EGU2020-3621, updated on 22 Oct 2021
https://doi.org/10.5194/egusphere-egu2020-3621
EGU General Assembly 2020

Space-time machine learning for modelling soil organic carbon change

Gerard Heuvelink[1], Marcos Angelini[2], Laura Poggio[3], Zhanguo Bai[3], Niels Batjes[3], Rik van den Bosch[3], Deborah Bossio[4], Sergio Estella[5], Johannes Lehmann[6], Guillermo Olmedo[2], and Jonathan Sanderman[7]

[1]ISRIC – World Soil Information and Wageningen University, Wageningen, the Netherlands (gerard.heuvelink@wur.nl)
[2]Instituto Nacional de Tecnologia Agropecuaria, Buenos Aires, Argentina
[3]ISRIC – World Soil Information, Wageningen, the Netherlands
[4]The Nature Conservancy, Arlington, USA
[5]Vizzuality, Madrid, Spain
[6]Cornell University, Ithaca, USA
[7]Woods Hole Research Center, Falmouth, USA

Spatially resolved estimates of change in soil organic carbon (SOC) stocks are necessary for supporting national and international policies aimed at achieving land degradation neutrality and climate mitigation through better land management. In this work we report on the development, implementation and application of a data-driven, statistical space-time method for mapping SOC stocks, using Argentina as a pilot area. We used the Quantile Regression Forest machine-learning algorithm to predict SOC stock at 0-30 cm depth at 250 m resolution for Argentina between 1982 and 2017, on an annual basis. The model was calibrated using over 5,000 SOC stock values from the 36-year time period and 35 environmental covariates. Most covariates were static and could only explain the spatial SOC distribution. SOC change over time was modelled using time series maps of the AVHRR NDVI vegetation index. These NDVI time series maps were pre-processed using a temporal low-pass filter to allow the SOC stock for a given year to depend on the NDVI of the current as well as preceding years. Spatial patterns of SOC stock predictions were persistent over time and comparable to baseline SOC stock maps of Argentina. Predictions had modest temporal variation with an average decrease for the entire country from 2.55 kg C m^{-2} to 2.48 kg C m^{-2} over the 36-year period (equivalent to a decline of 210.7 Gg C, 3.0% of the total 0–30 cm SOC stock in Argentina). The Pampa region had a larger estimated SOC stock decrease from 4.62 kg C m^{-2} to 4.34 kg C m^{-2} (5.9%) during the same period. For the 2001-2015 period, predicted temporal variation was 7-fold larger than that obtained using the Tier 1 approach of the Intergovernmental Panel on Climate Change and the United Nations Convention to Combat Desertification. Prediction uncertainties turned out to be substantial, mainly due to the limited number and poor spatial and temporal distribution of the calibration data, and the limited explanatory power of the covariates. Cross-validation confirmed that SOC stock prediction accuracy was limited, with a Mean Error of 0.03 kg C m^{-2} and a Root Mean Squared Error of 2.04 kg C m^{-2}. The model explained 45% of the SOC stock variation. In spite of the large

uncertainties, this work showed that machine learning methods can be used for space-time SOC mapping and may yield valuable information to land managers and policy makers, provided that SOC observation density in space and time is sufficiently large.