University of São Paulo
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Digital mapping of the soil available water capacity: insights for the resilience of agricultural systems to climate change

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Dissertation presented to obtain the degree of Master in Science. Area: Soil and Plant Nutrition

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RESUMO

Mapeamento digital da capacidade de água disponível no solo: insights para a resiliência dos sistemas agrícolas às mudanças climáticas

A capacidade de água disponível no solo (AWC) é uma função chave para a sobrevivência e o bem-estar humano. Entretanto, sua medição direta é trabalhosa e sua interpretação espacial é complexa. Estas dificuldades têm levado ao uso de formas indiretas de estimar a AWC. Entre elas, as técnicas de mapeamento digital do solo (DSM) surgemcomo uma alternativa à modelagem espacial das propriedades do solo. As técnicas de DSM geralmente aplicam modelos de aprendizagem de máquinas (ML) que não são fisicamente interpretáveis, limitando a possibilidade de construir novos conhecimentos na ciência do solo. Neste contexto, visamos identificar os padrões espaciais estimados pelo algoritmo Random Forest (RF) para prever AWC e, em um estudo de caso, mostrar que os mapas AWC digitais podem apoiar o planejamento agrícola em resposta aos efeitos locais da mudança climática. Para isso, foi aplicada uma abordagem baseada em dados usando atributos de solo determinados em laboratório (argila, areia e conteúdo de matériaorgânica), juntamente com uma função de pedotransferência (PTF), sensoriamento remoto, técnicas DSM, valores Shapley (interpretação do modelo) e dados meteorológicos. O mapa digital do solo AWC e os dados da estação meteorológica foram usados para calcular o balanço hídrico climatológico do solo para os períodos entre 1917-1946 e 1991-2020. A seleção de covariáveis usando os valores Shapley como critério contribuiu para a parcimônia do modelo, obtendo-se métricas de qualidade de ajuste de R^2 0,72, RMSE 16,72 mm m^{-1}, CCC 0,83, e Bias de 0,53 sobre o conjunto de validação. As maiores contribuições para a previsão de AWC do solo foram imagens multitemporais Landsat com pixels de solo descoberto, média diurna e variação anual de temperatu. O presente estudode caso mostra que as mudanças climáticas no local do estudo modificaram o regime pluviométrico, aumentando a quantidade de água retida no solo durante o período seco (deabril a agosto). A metodologia utilizada fornece insights para construir estratégias que permitam a adaptação dos sistemas agrícolas aos efeitos da mudança climática.

Palavras-chave: Aprendizagem de máquinas, Sensoriamento remoto, Valor Shapley,Mudanças climáticas, Serviços ecossistêmico

ABSTRACT

Digital mapping of the soil available water capacity: insights for the resilience of agricultural systems to climate change

Soil available water capacity (AWC) is a key function for human survival and well-being. However, its direct measurement is laborious and spatial interpretation is complex. These difficulties have led to the use of indirect ways of estimating AWC. Among those, digital soil mapping (DSM) techniques emerge as an alternative to spatial modeling of soil properties. DSM techniques commonly apply machine learning (ML) models which are not physically interpretable, limiting the possibility to build new knowledge in soil science. In this context, we aimed to identify the spatial patterns estimated by the Random Forest (RF) algorithm to predict AWC and, in a case study, to show that digital AWC maps can support agricultural planning in response to the local effects of climate change. To do so, a data-driven approach was applied using laboratory-determined soil attributes (clay, sand, and organic matter contents), together with a pedotransfer function (PTF), remote sensing, DSM techniques, Shapley values (model interpretation), and meteorological data. The AWC digital soil map and weather station data were used to calculate climatological soil water balances for the periods between 1917-1946 and 1991-2020. The selection of covariates using Shapley values as a criterion contributed to the parsimony of the model, obtaining goodness-of-fit metrics of R^2 0.72, RMSE 16.72 mm m-1, CCC 0.83, and Bias of 0.53 over the validation set. The highest contributing covariates for soil AWC predictionwere the Landsat multitemporal images with bare soil pixels, mean diurnal, and annual temperature range. The present case study shows that climate changes at the study site modified the rainfall regime, increasing the amount of water retained in the soil during thedry period (from April to August). The used methodology provides insights to build strategies that allow the adaptation of agricultural systems to the effects of climate change.

Keywords: Machine learning, Remote sensing, Shapley value, Climate change, Soilfunctions, Ecosystem services

INTRODUCTION

Soil available water capacity (AWC) is a key function for human survival and well-being (Keesstra et al., 2016). The AWC concept is defined as the difference between field capacity (FC) and permanent wilting point (PWP). The PWP is usually considered as the water content corresponding to a pressure head of -150 m (Garg et al., 2020), standardizedfor any weather and crop conditions. The FC is defined as the water content in the soil after saturation without evapotranspiration when free drainage reaches a negligible flow (Veihmeyer and Hendrickson, 1931). It is sometimes assumed to correspond to a specific pressure head, and the most common values used in this context are -0.6, -1 or -3.3 m.

The direct evaluation of AWC is laborious since it implies undisturbed samplingand analysis in specialized laboratories. Therefore, AWC is most commonly estimated indirectly, e.g. using pedotransfer functions (PTF) correlating readily available soil information such as particle size distribution and organic matter (OM) content with soil hydraulic properties (Barros et al., 2013; Inforsato and de Jong van Lier, 2021). While these approaches provide a specific point notion, the efficient management of water resources in agricultural areas requires a spatial and temporal understanding.

The understanding of land surface and atmospheric processes and their parameterization for agricultural water resources management advanced in recent years (Chartzoulakis and Bertaki, 2015). Earth observation techniques using different parts of the electromagnetic spectrum have been used for over three decades to monitor the Earth's surface (Weiss et al., 2020). These techniques are now being transferred to operational applications like agricultural land management, offering the opportunity for new observational and modeling perspectives (Bouma et al., 2015). In this context, Digital Soil Mapping (DSM) emerges as a technique to obtain explicit spatial information on soil properties at different scales (McBratney et al., 2003).

Despite significant advances in understanding soil spatial variability through pedometric and DSM techniques, there is a need to refine the methods of obtaining relevant soil data, in addition to an interpretation of the Machine Learning (ML) models used in DSM approaches (Wadoux et al., 2021). The ML models are "black boxes" of low interpretability since they find the correlations that best describe the patterns between soil properties and the covariates used in the modeling in a merely statistical manner (McBride, 2021). ML model interpretation techniques that emerged in other areas of knowledge were adapted recently to soil science in DSM approaches (Padarian et al., 2020; Wadoux et al., 2020). In that context, the game theory proposed by Shapley (1953) and adapted by

Lundberg and Lee (2017) is a helpful approach for the interpretation of ML models used in DSM (Wadoux and Molnar, 2022).

The predictions made by ML models should be associated with the soil-forming factors to drive new knowledge in soil science (Wadoux et al., 2020). In that context, our goals were i) to identify the spatial patterns detected by the Random Forest (RF) algorithmfor the prediction of soil AWC using a data-driven approach and Shapley values, and ii) to demonstrate that AWC digital soil maps coupled with meteorological data can be used to detect trends in soil water retention caused by climate change. The following hypotheses were constructed: i) the soil AWC is related to covariates that represent soil-forming factors; ii) in this context, game theory can be applied as a covariate reduction method to build a parsimonious model.

To pursue the objectives and test the hypotheses, the approach used to estimate the soil water AWC at each sampling point is described. Subsequently, the RF predictor model and the covariates used in its training are presented. Then, the model interpretation method is introduced, and the results are discussed. Finally, a case study is presented usingthe elaborated soil AWC map and a historical series of meteorological data to produce a normal soil water balance to support agricultural planning (sowing/planting and harvesting time) in response to the local effects of climate change.

CONCLUSIONS

Our results, obtained in a tropical scenario context, indicate that the RF algorithm captures spatially discriminant patterns of soil AWC when using climate and pedogenesis-related covariates retrieved from freely available datasets, platforms, and software. Multitemporal Landsat images with bare soil pixels, and mean diurnal and annual temperature ranges are promising covariates for modeling soil water dynamics.

Covariate refinement using SHAP value as a criterion is a useful strategy within DSM approaches as it allows the creation of parsimonious models and reduces the risk of overfitting. Although the constructed model showed robustness and high predictive power, the predictions made in soils with high textural gradients developed from siltstone presented higher values of uncertainty (~17 at 23 mm m^{-1}).

Finally, the proposed approach provides relevant insights for adaptive management and crop yield improvements in response to the local effects of climate change through adaptations of traditional planting and harvesting times and soil management practices.

REFERENCES

Alvares, C.A., Sentelhas, P.C., Dias, H.B., 2022. Southeastern Brazil inland tropicalization: Köppen system applied for detecting climate change throughout 100 years of meteorological observed data. Theor Appl Climatol 149, 1431–1450. https://doi.org/https://doi.org/10.1007/s00704-022-04122-4

Araújo Filho, J.C. de, Barros, A.H.C., Galvão, P.V.M., Teixeira, W.G., Lima, E. de P., Victoria, D. de C., de Andrade Júnior, A.S., Xavier, J.P. de S., Lumbreras, J.F., Coelho, M.R., Baca, J.F.M., Monteiro, J.E.B. de A., de Oliveira, F.C.S.F., Silva Filho, A.D., Barros, J.P.F.G., 2022. Avaliação, predição e mapeamento de água disponível em solos do Brasil, 1st ed. Embrapa Solos, Rio de Janeiro.

Barros, A.H.C., de Jong van Lier, Q., Maia, A. de H.N., Scarpare, F.V., 2013. Pedotransfer functions to estimate water retention parameters of soils in northeastern Brazil. Rev Bras Cienc Solo 37, 379–391. https://doi.org/10.1590/S0100-06832013000200009

Baumann, P., Lee, J., Behrens, T., Biswas, A., Six, J., McLachlan, G., Viscarra Rossel, R.A.,2022. Modelling soil water retention and water-holding capacity with visible–near- infrared spectra and machine learning. Eur J Soil Sci 73. https://doi.org/10.1111/ejss.13220

Baumgardner, M.F., Silva, L.R.F., Biehl, L.L., Stoner, E.R., 1986. Reflectance Properties of Soils. Advances in Agronomy 38, 1–44. https://doi.org/10.1016/S0065-2113(08)60672-0

Benites, V.M., Machado, P.L.O.A., Fidalgo, E.C.C., Coelho, M.R., Madari, B.E., 2007. Pedotransfer functions for estimating soil bulk density from existing soil survey reports in Brazil. Geoderma 139, 90–97. https://doi.org/10.1016/j.geoderma.2007.01.005

Blaschek, M., Roudier, P., Poggio, M., Hedley, C.B., 2019. Prediction of soil available water-holding capacity from visible near-infrared reflectance spectra. Sci Rep 9. https://doi.org/10.1038/s41598-019-49226-6

Böhner J., Köthe R., Conrad O., Gross J., Ringeler A., Selige T., 2002. Soil regionalisation by means of terrain analysis and process parameterisation. Soil classification 7, 213– 222.

Böhner, J., Selige, T., 2006. Spatial prediction of soil attributes using terrain analysis and climate regionalisation. Goettinger Geographische Abhandlungen 115, 13–28.

Bonfatti, B.R., Demattê, J.A.M., Marques, K.P.P., Poppiel, R.R., Rizzo, R., Mendes, W. de S., Silvero, N.E.Q., Safanelli, J.L., 2020. Digital mapping of soil parent material in a heterogeneous tropical area. Geomorphology 367. https://doi.org/10.1016/j.geomorph.2020.107305

Bouma, J., Kwakernaak, C., Bonfante, A., Stoorvogel, J.J., Dekker, L.W., 2015. Soil scienceinput in transdisciplinary projects in the Netherlands and Italy. Geoderma Regional 5, 96–105. https://doi.org/10.1016/j.geodrs.2015.04.002

Bouyoucos, G.J., 1962. Hydrometer method improved for making particle size analyses of soils. Agron J 54, 464–465.

Breiman, L., 2001. Random Forests. Mach Learn 45, 5–32. https://doi.org/https://doi.org/10.1023/A:1010933404324

Brus, D.J., Kempen, B., Heuvelink, G.B.M., 2011. Sampling for validation of digital soil maps. Eur J Soil Sci 62, 394–407. https://doi.org/10.1111/j.1365-2389.2011.01364.x

Chartzoulakis, K., Bertaki, M., 2015. Sustainable Water Management in Agriculture under Climate Change. Agriculture and Agricultural Science Procedia 4, 88–98. https://doi.org/10.1016/j.aaspro.2015.03.011

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., Böhner, J., 2015. System for Automated Geoscientific Analyses (SAGA) v. 2.1.4. Geosci Model Dev 8, 1991–2007. https://doi.org/10.5194/gmd-8-1991-2015

da Silva, T.G.F., de Moura, M.S.B., Zolnier, S., Soares, J.M., Vieira, V.J. de S., Júnior, W.G.F., 2012. Requerimento hídrico e coeficiente de cultura da cana-de-açúcar irrigada no semiárido brasileiro. Revista Brasileira de Engenharia Agrícola e Ambiental16, 64–71.

de Jong van Lier, Q., 2020. Física do Solo - baseada em processos. Piracicaba.

de Jong van Lier, Q., Pinheiro, E.A.R., Inforsato, L., 2019. Hydrostatic equilibrium between soil samples and pressure plates used in soil water retention determination: Consequences of a questionable assumption. Rev Bras Cienc Solo 43. https://doi.org/10.1590/18069657rbcs20190014

de Maria, I.C., Drugowich, M.I., Bortoletti, J.O., Vitti, A.C., Rossetto, R., Fontes, J.L., Tcatchenco, J., Margatho, S.M.F., 2016. Recomendações gerais para a conservação do solo na cultura da cana-de-açúcar (No. 216). Campinas.

de Melo, M.L.A., Inforsato, L., Pinheiro, E.A.R., de Jong van Lier, Q., 2023. Plant available water predicted by a flux-based approach. Geoderma 429, 116253. https://doi.org/10.1016/j.geoderma.2022.116253

Demattê, J.A.M., Fongaro, C.T., Rizzo, R., Safanelli, J.L., 2018. Geospatial Soil Sensing System (GEOS3): A powerful data mining procedure to retrieve soil spectral reflectance from satellite images. Remote Sens Environ 212, 161–175. https://doi.org/10.1016/j.rse.2018.04.047

Dias, H.B., Sentelhas, P.C., 2018. Sugarcane yield gap analysis in Brazil – A multi-model approach for determining magnitudes and causes. Science of the Total Environment 637–638, 1127–1136. https://doi.org/10.1016/j.scitotenv.2018.05.017

Dias, H.B., Sentelhas, P.C., 2017. Evaluation of three sugarcane simulation models and their ensemble for yield estimation in commercially managed fields. Field Crops Res 213, 174–185. https://doi.org/10.1016/j.fcr.2017.07.022

Dingre, S.K., Gorantiwar, S.D., 2020. Determination of the water requirement and crop coefficient values of sugarcane by field water balance method in semiarid region. Agric Water Manag 232. https://doi.org/10.1016/j.agwat.2020.106042

dos Santos, A.K.B., Popin, G.V., Gmach, M.R., Cherubin, M.R., Neto, M.S., Cerri, C.E.P., 2022. Changes in soil temperature and moisture due to sugarcane straw removal in central-southern Brazil. Sci Agric 79. https://doi.org/10.1590/1678-992X-2020-0309

Ermida, S.L., Soares, P., Mantas, V., Göttsche, F.M., Trigo, I.F., 2020. Google earth engine open-source code for land surface temperature estimation from the landsat series. Remote Sens (Basel) 12. https://doi.org/10.3390/RS12091471

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., Alsdorf, D.E., 2007. The shuttle radar topography mission. Reviews of Geophysics 45. https://doi.org/10.1029/2005RG000183

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37, 4302–4315. https://doi.org/10.1002/joc.5086

Fongaro, C.T., Demattê, J.A.M., Rizzo, R., Safanelli, J.L., Mendes, W. de S., Dotto, A.C., Vicente, L.E., Franceschini, M.H.D., Ustin, S.L., 2018. Improvement of clay and sand quantification based on a novel approach with a focus on multispectral satellite images. Remote Sens (Basel) 10. https://doi.org/10.3390/rs10101555

Garg, A., Bordoloi, S., Ganesan, S.P., Sekharan, S., Sahoo, L., 2020. A relook into plant wilting: observational evidence based on unsaturated soil–plant-photosynthesis interaction. Sci Rep 10. https://doi.org/10.1038/s41598-020-78893-z

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens Environ 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hengl, T., Nussbaum, M., Wright, M.N., Heuvelink, G.B.M., Gräler, B., 2018. Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. PeerJ 43. https://doi.org/10.7717/peerj.5518

Inforsato, L., de Jong van Lier, Q., 2021. Polynomial functions to predict flux-based field capacity from soil hydraulic parameters. Geoderma 404. https://doi.org/10.1016/j.geoderma.2021.115308

IUSS Working Group WRB, 2015. World reference base for soil resources 2014: International soil classification system for naming soils and creating legends for soil maps. FAO, Rome, Italy.

Keesstra, S.D., Bouma, J., Wallinga, J., Tittonell, P., Smith, P., Cerdà, A., Montanarella, L., Quinton, J.N., Pachepsky, Y., van der Putten, W.H., Bardgett, R.D., Moolenaar, S., Mol, G., Jansen, B., Fresco, L.O., 2016. The significance of soils and soil science towards realization of the United Nations sustainable development goals. SOIL 2, 111–128. https://doi.org/10.5194/soil-2-111-2016

Khaledian, Y., Miller, B.A., 2020. Selecting appropriate machine learning methods for digital soil mapping. Appl Math Model 81, 401–418. https://doi.org/10.1016/j.apm.2019.12.016

Kuhn, M., 2008. Building Predictive Models in R Using the caret Package. J Stat Softw 28, 1–23. https://doi.org/10.18637/jss.v028.i05

Liu, B., Zhou, W., Henderson, M., Sun, Y., Shen, X., 2022. Climatology of the Soil Surface Diurnal Temperature Range in a Warming World: Annual Cycles, Regional Patterns, and Trends in China. Earths Future 10. https://doi.org/10.1029/2021EF002220

Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.-I., 2020. From local explanations to global understanding with explainable AI for trees. Nat Mach Intell 2, 56–67. https://doi.org/10.1038/s42256-019-0138-9

Lundberg, S.M., Lee, S.-I., 2017. A Unified Approach to Interpreting Model Predictions, in: Guyon, I., Luxburg, U. v., Bengio, S., Wallach, H., Fergus, R., Vishwanathan, S., Garnett, R. (Eds.), Advances In Neural Information Processing Systems. pp. 4768–4777.

Marin, F.R., Jones, J.W., Singels, A., Royce, F., Assad, E.D., Pellegrino, G.Q., Justino, F., 2013. Climate change impacts on sugarcane attainable yield in southern Brazil. Clim Change 117, 227–239. https://doi.org/10.1007/s10584-012-0561-y

McBratney, A.B., Mendonça Santos, M.L., Minasny, B., 2003. On digital soil mapping. Geoderma 117, 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4

McBride, M.B., 2021. Estimating soil chemical properties by diffuse reflectance spectroscopy: Promise versus reality. Eur J Soil Sci. https://doi.org/10.1111/ejss.13192

Mello, F.A.O., Bellinaso, H., Mello, D.C., Safanelli, J.L., Mendes, W.D.S., Amorim, M.T.A., Gomez, A.M.R., Poppiel, R.R., Silvero, N.E.Q., Gholizadeh, A., Silva, S.H.G., Curi, N., Demattê, J.A.M., 2021. Soil parent material prediction through satellite multispectral analysis on a regional scale at the Western Paulista Plateau, Brazil. Geoderma Regional 26. https://doi.org/10.1016/j.geodrs.2021.e00412

Mello, F.A.O., Demattê, J.A.M., Rizzo, R., Mello, D.C. de, Poppiel, R.R., Silvero, N.E.Q., Safanelli, J.L., Bellinaso, H., Bonfatti, B.R., Gómez, A.M.R., Sousa, G.P.B., 2022. Complex hydrological knowledge to support digital soil mapping. Geoderma 409. https://doi.org/10.1016/j.geoderma.2021.115638

Mendes, W. de S., Demattê, J.A.M., 2022. Digital soil mapping outputs on soil classification and sugarcane production in Brazil. J South Am Earth Sci 116. https://doi.org/10.1016/j.jsames.2022.103881

Mendes, W. de S., Demattê, J.A.M., Bonfatti, B.R., Resende, M.E.B., Campos, L.R., Costa, A.C.S. da, 2021. A novel framework to estimate soil mineralogy using soil spectroscopy. Applied Geochemistry 127. https://doi.org/10.1016/j.apgeochem.2021.104909

Milne, G., 1936. Normal Erosion as a Factor in Soil Profile Development. Nature 138,548–549. https://doi.org/https://doi.org/10.1038/138548c0

Minasny, B., McBratney, A.B., 2018. Limited effect of organic matter on soil availablewater capacity. Eur J Soil Sci 69, 39–47. https://doi.org/10.1111/ejss.12475

Minoli, S., Jägermeyr, J., Asseng, S., Urfels, A., Müller, C., 2022. Global crop yields can be lifted by timely adaptation of growing periods to climate change. Nat Commun 13, 7079. https://doi.org/10.1038/s41467-022-34411-5

Mulder, V.L., de Bruin, S., Schaepman, M.E., Mayr, T.R., 2011. The use of remote sensing in soil and terrain mapping - A review. Geoderma 162, 1–19. https://doi.org/10.1016/j.geoderma.2010.12.018

Nelson, D.W., Sommers, L.E., 1996. Total Carbon, Organic Carbon, and Organic Matter,in: Methods of Soil Analysis, Part 3: Chemical Methods. John Wiley & Sons, Ltd, pp. 961–1006. https://doi.org/10.2136/SSSABOOKSER5.3.C34

Olaya, V., Conrad, O., 2009. Geomorphometry in SAGA, in: Developments in Soil Science. Elsevier Ltd, pp. 293–308. https://doi.org/10.1016/S0166-2481(08)00012-3

Oliveira, J.B., Prado, H., 1989. Carta Pedológica Semi-detalhada do Estado de São Paulo: Quadrícula de Piracicaba. Campinas.

Padarian, J., Mcbratney, A.B., Minasny, B., 2020. Game theory interpretation of digital soil mapping convolutional neural networks 6, 389–397. https://doi.org/10.5194/soil-6-389-2020

Pedregosa, F., Varoquaux, G. el, Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: Machine Learning inPython. Journal of Machine Learning Research 12, 2825–2830.

Pittaki-Chrysodonta, Z., Arthur, E., Moldrup, P., Knadel, M., Norgaard, T., Iversen, B. v., Jonge, L.W., 2019. Comparing Visible–Near-Infrared Spectroscopy and a Pedotransfer Function for Predicting the Dry Region of the Soil-Water Retention Curve. Vadose Zone Journal 18, 1–13. https://doi.org/10.2136/vzj2018.09.0180

Prado, H. do, Prado, T.A.B. do, 2022. Pedologia Fácil - Aplicações em solos tropicais, 6thed. Piracicaba.

Pribyl, D.W., 2010. A critical review of the conventional SOC to SOM conversion factor. Geoderma 156, 75–83. https://doi.org/10.1016/j.geoderma.2010.02.003

Probst, P., Wright, M.N., Boulesteix, A.L., 2019. Hyperparameters and tuning strategies for random forest. Wiley Interdiscip Rev Data Min Knowl Discov 9. https://doi.org/10.1002/widm.1301

R Core Team, 2021. A language and environment for statistical computing.

Rolim, G. de S., Sentelhas, P.C., Barbieri, V., 1998. Spreadsheets in Excel environment to calculate the soil water balance: Normal, sequential, crop, and potential and actual productivity. Revista Brasileira de Agrometeorologia 6, 133–137.

Safanelli, J.L., Demattê, J.A.M., Chabrillat, S., Poppiel, R.R., Rizzo, R., Dotto, A.C., Silvero, N.E.Q., Mendes, W. de S., Bonfatti, B.R., Ruiz, L.F.C., ten Caten, A., Dalmolin, R.S.D., 2021. Leveraging the application of Earth observation data for mapping cropland soils in Brazil. Geoderma 396. https://doi.org/10.1016/j.geoderma.2021.115042

Santos, H., Jacomine, P., Anjos, L., Oliveira, V., Lumbreiras, J., Coelho, M., Almeida, J., Oliveira, J., Cunha, T., 2018. Sistema Brasileiro de Classificação de Solos. Embrapa 5a edição, 1–355.

Sayão, V.M., dos Santos, N.V., de Sousa Mendes, W., Marques, K.P.P., Safanelli, J.L., Poppiel, R.R., Demattê, J.A.M., 2020. Land use/land cover changes and bare soil surface temperature monitoring in southeast Brazil. Geoderma Regional 22. https://doi.org/10.1016/j.geodrs 2020.e00313

Scarpare, F.V., Hernandes, T.A.D., Ruiz-Corrêa, S.T., Picoli, M.C.A., Scanlon, B.R., Chagas, M.F., Duft, D.G., Cardoso, T. de F., 2016. Sugarcane land use and water resources assessment in the expansion area in Brazil. J Clean Prod 133, 1318–1327. https://doi.org/10.1016/j.jclepro.2016.06.074

Shapley, L.S., 1953. A value for n-person games, in: Kuhn, H.W., Tucker, A.W. (Eds.), Contributions to the Theory of Games. Princeton University Press, pp. 31–40. https://doi.org/https://doi.org/10.1515/9781400881970

Soil Survey Staff, 1999. Soil Taxonomy: A Basic System of Soil Classification for Making and Interpreting Soil Surveys United States Department of Agriculture Natural Resources Conservation Service, 2nd ed. Washington.

Sorenson, P.T., Shirtliffe, S.J., Bedard-Haughn, A.K., 2021. Predictive soil mapping using historic bare soil composite imagery and legacy soil survey data. Geoderma 401. https://doi.org/10.1016/j.geoderma.2021.1153

Souza, C.M., Shimbo, J.Z., Rosa, M.R., Parente, L.L., Alencar, A.A., Rudorff, B.F.T., Hasenack, H., Matsumoto, M., Ferreira, L.G., Souza-Filho, P.W.M., de Oliveira, S.W., Rocha, W.F., Fonseca, A. v., Marques, C.B., Diniz, C.G., Costa, D., Monteiro, D., Rosa, E.R., Vélez-Martin, E., Weber, E.J., Lenti, F.E.B., Paternost, F.F., Pareyn, F.G.C., Siqueira, J. v., Viera, J.L., Neto, L.C.F., Saraiva, M.M., Sales, M.H., Salgado, M.P.G., Vasconcelos, R., Galano, S., Mesquita, V. v., Azevedo, T., 2020. Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine. Remote Sens (Basel) 12. https://doi.org/10.3390/RS12172735

Thornthwaite, C.W., Mather, J.R., 1955. The water balance. Drexel Institute of Technology Laboratory of Climatology, Centerton New Jersey.

Turek, M.E., de Jong van Lier, Q., Armindo, R.A., 2022. Parameterizing field capacity as the upper limit of available water in bucket-type hydrological models. Comput Electron Agric 194. https://doi.org/10.1016/j.compag.2022.106801

USGS, 2018. USGS EROS Archive - Digital Elevation - Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global [WWW Document]. Earth Resources Observation and Science (EROS). https://doi.org/10.5066/F7PR7TFT

van Genuchten, M.T., 1980. A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. Soil Science Society of America Journal 44, 892– 898. https://doi.org/10.2136/sssaj1980.03615995004400050002x

Veihmeyer, F.J., Hendrickson, A.H., 1931. The moisture equivalent as a measure of the field capacity of soils. Soil Sci 32, 181–192.

Wadoux, A.M.J.C., Heuvelink, G.B.M., Lark, R.M., Lagacherie, P., Bouma, J., Mulder, V.L., Libohova, Z., Yang, L., McBratney, A.B., 2021. Ten challenges for the future of pedometrics. Geoderma 401. https://doi.org/10.1016/j.geoderma.2021.115155

Wadoux, A.M.J.-C., Molnar, C., 2022. Beyond prediction: methods for interpreting complex models of soil variation. Geoderma 422, 115953. https://doi.org/10.1016/j.geoderma.2022.115953

Wadoux, A.M.J.C., Samuel-Rosa, A., Poggio, L., Mulder, V.L., 2020. A note on knowledge discovery and machine learning in digital soil mapping. Eur J Soil Sci 71, 133–136. https://doi.org/10.1111/ejss.12909

Weiss, M., Jacob, F., Duveiller, G., 2020. Remote sensing for agricultural applications: A meta-review. Remote Sens Environ 236, 111402. https://doi.org/10.1016/j.rse.2019.111402

Wilson, J.P., Gallant, J.C., 2000. Digital Terrain Analysis, in: Terrain Analysis: Principles and Applications. Wiley, pp. 1–27.

Zepp, S., Heiden, U., Bachmann, M., Wiesmeier, M., Steininger, M., van Wesemael, B., 2021. Estimation of Soil Organic Carbon Contents in Croplands of Bavaria from SCMaP Soil Reflectance Composites. Remote Sens (Basel) 13. https://doi.org/https://doi.org/10.3390/rs13163141

Zhao, R., Wang, K., Wu, G., Zhou, C., 2021. Temperature annual cycle variations and responses to surface solar radiation in China between 1960 and 2016. International Journal of Climatology 41, E2959–E2978. https://doi.org/10.1002/joc.6895