EGU21-4416
https://doi.org/10.5194/egusphere-egu21-4416
EGU General Assembly 2021

Deep Learning-based Soil Property Prediction for Remediation of Radioactive Contamination in Agriculture

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The Joint IAEA/FAO Division of Nuclear Techniques in Food and Agriculture, through its Soil and Water Management & Crop Nutrition Laboratory (SWMCNL), launched in October 2019, a new Coordinated Research Project (D15019) called “Monitoring and Predicting Radionuclide Uptake and Dynamics for Optimizing Remediation of Radioactive Contamination in Agriculture''. Within this context, the high-throughput characterization of soil properties in general and the estimation of soil-to-plant transfer factors of radionuclides are of critical importance.

For several decades, soil researchers have been successfully using near and mid-infrared spectroscopy (MIRS) techniques to estimate a wide range of soil physical, chemical and biological properties such as carbon (C), Cation Exchange Capacities (CEC), among others. However, models developed were often limited in scope as only small and region-specific MIR spectra libraries of soils were accessible.

This situation of data scarcity is changing radically today with the availability of large and growing library of MIR-scanned soil samples maintained by the National Soil Survey Center (NSSC) Kellogg Soil Survey Laboratory (KSSL) from the United States Department of Agriculture (USDA-NRCS) and the Global Soil Laboratory Network (GLOSOLAN) initiative of the Food Agency Organization (FAO). As a result, the unprecedented volume of data now available allows soil science researchers to increasingly shift their focus from traditional modeling techniques such as PLSR (Partial Least Squares Regression) to classes of modeling approaches, such as Ensemble Learning or Deep Learning, that have proven to outperform PLSR on most soil properties prediction in a large data regime.

As part of our research, the opportunity to train higher capacity models on the KSSL large dataset (all soil taxonomic orders included ~ 50K samples) makes it possible to reach a quality of prediction for exchangeable potassium so far unsurpassed with a Residual Prediction Deviation (RPD) around 3. Potassium is known for its difficulty of being predicted but remains extremely important in the context of remediation of radioactive contamination after a nuclear accident. Potassium can help reduce the uptake of radiocaesium by crops, as it competes with radiocaesium in soil-to-plant transfer.

To ensure informed decision making, we also guarantee that (i) individual predictions uncertainty is estimated (using Monte Carlo Dropout) and (ii) individual predictions can be interpreted (i.e. how much specific MIRS wavenumber regions contribute to the prediction) using methods such as Shapley Additive exPlanations (SHAP) values.

SWMCNL is now a member of the GLOSOLAN network, which helps enhance the usability of MIRS for soil monitoring worldwide. SWMCNL is further developing training packages on the use of traditional and advanced mathematical techniques to process MIRS data for predicting soil properties. This training package has been tested in October 2020 with thirteen staff members of the FAO/IAEA Laboratories in Seibersdorf, Austria.