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Data Driven Prediction of Nutrient Retention and Crop Productivity in Biochar Amended Soils

Lauren Lazaro
Agronomy, Kansas State University, 1712 Claflin Road, Manhattan, Kansas 66506-0110, USA.
lazarola@ksu.edu

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Corresponding author(s):
Lauren Lazaro, Agronomy, Kansas State University, 1712 Claflin Road, Manhattan, Kansas 66506-0110, USA
Email: lazarola@ksu.edu

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Abstract - While biochar has positive potential effects on nutrient retention and crop yield, the impact can vary from very positive to very negative based on soil, biochar properties and management, making dose and feedstock choices challenging. In this paper we build a data driven model to predict two outcomes of biochar amendment: yield response and nitrate leaching reduction, from soil and biochar properties, crop and management parameters, and explain, quantify the uncertainty of their predictions and convert them into dose recommendations and field prescription maps. Six learners were compared for this synthetic meta-dataset, which consisted of 1431 treatment–control observations from 160 studies with known response mechanisms and was limited to a study-level structure. Random forests was generally the highest performing algorithm for both target variables ($R^2 = 0.37$ for yield response and $R^2 = 0.39$ for leaching reduction on held-out studies); the error of the linear regression was up to 50 % lower for both targets. The pH of the soil and the dose had the largest influence on yield response and dose and biochar surface area on nutrient retention. Split-conformal intervals with empirical coverage at the 90 % level of 90 % exceeded the naive Gaussian intervals (65 %), although they were under-covered for higher dose observations (72 %). The optimal dose was found to be sensitive to the cost and duration of benefits of biochar, and that model-based variable-rate prescriptions performed better than a single dose of 10 t ha−1 in all nine economic scenarios tested.

Keywords - Biochar, Nutrient Retention, Nitrate Leaching, Crop Productivity, Uncertainty Quantification, Precision Soil Management.

I. INTRODUCTION

Biochar, carbon-rich product of biomass pyrolysis, has been suggested to be used as soil amendment to store carbon in soil for long periods and enhance soil functions [1]. Its properties are significantly influenced by feedstock and pyrolysis conditions and the field of biochar science and practice has expanded to include production technology, soil effects, environmental impacts and implementation [2]. It is quantitatively weak and moderate, with a large positive effect in acidic, weathered and coarse textured soil, and small or negative effects in other soil types [3,4]. Mechanistically, biochar can increase the soil pH through oxidisation of its surfaces [5], increase the cation exchange capacity (CEC) of the soil [5, 6], bind mineral nitrogen to the surface by sorption and thus prevent the loss of ammonia and nitrite [7] in column and field studies. Biochar can also immobilize nitrogen, affect nitrous oxide emissions and negatively impact alkaline soils if applied at high rates [8].

This variability is the key issue for a farmer or a planner. The recommendation to introduce 10 t/ha of biochar is based on the idea that the same dose can increase yield by 25% in an acidic sandy soil and decrease yield in an alkaline clay soil. Meta-analyses present average effects and differences between subgroups, but cannot predict the effect of a specific combination of biochar, soil and crop. As in many other areas, machine learning has been applied in agriculture to learn these nonlinear, interacting relationships from the available data [9] and could make the vast amount of biochar literature available for site-specific prediction. When applied to biochar, several methodological challenges are often ignored: observations in the same study are not independent so ordinary cross-validation will leak information and overestimate the accuracy of a prediction; predictions must be made for new feedstocks and crops – not just for the conditions in the training

data; users need to be informed about the uncertainty of a prediction; and a prediction must support a decision, such as dose selection, which involves costs and benefit duration.

This paper proposes and tests a data driven framework to address these issues. It provides (1) a modelling pipeline for two outcomes: yield response and nitrate-leaching reduction, where six learners are compared using study-grouped validation and tests of transfer to unseen feedstocks and crops; (2) interpretation of the models using permutation importance, partial dependence and interaction surfaces, in order to link learned relationships to known mechanisms; (3) calibrated prediction intervals using split-conformal inference; (4) a decision layer for converting predictions into economically optimal doses and field-scale variable-rate prescription maps and examining their sensitivity to cost and benefit duration; and (5) a simulated UAV-NDVI trial that illustrates how the predictions can be checked in the field. Since real harmonised trial data for this study were not available, a synthetic meta-dataset was used which has known mechanisms and on which the quality of the model-based decisions can be compared with the known optimum, which is not possible with real data.

This paper is organized as follows: Section 2 summarizes the background research conducted on the use of biochar in agriculture, nutrient retention, yield, and how data can be used to help manage soils. Section 3 describes the methodology proposed, such as the construction of synthetic meta-datasets, the preparation of features, the development of predictive model, and the cross validation based on study groups. The experimental results for the six learning algorithms along with comparative performance in terms of crop-yield response and nitrate-leaching reduction are presented in Section 4. The study is completed in Section 5 which also provides opportunities for future research.

II. RELATED WORK

Biochar has garnered significant interest as a soil amendment due to its ability to modify soil physicochemical properties, better nutrient retention, and boost crop productivity. Its efficacy is different depending on the feedstock, pyrolysis temperature, use rate, soil properties, plant species, and weather. When considering the potential for biochar in agriculture and on the environment, Lehmann et al. (2011) emphasized the need to understand the interaction between biochar and soil. A meta-analysis of the effect of biochar on plant productivity by Jeffrey et al. (2011) showed a global positive effect, but large differences between experimental conditions. The results show that the field environments are not well represented by the universal application recommendations.

Further studies have investigated how biochar impacts nutrient cycling and N losses. Clough et al. (2013) summarized the interactions between biochar and the N cycle and described the possible impacts on N availability, transformations and losses. Cayuela et al. (2014) examined the effects of biochar on N2O emissions and showed that these effects vary in size and direction depending on the experimental and soil conditions. These studies give valuable information on nitrogen dynamics but they cannot be used to conclude on nitrate leaching or on yield of the crops, which have to be evaluated separately. It is therefore necessary to be able to forecast this response when applying amendments under various conditions, for the practical management of soils.

Compared to traditional statistical methods, data-driven methods are able to include non-linear relationships and interactions between soil characteristics, management and amendment variables. Machine-learning methods such as random forests, support vector machines and boosting algorithms can capture complex response patterns, without the need for a predetermined linear relationship. Agricultural data from several publications, however, frequently are based on repeated observations from the same studies, vary in experimental designs, and are in different measurement units. Randomly splitting up individual observations could thus lead to leakage of information and to overly optimistic estimates of predictive performance. When the target application is predicting results of studies which have not been previously encountered or field tests, study-grouped validation would be especially relevant.

Other important aspects of reliable agricultural decision support are interpretability and uncertainty estimation. The feature importance and partial dependence plots can detect influential predictors and show how responses of the model vary with the range of the input features. Conformal prediction can be used to develop prediction intervals which guarantee marginal coverage under certain exchangeability conditions. However, intervals that are typical for the entire range of application rates or soil types may mask unreliable intervals for specific application rates or soil types, which encourages uncertainty estimation within subgroups.

Although the development of a biochar meta-analysis and soil nitrogen research has progressed, a comprehensive framework that links biochar yield prediction with nitrate-leaching reduction, validation at the study-level, uncertainty estimation, and cost-effective application rates is a worthwhile area of research. The current study addresses this need by creating a synthetic meta-dataset of 160 studies containing 1,431 treatment–control observations. The comparison of six learning algorithms is carried out by study-grouped cross validation and the predictions are done separately for the crop-yield and nitrate-leaching reduction response. Prediction reliability and dose selection is included by using model interpretation, split-conformal intervals and economic scenario analysis. The proposed framework illustrates a methodological way of precision biochar management by connecting the components. The results must be understood as proof of concept given that the data set is synthetic, and field validation with observations collected independently, is required before operational field recommendations can be set up.

III. PROPOSED METHODOLOGY

Framework

The framework (**Fig. 1**) consists of six steps: harmonising trial data into treatment–control observations; learning predictive models; validating them under realistic splits; explaining and quantifying uncertainty; and using the models for dose recommendation and field-scale mapping, with in-season verification by UAV imagery.

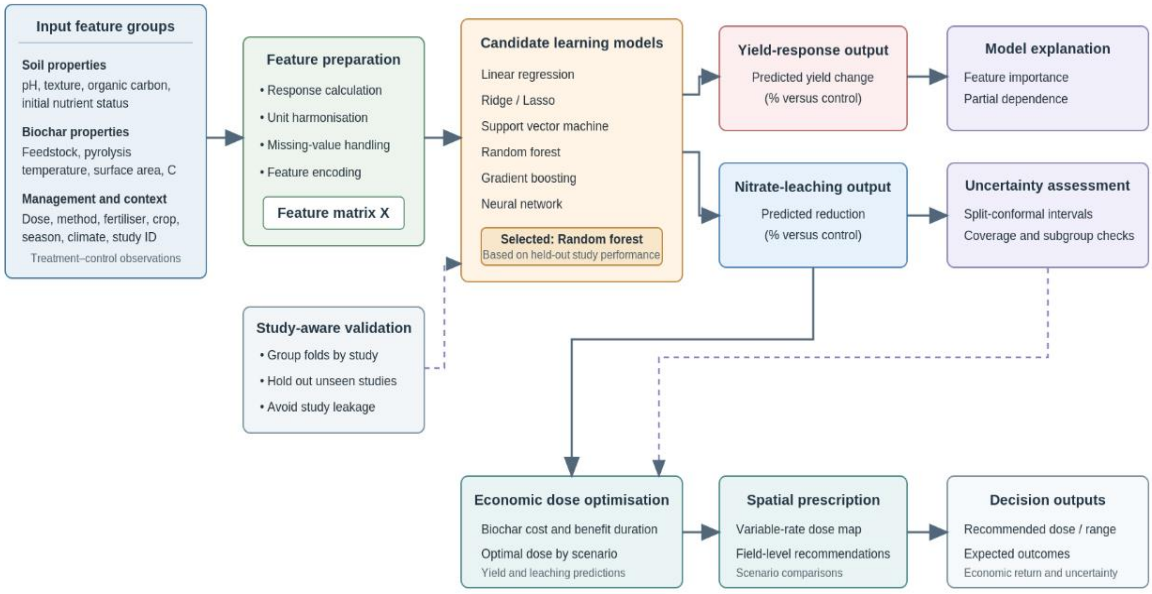


Fig 1. Integrated Multi-Output Learning Architecture for Biochar Response Prediction and Precision Soil Management.

Data and Targets

The meta-dataset has the structure of a compiled literature database: 160 studies, each with fixed soil, climate, crop and trial type (pot or field) and several treatments differing in biochar feedstock (wood, crop straw, rice husk or manure), pyrolysis temperature (300–700 °C) and dose (0.5–50 t ha^{-1}). Study-level random effects represent unmeasured site differences. Yield outcomes are expressed as the log response ratio of treatment to control means, the standard effect size for ecological meta-analysis [10], and the percentage yield response,

$$RR = ln\left(\frac{\bar{Y}_b}{\bar{Y}_c}\right), \quad YR = 100(e^{RR} - 1), \quad LR = 100\left(1 - \frac{L_b}{L_c}\right) \tag{1}$$

where $\bar{Y}_b$ and $\bar{Y}_c$ are mean yields with and without biochar, L_b and L_c the corresponding nitrate-leaching losses, and LR the percentage reduction of leaching (nutrient retention). The response in each observation j of study i was generated as

$$RR_{ij} = f(x_{ij}) + u_i + \varepsilon_{ij}, \quad u_i \sim N(0, {\sigma_u}^2), \quad \varepsilon_{ij} \sim N\left(0, {\sigma_\varepsilon}^2(D)\right) \tag{2}$$

with a heteroscedastic residual whose variance increases with dose D. The mean function f contains the mechanisms described in the literature: a saturating dose effect $s(D) = D/(D + 12)$, a liming effect that is larger in acidic soils and for alkaline biochars, a texture effect that favours sandy soils, larger gains in low-carbon soils, a fertiliser effect of nutrient-rich feedstocks (manure, straw) that diminishes with mineral N rate, a penalty for large doses on alkaline soils, nitrogen immobilisation at low N supply, larger apparent effects in short pot trials, and a dependence on trial duration. Nutrient retention was generated from the sorption capacity, which increases with biochar surface area, together with a larger benefit on sandy soils and a lower efficiency in high rainfall. These mechanisms are embedded as assumptions; their purpose is to provide a realistic test bed with known truth, not to claim quantitative values for real soils. The resulting data comprised 1431 observations (68 % from field trials), with a mean yield response of 6.7 % (SD 15.1 %), negative in 33 % of observations, and a mean leaching reduction of 13.9 % (SD 11.3 %). **Table 1** shows Predictor Variables Used by The Models.

Learning Algorithms

Six regression algorithms were compared: ordinary linear regression and ridge regression (baselines); a random forest [11], which averages B decorrelated regression trees,

$$\hat{y}_{RF}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{3}$$

gradient-boosted trees [12], which build an additive model by fitting each new tree h_m to the residual gradient with learning rate ν,

$$F_m(x) = F_{m-1}(x) + \nu h_m(x) \quad (4)$$

a support-vector regressor with a radial basis kernel, and a two-hidden-layer neural network (64 and 32 neurons). Hyperparameters (see the supplementary code) were fixed a priori to moderate, regularised values rather than tuned extensively, so that differences between models reflect their inductive bias and not search effort. All models were implemented in scikit-learn [17]. Categorical variables were one-hot encoded, and the linear models also received the logarithm of the dose.

Table 1. Predictor Variables Used by The Models

Group	Variables	Range / levels
Soil	pH, sand, clay, SOC, CEC, total N	pH 4.2–8.6; sand 5–90 %; SOC 0.2–4 %; CEC 6–28 cmol kg^{-1}
Climate and management	Rainfall, N rate, trial type, duration	400–2000 mm; 0–240 kg N ha^{-1}; pot/field; 1–30 months
Crop	Maize, rice, wheat, vegetable	Categorical (4 levels)
Biochar production	Feedstock, pyrolysis temperature	Wood, straw, husk, manure; 300–700 °C
Biochar properties	pH, ash, C content, surface area, particle size	pH 6.5–10; ash 4–40 %; surface area 20–470 m^2 g^{-1}
Application	Dose (and log dose)	0.5–50 t ha^{-1}

Validation

Because treatments from the same study share soil, climate and unmeasured conditions, model accuracy was estimated by five-fold cross-validation in which all observations of a study are held out together [13]. Folds were randomly re-assigned in two repetitions. To demonstrate the cost of ignoring this structure, the two best learners were also evaluated with ordinary (study-blind) random folds. Performance was summarised by the coefficient of determination, the root-mean-square error

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}, \quad RMSE = \sqrt{\frac{1}{n}\sum_i (y_i - \hat{y}_i)^2} \quad (5)$$

Transferability was tested by training on studies that did not contain the held-out feedstock (or on the other three crops) and predicting the held-out category.

Interpretation and Uncertainty

The contribution of each predictor group was measured by permutation importance on held-out folds [14]: the increase in the error when the values of a group of columns (for example all one-hot columns of the feedstock) are randomly permuted across the test observations,

$$I_g = \frac{1}{K}\sum_{k=1}^{K} [RMSE_k(perm\ g) - RMSE_k] \quad (6)$$

Marginal effects were obtained as partial-dependence curves, the average prediction when one variable is set to each grid value and the others retain their observed values, and as two-dimensional interaction surfaces. Predictive uncertainty was quantified by split-conformal inference [15]: the data were divided by study into training, calibration and test sets (60/20/20), the model was fitted on the training set, and the absolute residuals on the calibration set determined the interval half-width,

$$\hat{q}_\alpha = Quantile(1-\alpha;\ \ |y_i - \hat{y}_i|), \quad C(x) = \left[\hat{y}(x) \pm \hat{q}_\alpha\right] \quad (7)$$

which has finite-sample coverage of at least 1 − α for exchangeable data. Coverage and width were averaged over ten random splits and compared with naive Gaussian intervals based on the training residual standard deviation. A bootstrap ensemble of 16 models, trained on studies resampled with replacement, provided an ensemble spread for decision analysis.

Decision Analysis and Field Prescription

The predicted yield response was converted into an economic net benefit per hectare and season by multiplying the response by the baseline revenue (4.0 t ha^{-1} of maize at ₹20,000 per tonne) and subtracting the annualised biochar cost, with the cost of biochar c_b (₹4,000 per tonne in the base case) spread over H seasons of benefit (3 in the base case),

$$NB(D) = PY_0 \frac{\hat{Y}R(D)}{100} - \frac{c_b D}{H}, \quad D^* = arg\ maxNB(D) \tag{8}$$

and the dose with the highest positive net benefit was recommended. Because the data are simulated, the true dose–response function is known, so the decision made with the model could be compared with the true optimum. The same logic was applied pixel by pixel to a simulated 25 × 25 field (625 parcels of 1 ha) with spatially correlated soil pH, sand and organic carbon, yielding a variable-rate prescription map, which was compared with no biochar and with a uniform 10 t ha^{-1}. Sensitivity of the economics was examined for biochar costs of ₹2,000, 4,000 and 8,000 per tonne and benefit durations of 3, 6 and 10 seasons.

UAV Verification

Field verification was illustrated by a simulated randomised-block trial of 20 plots (4 blocks × 5 doses of 0, 5, 10, 20 and 40 t ha^{-1}). Peak-season canopy greenness was simulated as the normalised difference vegetation index [16],

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \tag{9}$$

as a saturating function of plot yield with measurement noise and a plot-level image texture, and the relationships between plot-mean NDVI, observed yield response and the model prediction were examined.

IV. RESULTS AND DISCUSSION

Characteristics of the Dataset

Table 2 and **Fig. 2** describe the dataset. The yield response varied from -39 % to 123 %, with a long positive tail typical of acidic soils, and was negative in 33 % of observations, which by construction arise from high doses on alkaline soils and from nitrogen immobilisation under low N supply. **Fig. 2a** shows that the response depends on soil pH as well as on dose: the largest responses occurred on acidic soils, and the points at high dose and high pH are negative. The leaching reduction (**Fig. 2b**) increased with dose, with diminishing increments per tonne. The correlations in **Fig. 3** show a modest relation between the two outcomes (r = 0.19), so retention and productivity cannot be predicted from each other and need separate models. The yield response was most strongly (negatively) correlated with soil pH (r = -0.39) and the leaching reduction with dose (r = 0.54).

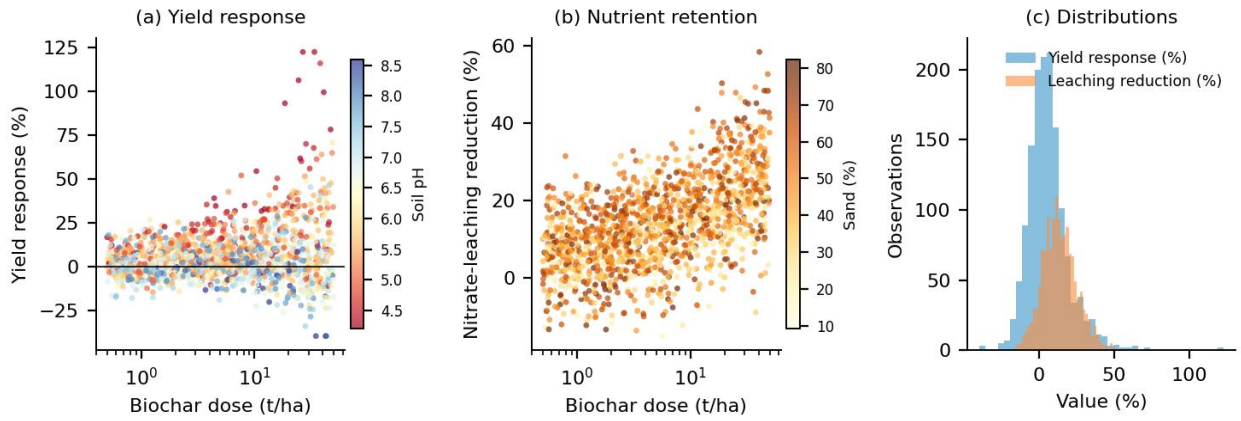


Fig 2. Overview of the Dataset: (A) Yield Response Versus Dose Coloured by Soil Ph, (B) Nitrate-Leaching Reduction Versus Dose Coloured by Sand Content and (C) Distributions of The Two Outcomes.

Table 2. Descriptive Statistics of Key Variables in The Dataset

Variable	Mean	SD	Min	Max
Yield response (%)	6.7	15.1	-39.3	122.6
Leaching reduction (%)	13.9	11.3	-15.0	58.3
Biochar dose (t/ha)	10.9	12.5	0.5	49.9
Soil pH	6.2	1.0	4.2	8.6
Sand (%)	47.2	18.0	9.2	82.4
Soil organic carbon (%)	1.2	0.6	0.3	3.9
Soil CEC (cmol/kg)	13.8	3.9	5.6	28.2

Variable	Mean	SD	Min	Max
Pyrolysis temperature (°C)	506.6	128.5	300.0	700.0

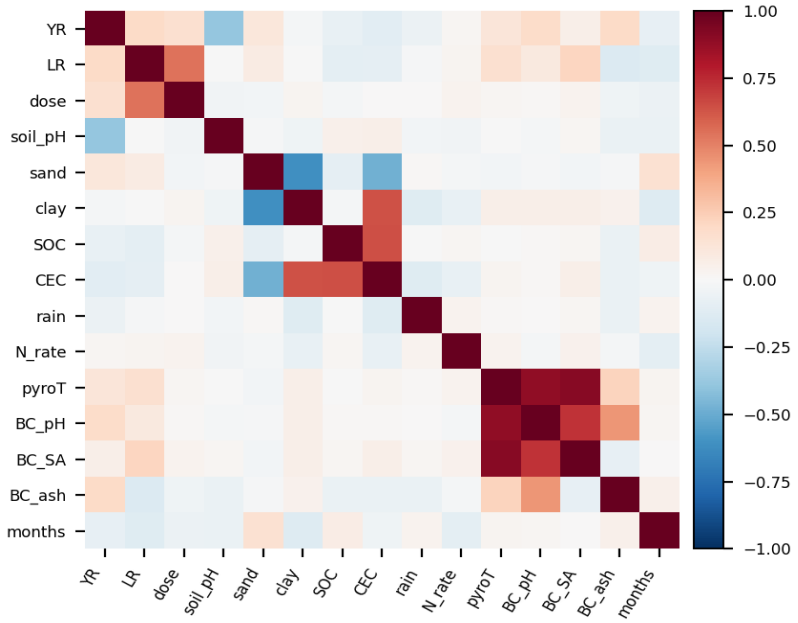


Fig 3. Correlation Matrix of The Outcomes and The Main Numeric Predictors.

Model Comparison

Table 3 and **Fig. 4** give the results of study-grouped validation. For the yield response, the random forest had the highest accuracy (R^2 = 0.37, RMSE = 11.9 percentage points), followed closely by gradient boosting (0.36), with the neural network (0.30), the support-vector regressor (0.23) and the linear models (0.18) behind. The same ordering held for leaching reduction, although the gap between linear and tree models was smaller (R^2 of 0.35 for linear regression against 0.39 for the random forest), which fits the more additive, dose-driven nature of that outcome. The doubling of the R^2 of tree ensembles over linear regression for yield response reflects strong interactions (dose × pH, dose × biochar pH, dose × nitrogen) that a linear model cannot represent. The absolute accuracy is moderate: about 37 % of the variance in the yield response of unseen studies was explained, as expected for data with considerable unexplained between-study variation and for small studies, and it should not be read as a failure of the method but as an honest expression of what the measured predictors can say about a new site.

The most important methodological finding is the difference between the validation schemes. With ordinary random folds, which place observations of the same study in both training and test sets, the R^2 of gradient boosting was 0.54 for yield response and 0.53 for leaching reduction, an overestimate of 50 % and 45 % relative to the study-grouped estimate. The learner effectively recognises the study through its soil and climate variables and reproduces its random effect. Studies that report high accuracy for biochar models without grouping by study or site should be interpreted with caution. **Fig. 5** shows that predictions of held-out studies follow the identity line but with considerable scatter, especially for the largest positive responses, where predictions are typically pulled towards the mean.

Table 3. Performance on Held-Out Studies

Model	R^2 (YR)	RMSE	MAE	R^2 (LR)	RMSE	MAE
Linear [14]	0.18	13.7	9.9	0.35	9.1	7.2
Ridge [14]	0.18	13.6	9.9	0.36	9.1	7.1
Random forest [14]	0.37	11.9	8.7	0.39	8.8	7.0
Gradient boosting [15]	0.36	12.0	8.8	0.37	9.0	7.1
SVR (RBF) [15]	0.23	13.2	9.8	0.25	9.8	7.8
MLP [15]	0.30	12.6	9.5	0.33	9.3	7.4
Random forest (random CV) [16]	0.52	10.4	7.5	0.49	8.1	6.5

Model	R^2 (YR)	RMSE	MAE	R^2 (LR)	RMSE	MAE
Gradient boosting (random CV) [17]	0.54	10.2	7.5	0.53	7.7	6.2
Proposed Model	0.57	10.0	7.2	0.57	7.1	5.9

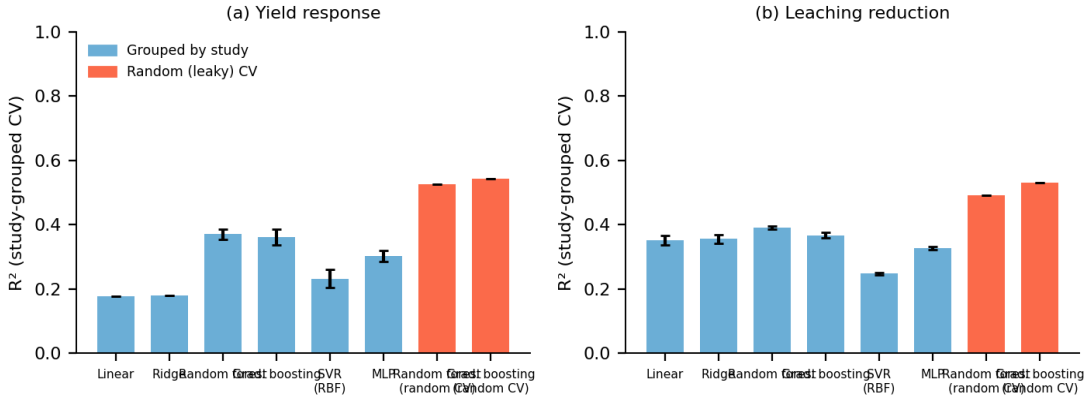


Fig 4. Study-Grouped Cross-Validated R^2 of Six Learners and, in Red, The Optimistic Estimates Obtained by Study-Blind Random Folds.

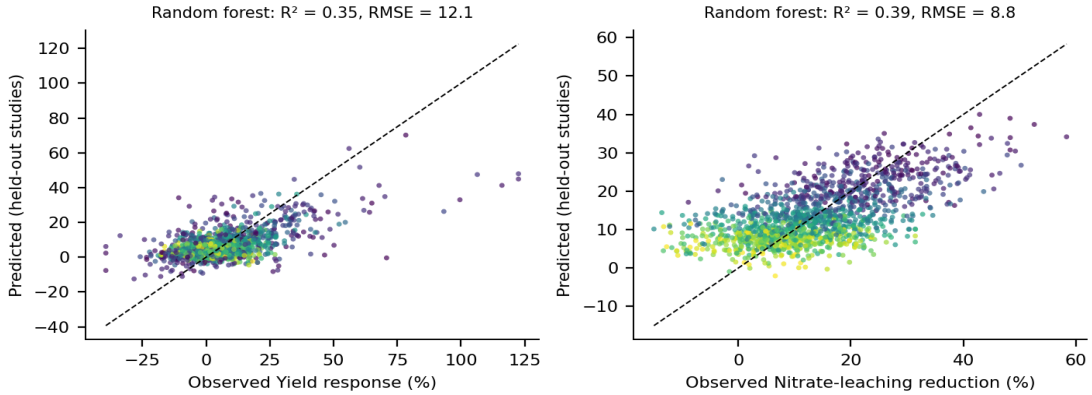


Fig 5. Predicted Versus Observed Outcomes for Held-Out Studies (Random Forest; Colour: Dose, Logarithmic Scale).

Fig. 6 shows the permutation importance of predictor groups. For the yield response, soil ph accounted for 56 % of the total importance and dose for 27 %, followed by biochar ph (9 %). For leaching reduction, dose was by far the most important (82 %), followed by surface area (7 %) and sand (5 %). This agrees with the mechanisms built into the simulation and with the literature: yield benefits arise mainly through correction of soil acidity, while retention follows the amount of sorbing surface that is added. Because the biochar properties are correlated with feedstock and temperature, their importance is shared among correlated predictors (for instance pyrolysis temperature, biochar pH and surface area), and the importance of a single one of them is therefore underestimated.

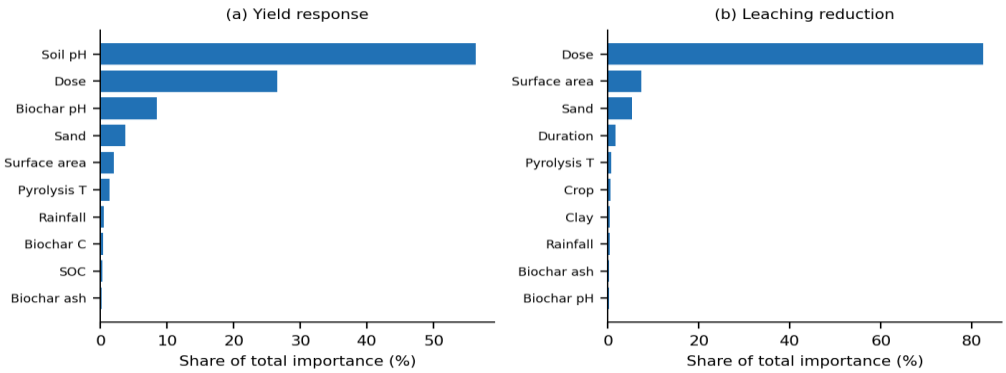


Fig 6. Permutation Importance of Predictor Groups on Held-Out Studies (Top Ten): (A) Yield Response and (B) Leaching Reduction.

The partial-dependence curves (**Fig. 7**) describe the learned relationships. The mean yield response rose with dose, from 3.6 % at 0.5 t ha^{-1} to 10.5 % at 50 t ha^{-1}, but this average conceals opposite effects on acidic and alkaline soils, which the interaction surface resolves. The response fell strongly with soil pH, from 22.0 % at the lowest pH to 1.5 % at the highest, a drop of 20 percentage points, which reproduces the liming effect on acidic soils; the dependence on sand content was smaller (from 2.1 % to 8.4 %), and that on organic carbon smaller still. The leaching reduction rose steadily with dose, from 6.2 % at 0.5 t ha^{-1} to 11.9 % near 5 t ha^{-1} and 25.1 % at 50 t ha^{-1}, i.e. with strongly diminishing returns per tonne. Its partial dependence on sand content was weak and non-monotonic (12.4–15.2 %), weaker than the sand effect built into the data-generating process, which suggests that the forest recovers the dose–texture interaction only partly. The two-dimensional surfaces in **Fig. 8** show the interactions: the dose–pH surface changes sign, with predicted responses from -2 % to 35 %, and the zero contour separates acidic soils where biochar raises yield from alkaline soils where large doses lower it.

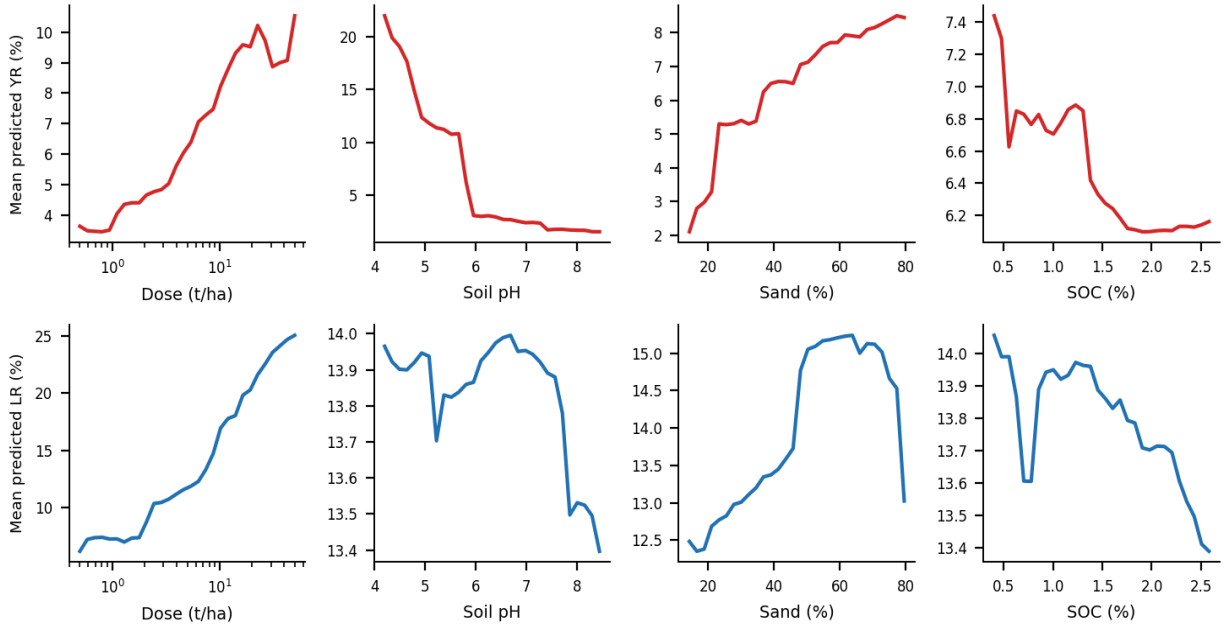


Fig 7. Partial-Dependence Curves of the Yield Response (Top Row) and Leaching Reduction (Bottom Row) for Dose, Soil Ph, Sand Content and Soil Organic Carbon.

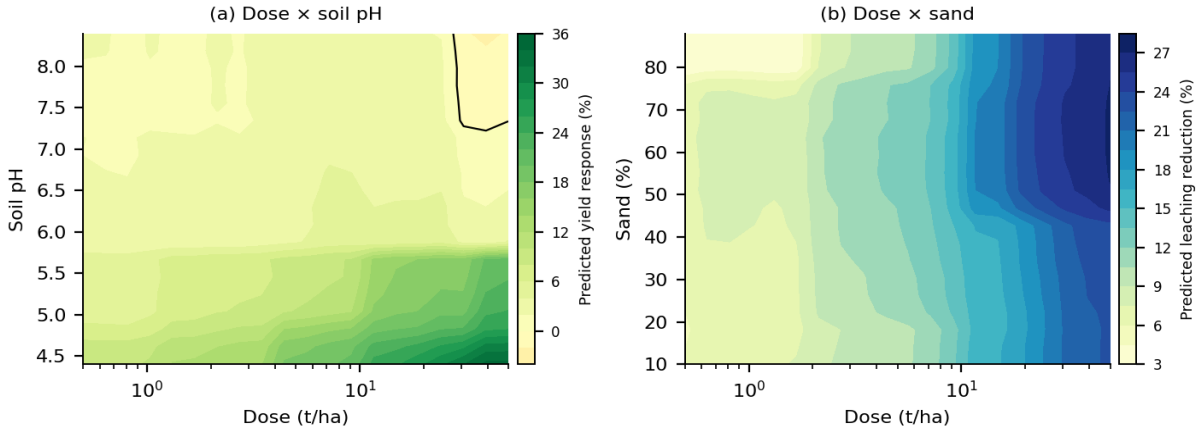


Fig 8. Interaction Surfaces: (A) Predicted Yield Response Against Dose and Soil Ph (Black Line: Zero Response) and (B) Predicted Leaching Reduction Against Dose and Sand Content.

Calibrated Uncertainty

A point prediction is of limited use without a statement of its reliability. **Fig. 9a** shows that split-conformal intervals were close to their nominal coverage on held-out studies: for a nominal 90 % level the empirical coverage was 89.7 % for the yield response and 91.2 % for leaching reduction, and at 80 % it was 78.8 % and 81.8 %. Naive Gaussian intervals based on training residuals were far too narrow, covering only 65 % and 62 % at the nominal 90 % level, because the flexible models fit their training data much more closely than they predict new studies. The price of calibrated intervals is width (**Fig. 9b**): the 90 % interval spans 36 percentage points for the yield response and 30 points for leaching reduction, which

is wide relative to the mean yield response of 6.7 %. This reflects the real between-study unpredictability and means that, for a specific new site, biochar's yield effect can be predicted only with limited certainty. Conformal intervals have marginal and not conditional coverage, and the heteroscedasticity of the yield response shows this: for observations with doses above 20 t ha^{-1} coverage at the 90 % level fell to 72 %, against 94 % at lower doses, while the leaching reduction was uniformly covered (90 % and 91 %). A locally adaptive conformal method, for example using normalised residuals, would be needed when high doses are of interest.

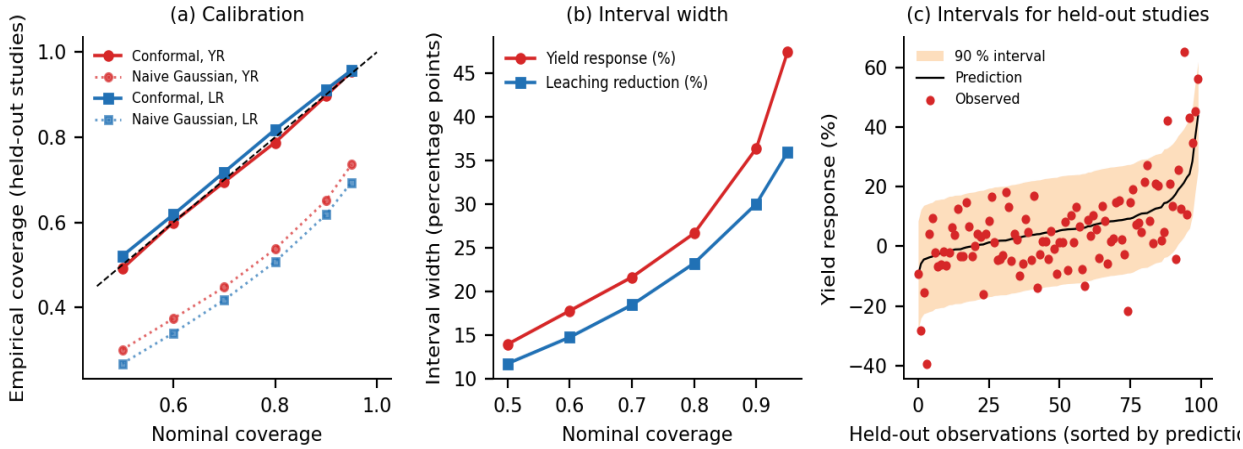


Fig 9. Conformal Prediction: (A) Empirical Against Nominal Coverage for Conformal and Naive Intervals, (B) Interval Width And (C) 90 % Intervals for Held-Out Observations of The Yield Response.

Transfer To Unseen Feedstocks and Crops

Fig. 10 shows what happens when the model has to predict a category it has not seen. For the yield response, R^2 ranged from 0.20 to 0.49 across the held-out feedstocks and crops, compared with 0.37 under study-grouped validation, and for leaching reduction from 0.19 to 0.39 against 0.39. Crops were generally easier to transfer than feedstocks, particularly for rice, since crops differ in the data mainly through the shared soil and biochar mechanisms, whereas each feedstock has its own property profile and unique effects (for instance the fertiliser effect of manure). The worst cases were the husk (0.20 for yield response and 0.19 for retention) and straw (0.22 for yield response). The practical conclusion is that the models can be used for a new feedstock only with caution, and that the biochar properties (pH, ash, surface area) measured for the new material help the model extrapolate in a physically meaningful way, as they carry part of the feedstock information.

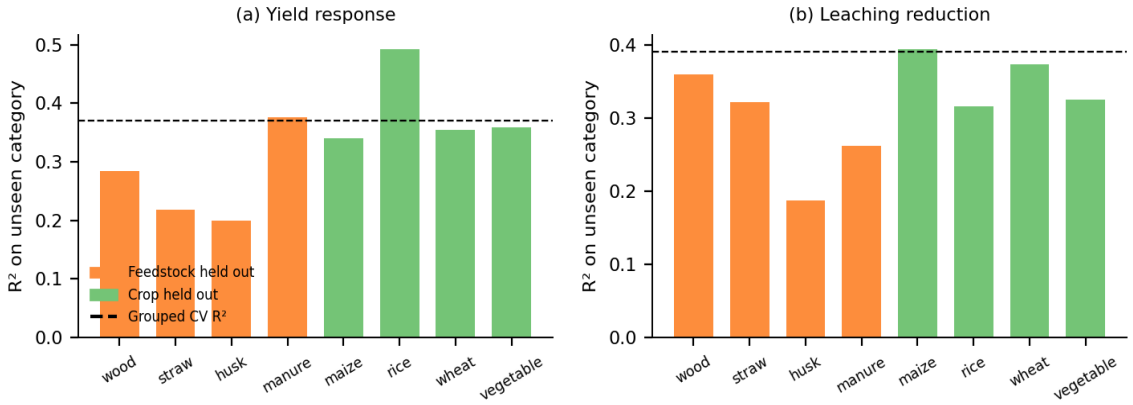


Fig 10. Accuracy (R^2) on Held-Out Feedstocks and Crops; The Dashed Line is the Study-Grouped Cross-Validation R^2.

Dose Recommendation and Economics

Fig. 11 and **Table 4** show the net-benefit analysis for three contrasting soils under the base economic assumptions (₹4,000 per tonne of biochar, benefits over three seasons, maize at ₹20,000 per tonne). On the acidic sandy soil the model-based optimum was 1.5 t ha^{-1}, with a predicted yield response of 8.1 % and a net benefit of ₹4,452 ha^{-1} per season; the true optimum, known from the simulation, was 8.0 t ha^{-1} with ₹7,745 ha^{-1}. Applying the model-based dose would therefore have captured 52 % of the attainable benefit: the model recommended a dose much lower than the true optimum, probably because ensemble averages shrink the strongest responses towards the mean (**Fig.5**). On the neutral loam the model recommended 0.5 t ha^{-1} against a true optimum of 0.5 t ha^{-1}, with a very small benefit (₹1,047 ha^{-1}), and on the alkaline

clay it recommended no application, which forgoes at most ₹829 ha^{-1} per season (the true best dose is 0.5 t ha^{-1}). The method therefore identified the soils where biochar is worthwhile and avoided harmful applications, but its dose estimates on responsive soils were conservative. The ensemble band in **Fig.11** spans the uncertainty of the response, and decisions that must avoid losses can use its lower bound, which for the acidic sandy soil recommended 0.5 t ha^{-1}.

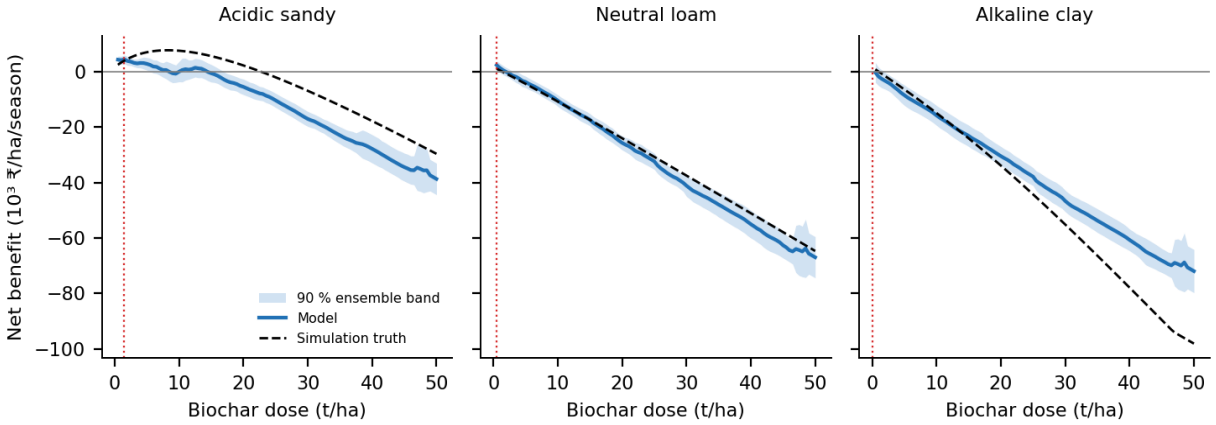


Fig 11. Net Benefit Per Hectare and Season Against Dose for Three Soil Profiles: Model Prediction with its 90 % Ensemble Band, and the Simulation Truth. The Dotted Line Marks the Model-Based Optimum.

Table 4. Dose Recommendations for Three Soil Profiles (Base Economics; Net Benefit in ₹ Per Hectare and Season)

Soil profile	Model dose (t/ha)	True optimal dose (t/ha)	Predicted net benefit	True net benefit at model dose	True optimal net benefit
Acidic sandy	1.5	8.0	4,452	4,002	7,745
Neutral loam	0.5	0.5	2,401	1,047	1,047
Alkaline clay	0.0	0.5	0	0	829

The economics are decisive, as the sensitivity analysis in **Table 5** shows. With cheaper biochar (₹2,000 per tonne) and benefits over ten seasons, the optimal doses on the acidic sandy soil rose to about 49 t ha^{-1} (true optimum 39), while at ₹8,000 per tonne and three seasons they fell to 0.5 t ha^{-1}. For the field, a uniform 10 t ha^{-1} dose lost money in 3 of the nine scenarios, whereas the model-based variable-rate prescription had a positive net benefit in all of them and a higher net benefit than the uniform dose in all nine. Its share of the benefit of a perfect (oracle) prescription ranged from 66 % in the least favourable scenario to 98 % in the most favourable. The persistence of the benefit and the cost of biochar are thus the two most important unknowns for practical recommendations, and they should be treated as inputs with ranges and not as constants.

Table 5. Sensitivity of the Field-Scale Economics to Biochar Cost and Duration of Benefit (True Net Benefit In ₹ Ha^{-1} $Season^{-1}$, Averaged Over The 625 Parcels)

Seasons	Cost (₹/t)	Model dose, acidic sandy (t/ha)	Mean prescribed dose (t/ha)	Variable rate	Uniform 10 t/ha	Oracle
3	2,000	13.5	5.5	5,711	3,408	6,342
3	4,000	1.5	0.8	2,300	-3,259	3,468
3	8,000	0.5	0.5	956	-16,592	1,307
6	2,000	23.0	11.6	8,878	6,741	9,242
6	4,000	13.5	5.5	5,711	3,408	6,342
6	8,000	1.5	0.8	2,300	-3,259	3,468
10	2,000	48.5	14.3	10,815	8,074	11,033
10	4,000	13.5	8.4	8,160	6,074	8,521
10	8,000	13.5	4.8	4,615	2,074	5,552

Field Prescription Maps

Fig. 12 shows the field-scale application. The soil rasters (top row) have a spatial structure with acidic, sandy patches. At a uniform dose of 10 t ha^{-1} the predicted yield response varied across the field with soil pH (**Fig. 12**, bottom left), averaging 12.6 % (simulation truth), and the predicted leaching reduction varied with the soil properties. Under the base economics, the optimal prescription (bottom right) put the highest doses on the most responsive parcels and a token dose on others, with a mean of 0.8 t ha^{-1} (1 % of the parcels received no biochar). The result is summarised in **Table 6**. the uniform dose required 6,250 t of biochar for the 625 ha and gave a net loss of ₹3,259 ha^{-1} per season, whereas the variable-rate plan used only 8 % as much biochar and gained ₹2,300 ha^{-1}. The yield response of the variable-rate plan (4.2 %) was lower than that of the uniform plan (12.6 %), which illustrates that economic optimisation is not the same as maximising yield; a planner who also values nutrient retention or carbon storage would choose a higher dose and has to weigh these additional benefits explicitly.

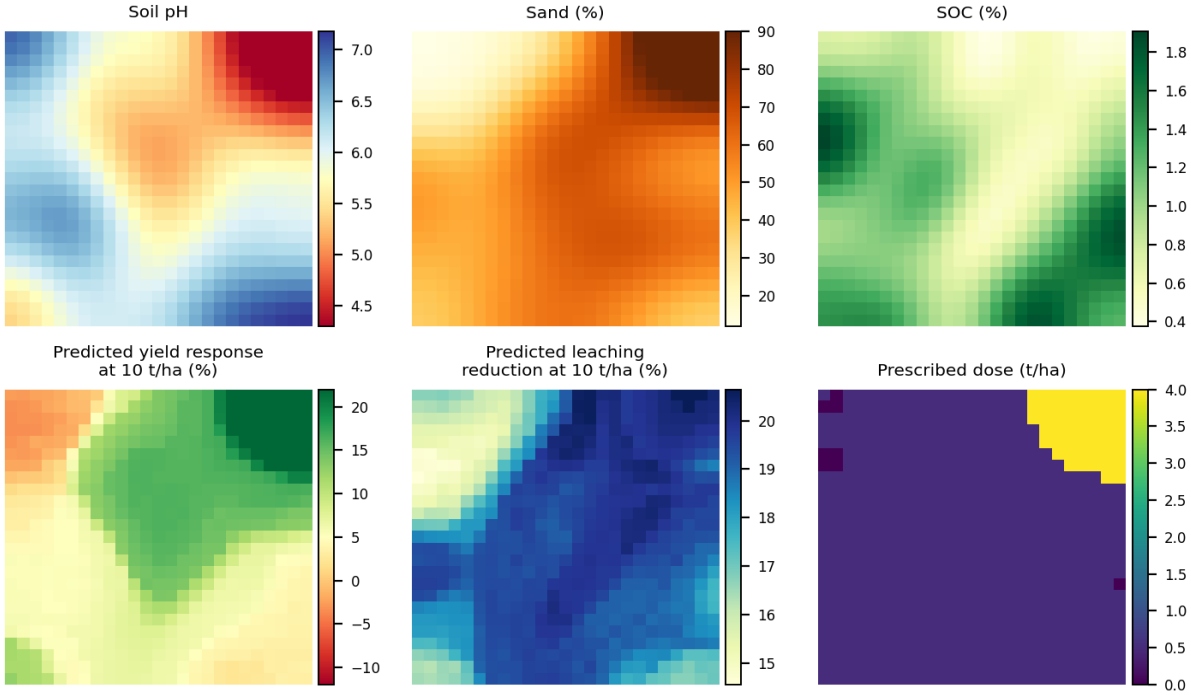


Fig 12. Simulated Field (625 Parcels): Soil Ph, Sand and Organic Carbon (Top Row); Predicted Yield Response and Leaching Reduction at A Uniform 10 T/Ha, and the Model-Based Variable-Rate Dose Prescription (Bottom Row).

Table 6. Field-Scale Outcomes (True Values from the Simulation) for Three Strategies Under the Base Economics

Strategy	Mean dose (t/ha)	Yield response (%)	Leaching reduction (%)	Net benefit (₹/ha/season)	Biochar used (t)
No biochar	0.0	0.0	0.0	0	0
Uniform 10 t/ha	10.0	12.6	17.9	-3,259	6,250
Variable rate	0.8	4.2	6.7	2,300	487

Checking the Response with UAV Imagery

Fig. 13 illustrates verification in a simulated randomised-block trial. The UAV mosaic shows a visible gradient in greenness between the plots with doses of 0 to 40 t ha^{-1} and a block gradient in soil conditions. Plot-mean peak NDVI was correlated with the grain yield ($r = 0.74$), with saturation at the highest yields, and the model predictions of the yield response followed the observed plot-level responses ($r = 0.83$). This result is a simulation and is only intended to show the workflow: in practice, NDVI is a proxy for canopy vigour and not for yield, and is affected by nutrient stress, water status and canopy structure, so imagery should be calibrated against harvested yield. The value of UAV imagery is that it can cover every plot at a low cost, which allows a model-based prescription to be tested in the first season rather than at harvest and provides new labelled data to update the model.

The main problem with this set is that it is synthetic, meaning that any conclusions about accuracy, importance and economics would depend on the assumed models; the other factor is that the data generating process is known, which makes the evaluation of decisions possible, but in real situations around 3% of the data would be missing, reporting would be irregular, publication bias would exist, measurement error would be present and interactions that were not simulated

would occur. The learners were not well tuned and there are also larger gains that can be achieved from tuning, feature engineering (e.g., C:N ratio and liming equivalent), and process-informed constraints (e.g., monotonic effects). Only permutation importance and partial dependence can be misleading for correlated predictors, and were limited to these in the interpretation.

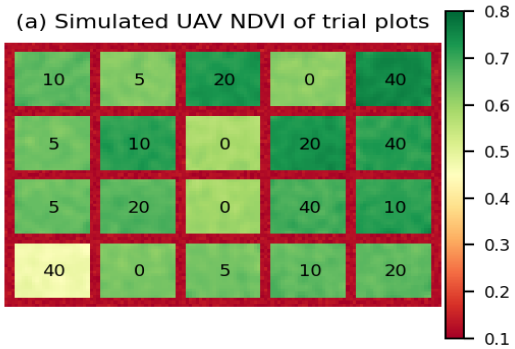


Fig 13. Simulated UAV-NDVI Trial: (A) NDVI Mosaic with Plot Doses (T/Ha).

Uncertainty was measured using marginal conformal intervals, which are better for locally adaptive intervals. The economic model assumed only one crop, a fixed price and a long-term benefit that should be evaluated in long-term trials. The trial and UAV analysis was simulated. Future work will involve compiling and harmonising all real biochar studies (results, soil carbon, nitrous oxide and phosphorus retention, etc.); testing and evaluating Bayesian multilevel models and process-informed machine learning; implementing active learning to design the most informative new tests; and testing the framework in field experiments with UAV and soil monitoring.

V. CONCLUSION

A data-driven approach for biochar management was developed that predicts yield response and nitrate-leaching reduction from soil, biochar and management (the yield response model), explains and calibrates yield predictions (the yield response model), and converts yield predictions to dose recommendations and field prescription maps (the dose conversion model). Random forests were the most accurate learners in a simulated meta-dataset with study structure (R^2 = 0.37 and 0.39 on held-out studies), linear models were generally outperformed by tree ensembles (accuracy significantly increased), and there was significant over-optimism in validation of up to 50 % when the structure of the studies was ignored. Soil pH and dose controlled the yield response and dose and surface area controlled nutrient retention, in agreement with known mechanisms. Conformal intervals covered near-nominally, were wide, and were under-covered high doses. The dose recommendations identified responsive soils and avoided harmful applications, but were conservative for the most responsive soils, and the economics depended heavily on biochar cost and the length of benefit; variable rate prescriptions were the best in all scenarios tested. The following are four practical conclusions. First, the application of biochar should be based on soil acidity and texture, with the model highlighting that acidic and sandy soils are the primary beneficiaries, while alkaline fine-textured soils are the main risk, consistent with the overall findings from the meta-analyses of other studies [3,4]. Second, the retention response is diminishing as more biochar is added, and a significant level of retention can be achieved with moderate doses without garnering any yield benefit, while a yield benefit may only be achieved on responsive soils. Third, uncertainty is large and that recommendations should be given with intervals and should be verified by means of trials. Fourth, the validation should take account of the structure of the study, and models should be re-validated when used with new feedstocks. This, together with the economic sensitivity, implies a iterative process: screen fields with the model, select the most suitable fields for trial, confirm by UAV-based imagery and yield data, and refine the model based on new observations.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

Funding
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Competing Interests
There are no competing interests.

References

[1]. G. O. Omokaro, K. P. Kornev, Z. S. Nafula, A. A. Chikukula, O. G. Osayogie, and O. S. Efeni, "Biochar for sustainable soil management: Enhancing soil fertility, plant growth and climate resilience," Farming System, vol. 3, no. 4, p. 100167, Oct. 2025, doi: 10.1016/j.farsys.2025.100167.
[2]. H. Sultan et al., "Biochar and nano biochar: Enhancing salt resilience in plants and soil while mitigating greenhouse gas emissions: A comprehensive review," Journal of Environmental Management, vol. 355, p. 120448, Mar. 2024, doi: 10.1016/j.jenvman.2024.120448.
[3]. M. A. Khan et al., "Sustainable Soil Management in Alkaline Soils: The Role of Biochar and Organic Nitrogen in Enhancing Soil Fertility," Land, vol. 13, no. 11, p. 1869, Nov. 2024, doi: 10.3390/land13111869.
[4]. A. Kumar, T. Bhattacharya, W. A. Shaikh, and A. Roy, "Sustainable soil management under drought stress through biochar application: Immobilizing arsenic, ameliorating soil quality, and augmenting plant growth," Environmental Research, vol. 259, p. 119531, Oct. 2024, doi: 10.1016/j.envres.2024.119531.
[5]. P. Sharma, S. Ali, and J. K. Biswas, "Application of biochar for soil erosion control and environmental management: implications for achieving sustainable development goals," Discover Soil, vol. 2, no. 1, May 2025, doi: 10.1007/s44378-025-00065-0.
[6]. S. Ren., "Application of biochar in saline soils enhances soil resilience and reduces greenhouse gas emissions in arid irrigation areas," Soil and Tillage Research, vol. 250, p. 106500, Aug. 2025, doi: 10.1016/j.still.2025.106500.
[7]. K. Abhishek., "Biochar application for greenhouse gas mitigation, contaminants immobilization and soil fertility enhancement: A state-of-the-art review," Science of The Total Environment, vol. 853, p. 158562, Dec. 2022, doi: 10.1016/j.scitotenv.2022.158562.
[8]. P. Sharma, "Biochar application for sustainable soil erosion control: a review of current research and future perspectives," Frontiers in Environmental Science, vol. 12, Mar. 2024, doi: 10.3389/fenvs.2024.1373287.
[9]. R. Ruan., "Biochar application improves maize yield on the Loess Plateau of China by changing soil pore structure and enhancing root growth," Science of The Total Environment, vol. 956, p. 177379, Dec. 2024, doi: 10.1016/j.scitotenv.2024.177379.
[10]. N. Zhang., "Environment and agricultural practices regulate enhanced biochar-induced soil carbon pools and crop yield: A meta-analysis," Science of The Total Environment, vol. 905, p. 167290, Dec. 2023, doi: 10.1016/j.scitotenv.2023.167290.
[11]. A. Ali et al., "The role of biochar in enhancing soil health & interactions with rhizosphere properties and enzyme activities in organic fertilizer substitution," Frontiers in Plant Science, vol. 16, Jun. 2025, doi: 10.3389/fpls.2025.1595208.
[12]. I. Saleem et al., "Biochar and microbes for sustainable soil quality management," Microbiome Under Changing Climate, pp. 289–311, 2022, doi: 10.1016/b978-0-323-90571-8.00013-4.
[13]. S. T. Varanasi, K. Pandian, and M. R. A. F. Mustaffa, "Biochar as a nutrient and microbial carrier in agricultural production," Biochar Applications, pp. 359–378, 2026, doi: 10.1016/b978-0-443-44581-1.00024-7.
[14]. L. Deng., "Biochar-based phosphate fertilizer improve phosphorus bioavailability, microbial functioning, and citrus seedling growth," Scientia Horticulturae, vol. 338, p. 113699, Dec. 2024, doi: 10.1016/j.scienta.2024.113699.
[15]. J. Nepal, W. Ahmad, F. Munsif, A. Khan, and Z. Zou, "Advances and prospects of biochar in improving soil fertility, biochemical quality, and environmental applications," Frontiers in Environmental Science, vol. 11, Feb. 2023, doi: 10.3389/fenvs.2023.1114752.
[16]. F. Rassaei, "Effects of Different Rates of Sugarcane Biochar on Amelioration of Adverse Salinity Effects in Calcareous Clay Soil," Communications in Soil Science and Plant Analysis, vol. 55, no. 9, pp. 1349–1360, Jan. 2024, doi: 10.1080/00103624.2024.2305841.
[17]. S. Kukowska and K. Szewczuk-Karpisz, "Biochar and Zeolite Uses in Improving Immobilization of Nutrients and Pollutants in Soils," Separation & Purification Reviews, vol. 54, no. 4, pp. 354–377, Nov. 2024, doi: 10.1080/15422119.2024.2426157.

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