

1 From linguistic evaluation to mechanistic verification: testing LLM-generated 2 farm recommendations

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18 Abstract

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

33 1. Introduction

34 Large language models (LLM), such as ChatGPT and Claude, are rapidly moving
35 from general purpose tools into agriculture and environmental decision-making,

36 including the generation of agronomic and farm management advice. Recent work
37 has tested LLMs on tasks ranging from answering certified agronomist exams (Silva
38 et al., 2023) to producing pest (Yang et al., 2024) or crop management advice (Wu et
39 al., 2024).

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

45 Agricultural systems are highly non-linear and coupled (Ahmed et al., 2025), where
46 the change of one lever may lead to a rebound effect in others (Godinot et al., 2024).
47 Changing management practices towards yield optimisation may come at the cost of
48 environmental performance (Kanter et al., 2018), such as increasing losses via
49 ammonia (NH₃) volatilisation, nitrous oxide (N₂O) emissions and nitrate leaching
50 (NO₃⁻) or decreasing soil organic carbon (SOC) sequestration (e.g., de Vries et al.,
51 2024). Conversely, the opposite can occur if management practices target
52 environmental performance with a reduction in crop yields.

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

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

67 This is important given the consequences of poor advice are not equally visible.
68 While yield losses are quickly detected by farmers and advisers, changes in NO₃⁻
69 leaching, NH₃ volatilisation, N₂O emissions or SOC are harder to observe and
70 measure, and may emerge outside the field or over longer timescales. A
71 recommendation can therefore appear agronomically sensible while shifting
72 environmental burdens elsewhere. As LLMs move closer to practical advisory use,
73 evaluating recommendations only through linguistic plausibility or agronomic
74 convention is insufficient.

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

87 2. Methods

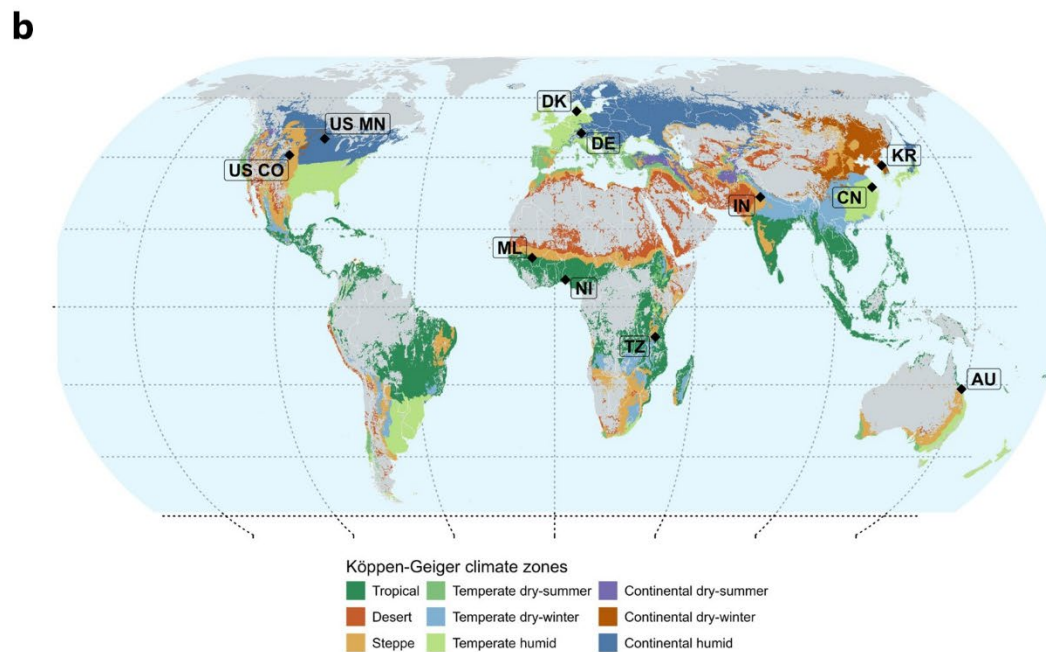
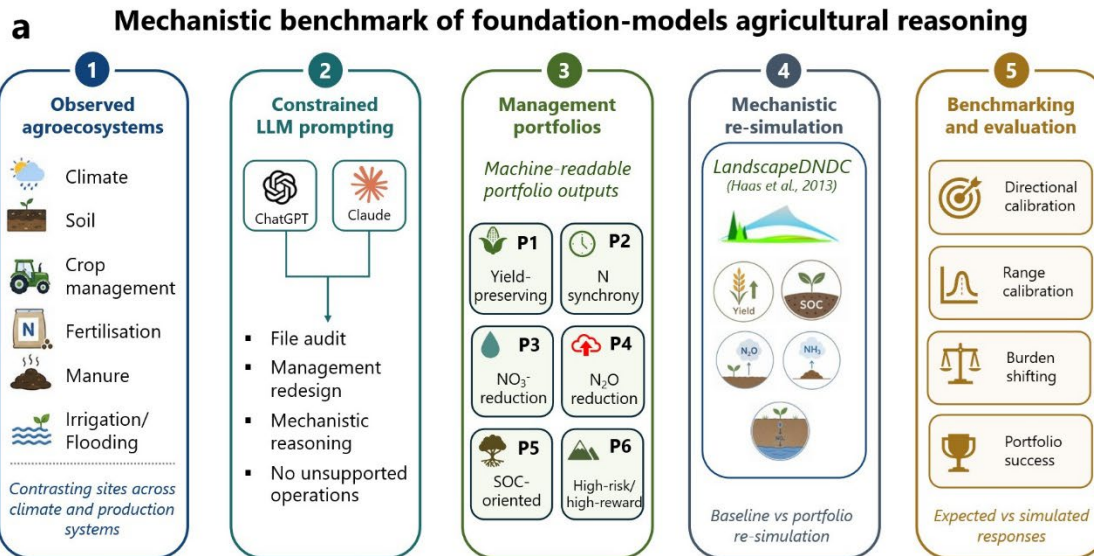
88 We demonstrate our framework using a stepwise procedure ([Figure 1a](#)) leveraging
89 data from 11 demonstration sites grounded in observed management practices. We
90 first designed a structured prompt file, so the LLMs redesigned the management
91 data from the demonstration sites and exported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

95 2.1. Observed agroecosystem data

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

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

109



110

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

118 **2.2. Experimental design**

119 **2.2.1. Mechanistic simulation with LandscapeDNDC**

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

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

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

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

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

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

148 2.2.2. Management portfolios generated by LLMs

149 **LLMs.** We selected ChatGPT v5.5 and Claude Opus v4.8 (last accessed 4 June
150 2026) as two frontier general-purpose foundation models capable of completing the
151 full benchmarking workflow. We used both models via web interface. Model inclusion
152 required the ability to: (i) ingest and audit the supplied LandscapeDNDC input files;
153 (ii) generate management portfolios under the predefined agronomic constraints; (iii)
154 distinguish observed, inferred and modified variables; and (iv) return valid machine-
155 readable outputs that could be translated into LandscapeDNDC simulations.

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

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

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

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

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

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

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

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

197 The output structure included: (i) input-file audits; (ii) compact baseline summaries;
198 (iii) inventories of modifiable management operations; (iv) process-risk diagnoses;
199 and (v) explicit management portfolios containing event-level modifications,

200 mechanistic rationales, expected directional environmental effects, broad pre-
201 simulation response ranges, trade-offs, uncertainty sources, and failure modes.

202 2.2.3. Mechanistic re-simulation

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

207 We compared the expected and simulated responses using both agricultural (crop
208 yields) and environmental target (N₂O and NH₃ emissions, NO₃⁻ leaching and SOC
209 sequestration) target variables.

210 2.3. Benchmarking and environmental agreement

211 2.3.1. Agreement metrics

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

215 **Directional agreement.** Did the LLM correctly predict the sign of change? For
216 instance, is the expected reduction of N₂O emissions by the LLMs in line with the
217 simulated changes by LDNDC?

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

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

227 2.3.2. Intervention evaluation

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

231 The conservative yield-preserving portfolio (P1) was considered successful when
232 yield losses did not exceed 2.5%. The nitrogen-synchrony portfolio (P2) was
233 considered successful when nitrogen-use efficiency increased. The NO₃⁻ leaching
234 reduction portfolio (P3) and N₂O-risk reduction portfolio (P4) were considered
235 successful when NO₃⁻ leaching and N₂O emissions decreased, respectively. The

236 soil-carbon-oriented portfolio (P5) was considered successful when SOC was
237 maintained or increased.

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

$$241 \quad \text{Environmental gain} = \frac{-\Delta\text{NO}_3^- - \Delta\text{N}_2\text{O} - \Delta\text{NH}_3 + \Delta\text{SOC}}{4}$$

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

250 3. Results

251 3.1. LLMs are directionally useful but quantitatively 252 discordant

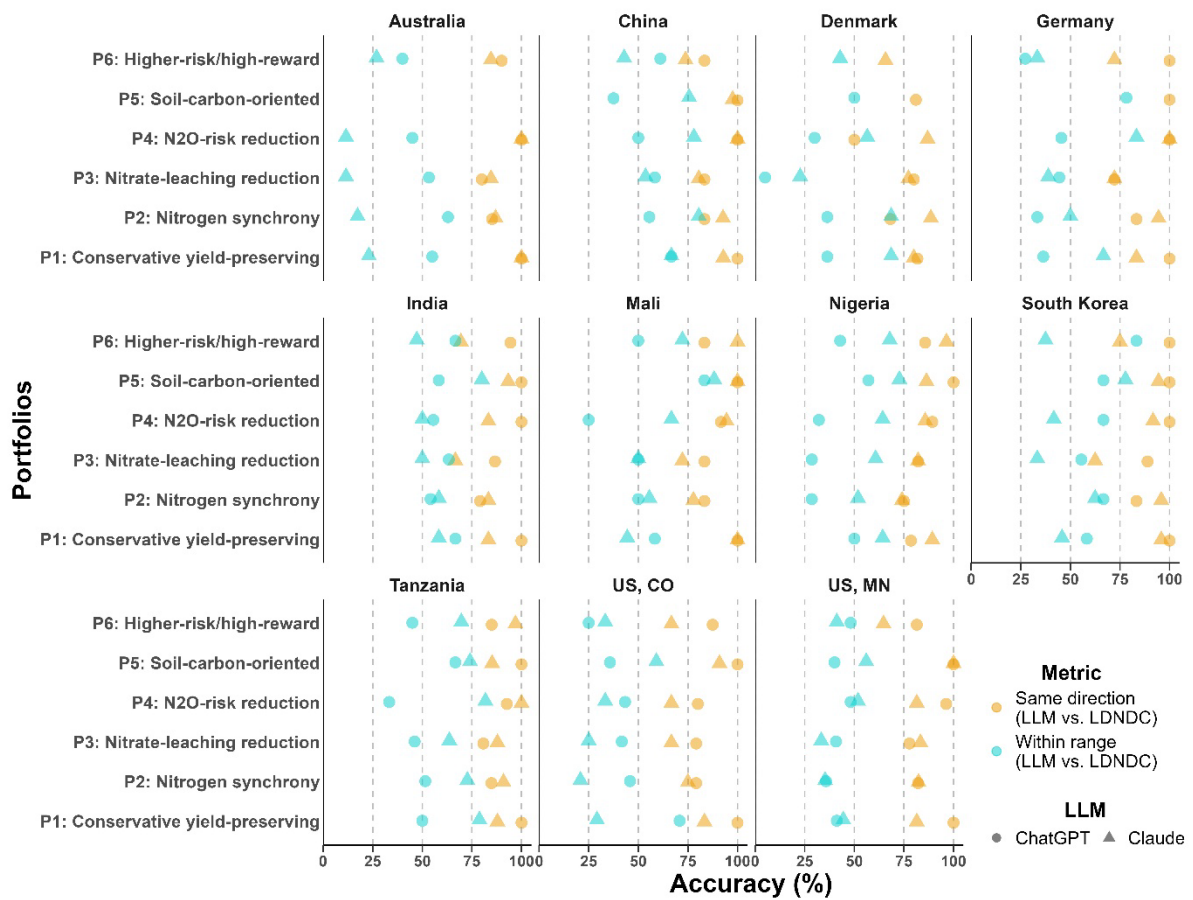
253 LLMs predicted the correct direction of agri-environmental change substantially more
254 often than they correctly guessed its magnitude (**Figure 2**) across agroecosystems
255 and portfolios. The directional agreement was $86 \pm 12\%$ across sites-portfolios, but
256 the within-range agreement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

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

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

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

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



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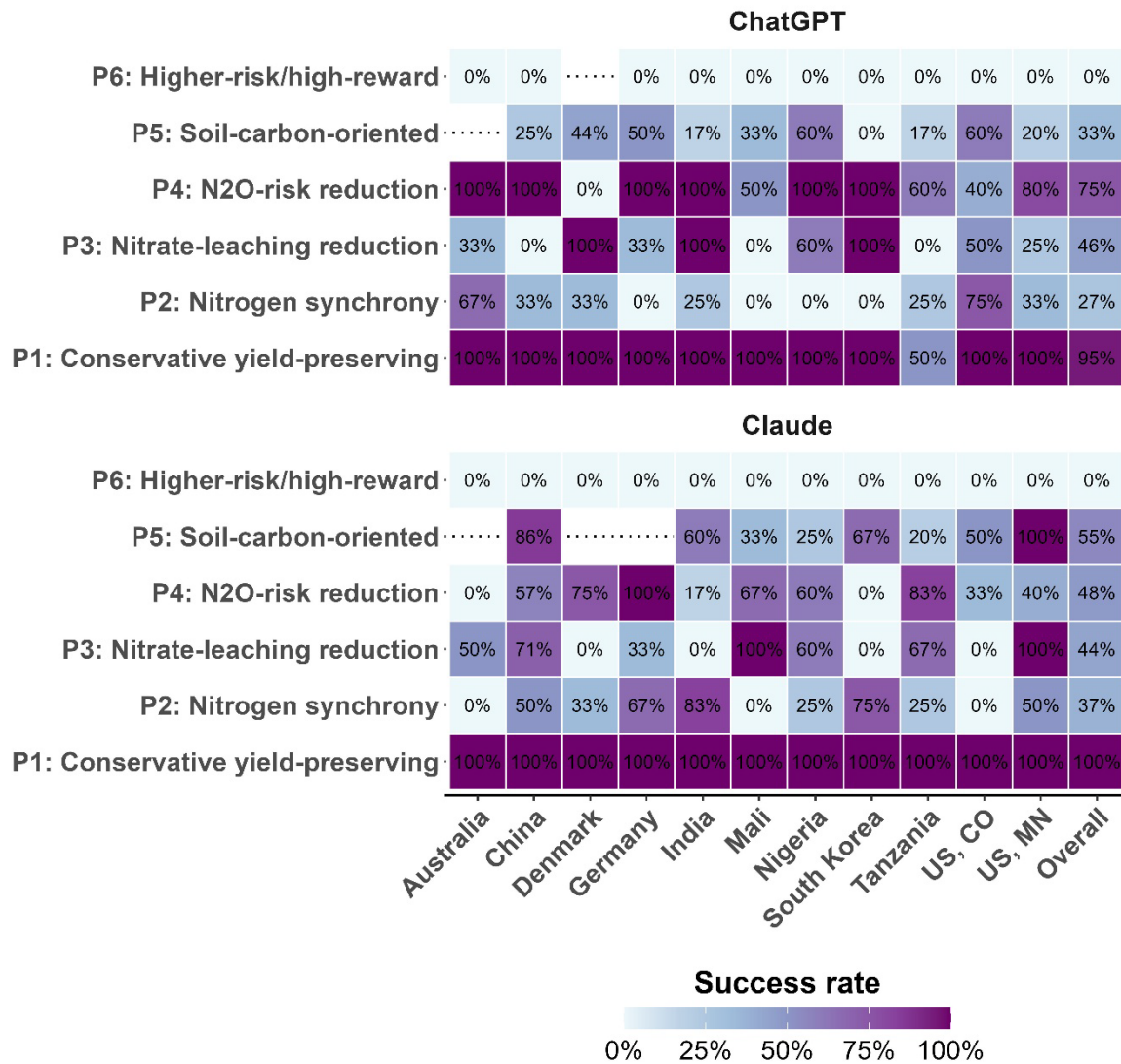
283 **Figure 2.** Directional and range agreement between LLM expectations and
 284 LandscapeDNDC simulated responses across sites and portfolios. The accuracy
 285 insofar as simulations where the recommended and observed practices followed the
 286 same direction (e.g., N_2O reductions were simulated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

288 3.2. Conservative portfolios succeed, but environmental 289 performance is poorly transferable

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

297 This consistency varied on a site-level. For P2-P5 portfolios, the success rates
298 ranged from 0% to 100% for the same portfolio across different agroecosystems, so
299 a strategy that succeeded at one site frequently failed at another. NO₃- leaching
300 reduction (P3) and nitrogen-synchrony (P2) portfolios were the most variable in this
301 respect, succeeding strongly at some sites while failing completely at others, pointing
302 to a limited transferability of LLM reasoning across heterogeneous conditions.

303 Success profiles also differed between the two models. ChatGPT achieved higher
304 success for N₂O risk reduction portfolios (P4; 75% versus 45%), whereas Claude
305 performed better for soil carbon-oriented portfolios (P5; 52% versus 33%). While
306 these differences cannot be interpreted as stable model properties, they indicate that
307 both models did not converge on the same strengths across different agri-
308 environmental targets.



309

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

312 **3.3. Target specific portfolios reveal the risks of**
 313 **environmental burden shifting**

314 Achieving the intended target of the portfolios did not necessarily translate into
 315 broader environmental improvements (Figure 4). Across the 84 evaluated site-LLM-
 316 portfolio combinations generated for the single target environmental portfolios (P2-
 317 P5), 35 achieved their intended objective. However, 18 out of these 35 also
 318 degraded the performance of at least one environmental non-target by more than
 319 2.5% relative to the baseline. Environmental burden shifting therefore affected
 320 approximately half of the portfolios that would otherwise have been classified as
 321 successful.

322 This pattern was not restricted to a single portfolio. Burden shifting occurred in 5 of
 323 the 11 successful NO₃⁻ leaching reduction portfolios (P3), 7 of the 15 successful N₂O
 324 risk reduction portfolios (P4), and 4 of the 7 successful soil carbon-oriented portfolios

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

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

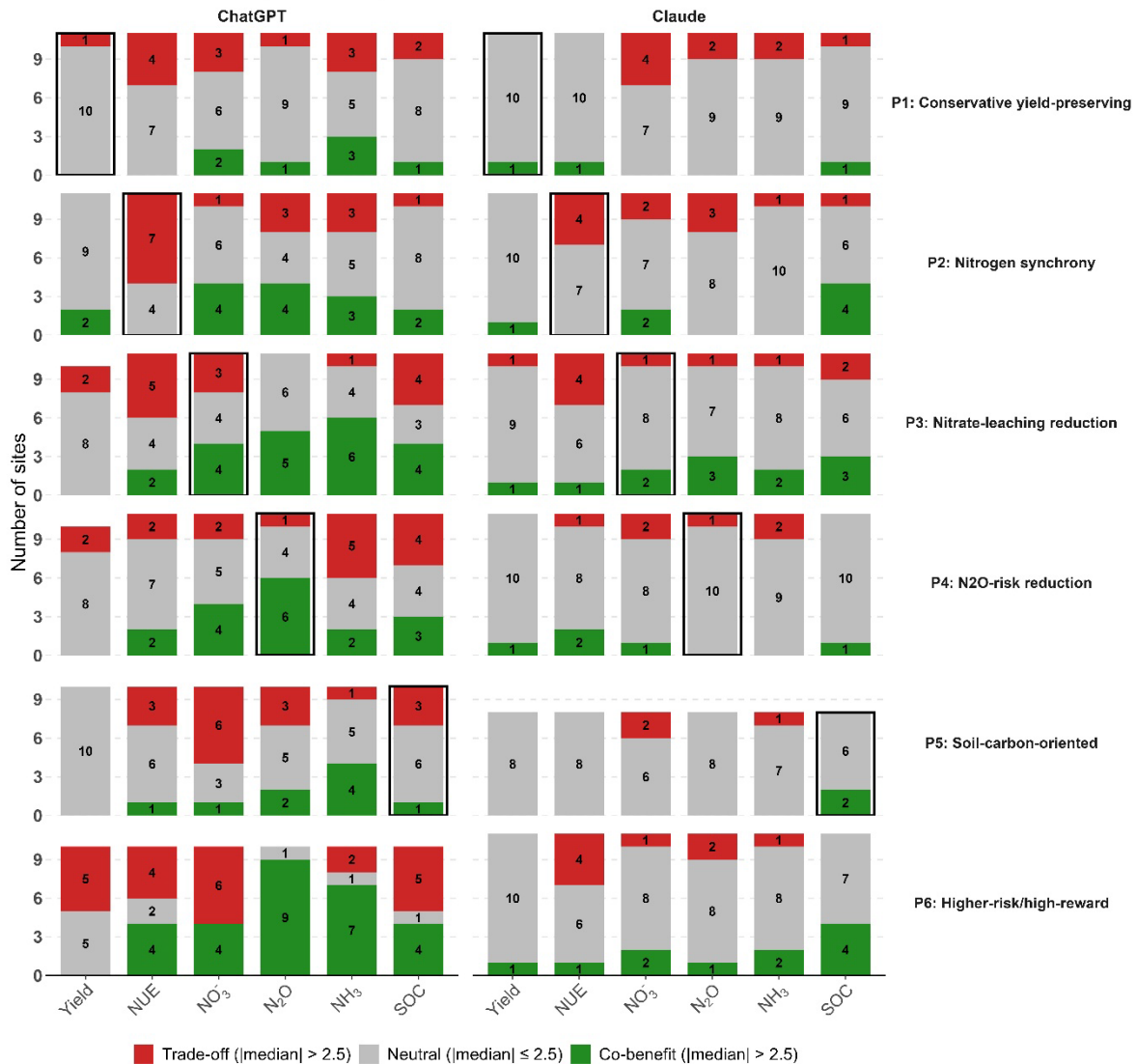
333 The higher-risk high-reward portfolios (P6) exposed the same tension from a multi-
334 objective perspective. Portfolios generated by ChatGPT often reduced N₂O and NH₃
335 emissions, but these were frequently accompanied by increased NO₃⁻ leaching, SOC
336 losses, or yield penalties. Conversely, those generated by Claude were generally
337 more conservative with most responses remaining close to baseline, but they also
338 rarely delivered broad multi-objective gains.

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

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

Portfolio trade-offs: site-level outcome counts

Number of sites where each metric improved (co-benefit), worsened (trade-off), or stayed neutral. Classification based on median % change across simulation years.



345

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

354 4. Discussion

355 4.1. LLMs as qualitative environmental priors

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

359 A clear target gradient emerged (yield > N₂O > NH₃ > NO₃⁻/SOC) consistent across
360 different sites and climate conditions. This gradient likely reflects how closely each
361 response is tied to the management the models changed.

362 Yield responded fairly directly to fertiliser amount and timing, the levers the models
363 adjusted. This is a well-documented relationship in agronomy, so the models had a
364 reasonable sense of how large the response would be. N₂O and NH₃ emissions had
365 a weaker response to management, as while both are driven by the amount of the
366 nitrogen supplied, their magnitude depends on soil temperature, moisture and other
367 environmental conditions during or immediately preceding field operations such as
368 irrigation, tillage or fertilisation. NO₃⁻ leaching is often more strongly mediated by
369 hydrological conditions, particularly drainage, precipitation and irrigation, which
370 determine whether the residual mineral nitrogen is transported below the root zone.
371 SOC responses are more challenging as they result from slow and interacting
372 changes in carbon inputs, decomposition and stabilisation processes, often against
373 large pre-existing soil carbon stocks.

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

381 This interpretation is reinforced by how the models were no better, sometimes even
382 worse, on a portfolio's own target objective. Explicitly prompting a NO₃⁻ leaching or
383 SOC objective did not ensure a stronger agreement with the simulated responses
384 and, in some cases, the performance was worse for the intended target itself. The
385 success gradient of the portfolios further suggests that performance depended on
386 the extent to which the recommended management perturbed the observed system:
387 conservative and small-change portfolios obtained high success rates as they barely
388 perturb the observed systems, whereas aggressive multi-objective portfolios faced
389 trade-offs that made success harder to measure. Despite purposely flagged as high-
390 risk high-reward, its low success rate indicates that LLMs may still underestimate the
391 environmental risks associated with more ambitious interventions.

392 LLMs therefore appear to encode useful qualitative agri-environmental heuristics, but
393 not a well calibrated representation of coupled carbon, nitrogen and water dynamics.
394 Making this distinction is important for how these systems can be used in agricultural
395 decision support: LLMs can generate plausible interventions but not act as
396 autonomous optimisers as their recommendations still require an independent
397 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

438 important for SOC, whose response depends on long-term carbon dynamics and
439 initial conditions (Giannini-Kurina et al., 2025). Third, our comparison remains a
440 model-versus-model evaluation: LandscapeDNDC imposes mass-balance and
441 process constraints, but its simulated responses should not be interpreted as
442 empirical ground truth. Fourth, LLM outputs may vary across model versions, prompt
443 wording, interfaces and repeated runs. Lastly, the benchmark focused primarily on
444 carbon and nitrogen dynamics and did not explicitly test whether phosphorus,
445 micronutrient or operational constraints could limit the feasibility of the proposed
446 interventions.

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

450 5. Conclusions

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

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