44-97RIB in all years. The target seeding rate was about 87,700 seeds ha^{-1}. Nitrogen fertilizer was applied as urea in two splits: 43% of the seasonal rate near V2 and 57% near V8. Irrigation was scheduled with the University of Minnesota Irrigation Management Assistant checkbook method, which estimates root-zone soil water deficit from crop evapotranspiration, precipitation, and soil water-holding capacity. Deficit-irrigation treatments were applied as proportional targets relative to full irrigation, but realized irrigation depth varied by site-year with weather and system operation.

Table 1. Key field operations and plant sampling dates at Becker and Westport during 2021–2024.

	Becker				Westport			
	2021	2022	2023	2024	2021	2022	2023	2024
Planting	7-May	16-May	4-May	1-May	18-May	23-May	11-May	24-May
V2 N application	28-May	8-Jun	24-May	31-May	9-Jun	14-Jun	1-Jun	25-Jun
V8 N application	25-Jun	28-Jun	15-Jun	26-Jun	28-Jun	6-Jul	22-Jun	9-Jul
V8 Plant sampling	25-Jun	28-Jun	23-Jun	3-Jul	29-Jun	6-Jul	22-Jun	12-Jul
R1 Plant sampling	23-Jul	27-Jul	19-Jul	22-Jul	29-Jul	3-Aug	31-Jul	6-Aug

Table 2. Realized seasonal irrigation depth by irrigation treatment at Becker and Westport during 2021–2024.

	Becker				**Westport**			
	2021	**2022**	**2023**	**2024**	**2021**	**2022**	**2023**	**2024**
I1	325	141	185	93	196	97	152	39
I2	232	106	151	77	152	72	132	35
I3	166	70	103	56	109	48	104	28
I4	34	0	15	17	23	0	51	17

Plant samples were collected at V8 and R1. At each sampling date, six representative plants were cut at ground level from the two center rows of each plot, avoiding plot borders. Samples were weighed fresh, oven-dried at 60 °C to constant weight, and used to determine aboveground biomass (AGB). Dried plant material was ground and analyzed for total N concentration. Plant N concentration (PNC) was reported on a dry matter basis and converted to g kg^{-1}.

The four prediction targets were PNC, AGB, PNU, and NNI. PNC and AGB were measured directly, whereas PNU and NNI were calculated from those measurements. NNI was calculated from observed PNC and the critical N concentration estimated from AGB using the maize critical nitrogen dilution curve of Plénet and Lemaire (1999). PNU was calculated from AGB and PNC using the plant N mass-balance relationship. Because the four variables are linked, the task was treated as constrained multi-target regression rather than as four separate regressions.

Predictor variables and feature slices

Field measurements, management records, weather data, hybrid information, and PlanetScope imagery were joined into one plot-stage tabular dataset. The dataset included 1,484 observations from V8 and R1 across two sites and four growing seasons. Observations without AGB or PNC were removed because both variables were needed to calculate PNU and NNI.

PlanetScope surface reflectance was used as the remote sensing input. The predictors were grouped into nested feature slices to test the value of added information: four-band PlanetScope imagery, eight-band PlanetScope imagery, and then environmental, genotypic, and management variables. PlanetScope values were selected or interpolated from cloud-free imagery within three days before plant sampling. This matched the remote sensing inputs to the destructive sampling date without using future information.

Continuous variables were imputed with the training-set median, and categorical variables were one-hot encoded. The preprocessing parameters were estimated from the training data only and then applied to validation or test observations.

TabPFN+FixNet modeling framework

TabPFN+FixNet used two modeling stages. First, Tabular Prior-Data Fitted Network (TabPFN) generated initial predictions for PNC, AGB, NNI, and PNU. TabPFN was used as the tabular foundation-model prior because it can make predictions on small tabular datasets through in-context learning, without training a new deep model from scratch for each task.

Prediction uncertainty was represented with multiple TabPFN runs based on different preprocessing configurations. For each target, predictive quantiles were generated and averaged across ensemble members. The median quantiles served as the initial point predictions, and the outer quantiles represented predictive spread. These outputs were used as inputs to the refinement step.

The second stage used FixNet as a neural refinement module. FixNet did not replace the TabPFN predictions, it learned a residual correction. Small corrections were expected when the initial prediction was already plausible, while larger corrections were allowed when the prediction conflicted with agronomic relationships. The refinement network used the TabPFN quantile outputs, the active predictor variables, and an agronomic context vector with growth stage, cumulative N applied, and cumulative irrigation depth. Feature-wise linear modulation allowed the correction to vary with crop stage and management context.

Physiological constraints and prediction correction

The refinement step was trained for both accuracy and physiological consistency. Cross-target constraints kept predicted NNI close to the value implied by predicted PNC and AGB through the critical N dilution curve. A similar constraint kept predicted PNU close to the value calculated from predicted AGB and PNC. Temporal constraints were also applied to paired V8 and R1 observations from the same plot to avoid unrealistic trajectories, such as decreasing AGB from V8 to R1 or extreme within-season changes in PNC and PNU. A drift penalty limited unnecessary movement away from the original TabPFN prediction.

Physiological losses were calculated after converting predictions back to physical units, so the constraints were applied to agronomic quantities rather than standardized model values. At inference, final projection, and algebraic closure were applied so the reported predictions followed the main relationships among AGB, PNC, PNU, and NNI.

Model evaluation

Model performance was evaluated in two ways. First, grouped out-of-fold cross-validation was applied to the 2021-2023 data, with groups used to limit leakage among observations from the same location, year, and plot. Second, the 2024 observations were kept as an independent temporal holdout. This holdout tested model performance in a new season that also included a modified irrigation treatment structure.

TabPFN+FixNet was compared with linear, kernel-based, tree-ensemble, tabular deep learning, and unconstrained foundation-model baselines. Predictive accuracy was evaluated with R^2 and normalized root mean square error. Physiological reliability was evaluated with constraint-compliance metrics for the expected cross-target and temporal relationships. Treatment-level N-response patterns were also checked, and for water-sufficient observations, predicted NNI was converted to three N-status classes for diagnostic evaluation.

Results

Model accuracy and physiological compliance

The grouped out-of-fold results showed the main limitation of unconstrained models. Several model families reached competitive R^2 and nRMSE values for AGB, PNC, PNU, and NNI, but their four outputs were not always physiologically compatible. Some predictions implied decreases in AGB from V8 to R1, disagreement between predicted PNU and the value calculated from AGB and PNC, or disagreement between predicted NNI and the value implied by the critical N dilution curve.

Adding FixNet and algebraic closure changed the accuracy-compliance balance. At the full feature slice, TabPFN+FixNet kept prediction accuracy close to the strongest unconstrained baselines and improved physiological compliance. In the out-of-fold evaluation, the model reached a mean R^2 of 0.89 across the four targets and 99.07% overall compliance. The unconstrained TabPFN baseline had similar point-prediction accuracy but lower compliance. The main gain from TabPFN+FixNet was therefore more consistent crop N-status prediction, rather than a large increase in target-level accuracy.

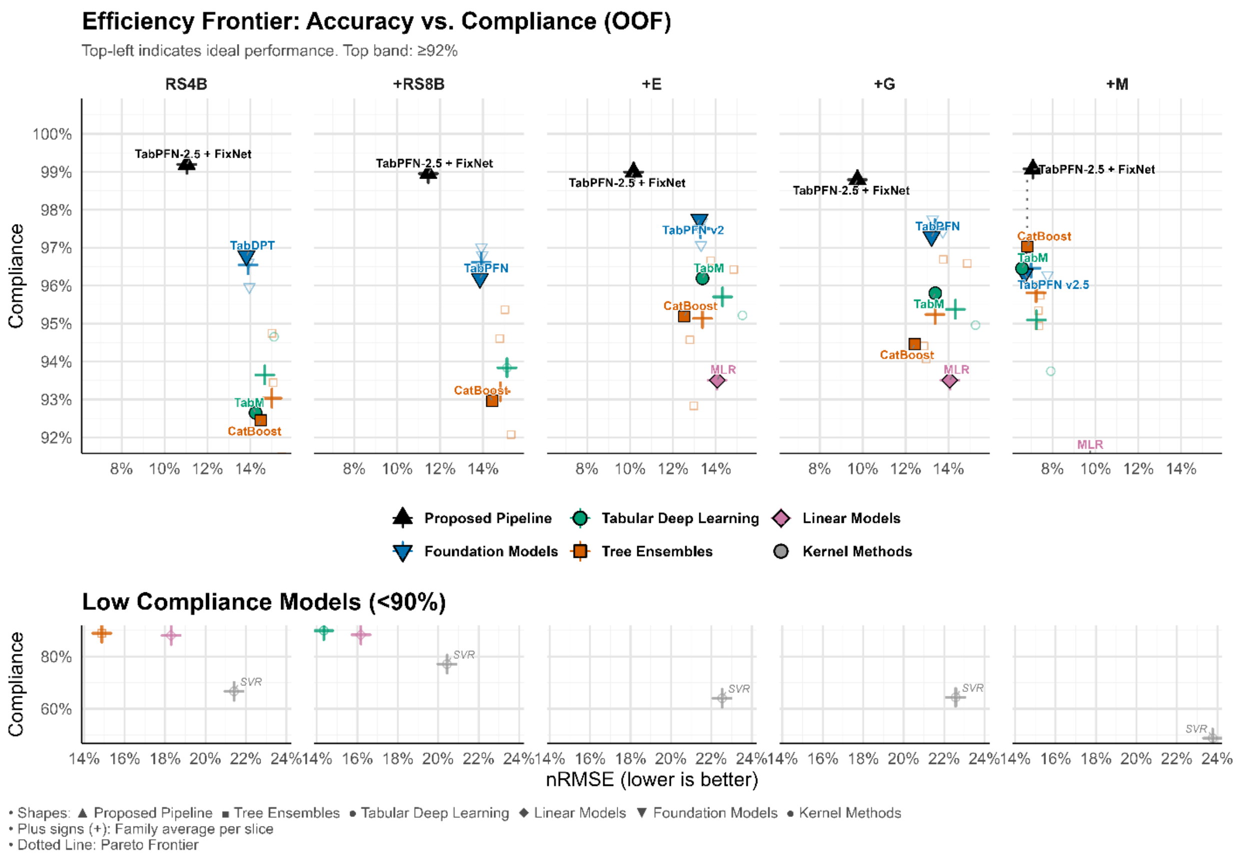

Figure 2. Accuracy–compliance trade-off across model families. Models closer to the upper-left region have lower prediction error and higher physiological compliance.

Performance on the 2024 temporal holdout

The 2024 season was held out as an independent test of temporal generalization under a new growing season and a modified irrigation treatment structure. With the full feature slice, the complete TabPFN+FixNet pipeline reached a mean R^2 of 0.91 across PNC, AGB, NNI, and PNU, with an nRMSE of 6.27% and 99.46% overall physiological compliance. Target-level R^2 values were 0.90 for PNC, 0.93 for AGB, 0.86 for NNI, and 0.93 for PNU.

The ablation results separated the roles of the two constraint components. The raw TabPFN prior reached 93.69% overall compliance. Adding projection and closure increased overall compliance to 97.48%, but temporal-growth compliance changed only slightly. In contrast, TabPFN+FixNet without projection increased temporal-growth compliance to 98.20%. The full pipeline reached 99.10% temporal-growth compliance and 99.46% overall compliance. Projection and closure mainly corrected algebraic inconsistencies among the N-status variables, while FixNet contributed more to the V8-R1 temporal behavior.

Table 3. Component ablation of TabPFN+FixNet on the 2024 temporal holdout at the full feature slice.

Condition	Description	Mean R^2	PNC R^2	AGB R^2	NNI R^2	PNU R^2	Temporal-growth compliance (%)	Overall compliance (%)
C0	TabPFN prior alone	0.92	0.92	0.95	0.87	0.93	88.29	93.69
C1	TabPFN + projection/closure, no FixNet	0.91	0.92	0.95	0.86	0.93	89.19	97.48
C2	TabPFN + FixNet, no projection	0.91	0.90	0.93	0.87	0.93	98.20	98.56
C3	Full TabPFN + FixNet + projection/closure	0.91	0.90	0.93	0.86	0.93	99.10	99.46

Preservation of treatment-level nitrogen response

Predicted outputs were also checked against the imposed N fertilizer treatments. This was used as an agronomic consistency check, not as a formal treatment-effect test, because N and irrigation variables were included as management covariates in the full model.

The predicted N-response patterns matched the observed treatment structure. PNC and NNI showed the strongest N-gradient response, while AGB and PNU had weaker adjusted N effects, especially in the out-of-fold evaluation. This pattern is agronomically reasonable because PNC and NNI are more directly linked to N status, whereas AGB also reflects growth stage, weather, water availability, and site-year effects. In the 2024 holdout, the predicted N effect was strong for PNC and NNI, with predicted N η^2 values of 0.81 for both variables. PNU showed a clearer N response in 2024, with a predicted N η^2 of 0.44.

Diagnostic classification using predicted NNI

For water-sufficient observations, predicted NNI was assigned to three diagnostic classes: N-deficient, near-critical, and N-surplus. This analysis examined whether continuous NNI estimates could be used for categorical N-status diagnosis when water limitation was minimized.

In the 2024 holdout, TabPFN+FixNet achieved 84.5% overall accuracy and a Cohen's kappa of 0.72 for the three-class diagnosis. The model performed best for the N-deficient and N-surplus classes. Precision, recall, and F1-score were 96%, 92%, and 94% for N-deficient observations and 82%, 80%, and 81% for N-surplus observations. The near-critical class was weaker, with precision, recall, and F1-score of 46%, 55%, and 50%. This was expected because the near-critical interval is narrow, so small continuous NNI errors can change the assigned class.

Direct NNI predictions and NNI recalculated from predicted AGB and PNC gave the same class assignments for the constrained model. That agreement is important for decision support, because it means the diagnostic class does not depend on which prediction pathway is used. In the unconstrained baseline, the direct and recalculated NNI pathways could diverge.

Summary and Conclusions

This study evaluated whether a tabular foundation model could be used for maize N-status prediction while keeping the outputs consistent with known crop N relationships. Several baseline models produced reasonable target-level accuracy, but their predictions could still conflict with the definitions linking AGB, PNC, PNU, and NNI. That kind of inconsistency limits the value of the prediction for crop N diagnosis, even when individual error metrics look acceptable.

TabPFN+FixNet improved this point by combining TabPFN predictions with a constraint-aware refinement step and final projection/closure. In the 2024 temporal holdout, the framework maintained high predictive accuracy and reached 99.46% overall physiological compliance. Projection and closure corrected algebraic mismatches among N-status variables, while FixNet improved the temporal plausibility of paired V8 and R1 predictions.

The predicted responses were also agronomically reasonable. PNC and NNI followed the expected N-rate gradient, and the predicted marginal means were closely aligned with the observed treatment means. Under water-sufficient conditions, predicted NNI separated N-deficient, near-critical, and N-surplus observations with 84.5% accuracy and a Cohen's kappa of 0.72. The near-critical class remained the most difficult, which is expected because observations near the diagnostic threshold are sensitive to small prediction errors.

The study was limited to two Minnesota sites and four growing seasons, and the approach should be tested across broader soils, climates, hybrids, and management systems. The framework also depends on the availability and timing of usable satellite imagery. Even so, the results show that combining satellite remote sensing, tabular foundation models, and agronomic constraints can provide accurate and internally consistent estimates of maize AGB, PNC, PNU, and NNI for in-season N-status diagnosis and variable-rate N management.

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