



(RESEARCH ARTICLE)



PREDICTIVE, SENSOR-INFORMED NITROGEN MANAGEMENT FOR RAINFED LOWLAND RICE USING MACHINE LEARNING AND DSSAT-CERES-RICE IN AFIKPO, EBONYI STATE, NIGERIA

Blessing O. Osuesu *

Department of Electrical/Electronic Engineering Technology, Akanu Ibiam Federal Polytechnic Unwana, Afikpo, Ebonyi State, Nigeria.

* Corresponding Author

ORCID Details

Blessing O. Osuesu: <https://orcid.org/0009-0001-9856-0748>

World Journal of Advanced Research and Reviews, 2026, 32(01), 1338–1348

Publication history: Received on 02 August 2026; revised on 18 October 2026; accepted on 20 October 2026

Article DOI: <https://doi.org/10.30574/wjarr.2026.32.1.2647>

Copyright © 2026 Author(s) retain the copyright of this article. This article is published under the terms of the Creative Commons Attribution License 4.0

ABSTRACT

Smallholder lowland rice in south-east Nigeria receives small, late, fixed nitrogen (N) doses, and it is unclear whether “smart” in-season N control adds value over a well-designed fixed schedule. DSSAT-CERES-Rice v4.8 was coupled with external controllers used to simulate rainfed, banded FARO 44 rice (literature-derived cultivar coefficients, not field-calibrated) at Afikpo (5.89°N, 7.92°E) over 33 seasons (1993–2025), using CHIRPS rainfall and NASA POWER temperature and radiation. The study compared four kinds of management: farmer practice (46 kg N ha⁻¹ at 21 days after transplanting); 30/40/30 split schedules at 40–120 kg N ha⁻¹; a reactive controller emulating a canopy N-stress sensor; and a three-stage gradient-boosting controller; trained on 2,970 simulated dose combinations and tested leave-one-year-out. The reactive controller out-yielded farmer practice by 0.39 t ha⁻¹ (p = 0.002), but only by applying 8 kg N ha⁻¹ more; at equal total N it yielded 0.44 t ha⁻¹ less than a fixed 30/40/30 split (p < 0.001). With N priced at 4 kg paddy per kg N, perfect in-season information was worth only 93 kg ha⁻¹ over the best history-based fixed schedule. The predictive controller captured little of this (+6 kg ha⁻¹, p = 0.72) for 1 July transplanting, against +90 kg ha⁻¹ (p < 0.001) for 1 June. Correcting N rate and timing relative to farmer practice was worth about 1,700 kg ha⁻¹. NASA POWER rainfall showed a strong drying trend, much weaker in CHIRPS, that changed one conclusion; all results are therefore reported with CHIRPS. In-season prediction adds value, but rate and timing dominate.

Keywords: Nitrogen use efficiency; Crop simulation; Machine learning; Precision agriculture; FARO 44; CHIRPS

1 INTRODUCTION

Rice demand in West Africa has outpaced production for decades, and the gap has been filled largely by imports [1,2]. In south-east Nigeria, rice is grown mainly by smallholders in rainfed lowlands, and yields of improved varieties such as FARO 44 fall well short of their potential. Nitrogen (N) is among the most manageable causes. In Nigerian trials, paddy yield rose from about 3.4 t ha⁻¹ without N by 1.3 t ha⁻¹ with only 40 kg N ha⁻¹ [3]. Smallholders, however, typically apply small, single, late doses.

N recovery by flooded rice is often below 40%, largely because urea broadcast into floodwater is lost before the crop can use it [4,5]. Chlorophyll-meter and leaf-colour-chart management, which apply N only when the leaves become pale, have raised N-use efficiency in irrigated rice [6]. Low-cost sensors now make automated N management feasible for smallholders, but the value of the information they provide is rarely compared with that of a well-chosen fixed schedule.

Machine learning (ML) is widely used to predict crop yield and N status [7,8]. Several studies also couple crop models with ML or reinforcement learning to learn management policies [9,10,11]. These studies mostly concern maize or wheat in data-rich regions. They usually compare learned policies with simple baselines, rather than with the best fixed schedule or with a perfect-information bound.

Two further problems affect such work in data-scarce regions. First, gridded weather products such as NASA POWER, built on the MERRA-2 reanalysis [12,13], and CHIRPS rainfall [14] can disagree strongly in Nigeria [15]. Second, the “automatic N” option in DSSAT 4.8 applies no fertiliser (Section 2.4).

This study addresses these gaps for rainfed FARO 44 rice at Afikpo, Ebonyi State. It had three aims:

- to compare farmer practice, fixed split schedules and a reactive sensor-triggered controller, including a comparison at equal total N;
- to develop a predictive ML controller that uses only the information available on each decision day, and to test it against the best fixed schedule and a perfect-information upper bound; and
- to quantify the value of in-season information and the sensitivity of the conclusions to planting date and to the weather data source.

2 MATERIALS AND METHODS

2.1 Site, weather and soil

Afikpo, Ebonyi State (5.89°N, 7.92°E, about 64 m a.s.l.), has a humid tropical climate with rains from April to October. Rice there is grown mostly in banded, rainfed lowlands.

Daily NASA POWER data [13] were converted to DSSAT format, giving TAV of 26.2 °C and AMP of 2.5 °C. One missing radiation day was interpolated, and dew point was derived from relative humidity. NASA POWER rainfall averaged 1,697 mm yr⁻¹, against a site climatology of about 2,022 mm [16], and showed a declining linear trend of 36 mm yr⁻¹ over 1993–2025 (ordinary least-squares regression of annual totals on year, $p < 0.001$). Daily CHIRPS v2.0 rainfall [14] was therefore downloaded through ClimateSERV. It averaged 2,000 mm yr⁻¹, with a June–October mean of 1,413 mm against a climatology of 1,412 mm. No rain-gauge record for Afikpo was available to validate either product. CHIRPS was preferred because it blends satellite estimates with station observations [14] and agreed with the site climatology; the NASA POWER trend is therefore treated as a probable product artefact, not a confirmed error.

The final weather combined CHIRPS rainfall with NASA POWER temperature, radiation and humidity for the 33 complete seasons, 1993–2025. Seasons were classed as dry, average or wet by terciles of June–October rainfall.

The soil was a three-layer Ultisol profile with a sandy loam surface (Table 1). Clay and silt content, organic carbon, total N, pH (H₂O) and bulk density were taken from SoilGrids 2.0 at the site coordinates (250 m resolution; [17]) and assigned to 0–20, 20–50 and 50–100 cm layers. The water-retention limits (LL, DUL and SAT) and saturated hydraulic conductivity were then estimated from texture, organic carbon and bulk density with the soil-profile tool in DSSAT (SBuild). When organic carbon is available for every layer, SBuild uses the pedotransfer functions of [18]. Surface parameters were also set in SBuild: albedo 0.13, evaporation limit 6 mm, drainage rate 0.40 d⁻¹ and runoff curve number 73.

Table 1: Soil profile EBAFI001

Depth (cm)	LL	DUL	SAT (cm ³ cm ⁻³)	Ksat (cm h ⁻¹)	Bulk density (g cm ⁻³)	Organic C (%)	Clay (%)	Total N (%)	pH
0–20	0.118	0.242	0.420	2.50	1.44	2.29	18.3	0.233	5.4
20–50	0.148	0.268	0.400	1.20	1.47	1.17	27.9	0.114	5.3
50–100	0.168	0.285	0.385	0.65	1.49	0.58	33.3	0.072	5.3

2.2 Crop model, management and cultivar

The open-source DSSAT CSM-CERES-Rice v4.8 (build 4.8.6; [19]; [20]), was used with water and N balances.

Every season used the same management:

- **Transplanting:** 1 July, with 21-day-old seedlings at 25 hills m^{-2} (20×20 cm) and 2 seedlings per hill. Nigerian lowland rice guidance recommends transplanting from mid-June to mid-July, depending on rainfall, with 2–3-week-old nursery seedlings [21], and about 82% of Ebonyi rice farmers transplant rather than broadcast [22].
- **Water:** a puddled paddy with 150 mm bunds and 2 mm d^{-1} percolation, and no irrigation.
- **Initial conditions:** each simulation started 30 days before transplanting, with soil water at the drained upper limit, 2 mg kg^{-1} NH_4^+ -N and 1 mg kg^{-1} NO_3^- -N, and 1 t ha^{-1} of rice straw.
- **Fertiliser:** urea broadcast onto the flooded soil (DSSAT codes FE005 and AP012).

Yields are reported at 14% moisture.

FARO 44 is not in the DSSAT library, and no local dataset was available for calibration. A literature-constrained parameter set was therefore derived from the IR 72 coefficients distributed with DSSAT 4.8 (cultivar IB0118 in RICER048.CUL), changing only two of them. P1 was lowered from 437.1 to 300 °C d, which gives a simulated sowing-to-maturity of 107 days (range 102–114). This falls within the reported 90–120 days [23,24]. G2 was reduced from 0.026 to 0.024 g, matching the reported 1000-grain weight [25]. All other coefficients were kept at their IR 72 values ($\text{P2R} = 61.0$, $\text{P5} = 371.8$, $\text{P20} = 11.58$, $\text{G1} = 77.8$, $\text{G3} = 1.0$, $\text{PHINT} = 83.0$, $\text{THOT} = 30.4$, $\text{TCLDP} = 15.0$ and $\text{TCLDF} = 15.0$). These adjustments match phenology and grain weight to published descriptions of FARO 44; they are not a calibration, and simulated yields and N responses were not validated against field observations. All results are therefore model-based comparisons of strategies, not field-validated yield estimates.

2.3 N management strategies

Each strategy was simulated in every one of the 33 seasons (Table 2), so all strategies faced identical weather. The farmer-practice baseline follows a survey of 120 Ebonyi rice farmers: all broadcast their fertiliser, 56% applied it once per season, mostly 2–3 weeks after planting, and urea was the most common product [26]. Their mean application, about 86 $\text{kg of product ha}^{-1}$, supplies roughly 20–40 kg N ha^{-1} , so 46 kg N ha^{-1} is a generous baseline and the gains reported over it are conservative.

Table 2: N management strategies (DAT = days after transplanting).

Code	Description	N schedule (DAT: kg N ha^{-1})
N0	Unfertilised control	—
FP46	Farmer practice: one broadcast urea dose about 3 weeks after transplanting (2 bags ha^{-1})	21: 46
SPL40 / SPL80 / SPL120	Recommended 30/40/30 split at transplanting, active tillering and panicle initiation	0, 21, 45 at 30/40/30% of 40, 80 or 120
A_NS10 / A_NS30	Reactive controller, crop N-stress trigger at 0.1 / 0.3	20 kg per trigger (Section 2.4)
A_LN20 / A_LN25	Reactive controller, leaf-N trigger at 2.0% / 2.5%	20 kg per trigger (Section 2.4)
FP54, SPL54	Fixed 54 kg N ha^{-1} as one dose at 21 DAT, or as a 30/40/30 split	matched to the mean N of A_NS10
FPmatch, SPLmatch	Fixed timing with A_NS10's season-specific total N	per season
ML	Predictive three-stage controller (Section 2.5)	0, 21, 45: chosen in season

2.4 Reactive controller

DSSAT 4.8 accepts Automatic-N settings, but the code that applies the fertiliser is commented out in the public source (Management/Fert_Place.for). With a 1% stress trigger, the N applied was zero and yields equalled those of N0. A sensor and controller outside the model was emulated in closed loop, as follows:

- Run all seasons with the doses decided so far.
- Read the daily signal: N-stress factor or leaf N.

- On the first day the signal crosses the threshold, schedule 20 kgNha⁻¹ for the next day. A day qualifies only if it falls between 7 and 60 DAT, at least 7 days after the previous dose, and the season total remains at or below 120 kgNha⁻¹.
- Repeat until no season triggers again.

The model is deterministic, and a dose affects only later days, so this reproduces a daily controller exactly.

2.5 Predictive ML controller

Decisions were made at transplanting ($d_0 \in \{0, 20, 40\}$), at 21 DAT ($d_{21} \in \{0, 20, \dots, 100\}$) and at 45 DAT ($d_{45} \in \{0, 20, \dots, 80\}$ kg N ha⁻¹). Each maximised net return in paddy equivalents:

$$\pi = Y_{14} - r(d_0 + d_{21} + d_{45})$$

Here Y_{14} is simulated paddy yield at 14% moisture (kg ha⁻¹); d_0 , d_{21} and d_{45} are the N doses (kg N ha⁻¹); and r is the N:paddy price ratio, i.e. the price of 1 kg of N divided by the farm-gate price of 1 kg of paddy, so that π is in kg paddy-equivalent ha⁻¹. The base case used $r = 4$, with 2 and 6 as alternatives [3]. π is a partial return over N cost only: application labour and all other costs were treated as equal across strategies and omitted, so additional split applications are not penalised.

All 90 dose combinations were simulated for every season (2,970 runs). The simulated sensor state on the day before each decision was recorded: crop N, LAI, tillers, leaf N, N stress, soil mineral N and flood depth. Weather features covered the period up to that day: rainfall, rainy days, radiation, temperature and degree days.

The policy was learned by backward induction (fitted value iteration; [27]), with one gradient-boosting regressor per stage ([28]; [29]; 400 trees, depth 3, learning rate 0.03):

- Stage 3 (45 DAT) predicted yield.
- Stages 2 and 1 predicted the best achievable value-to-go given the earlier doses.

Validation was leave-one-year-out: for each test season, the models were trained on the other 32 seasons, and decisions were made sequentially as the season unfolded. The held-out season was excluded from every step that used outcomes: model fitting, the value-to-go labels and the selection of BEST_FIXED. The gradient-boosting hyperparameters were fixed in advance and not tuned on the data. The chosen schedules were rerun in DSSAT, and yields agreed with the grid within 20 kg ha⁻¹ (0.3%). A random forest [30] served as an alternative learner.

Two benchmarks were computed on the same grid. BEST_FIXED was, for each held-out season, the grid schedule with the highest mean return across the other 32 (training) seasons. ORACLE was the best schedule chosen with perfect knowledge of the season. ORACLE minus BEST_FIXED is the value of perfect in-season information.

2.6 Statistics and sensitivity

Strategies were compared as a randomised complete block design, with season as the block. Pairwise differences were tested with Holm-adjusted paired t-tests [31] and summarised as letter groups [32]. Agronomic efficiency was computed as $AE_n = (Y - Y_0)/N$.

Sensitivity was tested by scaling G1 by 0.8, 0.9 and 1.1, by raising percolation to 5 mm d⁻¹, by repeating the analysis with NASA POWER rainfall, and by moving transplanting to 1 June, 15 June, 15 July and 1 August. The ML controller was also retrained and tested for 1 June and 15 July. Scripts and input files are available as described under Data and code availability.

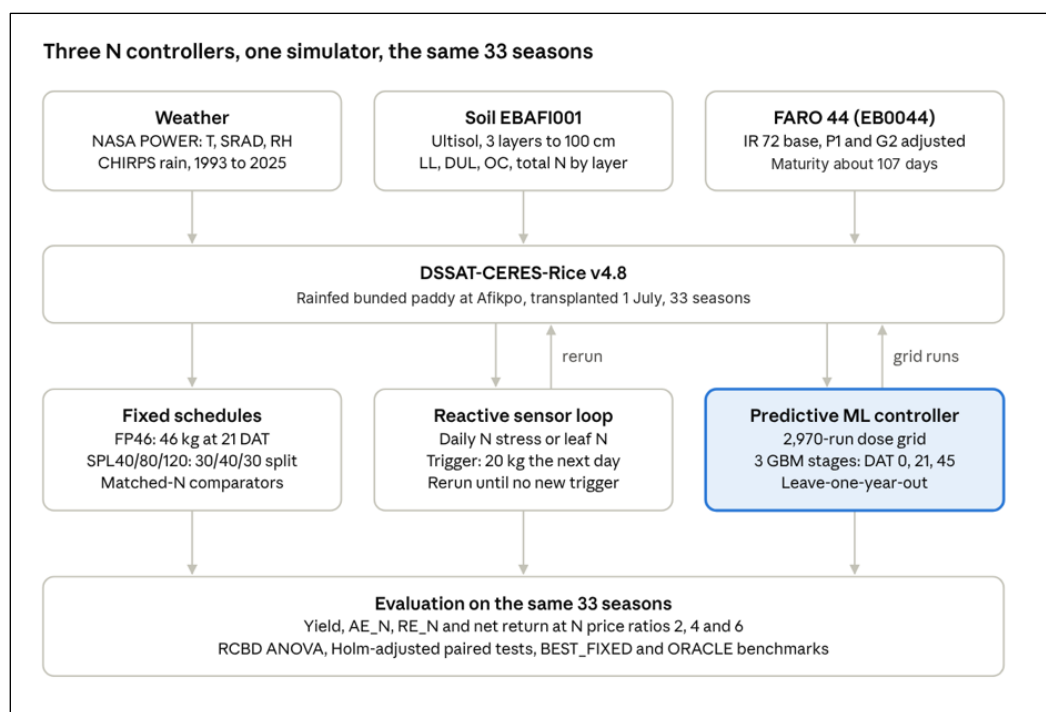


Figure 1: Study framework. All controllers drive the same DSSAT-CERES-Rice simulator over the same 33 seasons. The reactive loop reruns the model after each triggered dose. The predictive controller is trained on a full dose grid and tested leave-one-year-out.

3 RESULTS

3.1 Rainfall data source

NASA POWER and CHIRPS agreed in the 1990s, with annual means of 2,128 and 2,100 mm in 1993–2002, but then diverged (Fig. 2). By 2021–2025, NASA POWER gave 1,018 mm against 1,775 mm from CHIRPS. Annual totals were only weakly correlated between the two sources ($r = 0.42$).

The rainfall source changed the conclusions about the reactive controller. With NASA POWER rainfall, farmer practice was more variable (CV 15% vs 13%; worst season 3.93 vs 4.24 t ha⁻¹), and the advantage of A_{NS10} over FP46 shrank to 0.13 t ha⁻¹ and was not significant ($p = 0.27$). With CHIRPS it was 0.39 t ha⁻¹ ($p = 0.002$). All results below use CHIRPS.

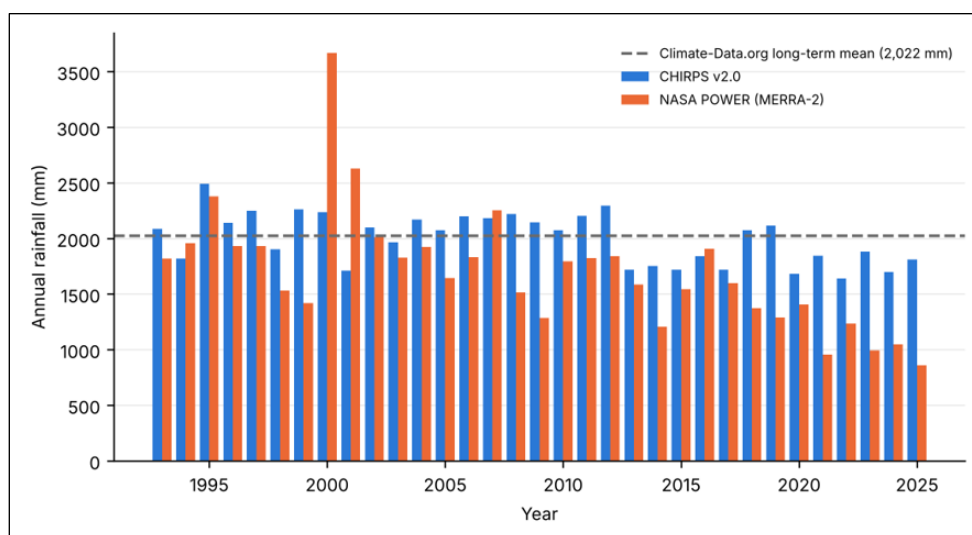


Figure 2: Annual rainfall at Afikpo, 1993–2025, from CHIRPS v2.0 and NASA POWER. The dashed line is the long-term climatology.

3.2 Fixed schedules and the reactive controller

FARO 44 reached anthesis 77 days and maturity 107 days after sowing. Strategy strongly affected yield ($F_{8,256} = 479.8$, $p < 0.001$; Table 3), much more than season did ($F_{32,256} = 10.6$).

Farmer practice (FP46) yielded 5.14 t ha^{-1} , no more than SPL40 (5.27 t ha^{-1} , $p = 0.12$), and was among the most variable strategies (CV 13%). Split schedules raised yield to 6.75 t ha^{-1} (SPL80) and 7.13 t ha^{-1} (SPL120), while AE_n fell from 51 to 32 kg kg^{-1} .

Table 3: Grain yield (14% moisture) over 33 seasons. Strategies sharing a letter do not differ (Holm-adjusted, $\alpha = 0.05$).

Strategy	N (kg ha^{-1})	Yield (t ha^{-1}), mean $\pm$ SD	AE_n (kg kg^{-1})	Group
SPL120	120	7.13 ± 0.39	32.4	a
SPL80	80	6.75 ± 0.49	43.8	b
A_LN25	117	5.86 ± 0.56	22.5	c
A_NS10	54	5.53 ± 0.54	42.8	d
SPL40	40	5.27 ± 0.65	50.8	de
FP46	46	5.14 ± 0.64	41.3	e
A_NS30	19	4.06 ± 0.39	43.9	f
A_LN20	74	3.71 ± 0.37	6.4	g
N0	0	3.24 ± 0.36	—	h

The N-stress controller (A_NS10) first triggered at 15–23 DAT and applied 40–60 kg N ha^{-1} per season (mean 54). It beat farmer practice by 0.39 t ha^{-1} ($p = 0.002$; in 22 of 33 seasons). At equal total N, however, it was no better than a single fixed dose and worse than a fixed 30/40/30 split (Table 4): its advantage came from applying more N, and waiting for stress cost yield relative to a basal dose.

Leaf N triggers performed poorly, because leaf N declines with crop age. The lower threshold fired too late (A_LN20: AE_n 6.4 kg kg^{-1}), and the higher one fired almost every week (A_LN25: 5.8 doses, 117 kg N).

Table 4: A_NS10 (mean 54 kg N ha^{-1}) versus fixed schedules.

Comparator	N (kg ha^{-1})	Yield (t ha^{-1})	A_NS10 – comparator (t ha^{-1})	p
FP46	46	5.14	+0.39	0.002
FP54 (one dose, 21 DAT)	54	5.40	+0.14	0.22
FPmatch (one dose, A_NS10 totals)	40–60	5.34	+0.19	0.053
SPL54 (30/40/30)	54	5.97	–0.44	< 0.001
SPLmatch (30/40/30, A_NS10 totals)	40–60	5.84	–0.31	0.004

3.3 Predictive ML controller

The stage-3 model predicted held-out yields with an RMSE of 255 kg ha^{-1} . It relied mainly on crop N (importance 0.69), LAI (0.13) and tiller number (0.10) at 44 DAT.

At $r = 4$, BEST_FIXED was the same schedule in every held-out season: 40, 60 and 20 kg N ha^{-1} at 0, 21 and 45 DAT. Perfect in-season information (ORACLE) was worth only 93 kg ha^{-1} more (Table 5). The ML controller varied seasonal totals from 60 to 140 kg N ha^{-1} and used 10 kg N ha^{-1} less than BEST_FIXED, but its yield was also slightly lower, and its net return was only 6 kg ha^{-1} higher ($p = 0.72$; better in 17 of 33 seasons, worse in 11).

The result was similar for other learners and prices. None of the gains was significant:

- **Random forest ($r = 4$):** -11 kg ha^{-1} ($p = 0.42$).
- **$r = 2$:** $+24 \text{ kg ha}^{-1}$ ($p = 0.15$; value of perfect information 81 kg ha^{-1}).
- **$r = 6$:** $+40 \text{ kg ha}^{-1}$ ($p = 0.23$; value of perfect information 109 kg ha^{-1}).

Table 5: Predictive controller versus benchmarks ($r = 4$, leave-one-year-out, 1 July transplanting).

Policy	N (kg ha^{-1}), mean (range)	Yield (t ha^{-1})	Net return (kg ha^{-1})
BEST_FIXED	120 (120–120)	7.17	6,693
ML controller	110 (60–140)	7.14	6,699
ORACLE	107 (60–160)	7.21	6,786

Across all strategies, correcting N rate and timing dominated. Net return rose from $4,958 \text{ kg ha}^{-1}$ under FP46 to $6,693 \text{ kg ha}^{-1}$ under BEST_FIXED, about 19 times the full value of perfect in-season information (Fig. 3).

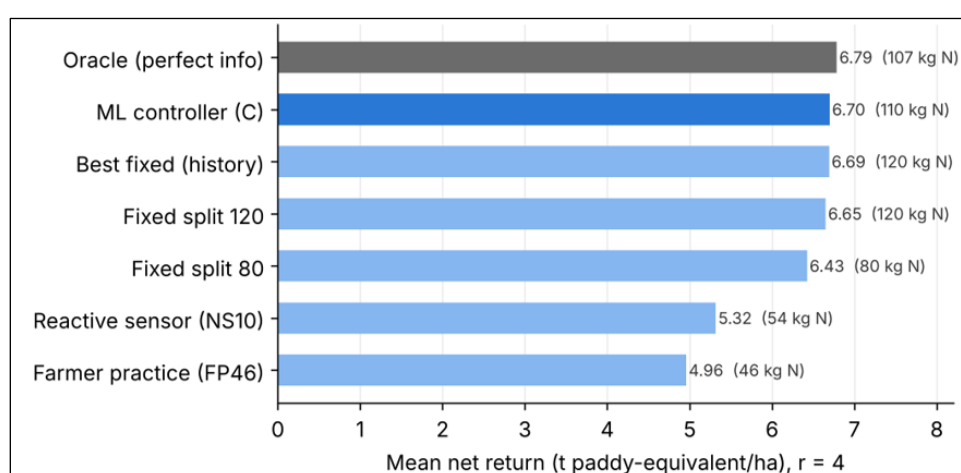


Figure 3: Mean net return by strategy for 1 July transplanting, with N priced at 4 kg paddy per kg N ($r = 4$). Labels give mean N applied.

3.4 Sensitivity

The ranking of the strategies held in every scenario (Table 6). SPL80 exceeded A_NS10 by $0.72\text{--}1.48 \text{ t ha}^{-1}$, and A_NS10 out-yielded FP46 by $0.20\text{--}0.61 \text{ t ha}^{-1}$ ($p \leq 0.013$) everywhere except with NASA POWER rainfall. Across the five planting dates, mean yield varied by at most 0.45 t ha^{-1} for any strategy.

Planting date did, however, change the value of in-season information. For 1 June transplanting, perfect information was worth 186 kg ha^{-1} , and the ML controller gained 90 kg ha^{-1} over BEST_FIXED with 13 kg N ha^{-1} less ($p < 0.001$; better in 26 of 33 seasons). For 15 July it was worth 100 kg ha^{-1} , and the ML controller gained 40 kg ha^{-1} ($p = 0.08$).

Table 6: Sensitivity of mean yield (t ha^{-1}) and of the controller comparisons. ML gain is ML minus BEST_FIXED net return (kg ha^{-1} , $r = 4$); “—” = not run.

Scenario	FP46	A_NS10	SPL80	SPL120	A_NS10 – FP46 (p)	ML gain (p)
Base (1 July)	5.14	5.53	6.75	7.13	+0.39 (0.002)	+6 (0.72)
1 June	5.16	5.77	6.58	7.16	+0.61 (< 0.001)	+90 (< 0.001)
15 June	4.93	5.52	6.50	7.07	+0.58 (< 0.001)	—
15 July	5.11	5.53	6.58	7.07	+0.42 (0.001)	+40 (0.08)
1 August	5.38	5.76	6.75	7.20	+0.38 (0.002)	—
G1 $\times$ 0.8	4.54	4.73	5.68	6.01	+0.20 (0.007)	—

G1 × 0.9	4.97	5.20	6.22	6.57	+0.23 (0.006)	—
G1 × 1.1	5.33	5.65	7.13	7.60	+0.31 (0.004)	—
Percolation 5 mm d ⁻¹	5.57	5.85	6.90	7.20	+0.28 (0.013)	—
NASA POWER rainfall	5.75	5.88	6.60	7.07	+0.13 (0.27)	—

4 DISCUSSION

4.1 Where the value lies

Moving from farmer practice to a good fixed schedule was worth about 1,700 kg paddy-equivalent ha⁻¹. That schedule includes a basal dose, a main dose at tillering and a small dose at panicle initiation. Perfect knowledge of each season would add only 81–109 kg ha⁻¹ more for 1 July transplanting, about 1.2–1.7% of net return. The ML controller captured almost none of that at 1 July and about half at 1 June. In this environment, the N rate and its split are the main lever, and in-season adaptation is at best a second-order refinement.

The value of perfect information is a useful yardstick for smart-farming proposals: it shows how much of a problem responds to in-season information before money is spent on sensing. In the bundled Afikpo paddy, season-to-season variation in N demand was modest, and season explained far less variance than strategy ($F = 10.6$ vs 479.8). The value of information also depended on planting date, being about twice as large for 1 June as for 1 July, possibly because an earlier crop meets more variable early-season conditions; we did not test this mechanism. The value is likely to be higher still where water supply is more erratic or N is more expensive.

4.2 Reactive versus predictive control

A trigger that waits for stress acts after growth has already been lost and cannot place N ahead of peak demand. Hence the reactive controller was no better than a single fixed dose at equal N, and it yielded less than a split that included a basal dose. Fixed leaf N thresholds failed because leaf N falls with crop age, which is why practical real-time N management in rice uses stage-specific or relative thresholds [6].

The predictive controller differed in two ways. It anticipated demand, deciding at 21 DAT before stress appeared. It also relied on crop N, LAI and tiller number, which can be observed with leaf-colour charts, SPAD meters or NDVI. Its potential benefit is to save N where the crop is already well supplied, as in chlorophyll-meter studies [6]. For 1 June it did so (13 kg N ha⁻¹ less and a higher net return). For 1 July the N saving came with a small yield loss, so net return barely changed.

With a value of information below 100 kg ha⁻¹, a 255 kg ha⁻¹ prediction error leaves little room for a learned policy to beat a good fixed schedule. Thirty-two training seasons are also few for three sequential models. Any deployment should therefore keep the controller within agronomic bounds and justify it by the value of information at the site. The oracle continuation labels used in fitted value iteration [27] are slightly optimistic. Reinforcement-learning environments built on DSSAT [10,11] could learn finer policies, and they should be judged against the same perfect-information bound.

4.3 Data and modelling pitfalls

The NASA POWER rainfall series showed a strong drying trend, much weaker in CHIRPS over the same years, that changed one conclusion: with it, the sensor controller's advantage over farmer practice was not significant. Gridded products can differ markedly in Nigeria [15], so they should be checked against an independent source before use. Without gauge data for Afikpo we cannot establish which product is closer to the truth; CHIRPS was preferred because it incorporates station data and agrees with the site climatology. In addition, the automatic-fertilisation option in DSSAT 4.8 silently applies no N. The closed-loop emulation used here is an exact substitute for deterministic models.

4.4 Limitations

FARO 44 was represented by a literature-constrained parameter set rather than a local calibration, and the model was not validated against field data for this cultivar or site. The results are simulation-based comparisons, not field-validated yield estimates. Simulated AE_n for the split schedules (32–51 kg kg⁻¹) exceeded the roughly 25 kg kg⁻¹ found in Nigerian field trials [3]. The response to N, and therefore the optimal rates (100–140 kg N ha⁻¹), are probably overstated, although the ranking of strategies was robust in the sensitivity tests.

Other simplifications:

- sensors were simulated without measurement error;
- one soil profile was used, and the ML controller was tested at three planting dates only;
- farmer practice was taken from a regional survey rather than measured at Afikpo;
- P, K, pests and weeds were not simulated;
- the rainfall products could not be validated against a local rain-gauge record;
- the controller was trained and tested within the same model.

Future work should calibrate FARO 44 on farm, add sensor noise and test the controller in field trials.

5 CONCLUSIONS

A simulation study of 33 rainfed seasons of FARO 44 rice at Afikpo, south-east Nigeria, supports five conclusions; they rest on model results that have not yet been validated in the field.

- Correcting N rate and timing relative to farmer practice was worth about 1,700 kg paddy-equivalent ha⁻¹, an order of magnitude more than any in-season adaptation.
- A reactive N-stress trigger improved on farmer practice only by applying more N; at equal N it was no better than a single fixed dose and worse than a 30/40/30 split.
- Perfect in-season information was worth only 81–109 kg ha⁻¹ for 1 July transplanting. A predictive gradient-boosting controller did not beat the best fixed schedule at that date (+6 kg ha⁻¹, $p = 0.72$), although it did for 1 June (+90 kg ha⁻¹, $p < 0.001$). The case for smart N control therefore depends on planting date and should be tested site by site.
- Gridded rainfall should be cross-checked before use: switching from NASA POWER to CHIRPS rainfall changed the significance of the sensor effect.
- DSSAT 4.8's Automatic-N option applies no N; closed-loop emulation is an exact alternative.
- Field calibration of FARO 44 and on-farm testing of the predictive controller are the next steps.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The meteorological data were obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project, funded through the NASA Earth Science/Applied Science Program. CHIRPS rainfall was provided by the Climate Hazards Center, University of California, Santa Barbara, and accessed through SERVIR ClimateSERV. Soil data were obtained from SoilGrids 2.0 (ISRIC – World Soil Information). Crop simulations used the DSSAT Cropping System Model, developed and maintained by the DSSAT Foundation.

Funding Source

This research was funded by the Tertiary Education Trust Fund (TETFund), Nigeria.

Disclosure of conflict of interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authorship contribution statement

Blessing O. Osuesu (sole author): Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. The author has read and approved the final manuscript.

Data and code availability

The weather files (CHIRPS and NASA POWER), the soil profile (EBAFI001) and FARO 44 cultivar files, all DSSAT experiment files and the Python scripts are provided as supplementary material with this article. The scripts cover weather conversion, experiment generation, the closed-loop controller, ML training and statistics.

REFERENCES

- [1] Seck PA, Diagne A, Mohanty S, Wopereis MCS. Crops that feed the world 7: rice. *Food Secur.* 2012;4(1):7–24. doi: 10.1007/s12571-012-0168-1
- [2] van Oort PAJ, Saito K, Amovin-Assagba E, van Bussel LGJ, van Wart J, de Groot H, et al. Assessment of rice self-sufficiency in 2025 in eight African countries. *Glob Food Sec.* 2015;5:39–49. doi: 10.1016/j.gfs.2015.01.002
- [3] Daudu CK, Ugbaje EM, Oyinlola EY, Tarfa BD, Yakubu AA, Amapu IY, et al. Lowland rice nutrient responses for the Guinea and Sudan Savannas of Nigeria. *Agron J.* 2018;110:1079–88. doi: 10.2134/agronj2017.08.0469
- [4] Cassman KG, Dobermann A, Walters DT. Agroecosystems, nitrogen-use efficiency, and nitrogen management. *Ambio.* 2002;31(2):132–40. doi: 10.1579/0044-7447-31.2.132
- [5] Ladha JK, Pathak H, Krupnik TJ, Six J, van Kessel C. Efficiency of fertilizer nitrogen in cereal production: retrospects and prospects. *Adv Agron.* 2005;87:85–156. doi: 10.1016/S0065-2113(05)87003-8
- [6] Peng S, Garcia FV, Laza RC, Sanico AL, Visperas RM, Cassman KG. Increased N-use efficiency using a chlorophyll meter on high-yielding irrigated rice. *Field Crops Res.* 1996;47:243–52.
- [7] Chlingaryan A, Sukkarieh S, Whelan B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. *Comput Electron Agric.* 2018;151:61–9. doi: 10.1016/j.compag.2018.05.012
- [8] Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: a review. *Sensors (Basel).* 2018;18(8):2674. doi: 10.3390/s18082674
- [9] Gautron R, Maillard OA, Preux P, Corbeels M, Sabbadin R. Reinforcement learning for crop management support: review, prospects and challenges. *Comput Electron Agric.* 2022;200:107182. doi: 10.1016/j.compag.2022.107182
- [10] Gautron R, Padrón EJ, Preux P, Bigot J, Maillard OA, Emukpere D. gym-DSSAT: a crop model turned into a reinforcement learning environment [Preprint]. arXiv:2207.03270. 2022 [cited 2026 Oct 4]. Available from: <https://arxiv.org/abs/2207.03270>
- [11] Wu J, Tao R, Zhao P, Martin NF, Hovakimyan N. Optimizing nitrogen management with deep reinforcement learning and crop simulations. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*; 2022. p. 1712–20.
- [12] Gelaro R, McCarty W, Suárez MJ, Todling R, Molod A, Takacs L, et al. The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *J Clim.* 2017;30(14):5419–54. doi: 10.1175/JCLI-D-16-0758.1
- [13] Sparks AH. nasapower: a NASA POWER global meteorology, surface solar energy and climatology data client for R. *J Open Source Softw.* 2018;3(30):1035. doi: 10.21105/joss.01035
- [14] Funk C, Peterson P, Landsfeld M, Pedreros D, Verdin J, Shukla S, et al. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci Data.* 2015;2:150066. doi: 10.1038/sdata.2015.66
- [15] Nwachukwu PN, Satgé F, El Yacoubi S, Pinel S, Bonnet MP. From TRMM to GPM: how reliable are satellite-based precipitation data across Nigeria? *Remote Sens.* 2020;12(23):3964. doi: 10.3390/rs12233964
- [16] Climate-Data.org. Climate: Afikpo [Internet]. [cited 2026 Jul 20]. Available from: <https://en.climate-data.org>
- [17] Poggio L, de Sousa LM, Batjes NH, Heuvelink GBM, Kempen B, Ribeiro E, et al. SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *SOIL.* 2021;7(1):217–40. doi: 10.5194/soil-7-217-2021
- [18] Rawls WJ, Brakensiek DL, Saxton KE. Estimation of soil water properties. *Trans ASAE.* 1982;25(5):1316–20.
- [19] Hoogenboom G, Porter CH, Boote KJ, Shelia V, Wilkens PW, Singh U, et al. The DSSAT crop modeling ecosystem. In: Boote KJ, editor. *Advances in crop modelling for a sustainable agriculture*. Cambridge (UK): Burleigh Dodds Science Publishing; 2019. p. 173–216. doi: 10.19103/AS.2019.0061.10
- [20] Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, et al. The DSSAT cropping system model. *Eur J Agron.* 2003;18(3–4):235–65. doi: 10.1016/S1161-0301(02)00107-7
- [21] LINKS – Catalysing Economic Growth for Northern Nigeria. Improved practices for lowland rice production [Internet]. Abuja (Nigeria): LINKS; 2020 [cited 2026 Oct 14]. Available from: https://www.links-nigeria.com/wp-content/uploads/2020/10/MAS_GUIDE-ON-LOWLAND-RICE-PRODUCTION_Final.pdf

- [22] Chidiebere-Mark N, Ohajianya D, Obasi P, Onyeagocha S. Profitability of rice production in different production systems in Ebonyi State, Nigeria. *Open Agric.* 2019;4(1):237–46. doi: 10.1515/opag-2019-0022
- [23] Seed Co. FARO 44 [Internet]. [cited 2026 Oct 9]. Available from: <https://seedcogroup.com/ng/fieldcrops/sc-partners/faro-44/>
- [24] Ugbaje EM. Maximizing yield and net returns to nitrogen, phosphorus and potassium fertilizer application in rice (*Oryza sativa* L.) production on lowland soils [master's dissertation]. Zaria (Nigeria): Ahmadu Bello University; 2018.
- [25] Mani H, Muhammad A, Mahmoud BA, Usman A. Response of rice varieties to nitrogen fertilization under irrigation at Talata Mafara, Sudan savanna. *J Food Nutr Agric.* 2018;1:17–20. doi: 10.21839/jfna.v1i1.126
- [26] Iwuchukwu JC, Obazi SA, Opata PI, Madukwe MC. Factors influencing inorganic fertilizer use among rice farmers in Ebonyi State, Nigeria. *J Agric Ext.* 2022;26(1):27–35. doi: 10.4314/jae.v26i1.4
- [27] Ernst D, Geurts P, Wehenkel L. Tree-based batch mode reinforcement learning. *J Mach Learn Res.* 2005;6:503–56.
- [28] Friedman JH. Greedy function approximation: a gradient boosting machine. *Ann Stat.* 2001;29(5):1189–232. doi: 10.1214/aos/1013203451
- [29] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in Python. *J Mach Learn Res.* 2011;12:2825–30.
- [30] Breiman L. Random forests. *Mach Learn.* 2001;45(1):5–32. doi: 10.1023/A:1010933404324
- [31] Holm S. A simple sequentially rejective multiple test procedure. *Scand J Stat.* 1979;6(2):65–70.
- [32] Piepho HP. An algorithm for a letter-based representation of all-pairwise comparisons. *J Comput Graph Stat.* 2004;13(2):456–66. doi: 10.1198/1061860043515