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REVERSE ENGINEERING OF BIOCHAR

Verónica L. Morales^{a,1,*}, Francisco J. Pérez-Reche^b, Simona M. Hapca^a, Kelly L. Hanley^c, Johannes Lehmann^c, Wei Zhang^d

^a*SIMBIOS Centre, Abertay University, Dundee DD1 1HG, UK*

^b*Institute for Complex Systems and Mathematical Biology, SUPA, Department of Physics, University of Aberdeen, Old Aberdeen AB24 3UE, UK*

^c*Department of Crop and Soil Sciences, Cornell University, Ithaca, NY 14853, USA*

^d*Department of Plant, Soil and Microbial Sciences; Environmental Science and Policy Program, Michigan State University, East Lansing, MI 48824, USA*

Abstract

This study underpins quantitative relationships that account for the combined effects that starting organic material biomass and peak pyrolysis temperature have on physico-chemical properties of biochar. Meta-data was assembled from published data of diverse biochar samples (n=102) to (i) obtain networks of intercorrelated properties and (ii) derive models that predict biochar properties. Assembled correlation networks provide a qualitative overview of the combinations of biochar properties likely to occur in a sample. Generalized Linear Models are constructed to account for the dependence of biochar properties on single or multiple variables with additive and/or interactive effects, non-Gaussian data distribution, and non-linear relationships. Generalized Linear Models are constructed to account for situations of varying complexity, including: dependence of biochar properties on single or multiple predictor variables, where dependence on multiple variables can have additive and/or interactive effects; non-linear relation between the response and predictors; and non-Gaussian data distributions. The web-tool *Biochar Engineering* implements the derived models to maximize their utility and distribution. Provided examples illustrate the practical use of the networks, models and web-tool to engineer biochars with prescribed properties desirable for hypothetical

*Corresponding author.

Email address: morales@ifu.baug.ethz.ch (Verónica L. Morales)

¹Present address: Inst. of Environmental Engineering, ETH Zürich, Zürich 8093, CH

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6 scenarios.

7 *Keywords:* physico-chemical properties, slow-pyrolysis, correlation networks,
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9 Generalized Linear Models, web-tool

10 11 12 1. INTRODUCTION

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15 Biochar, the product of biomass thermochemical conversion in an oxygen depleted
16 environment, has gained increasing recognition as a modernized version of an ancient
17 Amerindian soil management practice with at times wide-ranging agronomic and en-
18 vironmental gains (Lehmann et al., 2003; Atkinson et al., 2010; Novak and Busscher,
19 2013). Some of the most commonly acclaimed benefits of biochar application to soils
20 include: increased long-term C storage in soils (Atkinson et al., 2010; Joseph et al.,
21 2010; Cross and Sohi, 2011; Ennis et al., 2011; Karhu et al., 2011; Novak and Busscher,
22 2013), restored soil fertility (Glaser et al., 2002; Lehmann et al., 2003; Gaskin et al.,
23 2008; Novak et al., 2009; Atkinson et al., 2010; Laird et al., 2010; Beesley et al., 2011;
24 Lehmann et al., 2011; Enders et al., 2012; Spokas et al., 2012b; Novak and Busscher,
25 2013), improved soil physical properties (Novak et al., 2009; Joseph et al., 2010; En-
26 nis et al., 2011; Karhu et al., 2011; Lehmann et al., 2011; Novak and Busscher, 2013),
27 boosted crop yield and nutrition (Novak et al., 2009; Major et al., 2010; Lehmann et al.,
28 2011; Rajkovich et al., 2012; Spokas et al., 2012a; Novak and Busscher, 2013), enhanced
29 retention of environmental contaminants (Cornelissen et al., 2005; Loganathan et al.,
30 2009; Cao and Harris, 2010; Beesley et al., 2011), and reduced N-emission and leaching
31 (Spokas et al., 2012b; Novak and Busscher, 2013). Examples of the specific biochar
32 properties responsible for these benefits are summarized in Table 1.

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49 Biochar quality can be highly variable, and its performance as an amendment –
50 whether beneficial or detrimental– is often found to depend heavily on its intrinsic
51 properties and the particular soil it is added to (Lehmann et al., 2003; Novak et al.,
52 2009; Atkinson et al., 2010; Major et al., 2010; Lehmann et al., 2011; Spokas et al.,
53 2012a). As has been previously concluded, biochar application to soil is not a “one
54 size fits all” paradigm (Spokas et al., 2012a; Novak and Busscher, 2013). Consequently,
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6 detailed knowledge of the biochar properties and the specific soil deficiencies to be re-
7 mediated is critical to maximize the possible benefits and minimize undesired effects of
8 its use as a soil amendment. While soil deficiencies must be identified on a site-by-site
9 basis, it is conceivable that biochar properties can be engineered through the manipu-
10 lation of pyrolysis production parameters and proper selection of parent biomass type
11 (Zhao et al., 2013). The capacity to produce biochars with consistent and predictable
12 properties will, first, enable efficient matching of biochars to soils, and second, facilitate
13 the deployment of this soil management strategy at large and commercial scales. Al-
14 though the properties and effects of biochar samples produced from a variety of methods
15 and starting organic materialsbiomasses have been intensively studied, as yet, the an-
16 analytical techniques for characterization and effect quantification are not standardized.
17 This creates a challenge when comparing biochar properties and effects across studies.
18 At the same time, making such comparisons is imperative to gain a comprehensive
19 understanding of alterable biochar properties.
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32 The prevailing hypothesis in the literature is that the selection of peak pyrolysis
33 temperature and parent organic materialbiomass –as two key production variables– fun-
34 damentally affects resulting biochar properties. Identification of relationships between
35 production variables and biochar properties has been pursued by many investigators,
36 but has been limited to the small number of samples produced and analyzed for each
37 study (e.g., Karaosmanoğlu et al., 2000; Zhu et al., 2005; Gaskin et al., 2008; Nguyen
38 and Lehmann, 2009; Cao and Harris, 2010; Joseph et al., 2010; Keiluweit et al., 2010;
39 Cao et al., 2011; Cross and Sohi, 2011; Hossain et al., 2011; Mukherjee et al., 2011;
40 Enders et al., 2012; Rajkovich et al., 2012; Zhao et al., 2013), with few reports com-
41 bining measurements from more than one source (Cordero et al., 2001; Glaser et al.,
42 2002; Atkinson et al., 2010; Ennis et al., 2011; Spokas et al., 2012a). The knowl-
43 edge gained from the above studies does not provide a quantitative understanding of
44 the relationships between production variables and biochar properties. The shortcom-
45 ings responsible for such lack of systematic insight include: (i) reported trends that
46 are primarily qualitative with respect to the independent effect of parent biomass or
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6 temperature (e.g., decrease in labile carbon with increasing pyrolysis temperature for
7 selected samples (Cross and Sohi, 2011)), (ii) trends that are often in conflict with sim-
8 ilar samples of other studies (e.g., positive effect (Rajkovich et al., 2012) vs. negligible
9 effect (Nguyen and Lehmann, 2009) of temperature on pH for oak biochar), and (iii)
10 correlations that are not convincing (e.g., correlation $r = 0.5$ between volatile matter
11 content and microporous surface area (Mukherjee et al., 2011)). A recent study by
12 Zhao et al. (2013) reports, for the first time, a quantitative evaluation of the individual
13 influence of feedstock source and production temperature on various biochar properties.
14 The authors classified a variety of physical and chemical biochar properties as predom-
15 inantly controlled by either feedstock or temperature. While this initial knowledge is
16 critical to guide the production of designed biochar, it falls short when the influence of
17 both parameters is significant, as is the case with most properties of interest.
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28 The present study advances the quantitative approach one step further by con-
29 structing relationships that capture the combined influence that starting organic ma-
30 terialsbiomass and temperature has on various biochar physico-chemical properties of
31 agronomic and environmental interest. The first objective was to gather comparable
32 data from various sources to create an unbiased meta-data set on which to perform
33 statistical analyses. The second objective was to identify groups of inter-correlated
34 properties to gain an insight into how individual properties may be affected when oth-
35 ers are manipulated. The third objective was to underpin quantitative relationships
36 between production variables and the measured properties of biochar in the meta-data,
37 as listed in Table 1. The fourth objective was to implement the identified relationships
38 in a simple-to-use web application, which provides an estimate of the expected prop-
39 erties of biochar when produced under a user-defined set of production variables. The
40 overarching goal is to improve the efficiency in production of biochar with engineered
41 properties so that it can best match the needs of a particular soil or crop system.
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2. MATERIALS AND METHODS

2.1. Assembly of meta-data library

A library of meta-data (summarized in Table A.1) was created using information from 102 different biochar samples measured for 22 unique physical and chemical characteristics. To build the library, data were gathered from published studies that: (i) used slow-pyrolysis biochar, (ii) reported the production details, and (iii) extensively characterized the physical and chemical properties of biochar materials (Karaosmanoğlu et al., 2000; Cordero et al., 2001; Gaskin et al., 2008; Keiluweit et al., 2010; Mukherjee et al., 2011; Enders et al., 2012; Rajkovich et al., 2012). Production variable details for each study are summarized in Table 2. These studies were chosen because the analytical methods for characterization were similar, thus permitting the comparison of data across studies. Based on these selection criteria, we focused our efforts to test the effects of starting organic materials biomass and peak pyrolysis temperature on each of the 22 biochar characteristics. It is important to note that although additional pyrolysis production parameters varied among the samples in our meta-data, the distribution of these variables was too skewed or not documented in a sufficient number of studies to adequately test their effect.

2.2. Correlation matrix and networks

For the first statistical analysis, a correlation matrix was built to identify the links among the physical and chemical properties of biochar in this study (see Fig. 1). To construct the correlation matrix, the Pearson product-moment correlation coefficient for each pair of variables was determined using all complete pairs of observations on those variables. Significance of the relationships was simultaneously determined with a confidence interval of 0.95. Absolute value of correlation and its significance (p -values denoted by star symbols) are reported in the matrix. A threshold for the absolute value of correlation coefficient, $|r|$, of 0.75 was used arbitrarily chosen to resolve sufficiently strong relationships. The correlation matrix gives a great deal of information that is not always easy to interpret. In order to visualize the most relevant details, we

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5 identified the significant and strong enough correlated pairs of properties, and made a
6 network graph representation (see Fig. 2). The nodes of the graph represent the biochar
7 properties and edges are drawn between pairs of nodes if the properties are strongly
8 correlated and the relationship is significant ($|r| \geq 0.75$ and p -value < 0.001). Edge
9 thickness in the network graph is proportional to the correlation strength between node
10 pairs. From the correlation networks it is further possible to classify biochar properties
11 into interdependent groups or as independent properties. Alternative network graph
12 representations built with different correlation coefficient thresholds can be obtained
13 from the web-tool, as described in subsequent sections. The authors note that the only
14 difference between network representations of different correlation coefficient thresholds
15 is the number of connections which are displayed, meaning that weak correlations are
16 filtered out in order to ease analysis of network properties that are generally obscured
17 by the complexity of the complete (i.e., unfiltered) network.
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31 *2.3. Generalized Linear Model analyses*

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33 To accommodate for the different relationships between biochar properties and pro-
34 duction variables, a Generalized Linear Models (GLMs) approach was used. GLMs are
35 an extension of ordinary linear regression analysis that account for non-Gaussian dis-
36 tributions of the response as well as non-linear dependencies between explanatory and
37 response variables (the interested readers are referred to Myers et al. (2010) for greater
38 details). When there is a non-linear relation between the response and predictor, GLMs
39 can be used by applying a transformation to the response variable before fitting the
40 model. The other possibility consists in modelling the non-linear dependence by means
41 of a non-linear link function.
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51 *2.3.1. GLM candidates*

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53 The following steps have been used to build GLMs for the biochar system:

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57 (a) In this study, the response variables are the biochar properties listed in Table 1.

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59 The predictors correspond to the production variables which are parameterized
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by the pyrolysis peak temperature (T : 250-650 °C) and details about the starting organic materials biomass, which can be introduced in the model by two categorical variables. A first variable denoted as organic material biomass (B) contains the categories: bull manure, corn, dairy manure, digested dairy manure, food waste, grass, hazelnut, oak, paper waste, pine, poultry litter, and rapeseed. The second variable corresponds to a nested category for B referred to as feedstock class (F), and contains the categories: animal waste, plant material, or combination. Variable T was introduced as covariate in the model, while B and F were introduced as factors.

- (b) Under GLMs, the response is assumed to follow a probability density function $p(Resp|X)$ belonging to the exponential family (Myers et al., 2010). In this study the Gaussian and Gamma distributions were initially investigated. However, the Gamma distribution did not show a good fit for any of the response variables and therefore it will not be presented here. Instead, where the response variables did not meet the criteria for a Gaussian distribution, transformation of the response using the Log transform and the Box-Cox transform was applied. As a result, the data distributions we have investigated include (untransformed) Gaussian and two power-transformations for non-Gaussian data (Log transformed and Box-Cox transformed) to describe the biochar system.
- (c) A linear relation between the response (biochar property) and the predictors (production variables) of the form

$$g(E(y_i)) = \beta_{i0} + \sum_{j=1}^{N_c} \beta_{i,j} x_{i,j} + \sum_{j=1}^{N_c} \sum_{k=1}^{N_c} \beta_{i,jk} x_{i,j} x_{i,k} , \quad (1)$$

is assumed, where $E(y_i)$ signifies the expected values of the i -th response, N_c is the number of predictors, $x_{i,j}$ are the values of the predictor variables (dummy values are used for categorical predictors), and $g(\cdot)$ is the link function. In particular, the link functions *identity* and *log* were explored for all models. The β quantities are unknown parameters to be estimated by maximum-likelihood. The

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5 first contribution, β_{i0} , is referred to as the intercept. The parameters $\beta_{i,j}$ quantify
6 the effects of individual variables, while the parameters $\beta_{i,jk}$ account for combined
7 effects associated with interacting pairs of variables. The predictor variables were
8 assessed in all possible individual (B , T , F) and interacting ($B:T$, $F:T$) combi-
9 nations, as summarized in Table 3. That is, possible formulas relating biochar
10 property ($Resp$) to temperature (T), starting biomass (B) and feedstock class (F)
11 include: $Resp \sim T$, $Resp \sim B$, $Resp \sim B + T$, $Resp \sim B : T$, $Resp \sim B + B : T$,
12 $Resp \sim F$, $Resp \sim F + T$, $Resp \sim F : T$, $Resp \sim F + F : T$.
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22 With all the available options, 54 iterations of GLM models (covering 9 formula
23 possibilities, 3 data transformations, and 2 link functions) were tested to describe each
24 biochar property. These options provide the extra flexibility in the model to describe
25 the biochar system with alternative data transformations and link functions that are not
26 included in ordinary linear regression models, which are limited to Gaussian $p(Resp|X)$
27 and *identity* $g(\cdot)$.
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33 2.3.2. “Best” model selection and goodness-of-fit tests

34 The process of “best” model selection requires, first, grouping the GLMs by initial
35 data transformation type: untransformed, Log transformed, and Box-Cox transformed.
36 Quantitative diagnostics were determined for each model, including Akaike Information
37 Criterion (AIC) as an estimate of the quality of a model relative to the collection
38 of candidate models for the data, Shapiro-Wilk (SW) test to determine whether the
39 sample came from a Normally distributed population, and Durbin-Watson (DW) test to
40 detect autocorrelation in the residuals. Within each transformation group, the different
41 model formulations (summarized in Table 3) and the different link functions were ranked
42 by the individual model’s AIC score. The model with the lowest AIC was then selected
43 as the top candidate model in its group. This step reduces the list of candidate models
44 from 54 to 3, one for each transformation type.
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57 In the second step, the three candidates belonging to each data transformation
58 group were compared against each other. To do this, diagnostic plots were gener-
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ated for each candidate model, including: (i) residual plots to illustrate the distance of the data points from the fitted regression, (ii) Q-QNormal Quantile-Quantile plots to graphically compare the probability distribution of the data against a theoretical Normal distribution, (iii) square root of standardized residual plots to check for heterogeneity of the variance, and (iv) leverage with Cook's distance to identify outliers and points with disproportionate influence on regression estimates. Outlier points were removed from a data set only when the Cook's distance of a datum exceeded 0.5 and re-evaluation of the model did not result in new points with large Cook's distance. Performance of the candidate models for *SW* and *DW* tests, together with the diagnostic plots were used as goodness-of-fit tests to evaluate the assumptions of the models.

The following criteria were used to assess model adequacy. The residual plot was checked for a random scatter of points producing a flat-shapped trend to verify that the appropriate type of model was fitted. The Q-QNormal Quantile-Quantile plot was assessed for deviation from the theoretical distribution to confirm Normality in the residuals. The standardized residual plot was examined for a symmetric scatter and flat-shapped trend to test the homogeneity of the variance. The leverage plot was inspected for influential outliers when points fell far from the centroid or were isolated. *SW* quantitatively tested for assumptions of Normality (p -value ≥ 0.05), while *DW* evaluated the level of uncorrelation of the residuals (p -value ≥ 0.05). The "best" model was finally selected as that which satisfied the most criteria, preferring the simpler data transformation if diagnostics were comparable. All computations were performed using RStudio, version 0.96.331.

2.4. Interactive web-tool

The interactive web application *Biochar Engineering* (available at: <http://spark.rstudio.com/veromora/BiocharEng/>) was built to implement the GLMs constructed in this study into a user-friendly tool, which requires no prior knowledge of advanced statistics or programming language. It is accessible free of charge through a web browser as a stand-alone application hosted by Shiny-RStudio. The primary intention of the

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tool is to maximize the utility of the models herein developed so that anyone can use them to obtain a statistical outlook for expected physical and chemical properties of biochar from user-defined production values. As is demonstrated in examples to follow, the tool can be used to make informed decisions of the optimum selection of parent biomass type and peak pyrolysis temperature that is required to produce biochars with tailored physical and chemical properties.

3. RESULTS AND DISCUSSION

3.1. Correlation matrix and networks

Related biochar properties identified from the correlation matrix (Fig. 1) were used to build a network representation of the 22 responses included in this study (Fig. 2). From the generated networks, three groups of interdependent biochar properties were distinguished and five individual properties found to be independent (i.e., the correlation coefficient between any pair of properties was $|r| < 0.75$). As illustrated in Fig. 2, the first correlated group includes Fe, Yield, Ash, Ca, C, FixedC, and SSA(CO₂), which contains a mixture of positively and negatively correlated pairs. The second group includes EC, Na, P, K, Mg, Mn, Zn, and S, which contains all positive correlations (linked by solid edges). The third group includes C:N and pH_w, which are negatively correlated (linked by dashed edges). The five independent properties are represented as edge-free nodes and include BulkD, SSA(N₂), N, MatVol, and CEC. Interestingly, SSA(N₂) and CEC were found to have mostly very weak and insignificant relationships with all other biochar properties ($|r| \leq 0.53$ with p -value ≥ 0.01 and $|r| \leq 0.44$ with p -value ≥ 0.001 , respectively). The exception for CEC is its relationship with BulkD, which is significant albeit still weak ($|r| = 0.58$ with p -value < 0.001). As a result, SSA(N₂) and CEC could be considered the two most independent biochar properties, which are the least likely to be affected when other properties are modified. It is noted that Principal Component Analysis (analyzed with SPSS v.21) was initially explored to find clusters of biochar properties. However, the meta-data contained too many samples that were

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6 not characterized in full, thus producing an incomplete matrix that required the omis-
7 sion of a vast number of samples or of entire response variables from the analysis. As
8 these omissions were considered to affect the results excessively, a correlation matrix
9 and network approach was adopted being considered less biased by missing data.

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13 The networks of correlated properties provide an overview of which combinations of
14 biochar properties are more likely to occur in a given sample. The correlation networks
15 prove very useful as a tool for qualitative design of biochar samples with desired prop-
16 erties. For example, a hypothetically desirable biochar might be needed to neutralize
17 soil acidity (high pH_w), return lost macronutrients P and S that were removed during
18 harvest (high P and S), prevent excess atrazine from leaching into the groundwater
19 (high $\text{SSA}(\text{CO}_2)$ and/or high Ash), and maximize the amount of biochar produced by
20 pyrolysis (high Yield). Using the network diagram of Fig. 2, it is possible for example
21 to infer the following. A biochar sample engineered for high pH_w will not affect the
22 other desired properties, given that pH_w is in a separate network to all other proper-
23 ties of interest. The addition of macronutrient P will concomitantly supply S, as these
24 properties belong to the same positively correlated network. The remaining three prop-
25 erties belong to the same network from which we extrapolate that a single sample of
26 biochar has a negative tradeoff between high $\text{SSA}(\text{CO}_2)$ and high Ash², meaning that
27 it is less probable that a sample will have both high $\text{SSA}(\text{CO}_2)$ and high Ash. Yield
28 will be reduced if the sample is prioritized for high $\text{SSA}(\text{CO}_2)$ and (indirectly) maxi-
29 mized when high Ash content is favored. Networks obtained from different correlation
30 coefficient thresholds can be created in the web-tool as displayed in the *Networks* tab
31 and interpreted in the fashion described above. Increasing the correlation coefficient
32 threshold will simply result in the removal of weak connections from the final graphic,
33 while decreasing it will result in the display of more connections.

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²While $\text{SSA}(\text{CO}_2)$ is not directly linked to Ash, high $\text{SSA}(\text{CO}_2)$ implies high C and FixedC which, in turn, are negatively correlated with Ash. In other words, $\text{SSA}(\text{CO}_2)$ and Ash are indirectly anti-correlated.

3.2. Generalized Linear Models

In this section the versatility of GLMs as an extended linear regression approach is leveraged to model the biochar system. The candidate GLMs are compared against one another and the most appropriate models for each biochar property selected. Lastly, the “best” models are evaluated for goodness-of-fit.

3.2.1. GLM candidates

As indicated in the methods section, selection of the “best” model is a two-step process. First, the list of candidates is reduced to three. To do so, candidate models belonging to each of the three data transformation groups (untransformed, Log transformed and Box-Cox transformed) are ranked according to their *AIC* score. Top scoring models for each group are those with the lowest *AIC* value, and are reported in tables for each biochar property in section II of the supplementary data. The tables summarize the top candidate model for each data transformation group, where details of the model are reported concerning: formula, type of data transformation used, link function, *AIC*, *p*-value for the *SW* test, as well as *d* and *p*-value for the *DW* test. Second, diagnostic plots are generated for the reduced candidate list, and the overall “best” model is selected according to their relative performance in *SW* and *DW* tests and diagnostic plot criteria. Diagnostic plots of the overall “best” model are included in the same section of the supplementary data, and noted by a star in the table.

Model selection required a certain level of flexibility, as very few candidate models met all evaluating criteria. This is a common feature of real data sets of a limited size. Model performance in the *SW* test was relatively poor, since candidate GLMs of 15 of the biochar properties failed *SW* for all types of data transformation. Nevertheless, candidate GLMs of the remaining biochar properties consistently satisfied this criterion for the overall “best” model. Performance in *DW* was useful in quantitatively evaluating the assumption for uncorrelated residuals, but not to differentiate the candidate GLMs against each other because often all candidates satisfied or failed this criterion. Diagnostic plots, on the other hand, were much more insightful in il-

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6 illustrating the suitability and relative performance of the models, and were given more
7 consideration during “best” model selection.
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10 In general, all four diagnostic plots corresponding to one candidate model performed
11 well above the other two, and demonstrated that the goodness-of-fit (GOF) assumptions
12 were satisfactorily met. For certain biochar properties two candidate models produced
13 diagnostic plots of similar performance, in which case the model corresponding to the
14 simpler data transformation was given preference; that is, untransformed is simpler
15 than Log transformed, which is simpler than Box-Cox transformed. In the case of Na,
16 for example, diagnostic plots for Log and Box-Cox transformation GLMs showed a
17 nearly identical model improvement (see Figs. A.15 and A.16), and all three candidate
18 models performed the same for *SW* and *DW* (see Table A.16). Consequently, the
19 Log transformed model was selected as the “best” model. The models for Fe, N,
20 and SSA(N₂) were difficult to select given the pronounced heterogeneity in variance
21 and heavy deviation from the theoretical Q-QNormal Quantile-Quantile distribution
22 across all candidate models (see Fig. A.8, A.14 and A.21). These three models were
23 therefore considered to violate too many GOF criteria to be recommended for use with
24 confidence; the situation would improve with additional data. Irrespective of that,
25 the large proportion of properties found to be properly described by the corresponding
26 “best” model clearly demonstrates the feasibility of reverse engineering multiple biochar
27 properties simultaneously. We note that initial analysis with fewer samples comprising
28 the meta-data resulted in the selection of “best” models with satisfactory GOF criteria
29 that were very similar to those chosen from the larger data set (presented in Table 3).
30 This indicates that replication of suitable results (i.e., those that comply with GOF
31 standards) from different studies are consistent.
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51 Table 3 summarizes the “best” models chosen for all biochar properties, where the
52 last column indicates whether the model complies with GOF standards. The Maximum
53 Likelihood Estimates (MLEs) of the “best” model coefficients for each biochar property
54 are reported in section III of the supplementary data and can be requested from the
55 web-tool in the *Stats* tab.
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3.2.2. “Best” GLMs

The formulas of the “best” models (column 2 in Table 3) indicate that for the vast majority of cases it is imperative to have information about both starting organic material biomass and peak pyrolysis temperature to properly define the relationship between biochar properties and production variables. In the simplest case a single predictor variable statistically dominates. We find that this only occurs for S, which depends entirely on B , while T is not statistically significant (as shown in Fig. 3A). No response variable was found to depend exclusively on T . The next level of complexity is that in which the response depends on both B and T , but the two factors do not interact ($B+T$). This occurs for pH_w , Ash, C:N, and most micronutrients. In this type of relationship, B affects the response, but the rate at which T has an influence is the same across all types of B (illustrated in Fig. 3B). The following level of complexity is that in which there is a significant interaction between B and T , but no main effect of B ($B:T$), as in the case for $\text{SSA}(\text{CO}_2)$ and FixedC. A general trend in this type of relationship is that the rate of change in the response with the increase in T is different for the different B , whereas the intercept is the same (as shown in Fig. 3C). Finally, the most complex relationship is given by the full model ($B+B:T$ or $F+F:T$). In this model, both intercept and temperature regression slope are significantly different for the different B (or F). The relationships for BulkD, $\text{SSA}(\text{N}_2)$, Yield, EC, CEC, MatVol, C, N, P, Ca, and K fall into this category. In this case, changes in B (or F) and T are not trivial, as the relationship permits the greatest level of flexibility and rules out any general trends (as in Fig. 3D).

For the three simplest relationships (B , $B+T$, and $B:T$), a change in B does not affect the response order relative to the other types of B . Conversely, for the most complex relationship ($B+B:T$ or $F+F:T$), a change in organic material biomass affects the response in such a way that it crosses over responses from other organic material biomass types as T changes; thereby not necessarily maintaining the relative order among the different types of organic material biomass. This assessment of multiple predictor variable influence corroborates the perception that biochar properties are deeply shaped by

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5 the collective effect of both production variables, whether additive and/or interactive.
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7 Furthermore, it warrants against statistical bias that is introduced when biochar pro-
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9 duction decisions are based on the dominance of a single variable on a biochar property
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11 of interest. Interestingly, only the “best” model for MatVol favored the nested start-
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13 ing organic material biomass, F . All other “best” models performed better when this
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15 information was entered in its more detailed form, B .

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17 The frequency in response variable transformation for the selected “best” models
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19 (column 3 in Table 3) indicates that a minority of the data are Normally distributed and
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21 meet the constant variance assumption. Most responses require power-transformation
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23 to stabilize their variance. Specifically, 7 response variables were satisfactorily modeled
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25 without transformation of the response values, while 9 others needed Log transforma-
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27 tion and the remaining 6 required the more advanced Box-Cox transformation. This
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29 observation draws attention to the fact that non-constant variance is ubiquitous in
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31 the characteristics of biochar, which requires transformation of the response variable
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33 to comply with Normality assumptions. Depictions of different functional shapes are
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35 presented in Fig. 4 for models sharing the same formula ($B+T$) and *identity* link. In
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37 this figure, (A) is the reference for the untransformed response for pH_w , (B) is the Log
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39 transformed response for Mn, and (C) is the Box-Cox transformed response for Ash. In
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41 these plots, it is evident that the untransformed data have a perfectly linear relation-
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43 ship. In contrast, Log and Box-Cox transformations are suitable to describe non-linear
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45 behavior associated with a more cumbersome relationship between biochar properties
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47 and production variables.

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49 Similarly, the prevalence of non-linear link functions in the “best” model population
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51 (column 4 in Table 3) exposes the common violation of the linearity assumption. It is
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53 interesting that all 7 responses that demonstrated constant variance (i.e., not requiring
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55 data transformation) also met the linearity assumption (favoring *identity* link function).
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57 This was also the case for 8 of the responses with unequal variances that required data
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59 transformation. The remaining 7 responses required transformation to address variance
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61 instability and the *log* link function to further correct for non-linearity. The *log* link
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5 function contributes to the non-linear function shape of the response in a way that
6 resembles that of Log and Box-Cox data transformation. Fig. 4 illustrates this effect
7 for responses that have been Log transformed. The data in (B) satisfies the linearity
8 assumption and is adequately modeled with the *identity* link function. In contrast,
9 the property in (D) needs a *log* link function to adjust for non-linearity. In short,
10 both non-Gaussian and non-linear features were found to be ubiquitous in the biochar
11 system.
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20 3.3. Biochar Engineering: *the web-tool*

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22 The *Biochar Engineering* tool is an integrated calculator for the biochar models
23 in Table 3. The web-tool can be navigated through the various tabs on display at
24 the top of the page. The *About* tab introduces the tool, the *Graphic* and *Table* tabs
25 contain the model results, the *Stats* tab summarizes individual model parameters, and
26 the *Networks* tab displays networks of correlated biochar properties. The side bar
27 panel is always visible and can be modified at any time to re-run the model with new
28 input variable values for organic materialbiomass, peak temperature, and confidence
29 coefficient, request the statistical summary of a specific response model, set a correlation
30 coefficient cutoff for the networks, and download the output of any tab. The model
31 output for the user-defined production variables is automatically generated and updated
32 in the *Graphic* and *Table* tabs. Correlation networks are similarly updated in the
33 *Networks* tab for newly defined correlation coefficients. Ultimately, this information can
34 be used to select production variable values that yield biochar with the most desirable
35 set of properties for the user, thereby facilitating the possibility to efficiently engineer
36 biochar resources to meet multiple agricultural demands.
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51 3.4. Using GLMs and web-tool to engineer a biochar

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53 Recommendations for the use of the GLMs in Table 3 cannot be generalized be-
54 cause they depend on the particular set of properties needed from biochar to mitigate
55 deficiencies in a specific soil or crop, as well as on the type of organic materialbiomass
56 available and limitations of the pyrolysis unit. Rather than attempting to examine all
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possible scenarios, this section presents two examples that demonstrate how the GLMs and the web-tool can be used to engineer the hypothetical biochar described in section 3.1 (requiring high pH_w , high P and S, high $\text{SSA}(\text{CO}_2)$ and/or high Ash, and high Yield). In the first example we assume a situation where all production variables can be modified, and identify the optimum combination of starting organic material biomass and temperature that return the desired qualities. In the second example we assume a situation where the type of starting organic material biomass is fixed (e.g., to concurrently dispose of a byproduct from another process), and determine the temperature that is most suitable to obtain the desired qualities.

3.4.1. A worked example for total optimization of production variables

In the case where all production variables can be modified, we propose to refer to the prediction plots corresponding to the properties of interest. Prediction plots for all properties analyzed in this study are included in Fig. A.24-A.45 of the supplementary data; see the particular case for pH_w in Fig. 5. To facilitate interpretation of the model results, the predictive plots are presented as composite figures where each subfigure corresponds to a unique type of starting organic material biomass and the property of interest is plotted as a function of pyrolysis temperature. The predicted (mean) values are presented as a solid line, while regions corresponding to 75, 85, and 95% confidence intervals are indicated by the shaded regions (dark gray, gray, light gray, respectively). For reference, the data points from the meta-data are overlaid as solid circles.

We begin by analyzing Fig. 5 to identify the variables that can deliver biochar with high pH_w . This figure shows that as T increases pH_w increases, and this rate is constant across all B . Among the different types of B included in the pH_w model, biochars made from Poultry litter would typically result in the highest achievable pH_w at any T , followed by Digested dairy manure, Corn, Food waste, and Paper waste. Next, we analyze the predictive plot for P (Fig. A.38). From this figure it is apparent that most B s result in biochars with low P concentrations that are minimally variable with T ; crossovers associated with the $B:T$ coupling are mainly observed on the low T range.

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Notably, samples made from Poultry litter contain the highest concentration of P (by orders of magnitude greater than samples of lowest P), with Food waste and Digested dairy manure following significantly behind in P concentration. Then, we examine the predictive plot for S (Fig. A.40), which is exclusively dependent on B (in agreement with the “best” model formula for S in Table 3). It is easy to distinguish that Poultry litter has the highest S content, followed by Digested dairy manure and Dairy manure. Next, we consider predictions for SSA(CO₂) (Fig. A.41), which also show a general increase in response with T at rates that depend on B (cf. formula $B:T$ for the “best” SSA(CO₂) model). From these predictions we identify that Hazelnut, Pine and Oak produce the highest possible SSA(CO₂), which is enhanced as T is increased. Conversely, the predictive plot for Ash (Fig. A.24) indicates that this property is typically around 30% and generally increases with T . Paper waste, Poultry litter and Food waste are ranked highest among the B types to show high ash at all T levels. Lastly, the predictive plot for Yield (Fig. A.44) demonstrates a pronouncedly decreasing trend with increasing T for all B types, with crossovers throughout, as expected from the “best” model formula $B+B:T$ given in Table 3 for Yield. It is evident that biochars from Paper waste and Poultry litter produce the highest yield for the range of T investigated.

Based on the above observations, we conclude that Poultry litter pyrolysed at T above 500°C will return a biochar that meets most of the needed hypothetical properties. More concrete recommendations of T will depend on the producer’s choice to compromise between Ash and Yield, which have opposing trends with T . One way to facilitate this decision is to refer to the predictions made by the *Biochar Engineering* web-tool at various temperatures. By specifying in the side bar panel the Organic MaterialBiomass (Poultry), Peak Temperature (a value in the range 500-600°C), and a satisfactory Confidence Coefficient (e.g., 0.8), the web-tool automatically generates a table (located in the *Table* tab) that summarizes the expected biochar properties for the input variables. For discrete temperatures at 500, 550, and 600°C, the biochar would be expected to have an Ash content of 56.60, 61.31, and 66.4%, and Yield of 65.76, 64.38, and 63.03%, respectively. Considering that Ash is increased by 10% and Yield

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6 is only reduced by 2% when T is increased from 500 to 600°C, one might accept the
7 small penalty in yield for gaining more ash. Assuming all other considerations are sat-
8 isfactory in this hypothetical scenario, one could conclude that the customized biochar
9 with the above listed characteristics is best produced by pyrolysing Poultry litter at
10 600°C. For a comprehensive outlook on the expected range of all 22 physico-chemical
11 properties, the user may refer to the output generated in the *Graphic* or *Table* tabs of
12 the web-tool, and save the results with the download buttons for future reference.
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20 *3.4.2. A worked example for restrictions in starting organic materialbiomass*

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22 A similar approach to that followed in the first example can be used to engineer
23 a biochar for cases in which the type of organic materialbiomass is fixed. Take for
24 instance a corn farm, which is interested in selling its corn stover resources as high
25 quality biochar because livestock feed and bioenergy prices are low. The properties
26 required from the biochar, as specified by the client, are assumed to be the same as
27 those for the hypothetical biochar considered above. In this case, the farmer or py-
28 rolysis contractor would be referred to the web-tool directly. In the side bar panel,
29 the Organic MaterialBiomass should be set to Corn and a suitable Confidence Coeffi-
30 cient selected (e.g., 0.8). The Peak Temperature slider can then be used to study the
31 changes in biochar properties with temperature, as the only production variable that
32 can be adjusted. The model output results can be monitored in either the *Graphic*
33 tab (bar plots indicate predicted values with error bars marking the confidence interval
34 range) or in the *Table* tab (table summary of predicted values with their corresponding
35 standard error and confidence interval). By shifting the Peak Temperature slider from
36 low to high temperatures it is evident that Yield is diminished, SSA(CO₂), pH_w, Ash,
37 and P are intensified, and S remains constant. Assuming in addition to the required
38 biochar properties that in order to make a profit, the Yield should be at least 30%,
39 we can conclude that the corn stover should be pyrolysed at 467°C, so the lower end
40 of the expected yield range is above 30%. The *Table* tab of the web-tool (see screen-
41 shot in Fig. 6) summarizes the expected value and confidence interval for each biochar
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property, according to the production variables specified. For corn pyrolysed at 467°C, the estimated range (with 80% confidence level) for the desired properties is: 8.6-9.9 pH_w, 1647-2214 Total (mg/kg) P, and 633.1-869.9 Total (mg/kg) S, 330.6-450.6 m²/g SSA(CO₂), 11.8-16.2% Ash, and 30.0-33.1% Yield.

4. CONCLUSION

Statistical results demonstrate that arbitrary choices of starting organic material biomass or peak pyrolysis temperature are unlikely to produce biochar with prescribed physico-chemical properties. Generalized Linear Models were used to quantify the combined effect that starting organic material biomass and peak temperature has on different biochar properties. These properties are typically non-Gaussian and exhibit non-linear dependence on the two predictor variables. Proper description of most biochar properties by GLMs demonstrates the feasibility to engineer biochar. A web-application of the GLMs together with correlation networks are offered as tools to guide biochar engineering.

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Captions, Figures and Tables

Figure 1. Correlation matrix of biochar properties. The diagonal indicates the biochar properties. The upper triangular sector shows the absolute value of correlation between pairs of properties and significance symbol (defined in the legend). Highly correlated pairs (with $|r| \geq 0.75$) are highlighted in bold font. The lower triangular sector displays the respective bivariate scatterplots with a trend line.

Figure 2. Correlation networks of inter-correlated biochar properties ($|r| \geq 0.75$). Nodes represent individual biochar properties, and edges indicate whether the correlation is positive (solid line) or negative (dashed line). Line thickness is proportional to the correlation strength.

Figure 3. Formula interpretation for GLMs of link *identity*. (A) $Resp \sim B$. (B) $Resp \sim B + T$. (C) $Resp \sim B:T$. (D) $Resp \sim B + B:T$.

Figure 4. Data transformation interpretation for GLMs of link *identity* and Formula $B+T$. (A) Untransformed. (B) Log transformed. (C) Box-Cox transformed. (D) Log transformed of link *log*.

Figure 5. Model predictions for pH_w content (solid line) with confidence intervals for 75, 85, and 95% (dark gray, gray, light gray shading, respectively). Data points from meta-data are overlain (solid circles).

Figure 6. Interface of the *Biochar Engineering* tool. Model output compiled in the *Table* tab.

Table 1. Benefits from specific biochar properties.

Table 2. Production details of meta-data.

Table 3. Possible GLM formulas relating biochar property (*Resp*) to starting organic material biomass (*B*), feedstock class (*F*), and temperature (*T*).

Table 43. Summary of “best” models selected for each biochar characteristic.

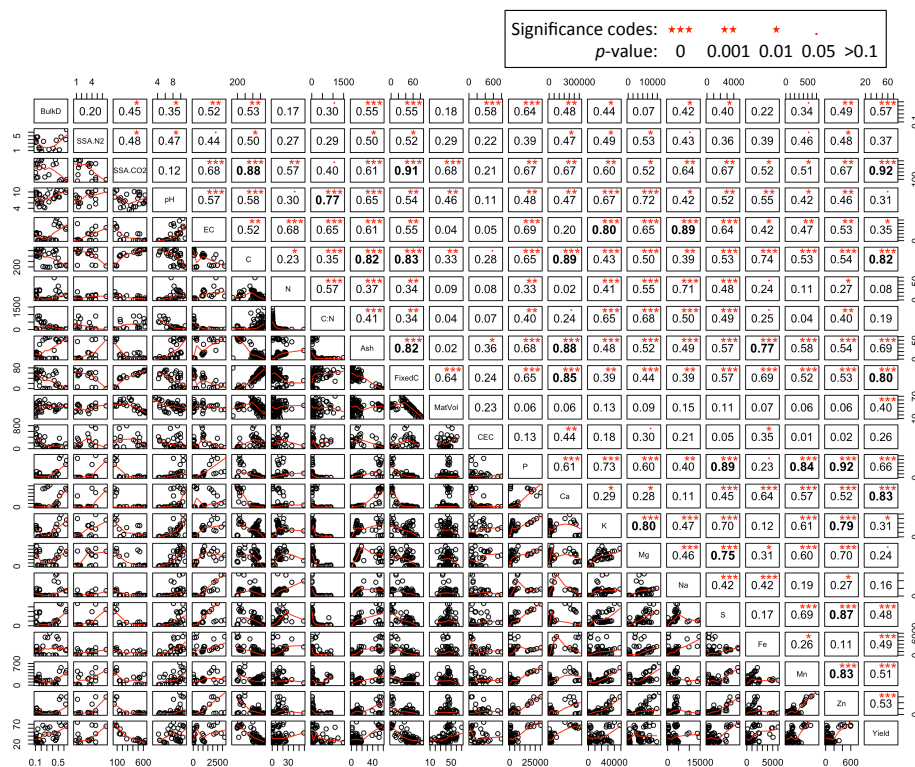


Figure 1:

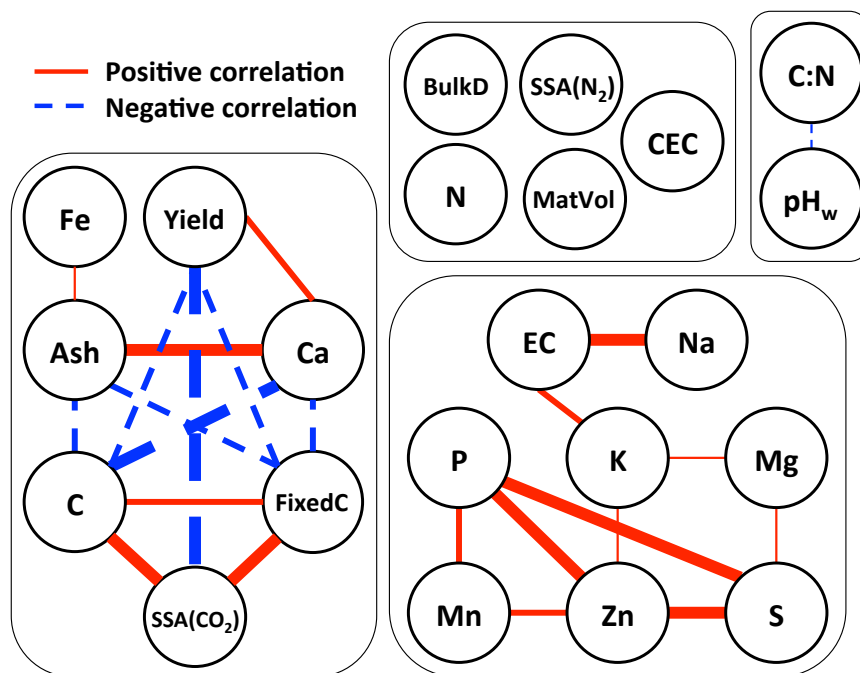


Figure 2:

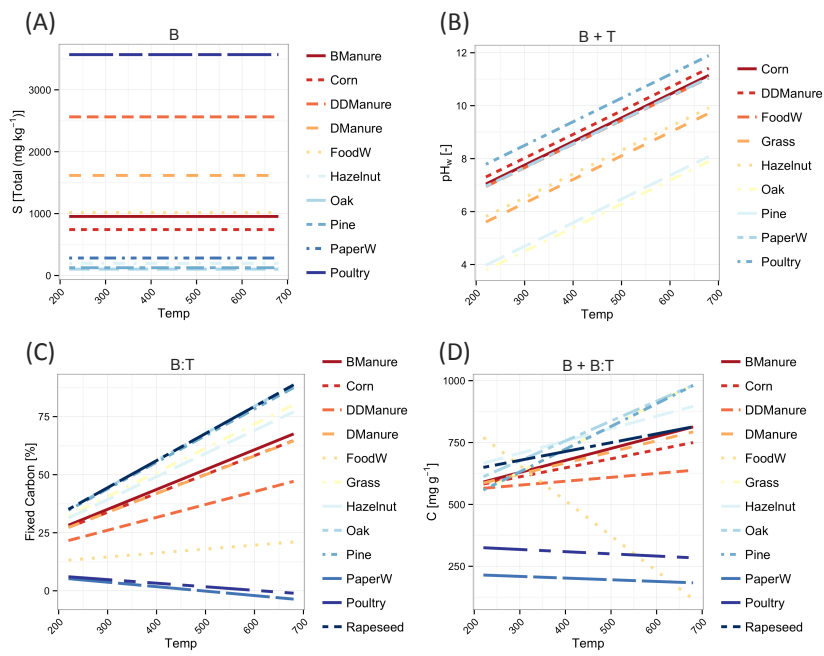


Figure 3:

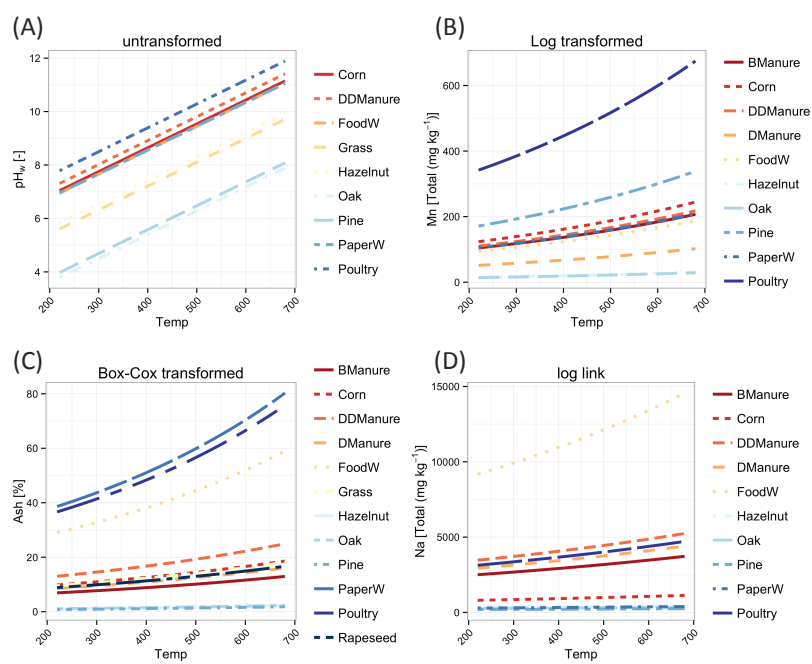


Figure 4:

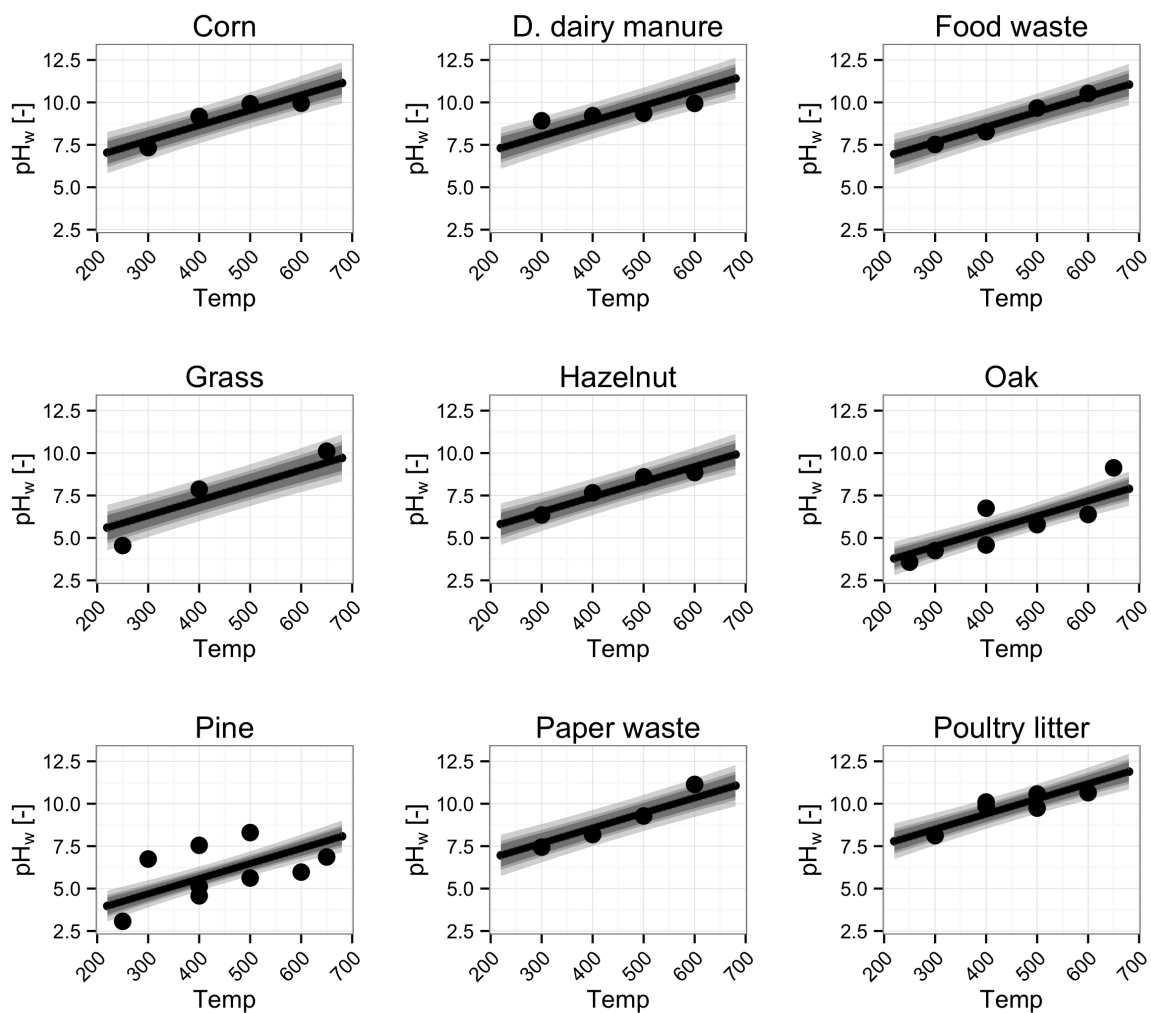


Figure 5:

Biochar Engineering

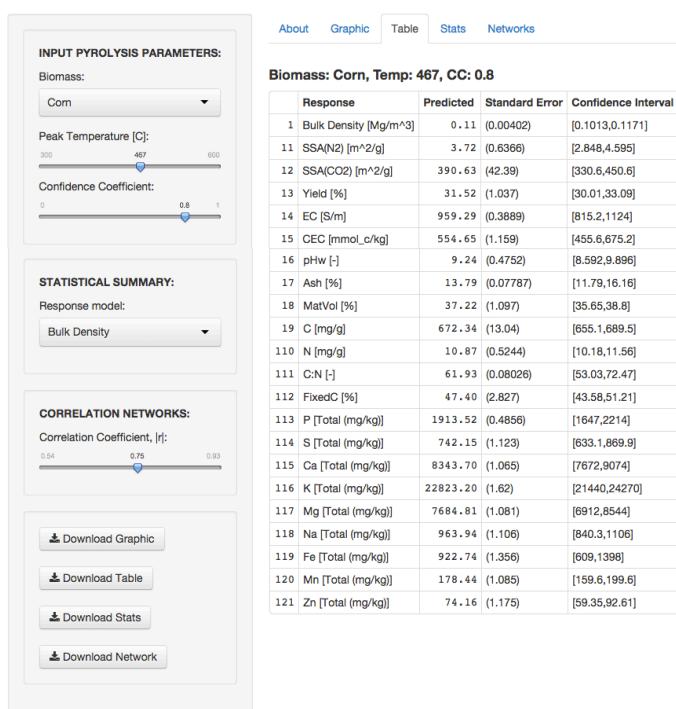


Figure 6:

Table 1:

Biochar property	Agronomic and environmental benefits
BulkD [Mg m^{-3}]	Low bulk density biochar can reduce the density of compacted soils, thereby improving root penetration (Ennis et al., 2011; Atkinson et al., 2010; Novak and Busscher, 2013), water drainage and aeration (Joseph et al., 2009; Laird et al., 2010). The latter may mitigate green house gas emissions (Karhu et al., 2011).
SSA(N_2), SSA(CO_2) [$\text{m}^2 \text{g}^{-1}$]	High nanopore and micropore specific surface area, respectively, may increase the sorptive affinity of organic compounds to biochars (Beesley et al., 2011; Cornelissen et al., 2005), and improve water holding capacity (Karhu et al., 2011).
Yield [%]	Yield reflects the quantity of biochar material produced from the pyrolysis process.
EC [mS m^{-1}]	Electrical conductivity indicates the quantity of salt contained in the biochar. High EC can stabilize soil structure (Joseph et al., 2009; Hossain et al., 2011).
CEC [$\text{Av} (\text{mmol}_c \text{kg}^{-1})$]	Increased cation exchange capacity can improve the soil's ability to hold and exchange cations (Chapman, 1965; Glaser et al., 2002).
pH _w [-]	Soil solution pH directly affects soil surface charge, which determines the type of exchangeable nutrients and mineral ions it attracts (Mukherjee et al., 2011). Additionally, the buffering capacity of biochar can neutralize acidic soils, reduce aluminum toxicity and change the soil microbial community structure (Abe, 1988; Lehmann et al., 2011).
Ash [%]	Ash may improve the sorption capacity of biochar for organic compounds and metals (Cao et al., 2011).
MatVol [%]	Volatile matter affects biochar longevity in soil (Enders et al., 2012; Lehmann et al., 2011). Residual volatiles can also impact organic substance sorption by blocking pores and changing surface chemical interactions (Novak and Busscher, 2013; Zhu et al., 2005; Sander and Pignatello, 2005).
C [mg g^{-1}]	Total carbon in organic matter benefits the soil.
N [mg g^{-1}]	Total nitrogen in the biochar supplies a macronutrient, but its availability is limited. Biochar may strongly sorb ammonia and act as a nitrogen-rich soil amendment (Spokas et al., 2012b).
C:N [-]	Carbon to nitrogen ratio influences the rate of decomposition of organic matter and release of soil nitrogen (Novak et al., 2009).
FixedC [%]	Fixed carbon is non-labile and therefore is a property attributed to biochar stability (Keiluweit et al., 2010; Enders et al., 2012; Rajkovich et al., 2012).
P, S [Total (mg kg^{-1})]	Macronutrients provided by biochar, which can improve soil fertility.
Ca, K, Mg, Na, Fe, Mn, Zn [Total (mg kg^{-1})]	Micronutrients provided by biochar, which can improve soil fertility.

Notes: BulkD = Bulk Density, SSA = Specific Surface Area, EC = Electrical Conductivity, CEC = Cation Exchange Capacity,

MatVol = Volatile Matter, FixedC = Fixed Carbon

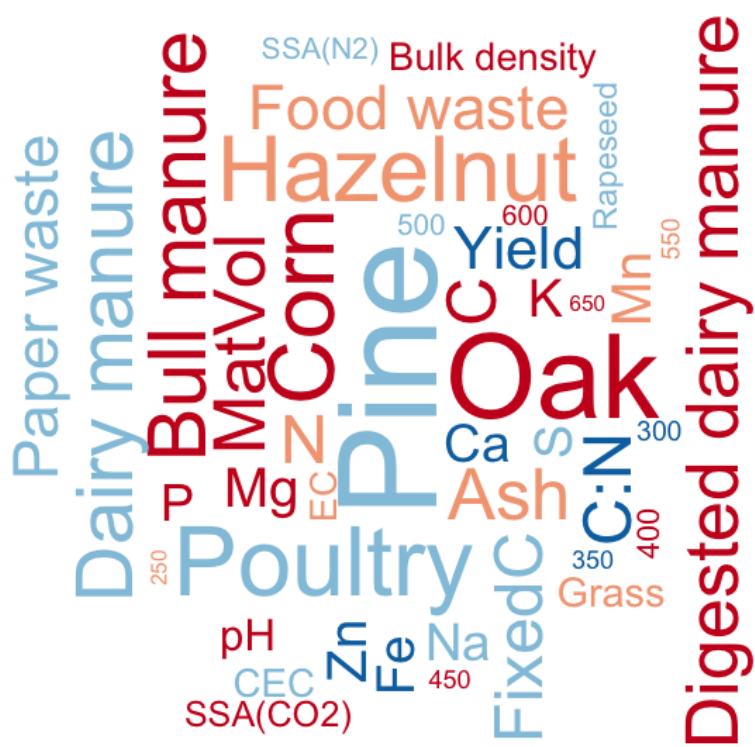
Table 2:

Biomass	Feedstock	Milling size [μm]	Moisture [%]	Reactor type	Feed capacity	Oxygen limitation	Heat rate	Holding time [min]	Peak temp. [$^{\circ}\text{C}$]	Reference
Bull manure	animal	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Enders et al., 2012)
Corn	plant	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Dairy manure	animal	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Enders et al., 2012)
Digested dairy manure	animal	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Food waste	combo	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,400,500,600	(Rajkovich et al., 2012)
Grass (<i>Tall fescue</i>)	plant	<1500	na	closed container muffle furnace	na	yes*	na	60	300,400,500,600	(Kehlweit et al., 2010)
Grass (<i>Tripsacum floridanum</i>)	plant	50,000	(5d drying at 60°C)	batch pyrolysis oven	4,749 cm^3	N_2	26°C	60	250,400,650	(Mukherjee et al., 2011)
Hazelnut	plant	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Oak (<i>Quercus rotundifolia</i>)	plant	177-250	na	horizontal tube furnace	na	N_2	continuous flow	120	300,350,400,450,500,550,600	(Cordero et al., 2001)
Oak (<i>Quercus lobata</i>)	plant	50,000	(5d drying at 60°C)	batch pyrolysis oven	4,749 cm^3	N_2	26°C	60	250,400,650	(Mukherjee et al., 2011)
Oak	plant	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Paper waste	plant	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,400,500,600	(Rajkovich et al., 2012)
Pine (<i>Pinus halepensis</i>)	plant	177-250	na	horizontal tube furnace	na	N_2	continuous flow	120	300,350,400,450,500,550,600	(Cordero et al., 2001)
Pine (<i>Pinus ponderosa</i>)	plant	<1500	na	closed container muffle furnace	na	yes*	na	60	300,400,500,600	(Kehlweit et al., 2010)
Pine (<i>Pinus taeda</i>)	plant	na	na	batch pyrolysis unit	na	N_2	na	na	400,500	(Gaskin et al., 2008)
Pine (<i>Pinus taeda</i>)	plant	50,000	(5d drying at 60°C)	batch pyrolysis oven	4,749 cm^3	N_2	26°C	60	250,400,650	(Mukherjee et al., 2011)
Pine	plant	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Poultry litter	animal	na	na	batch pyrolysis unit	na	N_2	na	na	400,500	(Gaskin et al., 2008)
Poultry litter	animal	149-850	10	kiln	3000 g	N_2	$3^{\circ}\text{C } 15\text{-}20 \text{ min}^{-1}$	80-90	300,350,400,450,500,550,600	(Rajkovich et al., 2012; Enders et al., 2012)
Rapeseed	plant	<1000	12.6	tubular reactor	30 g	N_2	$5^{\circ}\text{C } \text{min}^{-1}$	30	400,500,600	(Karacsmanoglu et al., 2000)

* Details not specified.

Table 3:

Response	Formula	Transformation	Link	GOF
BulkD	B + B:T	Box-Cox Transf	identity	✓
SSA(N ₂)	B + B:T	-	identity	✗
SSA(CO ₂)	B:T	-	identity	✓
Yield	B + B:T	Log Transf	log	✓
EC	B + B:T	Box-Cox Transf	log	✓
CEC	B + B:T	Log Transf	log	✓
pH _w	B + T	-	identity	✓
Ash	B + T	Box-Cox Transf	identity	✓
MatVol	F + F:T	-	identity	✓
C	B + B:T	-	identity	✓
N	B + B:T	-	identity	✗
C:N	B + T	Box-Cox Transf	identity	✓
FixedC	B:T	-	identity	✓
P	B + B:T	Box-Cox Transf	log	✓
S	B	Log Transf	identity	✓
Ca	B + B:T	Log Transf	identity	✓
K	B + B:T	Box-Cox Transf	identity	✓
Mg	B + T	Log Transf	identity	✓
Na	B + T	Log Transf	log	✓
Fe	B + T	Log Transf	log	✗
Mn	B + T	Log Transf	identity	✓
Zn	B + T	Log Transf	log	✓



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Highlights:

- Starting biomass and peak pyrolysis temperature jointly affect biochar properties.
- 19 different physico-chemical properties of biochar were properly modeled by GLM.
- Models reveal complex relationships between biochar properties and predictors.
- Ubiquitous non-Gaussian and non-linear attributes were accounted for in GLMs.
- Proposed correlation networks, models and web-tool can be used to engineer biochar.

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