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Supplementary information

Different climate sensitivity of particulate and mineral-associated soil organic matter

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Different climate sensitivity of particulate and mineral-associated soil organic matter

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Supplementary Materials

Figures S1-S6
Tables S1 and S2

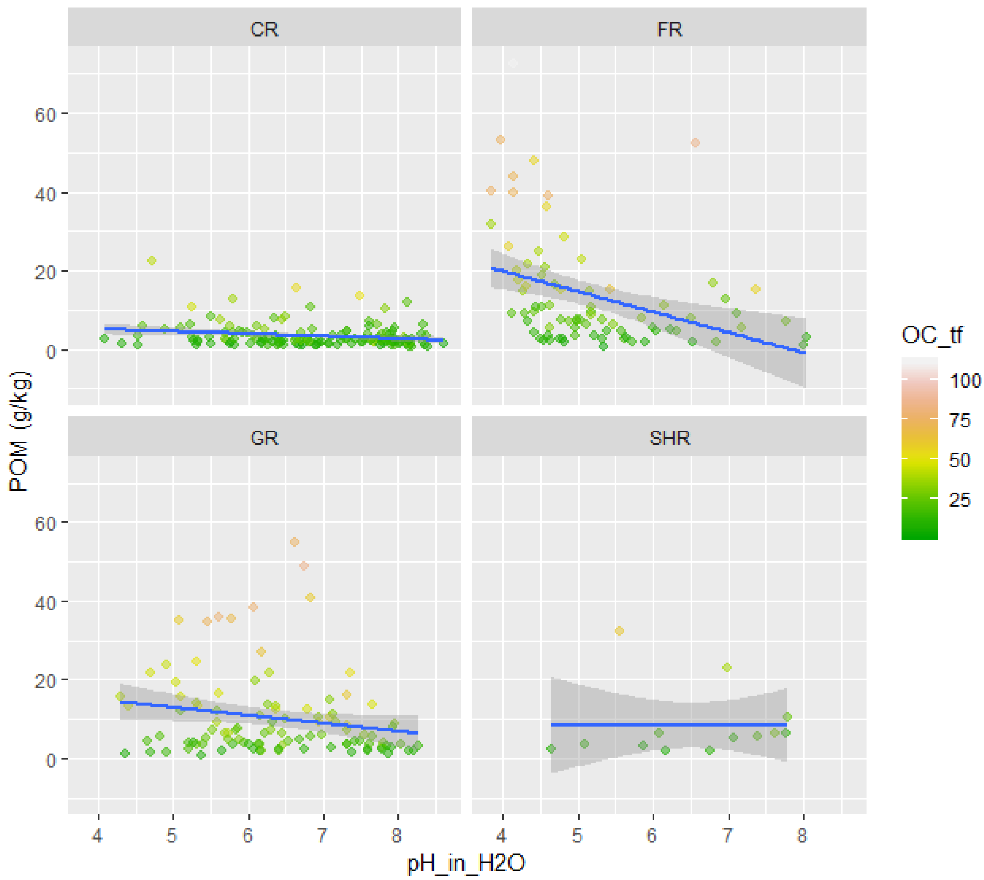

Fig. S1| Scatter plot between C in particulate organic matter (POM, g C kg^{-1} soil) and soil pH (in water) across major land covers in the EU and UK. The plot was built with the 352 soil samples fractionated by size (53 µm) after dispersion. The legend represents the total organic carbon content (g C kg^{-1}). CR= cropland, FR=forest, GR=grassland and SHR=shrubland.

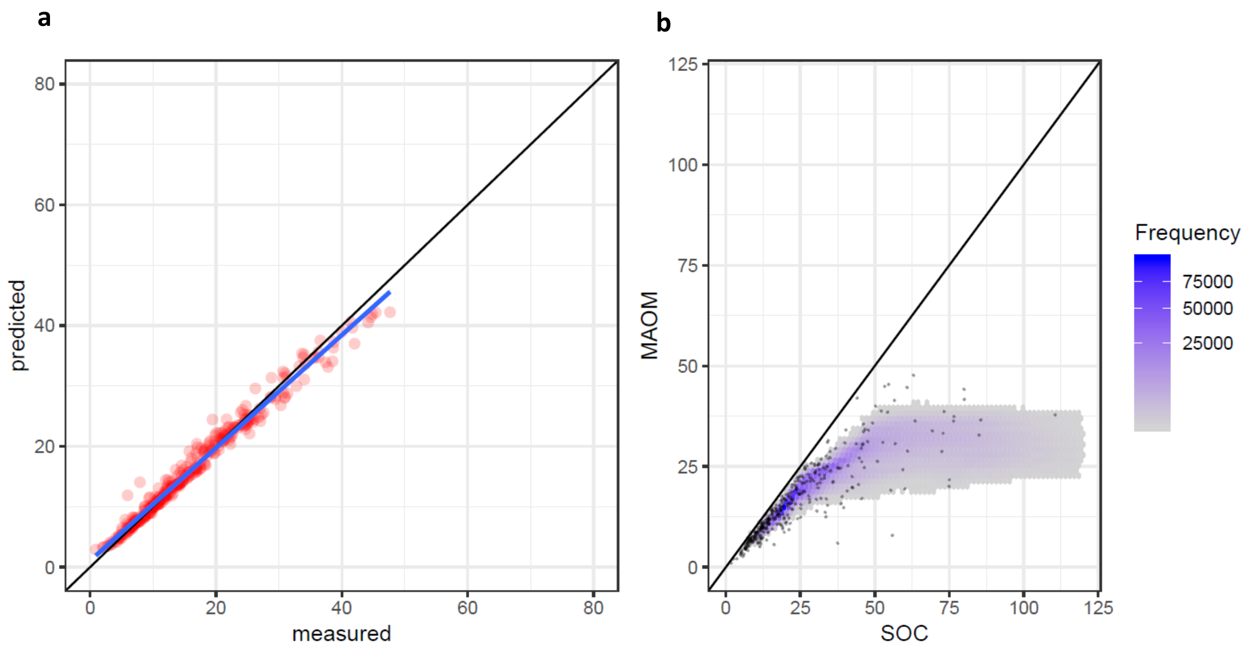

Fig. S2| Randon Forest validation. a) Predicted vs measured MAOM (g C kg^{-1} soil). **b)** Scatter plot of MAOM and total organic C values with measured data (black points, n=352); the shaded area represents the density of the predicted MAOM at the EU level by Random Forest upscaling.

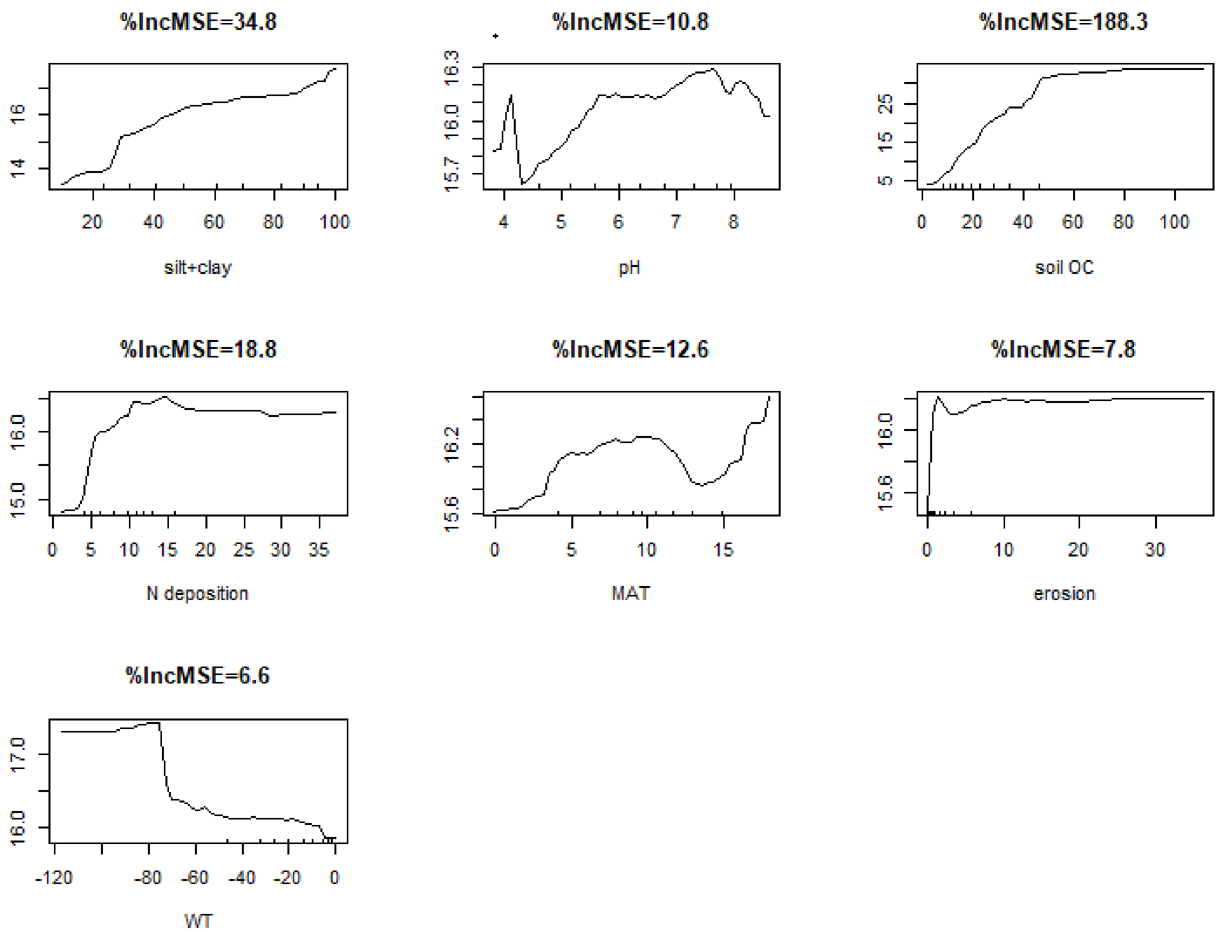

Fig. S3| Partial Dependence Plots. Marginal effect of the variables selected on MAOM (g C kg^{-1} soil) predictions (n=352 points). %incMSE indicates the increase of the Mean Squared Error when given variable is randomly permuted. MAT = mean annual temperature; WT = water table depth

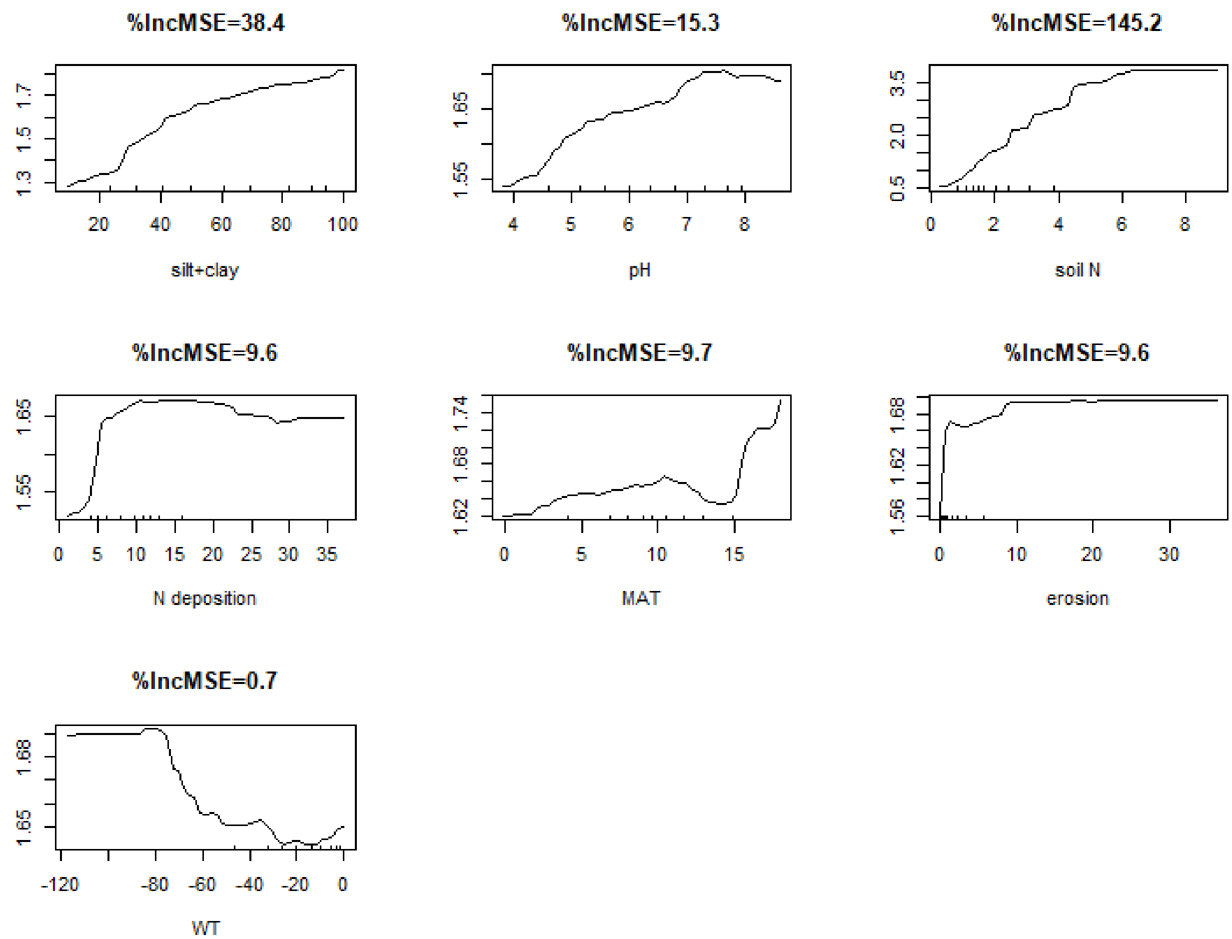

Fig. S4| Partial Dependence Plots. Marginal effect of the variables selected on MAON (g N kg^{-1} soil) predictions (n=352 points). %incMSE indicates the increase of the Mean Squared Error when given variable is randomly permuted. MAT = mean annual temperature; WT = water table depth

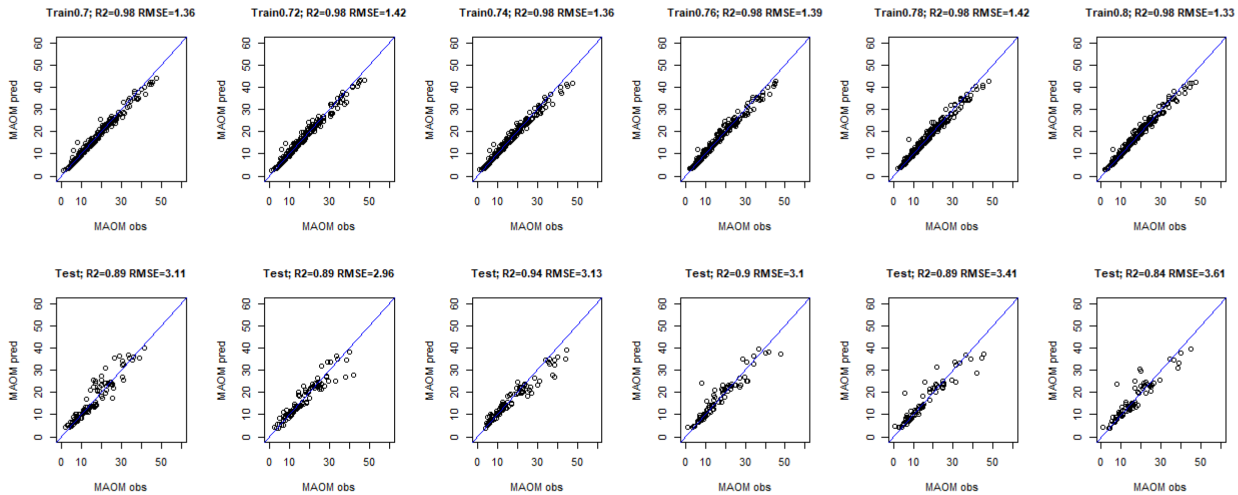

Fig. S5| Random Forest cross validation. Random forest predictions of MAOM (g C kg^{-1} soil) with different sets of training datasets ranging from 70 to 80% of LUCAS data (n=352). The figures reported the r^2 and root mean square errors (RMSE) between observed and predicted values. In the training dataset, the bias ranges between -0.02 and 0, and the root relative squared error (RRSE) between 0.14 and 0.16; in the testing dataset, the bias ranges between -0.03 and 0.75, and the RRSE between 0.25 and 0.37.

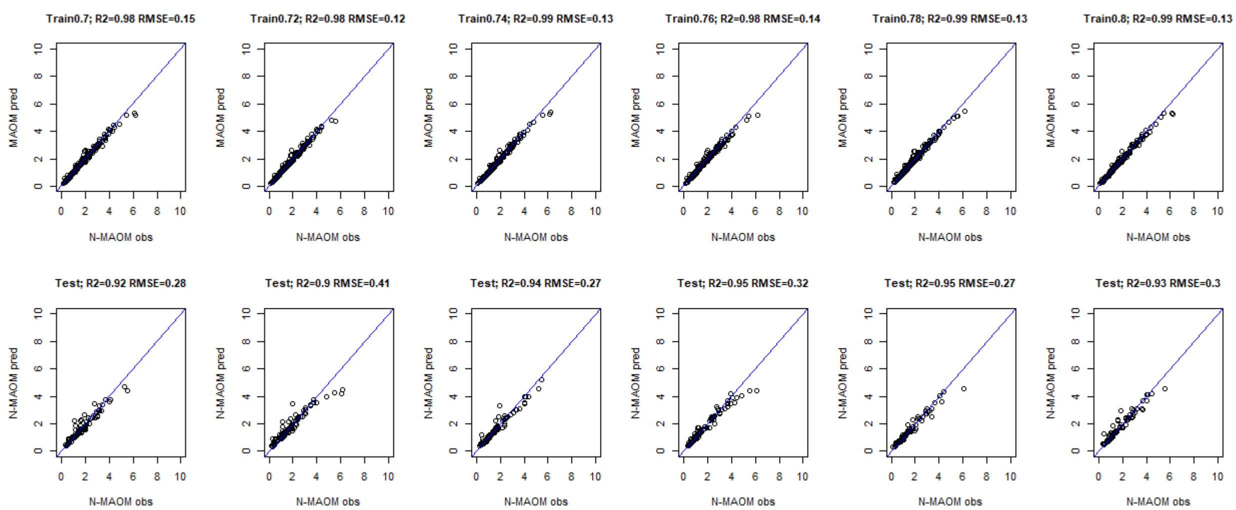

Fig. S6| Random Forest cross validation. Random forest predictions of MAON (g N kg^{-1} soil) with different sets of training datasets ranging from 70 to 80% of LUCAS data (n=352). In the training dataset, the bias ranges between -0.002 and 0.002, and the root relative squared error (RRSE) between 0.12 and 0.13; in the testing dataset, the bias ranges between -0.03 and 0.75, and the RRSE between 0.25 and 0.31.

Table S1| Spatial datasets used to upscale the Random Forest model predicting MAOM and POM.

Layer	reference	URL
Topsoil physical properties in the EU (texture, coarse fragment, bulk density)	Ballabio C., Panagos P., Montanarella L. Mapping topsoil physical properties at European scale using the LUCAS database (2016) Geoderma, 261 , pp. 110-123.	https://esdac.jrc.ec.europa.eu/content/topsoil-physical-properties-europe-based-lucas-topsoil-data
Topsoil chemical properties in the EU (pH, nitrogen, carbon*)	Ballabio, C., Lugato, E., Fernández-Ugalde, O., Orgiazzi, A., Jones, A., Borrelli, P., Montanarella, L. and Panagos, P., 2019. Mapping LUCAS topsoil chemical properties at European scale using Gaussian process regression. Geoderma, 355: 113912.	https://esdac.jrc.ec.europa.eu/content/chemical-properties-european-scale-based-lucas-topsoil-data
Topsoil physical and chemical properties (ISRIC-SoilGrid) (Soil organic carbon content and stock, nitrogen content, bulk density, gravel content); Version 2020	Hengl T, Mendes de Jesus J, Heuvelink GBM, Ruiperez Gonzalez M, Kilibarda M, Blagotić A, et al. (2017) SoilGrids250m: Global gridded soil information based on machine learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748	https://www.isric.org/explore/soilgrids
Soil erosion by water	Panagos, P., Borrelli, P., Poesen, J., Ballabio, C., Lugato, E., Meusburger, K., Montanarella, L., Alewell, .C. 2015. The new assessment of soil loss by water erosion in Europe. Environmental Science & Policy. 54: 438-447. DOI: 10.1016/j.envsci.2015.08.012	https://esdac.jrc.ec.europa.eu/themes/erosion
Current and future climate	Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37 (12): 4302-4315.	https://www.worldclim.org/data/worldclim21.html https://www.worldclim.org/data/v1.4/cmip5_30s.html
Average annual atmospheric N deposition (2006-2010)	Simpson, D., Benedictow, A., Berge, H., Bergström, R., Emberson, L.D., Fagerli, H., et al. 2012. The EMEP MSC-W chemical transport model – technical description. Atmos Chem Phys. Aug;12(16):7825–65.	
Global patterns of groundwater table depth	Fan, Y., Miguez-Macho, G., Jobbágy, E.G., Jackson, R.B., Otero-Casal, C. 2017. Hydrologic regulation of plant rooting depth, Proceedings of the National Academy of Sciences 114 (40), 10572-10577, doi: 10.1073/pnas.1712381114	https://aquaknow.jrc.ec.europa.eu/content/global-patterns-groundwater-table-depth-wtd

*updated version based on LUCAS 2009-2015 data, under release

Table S2| Spatial datasets and Random Forest (RF) model combinations used to propagate the uncertainty in MAOM and POM spatial predictions.

	SP1	SP2	SP3	SP4
Soil organic carbon content and N (JRC-ESDAC)	x	x		
Soil organic carbon content and N (ISRIC)			x	x
Silt+clay (JRC-ESDAC)	x		x	
Silt+clay (ISRIC)		x		x
N deposition	x	x	x	x
Water table depth	x	x	x	x
pH	x	x	x	x
Soil erosion	x	x	x	x
RF model	All data	RF1	RF2	RF3

The random forest models RF1, RF2, RF3 were obtained by bootstrapping the original datasets (n=352) with repetitions.