26th International Congress on Modelling and Simulation, Adelaide, SA, Australia, 30 Nov–4 Dec 2025
mssanz.org.au/modsim2025

Boundary line analysis for estimating attainable soil organic carbon across Australian grain regions and farm-level constraints

B Hossen [a], **P Filippi** [a], **N Hoskin** [a], **D Al-Shammari** [a], **SB Karunaratne** [b] **and TFA Bishop** [a]

[a] *Precision Agriculture, Hydrology & Geoinformation Science Laboratory, Sydney Institute of Agriculture, School of Life and Environmental Sciences, The University of Sydney, Sydney, New South Wales, Australia*
[b] *CSIRO Agriculture and Food, Black Mountain, Australian Capital Territory*
Email: billal.hossen@sydney.edu.au

Abstract: Soil Organic Carbon (SOC) is a determining factor of soil health and agricultural crop productivity. The SOC level has generally declined since European settlement of Australia due to the clearing of native vegetation for agriculture. To enhance soil health and crop yield, it is necessary to determine the attainable SOC potential and site-specific soil constraints that limit SOC buildup. To achieve this, we applied a Boundary Line Analysis (BLA) model to a dataset consisting of 1,782 soil samples, categorised by the Bureau of Meteorology (BOM)'s seasonal rainfall zones, collected from 72 farms across the grain-growing (cropland) regions of Australia. We utilised our laboratory-measured value of clay content and exchangeable sodium percentage (ESP) as predictors to assess attainable SOC levels in topsoils (0-30 cm) with the BLA model. We created a digital soil map for a representative farm in the Wimmera, Victoria, to illustrate how the BLA can be used to identify limiting factors. Next, we applied the developed BLA models to that farm to determine the attainable SOC at the field scale for given maps of two soil properties (clay and ESP). The BLA result showed that attainable SOC ranged from 1.2% (mean minimum attainable SOC) to 1.41% (mean maximum attainable SOC) across the rainfall regions. In contrast, the mean value of actual (measured) SOC was 0.71 % (SD = 0.42), with an interquartile range of 0.45 to 0.84, across the grain growing region of Australia. These findings suggest a considerable opportunity for substantial SOC sequestration, with possible increases ranging from 0.49 - 0.7 %, depending on rainfall zones and management practices. In addition, the BLA produced spatial maps showing the spatial variability of attainable SOC based on clay and ESP across the case study farm. Furthermore, the limiting factor map revealed that clay is the most limiting factor for SOC storage, affecting 55% of the field, followed by ESP, which impacts 45% of the field. We considered two soil properties in this study; however, future studies will include more soil properties such as electrical conductivity (EC), cation exchange capacity (CEC), pH and silt+clay, as predictors in the BLA model. The BLA model will also be applied to the subsoil (up to 1 m) to evaluate the process in the subsoil that affects the SOC within the profile. This BLA model is reproducible and can be applied across all 72 grain-growing farms in Australia to quantify the potential SOC and identify the site-specific soil constraints for each individual farm. Consequently, this approach offers a rapid and effective decision-support tool for farmers and farm managers to execute site-specific soil and agronomic management to improve soil carbon levels.

Keywords: *Maximum achievable SOC, soil carbon benchmarking, SOC sequestration, digital soil mapping, site-specific soil management.*

1. INTRODUCTION

Soil organic carbon (SOC) is one of the key factors in determining the health, sustainability, and productivity of soil (Castaldi et al., 2019). It enhances the stability of soil aggregates (Wang et al., 2019), improves the availability and cycling of nutrients (Wang et al., 2019) and boosts the water holding capacity of soil (Mirchooli et al., 2020). SOC loss is a common phenomenon in agricultural farms, which has led to a global loss of 133 Gt carbon (Sanderman et al., 2017). However, it is crucial to maintain appropriate levels of SOC to improve and sustain crop yield (Ma et al., 2023). The process of determining and establishing the benchmarks for low, medium, and high levels of SOC storage is complicated. These thresholds are highly varied and dependent on a number of site-specific factors such as soil texture, agricultural management practices and potential for carbon storage in a particular soil (Drexler et al., 2022) and soil-forming factors including parent material, topography, climate, organisms, time, and human intervention (Richter & Yaalon, 2012).

A range of statistical methods have been used to determine the attainable SOC or SOC potentials. Hassink (1997) used the relationship between SOC and fine particle-size fraction and fitted a linear least squares regression to determine the maximum carbon storage capacity. A similar method was also applied by Chenu et al. (2019), Beare et al.(2014), and Jien et al. (2025) to determine the attainable SOC. Georgiou et al. (2022) and Karunaratne et al. (2024) employed quantile regression, while Viscarra Rossel et al. (2024) used the frontier line analysis. Furthermore, some researchers utilised Boundary Line Analysis (BLA), such as Feng et al. (2013), Beare et al. (2014), Fujisaki et al. (2018) and Jien et al. (2025) for estimating soil organic carbon storage capacity. However, Feng et al. (2013) and Jien et al. (2025) reported that BLA is more efficient in terms of attainable SOC estimation than others, such as linear regression or quantile regression. Accordingly, we implemented a BLA model in our study.

BLA is a statistical method, first introduced by Webb (1972), which states that a biological reaction to a particular environmental variable is only expressed in a subset of observations where other factors are not limiting. The approach seeks to determine the relationship between a target variable (x) and maximum yields obtained (y) with other variables not held constant or optimal (Makowski et al., 2007). The process involves fitting a line to the data cloud's edge, which is often the higher part (Hajjarpoor et al., 2018). This boundary line indicates the maximum attainable response, also often referred to as potential response, under a condition when a parameter of interest lies on the x-axis. Traditionally, it has been widely utilised to determine the potential crop yield and yield-limiting factors (Casanova et al., 1999; Kitchen et al., 2003; Shatar & McBratney, 2004; Tittonell et al., 2008). However, a multivariate BLA, by integrating multiple univariate BLAs, offers a strong, comprehensive framework for determining the site-specific limiting factor affecting a response variable, like crop yield or soil organic carbon. This concept is demonstrated by Shatar & McBratney (2004), while they identified site-specific causes of yield variation and yield potentials by applying the law of minimum in a multivariate BLA model. In this study, we implemented the BLA approach to estimate attainable SOC across diverse grain-growing regions of Australia. The BLA estimates are contextualised within the existing field conditions; thus, the term “attainable” is used in relation to these current constraints. We also identified and illustrated spatially the most limiting soil factor for SOC storage across a representative farm, which offers an informed decision tool for farmers to make a site-specific soil management plan.

2. MATERIALS AND METHOD

2.1. Study area and dataset

The study area comprises 72 farms from across the grain-growing regions of Australia (Figure 1). These farms were selected with the assistance of growers or local consultants, with the main objective of identifying an area which was representative of grain-cropping soils within the local region. Twenty-five sampling sites were selected using stratified random sampling based on covariates, and soil cores were sampled and analysed at four depth intervals to a maximum depth of 1 m (0-15 cm, 15-30 cm, 30-60 cm, 60-100 cm). This was performed following a similar approach by Filippi et al. (2024) and Wang et al. (2024). In this study, we considered the topsoil (0-30 cm) layer as it reflects the processes that control SOC accumulation, regulated by texture, minerology and aggregate protection.

2.2. BOM seasonal rainfall classification

The study area covers diverse regions of Australia, and represents a wide range of soil types, terrain and climates. Rainfall has a significant impact on the potential of soil carbon accumulation and stabilisation (Minasny et al., 2013; Viscarra Rossel et al., 2014). Wetter zones typically offer larger soil organic carbon potential than drier ones, as rainfall regulates biomass production and organic matter input. Accordingly, our datasets were classified into six categories (Table 1) based on the Bureau of Meteorology's (BOM) seasonal rainfall zones[1]) in order to capture this climatic influence.

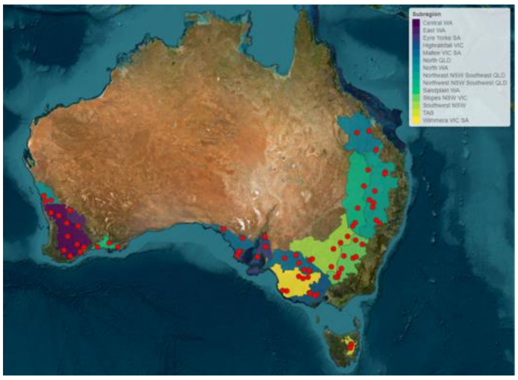


Figure 1: Location of farms sampled overlaying the grain-growing regions of Australia

Table 1: Classification of soil sample sites based on BOM seasonal rainfall class

SL No	Soil sample sites	No. of farms	Rainfall zone
1	324	13	Summer 350-650 mm
2	183	8	Uniform 500-800 mm
3	75	3	Uniform 250-500 mm
4	225	9	Winter 250-500 mm
5	300	12	Winter dominant 500-800 mm
6	675	27	Winter dominant 250-500 mm

2.3. Fitting the Boundary Line

In this study, we followed the BLA procedures outlined by Shatar & McBratney (2004) and Lark et al. (2020) employing two denoising methods—outlier removal and information extraction—to improve the reliability of the boundary line computation. This study employed the Mahalanobis distance (Mahalanobis, 1936) and kernel density estimation (KDE) (Parzen, 1962) techniques to reduce outliers and identify significant points for the BLA in the point cloud, resulting in a more precise estimation of the boundary line. Four general steps were followed in order to implement BLA: 1. Categorising the response variable (y) based on its predictor (x) values. 2. Elimination of outliers. 3. Selection of data points that exemplify the greatest response for each dependent variable. 4. Employ a function to model a curve based on the data obtained from the third stage, which in this case was a spline. We implemented this methodology to develop a BLA model for estimating attainable SOC with respect to individual soil properties (clay content and ESP).

2.4. Identification of the site-specific factors limiting SOC within a field

Two digital soil maps for clay content and ESP were created for an example farm in the Wimmera, Victoria, through the adoption of the method described by Filippi et al. (2024) and Wang et al. (2024). We applied our BLA model, developed in the previous step, on these digital soil maps to determine the spatial distribution of attainable SOC. Next, a multistep BLA approach was employed, adapted from the methodologies outlined by Shatar & McBratney (2004), to determine the site-specific limiting factor that restricts SOC storage. In this method, a multivariate boundary line model was constructed integrating the univariate BLA model found previously using the von Liebig-type response framework suggested by Casanova et al. (1999). This model complies with Liebig's Law of the Minimum (von Liebig, 1863), which states that the most limiting factor determines the achievable level of a response variable.

3. RESULTS

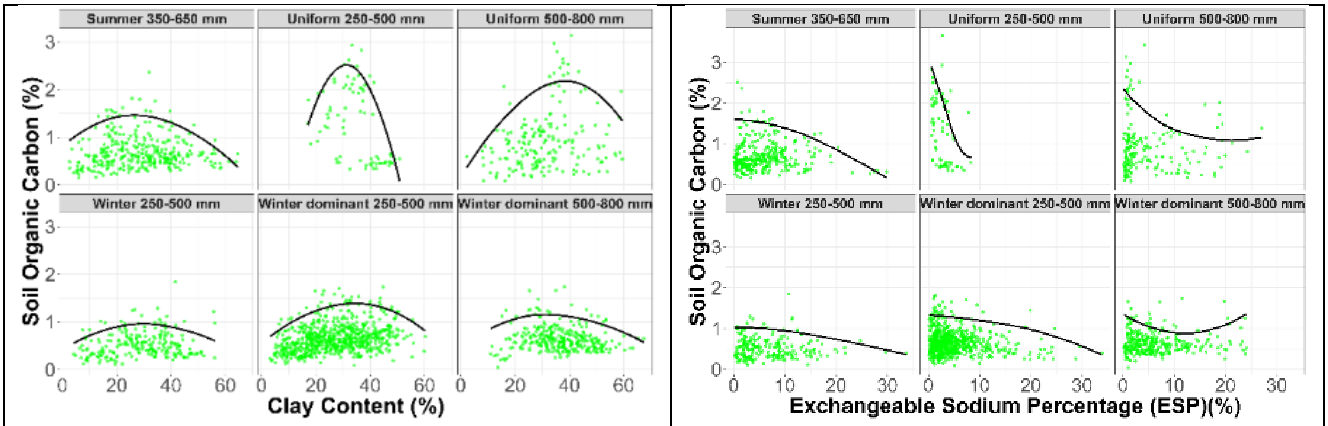
3.1. Attainable Soil Organic Carbon based on BLA

The results of the BLA are shown in Figure 2, categorised by six different rainfall zones for the 0-30 cm soil layer. These results demonstrate the relationship between SOC and, clay and ESP. The laboratory measured

[1] (http://www.bom.gov.au/climate/maps/averages/climate-classification/?maptype=seasb

SOC values throughout the sampled sites are represented by the green scatter points, while the boundary lines (black curves) indicate the attainable upper limit of SOC given the specific values of each soil property.

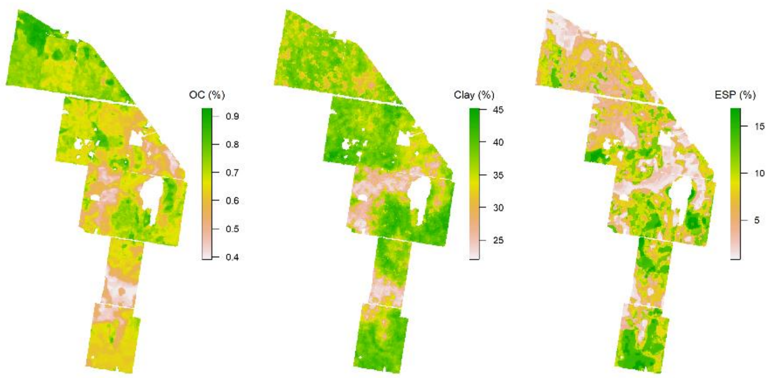
Across many of the rainfall zones, a distinct quadratic pattern of a boundary line was seen with moderate clay content (about 25-50%) corresponding to the maximum achievable SOC levels (Fig. 2a). The Uniform 250-500 mm and Uniform 500-800 mm rainfall zones showed the highest attainable SOC (more than 2%) while Winter 250-500 mm and Winter dominant 500-800 mm showed comparatively lower attainable SOC, just above 1%. Other regions exhibited a moderate level. From Figure 2b, the BLA model shows a consistent negative trend between attainable SOC and ESP across all rainfall zones, suggesting that rising sodicity tends to limit SOC accumulation. It is also observed that the Uniform 250–500 mm and Uniform 500–800 mm zones had the largest SOC level, with the boundary line exceeded by 2%. In contrast, other zones remained at or slightly above 1%, similar to the pattern in Figure 2a.



(a) (b)

Fig 2. Boundary line analysis (BLA) plots grouped by BOM seasonal rainfall class, which illustrate the relationship between Soil Organic Carbon (SOC) (%) and a) Clay content (%), b) Exchangeable Sodium Percentage (ESP)(%).

Figure 3 illustrates a series of spatial analyses where Figure 3 (a-c) illustrates the spatial distribution of actual (laboratory-measured) SOC, clay and ESP content, respectively, for the case study farm. Figures 3d and 3e illustrate the maximum attainable organic carbon potential from clay and ESP after applying the BLA model, which was developed from our dataset across the rainfall zone, on this farm. The predicted attainable SOC levels were consistently higher in areas with a higher clay content around 30-40% (Fig. 3d), especially in the central region of the farm. From Figure 3d, it is observed that a higher SOC accumulation is associated with an area of the farm where ESP is less, i.e below 10%. The attainable SOC potential is very low in the higher sodic areas, likely due to inadequate soil structure, impaired aeration, restricted microbial activity and poor plant growth. Figure 3f represents the limiting factor map, which is created based on the lowest attainable SOC from clay and ESP in a multivariate model. It is observed that clay was found to be a limiting factor for 55% of the study area, and ESP was the limiting factor in 45%.



(a) (b) (c)

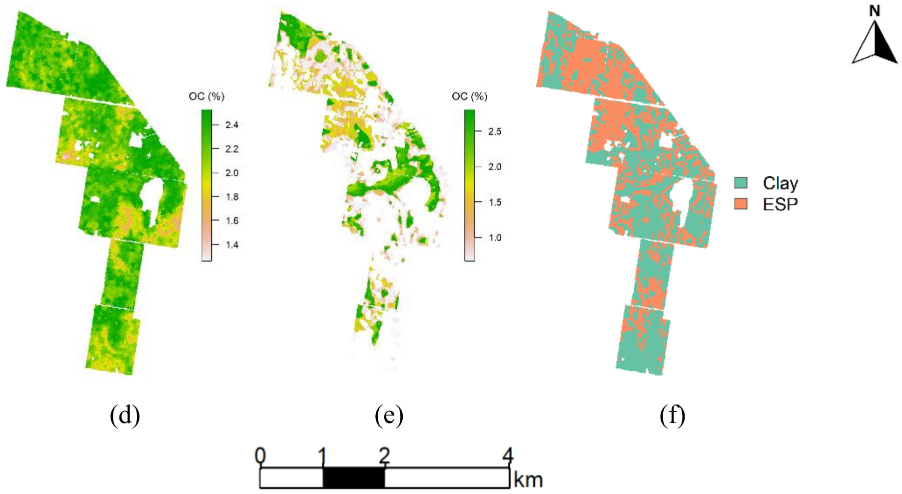


Fig 3. (a) Soil organic carbon content(measured); (b) Clay content(measured); (c) Exchangeable Sodium percentage (ESP) (measured); (d) Attainable SOC level from BLA between SOC and Clay content; (e) Attainable SOC level from BLA between SOC and ESP; (f) Limiting Factor Map

4. DISCUSSIONS

From the results of the BLA model for both key soil properties (clay and ESP), it is evident that the attainable maximum SOC varies among different rainfall zones. Orgill et al. (2017) found that higher SOC stocks in Australian soil are highly linked with higher summer and spring rainfall. They also showed that parent material influenced the SOC fraction stock in the 0–30 cm soil layer within a rainfall zone. From the result of BLA with clay, the ideal clay content for maximising attainable SOC was around 30-60%, after which it declined. This corresponds with studies indicating that excessive clay above a specific threshold may restrict aeration and microbial activity (Six et al., 2002). A convex curve was observed in the Uniform 500-800 mm and Winter dominant 500-800 mm zones in the BLA model with ESP (Fig. 2b), indicating that a high ESP (>20 %) increases the attainable SOC potential, which is in contradiction to high ESP causing the net depletion of SOC (Basak et al., 2021). However, the drivers for this may be the co-occurrence of significant clay content in these areas, or there are scarce or unrepresentative data points in these particular zones, which require careful interpretation or the prevalence of sodicity in some of Australia's most productive soils, such as Vertosols (Dang et al., 2006).

Based on the multivariate BLA model, the generated spatial limiting factor map is very insightful for understanding and quantifying the soil constraints to SOC build-up across a farm. From Figure 3f, it is found that soil ESP is the limiting factor for SOC stabilisation across the farm, affecting approximately half of the field (45%). This offers a clear and implementable guideline for soil management. By adding gypsum, for example, the ESP can be reduced, leading to improved microbial activity, biomass production and creating an environment for SOC buildup. This outcome demonstrates a significant potential for carbon sequestration through sodicity management.

5. CONCLUSION

The BLA model is especially pertinent to the Australian setting, as these soils tend to have very low organic carbon and show significant regional geographic variability. According to our study, the mean value of Australian grain growing regions' topsoil SOC is 0.71 (SD = 0.42), with an interquartile range of 0.45 to 0.84, which is regarded as very low for crop productivity and soil health. However, the BLA model shows that, depending on the rainfall zone and related soil properties, achievable SOC levels can surpass 1% and even approach 2.5% under ideal soil conditions. So, there is a potential gap between actual and attainable SOC, highlighting the substantial opportunities for carbon sequestration through better soil management techniques. Measuring this gap is essential for developing targeted interventions to improve SOC storage and foster climate-resilient, sustainable agriculture in Australia. This is crucial for a range of stakeholders and for providing benchmarks for land managers. In addition, the limiting factor map suggests that ameliorating the soil constraints that are manageable may increase the possibility for SOC sequestration. So, it facilitates farmers and land managers in executing site-specific soil management to improve soil health and crop productivity. So, the BLA model is a dynamic rather than a static system; If the existing adverse field conditions are removed, then the measured SOC will be different, and the boundary line will give a different value. Finally, this conceptual framework of BLA modelling is reproducible, can be customised with additional soil properties and can be adapted to any agricultural farm throughout Australia.

ACKNOWLEDGMENTS

We would like to acknowledge funding of this work by the Grains Research and Development Corporation (GRDC) through the '3D PAWC and constraint mapping' project (UOS2206-009RTX), as well as the valued collaboration of growers, consultants, and corporate businesses.

REFERENCES

Basak, N., Sheoran, P., Sharma, R., Yadav, R. K., Singh, R. K., Kumar, S., Krishnamurthy, T., & Sharma, P. C. (2021). Gypsum and pressmud amelioration improve soil organic carbon storage and stability in sodic agroecosystems. *Land Degradation & Development*, *32*(15), 4430-4444.

Beare, M., McNeill, S., Curtin, D., Parfitt, R., Jones, H., Dodd, M., & Sharp, J. (2014). Estimating the organic carbon stabilisation capacity and saturation deficit of soils: a New Zealand case study. *Biogeochemistry*, *120*(1), 71-87.

Casanova, D., Goudriaan, J., Bouma, J., & Epema, G. (1999). Yield gap analysis in relation to soil properties in direct-seeded flooded rice. *Geoderma*, *91*(3-4), 191-216.

Castaldi, F., Hueni, A., Chabrillat, S., Ward, K., Buttafuoco, G., Bomans, B., Vreys, K., Brell, M., & van Wesemael, B. (2019). Evaluating the capability of the Sentinel 2 data for soil organic carbon prediction in croplands. *ISPRS Journal of Photogrammetry and Remote Sensing*, *147*, 267-282.

Chenu, C., Angers, D. A., Barré, P., Derrien, D., Arrouays, D., & Balesdent, J. (2019). Increasing organic stocks in agricultural soils: Knowledge gaps and potential innovations. *Soil and Tillage Research*, *188*, 41-52.

Dang, Y., Routley, R., McDonald, M., Dalal, R., Singh, D., Orange, D., & Mann, M. (2006). Subsoil constraints in Vertosols: crop water use, nutrient concentration, and grain yields of bread wheat, durum wheat, barley, chickpea, and canola. *Australian Journal of Agricultural Research*, *57*(9), 983-998.

Drexler, S., Broll, G., Flessa, H., & Don, A. (2022). Benchmarking soil organic carbon to support agricultural carbon management: A German case study#. *Journal of Plant Nutrition and Soil Science*, *185*(3), 427-440.

Feng, W., Plante, A. F., & Six, J. (2013). Improving estimates of maximal organic carbon stabilization by fine soil particles. *Biogeochemistry*, *112*(1), 81-93.

Filippi, P., Whelan, B. M., & Bishop, T. F. (2024). Proximal and remote sensing–what makes the best farm digital soil maps? *Soil Research*, *62*(2).

Fujisaki, K., Chapuis-Lardy, L., Albrecht, A., Razafimbelo, T., Chotte, J.-L., & Chevallier, T. (2018). Data synthesis of carbon distribution in particle size fractions of tropical soils: Implications for soil carbon storage potential in croplands. *Geoderma*, *313*, 41-51.

Georgiou, K., Jackson, R. B., Vindušková, O., Abramoff, R. Z., Ahlström, A., Feng, W., Harden, J. W., Pellegrini, A. F., Polley, H. W., & Soong, J. L. (2022). Global stocks and capacity of mineral-associated soil organic carbon. *Nature communications*, *13*(1), 3797.

Hajjarpoor, A., Soltani, A., Zeinali, E., Kashiri, H., Aynehband, A., & Vadez, V. (2018). Using boundary line analysis to assess the on-farm crop yield gap of wheat. *Field Crops Research*, *225*, 64-73. https://doi.org/10.1016/j.fcr.2018.06.003

Hassink, J. (1997). The capacity of soils to preserve organic C and N by their association with clay and silt particles. *Plant and soil*, *191*(1), 77-87.

Jien, S.-H., Minasny, B., Yang, B.-J., Liu, Y.-T., Yen, C.-C., Ocba, M. A., Zhang, Y.-T., & Syu, C.-H. (2025). Enhancing Soil Carbon Storage: Developing high-resolution maps of topsoil organic carbon sequestration potential in Taiwan. *Geoderma*, *459*, 117369.

Karunaratne, S., Asanopoulos, C., Jin, H., Baldock, J., Searle, R., Macdonald, B., & Macdonald, L. M. (2024). Estimating the attainable soil organic carbon deficit in the soil fine fraction to inform feasible storage targets and de-risk carbon farming decisions. *Soil Research*, *62*(2).

Kitchen, N., Drummond, S., Lund, E., Sudduth, K., & Buchleiter, G. (2003). Soil electrical conductivity and topography related to yield for three contrasting soil–crop systems. *Agronomy Journal*, *95*(3), 483-495.

Lark, R. M., Gillingham, V., Langton, D., & Marchant, B. P. (2020). Boundary line models for soil nutrient concentrations and wheat yield in national-scale datasets. *European Journal of Soil Science*, *71*(3), 334-351.

Ma, Y., Woolf, D., Fan, M., Qiao, L., Li, R., & Lehmann, J. (2023). Global crop production increase by soil organic carbon. *Nature Geoscience*, *16*(12), 1159-1165.

Mahalanobis, P. C. (1936, 2018/12/01). On the Generalized Distance in Statistics. *Proceedings of the National Institute of Science of India, 2*(1), 49-55. https://doi.org/10.1007/s13171-019-00164-5

Makowski, D., Doré, T., & Monod, H. (2007). A new method to analyse relationships between yield components with boundary lines. *Agronomy for Sustainable Development*, *27*(2), 119-128. https://doi.org/10.1051/agro:2006029

Minasny, B., McBratney, A. B., Malone, B. P., & Wheeler, I. (2013). Digital mapping of soil carbon. *Advances in agronomy*, *118*, 1-47.

Mirchooli, F., Kiani-Harchegani, M., Darvishan, A. K., Falahatkar, S., & Sadeghi, S. H. (2020). Spatial distribution dependency of soil organic carbon content to important environmental variables. *Ecological Indicators*, *116*, 106473.

Orgill, S. E., Condon, J. R., Conyers, M. K., Morris, S. G., Murphy, B. W., & Greene, R. S. (2017). Parent material and climate affect soil organic carbon fractions under pastures in south-eastern Australia. *Soil Research*, *55*(8), 799-808.

Parzen, E. (1962). On estimation of a probability density function and mode. The annals of mathematical statistics, 33(3), 1065-1076.

Richter, D. d., & Yaalon, D. H. (2012). "The changing model of soil" revisited. *Soil Science Society of America Journal*, *76*(3), 766-778.

Sanderman, J., Hengl, T., & Fiske, G. J. (2017). Soil carbon debt of 12,000 years of human land use. *Proceedings of the National Academy of Sciences*, *114*(36), 9575-9580.

Shatar, T., & McBratney, A. (2004). Boundary-line analysis of field-scale yield response to soil properties. *The Journal of Agricultural Science*, *142*(5), 553-560.

Six, J., Conant, R. T., Paul, E. A., & Paustian, K. (2002). Stabilization mechanisms of soil organic matter: implications for C-saturation of soils. *Plant and soil*, *241*(2), 155-176.

Tittonell, P., Shepherd, K. D., Vanlauwe, B., & Giller, K. E. (2008). Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya—An application of classification and regression tree analysis. *Agriculture, Ecosystems & Environment*, *123*(1-3), 137-150.

Viscarra Rossel, R., Webster, R., Zhang, M., Shen, Z., Dixon, K., Wang, Y. P., & Walden, L. (2024). How much organic carbon could the soil store? The carbon sequestration potential of Australian soil. *Global Change Biology*, *30*(1), e17053.

Viscarra Rossel, R. A., Webster, R., Bui, E. N., & Baldock, J. A. (2014). Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. *Global Change Biology*, *20*(9), 2953-2970.

von Liebig, J. F. (1863). *The natural laws of husbandry*. Walton & Maberly.

Wang, J., Filippi, P., Haan, S., Pozza, L., Whelan, B., & Bishop, T. F. (2024). Gaussian process regression for three-dimensional soil mapping over multiple spatial supports. *Geoderma*, *446*, 116899.

Wang, S., Fan, J., Zhong, H., Li, Y., Zhu, H., Qiao, Y., & Zhang, H. (2019). A multi-factor weighted regression approach for estimating the spatial distribution of soil organic carbon in grasslands. *Catena*, *174*, 248-258.

Webb, R. (1972). Use of the boundary line in the analysis of biological data. *Journal of Horticultural Science*, *47*(3), 309-319.

