From linguistic evaluation to mechanistic verification: testing LLM-generated farm recommendations

João Serra[1,2,3*]; David Kraus[1,4]; Michal Antala[1,2]; Morten Graversgaard[1,2]; Meshach Ojo Aderele[1,2]; Jaber Rahimi[1,4]; Franca Giannini-Kurina[1]; Mary Grace Barbarias[1,2]; Tom Cripps[1,2]; Sevval Durmazbilek Frank[1,2]; Sheng Wang[1,2]; Claire Treat[1,2]; Klaus Butterbach-Bahl[1,2,4]

[1] Department of Agroecology, Aarhus University, Blichers Allé 20, 8830, Tjele, Denmark

[2] Pioneer Center Land-CRAFT, Department of Agroecology, Aarhus University, Aarhus, Denmark

[3] Forest Research Centre, Associate Laboratory TERRA, School of Agriculture, University of Lisbon, 1349-017, Lisbon, Portugal

[4] Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Karlsruhe Institute of Technology (KIT), Garmisch-Partenkirchen, Germany

* Corresponding author: jserra@agro.au.dk

Peer review status:

This is a non-peer-reviewed preprint submitted to EarthArXiv.

Abstract

Large language models (LLM) are increasingly used to generate farm-management advice, but their biophysical consequences remain largely unverified. We introduce a process-based verification framework that combines management portfolios generated by ChatGPT and Claude with the process-based model LandscapeDNDC across 11 contrasting agroecosystems. The LLMs produced agronomically plausible interventions, privileging changes in fertiliser timing, splitting and rates, and generally preserved crop yields. However, their agreement was markedly weaker for environmental targets like nitrogen losses and soil organic carbon. LLMs predicted the direction of agri-environmental change more reliably than its magnitude: directional agreement averaged 86%, whereas only 49% of simulated responses fell within the expected ranges. Portfolios that targeted several targets simultaneously rarely performed consistently across sites. Our results show that process-based models can screen AI-generated farm recommendations for environmental burden shifting before they are used in practice.

1. Introduction

Large language models (LLM), such as ChatGPT and Claude, are rapidly moving from general purpose tools into agriculture and environmental decision-making, including the generation of agronomic and farm management advice. Recent work has tested LLMs on tasks ranging from answering certified agronomist exams (Silva et al., 2023) to producing pest (Yang et al., 2024) or crop management advice (Wu et al., 2024).

However, the way these systems have been evaluated has remained largely linguistic or knowledge-based, judging whether advice is coherent, conventional or factually correct against reference information or expert rules, not whether its biophysical consequences match process-based simulations of both agricultural and environmental targets.

Agricultural systems are highly non-linear and coupled (Ahmed et al., 2025), where the change of one lever may lead to a rebound effect in others (Godinot et al., 2024). Changing management practices towards yield optimisation may come at the cost of environmental performance (Kanter et al., 2018), such as increasing losses via ammonia (NH_3) volatilisation, nitrous oxide (N_2O) emissions and nitrate leaching (NO_3^-) or decreasing soil organic carbon (SOC) sequestration (e.g., de Vries et al., 2024). Conversely, the opposite can occur if management practices target environmental performance with a reduction in crop yields.

Even plausible farm recommendations can thus shift agri-environmental burdens with unintended consequences elsewhere. Process-based models, such as LandscapeDNDC (Haas et al., 2013) and DAYCENT (Del Grosso et al., 2005), provide a way to test whether the recommended effects are mechanistically consistent since they simulate coupled nutrient-water dynamics, revealing whether a recommendation's rebound effect plays out the way claimed. Additionally, they are biophysically consistent due to the consistent use of mass balance checks and process constraints.

This positions process-based models as a verification layer that independently and mechanistically checks the management proposed by an external source. Although process-based crop models have been integrated into optimisation agents (Overweg et al., 2021), none has been used to verify whether management portfolios generated by general-purpose LLMs are coherent once coupled carbon, nitrogen and water processes are considered.

This is important given the consequences of poor advice are not equally visible. While yield losses are quickly detected by farmers and advisers, changes in NO_3^- leaching, NH_3 volatilisation, N_2O emissions or SOC are harder to observe and measure, and may emerge outside the field or over longer timescales. A recommendation can therefore appear agronomically sensible while shifting environmental burdens elsewhere. As LLMs move closer to practical advisory use, evaluating recommendations only through linguistic plausibility or agronomic convention is insufficient.

Here, we test whether agronomically plausible recommendations generated by LLMs are environmentally coherent once their consequences are evaluated within a mass-balanced representation of coupled carbon, nitrogen and water dynamics. We use ChatGPT and Claude to modify observed management practices within a constrained set of site-supported interventions and re-simulate the resulting portfolios with LandscapeDNDC. We next evaluate whether the LLMs anticipate the direction and magnitude of the simulated responses, whether the portfolios achieve their intended targets across sites and whether apparent improvements shift environmental burdens to non-targeted variables. More broadly, we examine the value of a proposer-verifier architecture in which generative models explore feasible management options while process-based models screen recommendations before practical use.

2. Methods

We demonstrate our framework using a stepwise procedure (**Figure 1a**) leveraging data from 11 demonstration sites grounded in observed management practices. We first designed a structured prompt file, so the LLMs redesigned the management data from the demonstration sites and exported their standardised suggestions into up to six management portfolios. We next conducted simulations using the observed and recommended management practices, and benchmarked and evaluated their overall agreement.

2.1. Observed agroecosystem data

We compiled 11 demonstration sites taken from the LandscapeDNDC sandbox, a curated collection of previously calibrated and evaluated data across the world. These sites are observed agroecosystem, spanning 10 countries and 6 Köppen-Geiger climate zones (**Figure 1b**), selected to represent contrasting climates and production systems rather than statistically representative samples. Each site is represented by LandscapeDNDC input files describing climate, soil properties, air chemistry, crop and field operations (organic and synthetic fertilisation, tillage, irrigation, sowing/harvesting and cutting).

These sites represent our baseline conditions. Sites were restricted to only crop- and grasslands, and ranged from temperate cereal systems to tropical rice, and from Global South- to North countries. Crop rotations include monocropping (e.g., maize, rice, cabbage), double cropping (e.g., spring wheat-winter wheat, maize-soybean) to complex crop rotations.

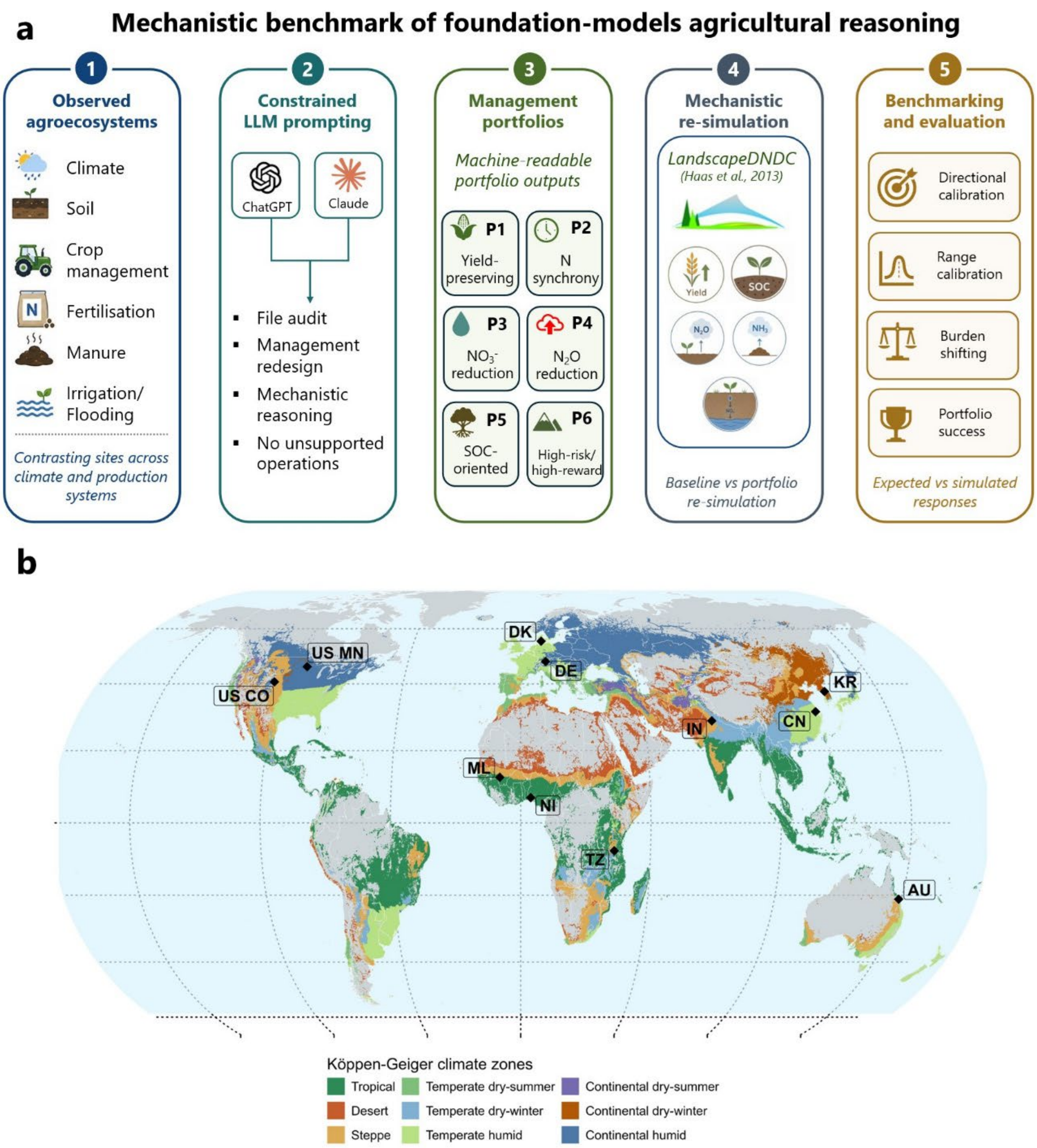

Figure 1. (a) Overview of main methodological steps from observed management practices in contrasting sites across the world, to LLMs prompting, re-design of management practices according to different portfolios, to a re-simulation using the process-based model LandscapeDNDC *(Haas et al., 2013)* to benchmark and evaluation of the environmental reasoning of both ChatGPT and Claude. **(b)** Spatial distribution of the selected sites and their respective Koppen-Geiger climate zones within cropland.

2.2. Experimental design

2.2.1. Mechanistic simulation with LandscapeDNDC

LandscapeDNDC is a simulation framework designed for terrestrial ecosystem models on site and regional scales (https://ldndc.imk-ifu.kit.edu/about/model.php;

(Haas et al., 2013). This process-based modelling framework can simulate carbon, nitrogen and water processes in cropland, grassland and forest. In this framework, a set of different modules are used to simulate plant growth and other processes: plant physiology (PlaMox), micro-climate (CanopyECM), water balance (WatercycleDNDC), air chemistry (airchemistryDNDC) and soil biogeochemistry (MeTrx) (Rahimi et al., 2024).

The model has been parameterized, calibrated, and validated using measurements gathered from a wide range of ecosystems, including temperate regions (Molina-Herrera et al., 2016), tropical areas (Kraus et al., 2015), and African savannahs (Rahimi et al., 2021). It has been used for different purposes, such as estimating yield gaps, grassland productivity, water balance, gaseous emissions, residue management, and NO_3^- leaching. The model has also been previously calibrated, validated, and used, for example, to simulate SOC, crop productivity, and soil GHG emissions in Denmark (Grados et al., 2024; Rahimi et al., 2024).

Importantly, we used calibrated site- and crop parameters for each site (data not shown).

Our objective here was not to test whether LLMs independently close carbon, nitrogen and water balances, but rather to test whether recommendations generated without explicit mass-balance constraints are coherent when evaluated with a mechanistic representation that imposes such constraints. Paired baseline and intervention simulations reduce the influence of systematic model biases, even though they do not eliminate uncertainty in the simulated response.

LandscapeDNDC should therefore be interpreted as a mechanistic stress-testing environment rather than as ground truth. LandscapeDNDC thus serves as a mechanistic reference with mass-balance and physical constraints that the LLMs lack, not as ground truth for agricultural and environmental processes.

2.2.2. Management portfolios generated by LLMs

LLMs. We selected ChatGPT v5.5 and Claude Opus v4.8 (last accessed 4 June 2026) as two frontier general-purpose foundation models capable of completing the full benchmarking workflow. We used both models via web interface. Model inclusion required the ability to: (i) ingest and audit the supplied LandscapeDNDC input files; (ii) generate management portfolios under the predefined agronomic constraints; (iii) distinguish observed, inferred and modified variables; and (iv) return valid machine-readable outputs that could be translated into LandscapeDNDC simulations.

Prompt. The LLM were prompted using a structured management redesign query aimed at generating coherent agricultural management portfolios from observed LandscapeDNDC input files. Specifically, we fed the LLMs with input files concerning climate, air chemistry, soil, field operations and species/soil parameters when available.

The prompt restricted recommendations to agronomically plausible and mechanistically interpretable changes, rather than allowing unconstrained advice. Specifically, the models were instructed to: (i) audit all LandscapeDNDC input files before proposing interventions; (ii) distinguish observed, inferred, modified, and unknown variables; (iii) avoid unsupported operations or fabricated values; and (iv) generate management changes only within the observed simulation period.

The prompt defined the primary objective as generating management portfolios capable of improving environmental performance while maintaining or minimally reducing yield relative to the observed baseline system. The target environmental objectives included (i) reducing NO_3^- leaching risk, (ii) reducing N_2O emission risk, (iii) improving nitrogen synchrony, (iv) reducing excessive mineral nitrogen exposure, and (v) maintaining or improving soil organic carbon where plausible.

LLMs were instructed to generate multiple internally coherent portfolio scenarios for each site-event case: P1 Conservative yield-preserving scenario, P2 Nitrogen synchrony, P3 NO_3^- leaching risk reduction, P4 N_2O emission risk reduction, P5 Soil carbon oriented, P6 (optional) High risk-reward portfolios.

These portfolios could simultaneously modify multiple management practices, including planting timing, harvest timing, fertilizer timing and splitting, manure timing, tillage operations, residue handling, and cover-crop management, provided that all interventions remained agronomically plausible according to the observed management practices.

We did not allow the LLMs to add field operations not described in each site to maximise the realism of the suggestions as some practices require machinery not readily available (e.g., for manure spreading or tillage). Additionally, we also deliberately avoided introducing LLM suggested crop rotations as specific seeds may not be available, as well as other inputs, such as different types of synthetic and organic fertilisers.

Our prompt further required explicit mechanistic reasoning linked to nutrient synchrony, mineral nitrogen exposure, crop uptake dynamics, denitrification risk, volatilization risk, residue effects, and seasonal hydrological conditions. The expected environmental responses were limited to qualitative or semi-quantitative pre-simulation expectations, and the model was explicitly instructed not to generate simulated results or precise process predictions.

Outputs. The outputs provided by the LLMs followed a fully structured JSON schema to ensure reproducibility and direct translation into LandscapeDNDC management modifications.

The output structure included: (i) input-file audits; (ii) compact baseline summaries; (iii) inventories of modifiable management operations; (iv) process-risk diagnoses; and (v) explicit management portfolios containing event-level modifications, mechanistic rationales, expected directional environmental effects, broad pre-simulation response ranges, trade-offs, uncertainty sources, and failure modes.

2.2.3. Mechanistic re-simulation

We next parsed the JSON files provided by the LLMs and re-generated the input files required to run LandscapeDNDC. The model was then used to re-simulate the generated management practices. These were then compared with the baseline simulations to quantify their relative change.

We compared the expected and simulated responses using both agricultural (crop yields) and environmental target **(**N_2O and NH_3 emissions, NO_3^- leaching and SOC sequestration) target variables.

2.3. Benchmarking and environmental agreement

2.3.1. Agreement metrics

To quantify the agreement with the mechanistic reasoning of the outputs generated for each portfolio per the LLMs, we benchmark direction and range relative to the process-based model.

Directional agreement. Did the LLM correctly predict the sign of change? For instance, is the expected reduction of N_2O emissions by the LLMs in line with the simulated changes by LDNDC?

Range agreement. Did the simulations fall within the LLM expected range? For each portfolio x site, the LLMs provided an expected range of change. For instance, the LLM expects that implementing the portfolio would lead to simulated changes between -10 and -25% and the LDNDC simulations show a -15% change, thus pointing to an agreement. We then computed the proportion of LDNDC simulations inside the LLM range.

We additionally used Pearson's correlation coefficient (r) to quantify the correspondence between the midpoint of the expected response range and the simulated response.

2.3.2. Intervention evaluation

We evaluated whether each management portfolio achieved its intended agri-environmental target relative to the corresponding baseline simulation. Success was defined using the simulated relative change in the portfolio-specific target variable.

The conservative yield-preserving portfolio (P1) was considered successful when yield losses did not exceed 2.5%. The nitrogen-synchrony portfolio (P2) was considered successful when nitrogen-use efficiency increased. The NO_3^- leaching reduction portfolio (P3) and N_2O-risk reduction portfolio (P4) were considered successful when NO_3^- leaching and N_2O emissions decreased, respectively. The soil-carbon-oriented portfolio (P5) was considered successful when SOC was maintained or increased.

As a current proof-of-concept, the higher-risk/high-reward portfolio (P6) was evaluated separately because it did not target a single target. We calculated an equally weighted environmental-gain index as:

$$\text{Environmental gain} = \frac{-\Delta NO_3^- - \Delta N_2O - \Delta NH_3 + \Delta SOC}{4}$$

where each term represents the percentage change relative to the baseline simulation. A P6 portfolio was classified as successful only when all environmental targets improved simultaneously: NO_3^- leaching, N_2O emissions and NH_3 emissions decreased, SOC increased, the mean environmental-gain index exceeded 2.5%, and yield losses remained below 2.5%. We deliberately used non-compensatory criterion where improvements in one target could not offset the reduction in another because the objective was to identify genuine multi-objective gains rather than burden shifting.

3. Results

3.1. LLMs are directionally useful but quantitatively discordant

LLMs predicted the correct direction of agri-environmental change substantially more often than they correctly guessed its magnitude (**Figure 2**) across agroecosystems and portfolios. The directional agreement was 86 ± 12% across sites-portfolios, but the within-range agreement was often below 50% (49 ± 18%). This gap between direction (83-89%) and quantitative agreement (~49%) was consistent in both ChatGPT and Claude and points that current LLMs encode stronger qualitative agri-environmental heuristics than a quantitative process-understanding.

We next examined how agreement varied among portfolios and sites. We found that directional agreement was also consistently high across the different portfolios but depended on the underlying objectives. Soil-carbon oriented (P5), conservative yield-preserving (P1) and N_2O risk reduction (P4) portfolios obtained the strongest directional agreement with LandscapeDNDC simulated responses, each averaging above 90%. The remaining portfolios showed lower, albeit still substantial, directional agreement, ranging from 77-83%.

Range agreement was weaker and more site-specific. The highest within-range agreement occurred in China, India, Mali, and South Korea, where 58-61% of simulated responses fell within the expected ranges. In contrast, Australia and the US Colorado site showed the lowest agreement, at 35% and 33%, respectively.

Quantitative agreement also varied strongly among response variables and climate regimes. Yield responses had the most consistent positive correspondence between expected and simulated changes (r = 0.2-0.6), whereas agreement was more moderate for N_2O emissions (r = 0.1-0.6), weak for NH_3 emissions, and close to zero for NO_3^- leaching and SOC. Some target-climate combinations were negatively correlated, particularly NO_3^- leaching in temperate systems (r = -0.3), where larger expected changes corresponded to smaller simulated responses.

Our results thus indicate that LLMs were often useful for identifying the likely direction of management effects, but markedly less reliable for estimating the magnitude of environmental responses governed by coupled hydrological and biogeochemical processes.

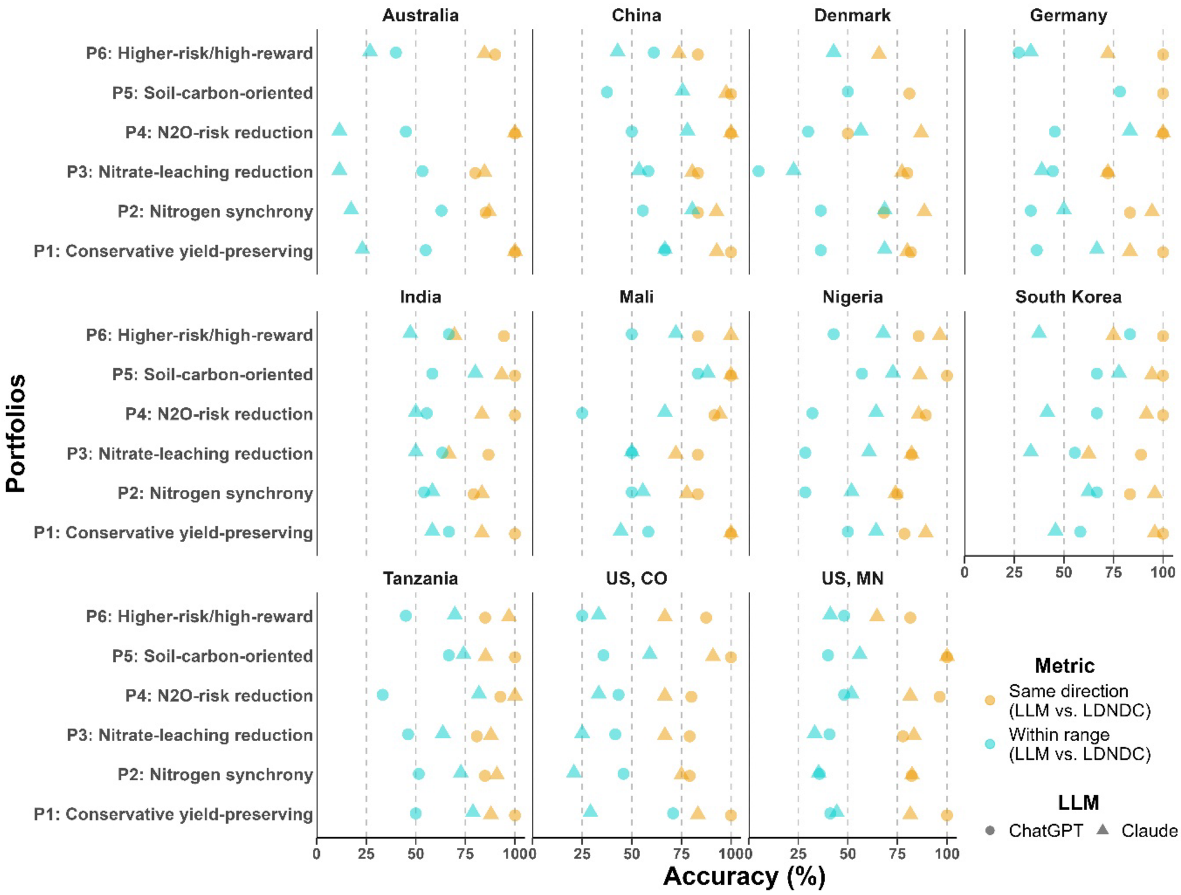

Figure 2. Directional and range agreement between LLM expectations and LandscapeDNDC simulated responses across sites and portfolios. The accuracy insofar as simulations where the recommended and observed practices followed the same direction (e.g., N_2O reductions were simulated in both) and the range expected by the LLMs were estimated.

3.2. Conservative portfolios succeed, but environmental performance is poorly transferable

Portfolio success, defined as the simulated response in line with the intended direction for that portfolio's target, varied markedly by portfolio type (**Figure 3**). Conservative yield-preserving portfolios (P1) succeeded almost universally, with overall success rates of 95-98% for Claude and ChatGPT. Contrastingly, the high-risk high-reward portfolio (P6) failed to achieve its objective at every site in both LLMs. The other portfolios were within these success rates but were far less consistent in their performance.

This consistency varied on a site-level. For P2-P5 portfolios, the success rates ranged from 0% to 100% for the same portfolio across different agroecosystems, so a strategy that succeeded at one site frequently failed at another. NO_3- leaching reduction (P3) and nitrogen-synchrony (P2) portfolios were the most variable in this respect, succeeding strongly at some sites while failing completely at others, pointing to a limited transferability of LLM reasoning across heterogeneous conditions.

Success profiles also differed between the two models. ChatGPT achieved higher success for N_2O risk reduction portfolios (P4; 75% versus 45%), whereas Claude performed better for soil carbon-oriented portfolios (P5; 52% versus 33%). While these differences cannot be interpreted as stable model properties, they indicate that both models did not converge on the same strengths across different agri-environmental targets.

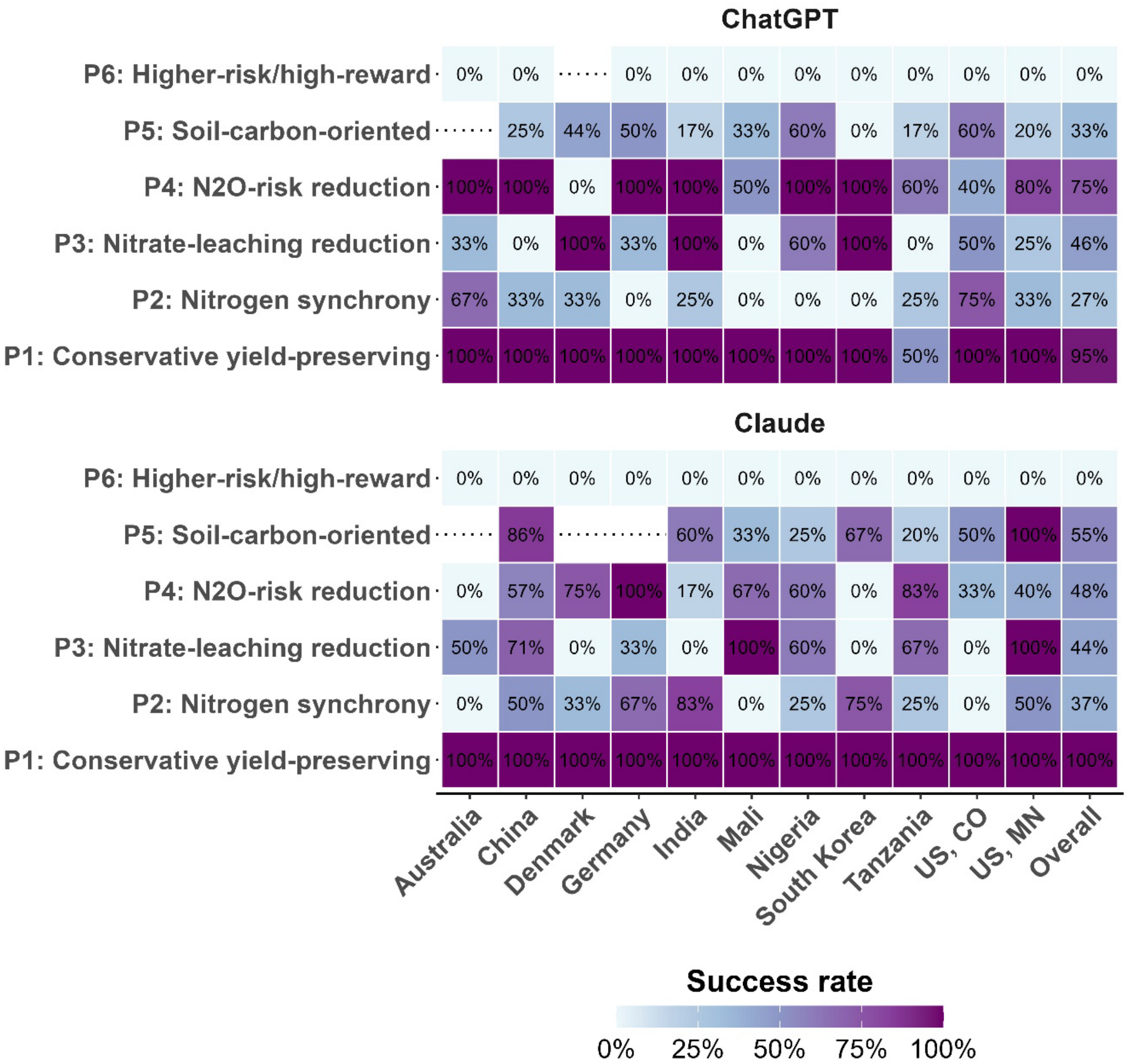

Figure 3. Portfolio objective success rate according to the different environmental targets.

3.3. Target specific portfolios reveal the risks of environmental burden shifting

Achieving the intended target of the portfolios did not necessarily translate into broader environmental improvements (Figure 4). Across the 84 evaluated site-LLM-portfolio combinations generated for the single target environmental portfolios (P2-P5), 35 achieved their intended objective. However, 18 out of these 35 also degraded the performance of at least one environmental non-target by more than 2.5% relative to the baseline. Environmental burden shifting therefore affected approximately half of the portfolios that would otherwise have been classified as successful.

This pattern was not restricted to a single portfolio. Burden shifting occurred in 5 of the 11 successful NO_3^- leaching reduction portfolios (P3), 7 of the 15 successful N_2O risk reduction portfolios (P4), and 4 of the 7 successful soil carbon-oriented portfolios

(P5). Both nitrogen-synchrony portfolios (P2) that increased NUE also worsened at least one non-target outcome, although the small number of successful cases limits interpretation.

The conservative yield-preserving portfolios (P1) provided an important counterpoint. Yield losses were below 2.5% in 21 of the 22 site × LLM combinations, but 13 of these yield-preserving cases still worsened at least one environmental outcome beyond the 2.5% threshold. Preserving yields was therefore not a reliable proxy for environmental coherence.

The higher-risk high-reward portfolios (P6) exposed the same tension from a multi-objective perspective. Portfolios generated by ChatGPT often reduced N_2O and NH_3 emissions, but these were frequently accompanied by increased NO_3^- leaching, SOC losses, or yield penalties. Conversely, those generated by Claude were generally more conservative with most responses remaining close to baseline, but they also rarely delivered broad multi-objective gains.

Our results demonstrate why farm management recommendations must not be evaluated against a single agri-environmental target alone. An intervention may appear successful while shifting environmental burdens toward other pathways.

Mechanistic verification is therefore needed not only to reject ineffective recommendations, but also to identify where apparently successful portfolios shift environmental burden across different pathways.

Figure 4. Site-specific trade-offs generated in the LLM management portfolios. Bars show the number of sites where each simulated outcome changed in a desirable direction (green), remained within ±2.5% threshold of the corresponding baseline (grey), or changed in an undesirable direction (red), according to the median response across simulation years. Black outlines identify the portfolio-specific target metric; P6 is not outlined since it targets multiple environmental outcomes simultaneously. Desirable changes in non-target variables represent co-benefits, whereas undesirable changes indicate potential environmental burden shifting.

4. Discussion

4.1. LLMs as qualitative environmental priors

The direction of agri-environmental target variables expected by LLMs was generally in line with a process-based simulation. However, the expected magnitude was more erratic and, sometimes, even negatively correlated with the mechanistic simulation.

A clear target gradient emerged (yield > N_2O > NH_3 > NO_3^-/SOC) consistent across different sites and climate conditions. This gradient likely reflects how closely each response is tied to the management the models changed.

Yield responded fairly directly to fertiliser amount and timing, the levers the models adjusted. This is a well-documented relationship in agronomy, so the models had a reasonable sense of how large the response would be. N_2O and NH_3 emissions had a weaker response to management, as while both are driven by the amount of the nitrogen supplied, their magnitude depends on soil temperature, moisture and other environmental conditions during or immediately preceding field operations such as irrigation, tillage or fertilisation. NO_3^- leaching is often more strongly mediated by hydrological conditions, particularly drainage, precipitation and irrigation, which determine whether the residual mineral nitrogen is transported below the root zone. SOC responses are more challenging as they result from slow and interacting changes in carbon inputs, decomposition and stabilisation processes, often against large pre-existing soil carbon stocks.

The LLMs therefore performed best when the target response was relatively direct, visible and well represented in agronomic knowledge. Their performance deteriorated for slower, weather-mediated and indirectly observed environmental processes. This is precisely where having a mechanistic verification layer becomes more valuable. Crop yields are already routinely monitored and optimised by farmers and other advisors. Conversely, environmental targets are less visible, more site-dependent and more difficult to infer from only changes in management practices.

This interpretation is reinforced by how the models were no better, sometimes even worse, on a portfolio's own target objective. Explicitly prompting a NO_3^- leaching or SOC objective did not ensure a stronger agreement with the simulated responses and, in some cases, the performance was worse for the intended target itself. The success gradient of the portfolios further suggests that performance depended on the extent to which the recommended management perturbed the observed system: conservative and small-change portfolios obtained high success rates as they barely perturb the observed systems, whereas aggressive multi-objective portfolios faced trade-offs that made success harder to measure. Despite purposely flagged as high-risk high-reward, its low success rate indicates that LLMs may still underestimate the environmental risks associated with more ambitious interventions.

LLMs therefore appear to encode useful qualitative agri-environmental heuristics, but not a well calibrated representation of coupled carbon, nitrogen and water dynamics. Making this distinction is important for how these systems can be used in agricultural decision support: LLMs can generate plausible interventions but not act as autonomous optimisers as their recommendations still require an independent mechanistic verification.

4.2. Hidden environmental trade-offs require external verification

The uneven agreement between the expectations of LLMs and LandscapeDNDC simulations motivates a proposer-verifier architecture for agri-environmental decision support. In this architecture, LLMs generate plausible interventions given on-farm constraints, synthesise agronomic knowledge and explore alternative management strategies. Process-based models then act as an independent verification layer, testing whether the expected consequences are plausible once the proposed interventions are re-simulated within the coupled carbon, nitrogen and water dynamics.

This division of functions is particularly important as LLMs performed least reliably for the environmental targets that are hardest to observe directly. A recommendation may appear agronomically plausible and preserve crop yields while still shifting environmental burdens or amplifying losses under specific hydrological and climatic conditions, the kind of consequence a mechanistic verifier can identify but the LLMs could not.

The site-level variability further limits the extent to which LLMs can be generalised across different agroecosystems. The same portfolio produced distinctly different success rates per site, with some objectives ranging from near success to complete failure depending. This indicates that apparently transferable agronomic heuristics can break down when applied across contrasting climates, soil conditions and management regimes. This is also a known challenge across agricultural management services (Schut and Giller, 2020) and the mitigation potential of environmental losses (Cui et al., 2024). Mechanistic verification is therefore not only a safeguard against implausible recommendations, but also a way of identifying where otherwise reasonable interventions stop to be environmentally coherent.

Our framework should not be interpreted as a fully operational digital twin. LandscapeDNDC was used here as a common mechanistic stress testing environment rather than an empirically calibrated reference point. A mature digital-twin architecture would require site-specific calibration, data assimilation and uncertainty propagation. Nevertheless, we demonstrate the usefulness of separating recommendation prompts from a mechanistic verification. LLMs can suggest a wider range of management options, but process-based models are needed to test whether those options remain plausible under local biophysical conditions.

4.3. Limitations

Several limitations should be considered when interpreting our preliminary results. First, the benchmark was conducted across a limited set of demonstration sites selected to represent contrasting agroecosystems rather than a statistically representative sample of global farming systems. Second, LandscapeDNDC was used as a single mechanistic verifier without spin up period. This is particularly important for SOC, whose response depends on long-term carbon dynamics and initial conditions (Giannini-Kurina et al., 2025). Third, our comparison remains a model-versus-model evaluation: LandscapeDNDC imposes mass-balance and process constraints, but its simulated responses should not be interpreted as empirical ground truth. Fourth, LLM outputs may vary across model versions, prompt wording, interfaces and repeated runs. Lastly, the benchmark focused primarily on carbon and nitrogen dynamics and did not explicitly test whether phosphorus, micronutrient or operational constraints could limit the feasibility of the proposed interventions.

Ongoing work is extending this proof-of-concept with repeated prompts, additional models, different interfaces and independent plausibility checks of the generated management portfolios.

5. Conclusions

Here we show how two large language models (Claude and ChatGPT) generated agronomically plausible management portfolios and frequently anticipated the direction of agri-environmental change. However, their quantitative agreement with the process-based simulations using the model LandscapeDNDC remained uneven. Environmental responses were less transferable across sites than crop yield responses, particularly for nitrate leaching, ammonia emissions and soil organic carbon. Our results support a hybrid decision-support architecture in which large language models explore candidate interventions while process-based models provide an external mechanistic verification layer before recommendations are applied in practice.

References

Ahmed, N., Xinagyu, G., Alnafissa, M., Ali, A., Ullah, H., 2025. Linear and non-linear impact of key agricultural components on greenhouse gas emissions. Sci Rep 15, 5314. https://doi.org/10.1038/s41598-025-88159-1

Allu, A.R., Mesapam, S., 2025. Impact of remote sensing data fusion on agriculture applications: A review. European Journal of Agronomy 164, 127478. https://doi.org/10.1016/j.eja.2024.127478

Aramburu-Merlos, F., van Loon, M.P., van Ittersum, M.K., Grassini, P., 2024. High-resolution global maps of yield potential with local relevance for targeted crop production improvement. Nat Food 1–6. https://doi.org/10.1038/s43016-024-01029-3

Cui, X., Bo, Y., Adalibieke, W., Winiwarter, W., Zhang, X., Davidson, E.A., Sun, Z., Tian, H., Smith, P., Zhou, F., 2024. The global potential for mitigating nitrous oxide emissions from croplands. One Earth 7, 401–420. https://doi.org/10.1016/j.oneear.2024.01.005

de Vries, W., Posch, M., Simpson, D., de Leeuw, F.A.A.M., van Grinsven, H.J.M., Schulte-Uebbing, L.F., Sutton, M.A., Ros, G.H., 2024. Trends and geographic variation in adverse impacts of nitrogen use in Europe on human health, climate, and ecosystems: A review. Earth-Science Reviews 253, 104789. https://doi.org/10.1016/j.earscirev.2024.104789

Del Grosso, S.J., Mosier, A.R., Parton, W.J., Ojima, D.S., 2005. DAYCENT model analysis of past and contemporary soil N2O and net greenhouse gas flux for major crops in the USA. Soil and Tillage Research, Greenhouse Gas Contributions and Mitigation Potential in Agricultural Regions of North America 83, 9–24. https://doi.org/10.1016/j.still.2005.02.007

Giannini-Kurina, F., Serra, J., Christensen, B.T., Eriksen, J., Hutchings, N.J., Olesen, J.E., Jensen, J.L., 2025. Modelling and validating soil carbon dynamics at the long-term plot scale using the *rCTOOL* R package. Environmental Modelling & Software 183, 106229. https://doi.org/10.1016/j.envsoft.2024.106229

Godinot, O., Jouan, J., Nesme, T., Carof, M., 2024. Evidence of a rebound effect in agriculture: Crop-livestock reconnection beyond the farm gate does not always lead to more sustainable nitrogen management. Agricultural Systems 221, 104137. https://doi.org/10.1016/j.agsy.2024.104137

Grados, D., Kraus, D., Haas, E., Butterbach-Bahl, K., Olesen, J.E., Abalos, D., 2024. Common agronomic adaptation strategies to climate change may increase soil greenhouse gas emission in Northern Europe. Agricultural and Forest Meteorology 349, 109966. https://doi.org/10.1016/j.agrformet.2024.109966

Haas, E., Klatt, S., Fröhlich, A., Kraft, P., Werner, C., Kiese, R., Grote, R., Breuer, L., Butterbach-Bahl, K., 2013. LandscapeDNDC: a process model for simulation of biosphere–atmosphere–hydrosphere exchange processes at site and regional scale. Landscape Ecol 28, 615–636. https://doi.org/10.1007/s10980-012-9772-x

Kanter, D.R., Musumba, M., Wood, S.L.R., Palm, C., Antle, J., Balvanera, P., Dale, V.H., Havlik, P., Kline, K.L., Scholes, R.J., Thornton, P., Tittonell, P., Andelman, S., 2018. Evaluating agricultural trade-offs in the age of sustainable development. Agricultural Systems, Agricultural Systems Perspectives on Global Food Security 163, 73–88. https://doi.org/10.1016/j.agsy.2016.09.010

Kraus, D., Weller, S., Klatt, S., Haas, E., Wassmann, R., Kiese, R., Butterbach-Bahl, K., 2015. A new LandscapeDNDC biogeochemical module to predict CH4 and N2O emissions from lowland rice and upland cropping systems. Plant Soil 386, 125–149. https://doi.org/10.1007/s11104-014-2255-x

Molina-Herrera, S., Haas, E., Klatt, S., Kraus, D., Augustin, J., Magliulo, V., Tallec, T., Ceschia, E., Ammann, C., Loubet, B., Skiba, U., Jones, S., Brümmer, C., Butterbach-Bahl, K., Kiese, R., 2016. A modeling study on mitigation of N2O emissions and NO3 leaching at different agricultural sites across Europe using LandscapeDNDC. Science of The Total Environment 553, 128–140. https://doi.org/10.1016/j.scitotenv.2015.12.099

Overweg, H., Berghuijs, H.N.C., Athanasiadis, I.N., 2021. CropGym: a Reinforcement Learning Environment for Crop Management. https://doi.org/10.48550/arXiv.2104.04326

Rahimi, J., Ago, E.E., Ayantunde, A., Berger, S., Bogaert, J., Butterbach-Bahl, K., Cappelaere, B., Cohard, J.-M., Demarty, J., Diouf, A.A., Falk, U., Haas, E., Hiernaux, P., Kraus, D., Roupsard, O., Scheer, C., Srivastava, A.K., Tagesson, T., Grote, R., 2021. Modeling gas exchange and biomass production in West African Sahelian and Sudanian ecological zones. Geoscientific Model Development 14, 3789–3812. https://doi.org/10.5194/gmd-14-3789-2021

Rahimi, J., Haas, E., Scheer, C., Grados, D., Abalos, D., Aderele, M.O., Blicher-Mathiesen, G., Butterbach-Bahl, K., 2024. Aggregation of activity data on crop management can induce large uncertainties in estimates of regional nitrogen budgets. npj Sustain. Agric. 2, 7. https://doi.org/10.1038/s44264-024-00015-3

Schut, A.G.T., Giller, K.E., 2020. Soil-based, field-specific fertilizer recommendations are a pipe-dream. Geoderma 380, 114680. https://doi.org/10.1016/j.geoderma.2020.114680

Silva, B., Nunes, L., Estevão, R., Aski, V., Chandra, R., 2023. GPT-4 as an Agronomist Assistant? Answering Agriculture Exams Using Large Language Models. https://doi.org/10.48550/arXiv.2310.06225

Wu, J., Lai, Z., Chen, S., Tao, R., Zhao, P., Hovakimyan, N., 2024. The New Agronomists: Language Models are Experts in Crop Management. https://doi.org/10.48550/arXiv.2403.19839

Yang, S., Yuan, Z., Li, S., Peng, R., Liu, K., Yang, P., 2024. GPT-4 as Evaluator: Evaluating Large Language Models on Pest Management in Agriculture. https://doi.org/10.48550/arXiv.2403.11858