Soil electrical conductivity EC modelling based on LUCAS topsoil (2015-2018) using machine learning approach to classify salt affected soils

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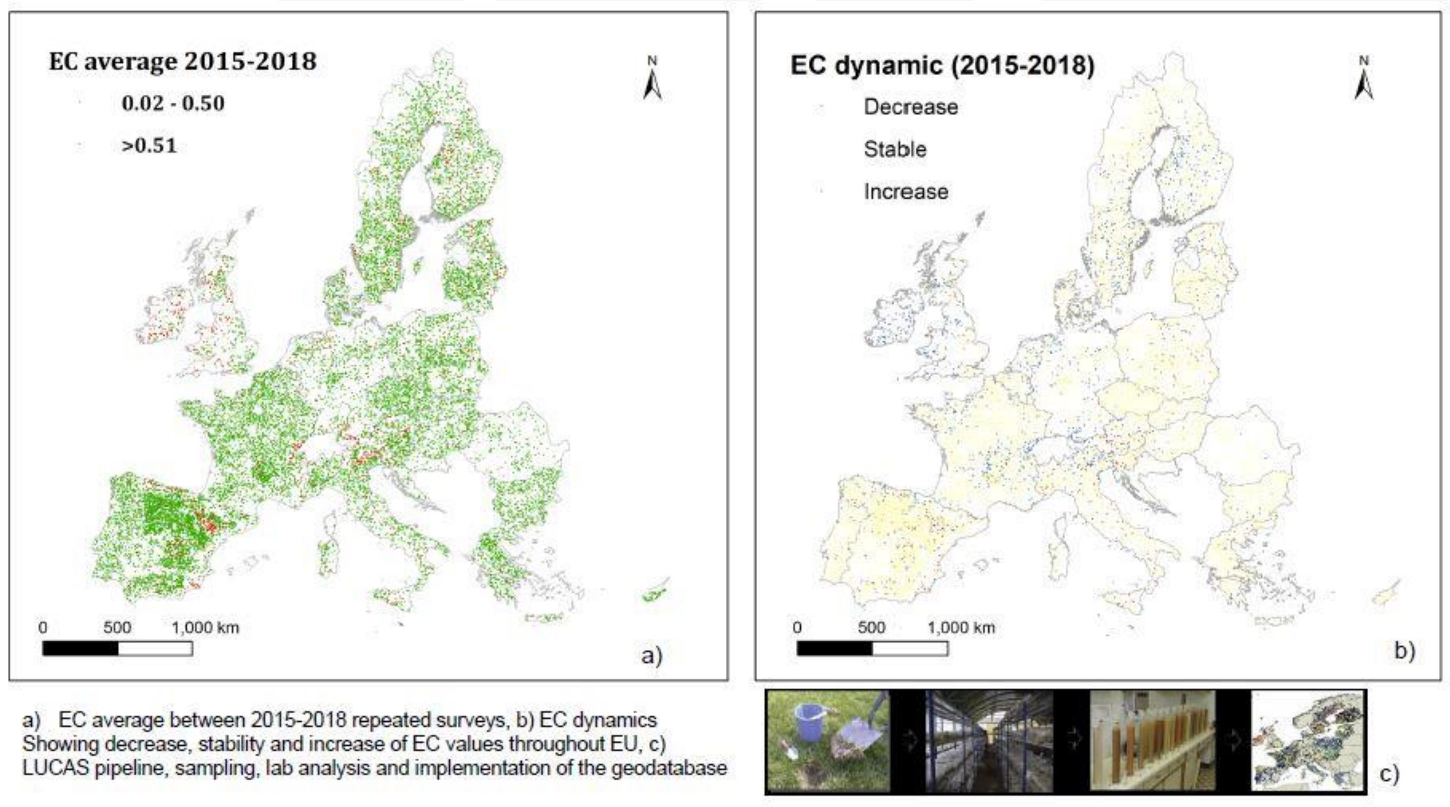
INTRODUCTION

To contribute to the efforts of the International Network on Salt affected Soils (which is based on a country driven support and to cope with inter seasonal variability, we performed a modelling exercise based on soil Electrical Conductivity (collected during the soil LUCAS surveys The aim of this work is to predict potential salt affected soils (EC 0 5 dS m 1 and unaffected 0 50 dS m 1 for the European countries using a digital soil mapping approach The reduced threshold 0 5 dS m 1 instead of 0 75 dS m 1 as proposed by FAO) reflects the possible early sign of salinization state in European soils which shows a moderate salinity 2 4 dS m 1 in the worst cases

DATA



a) EC average between 2015-2018 repeated surveys, b) EC dynamics Showing decrease, stability and increase of EC values throughout EU, c) LUCAS pipeline, sampling, lab analysis and implementation of the geodatabase

LUCAS Topsoil

Electrical conductivity EC

The EC training data used in this work, consisted in the mean ECs of two surveys, (15435 points). 75% of the total LUCAS survey points

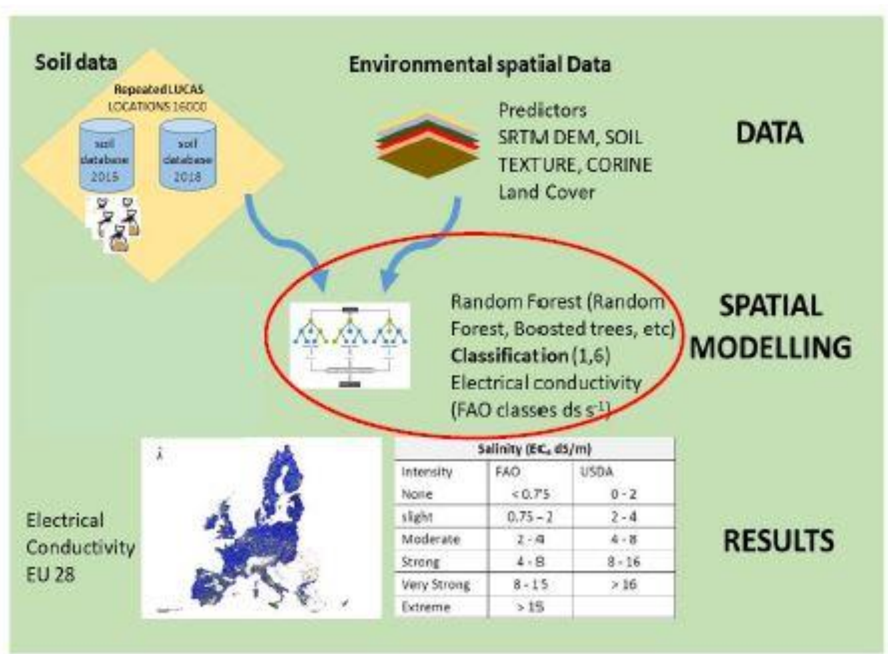
Environmental properties

500 m spatial resolution:

- topography and related indices (Farr et al., 2007),
- Soil hydraulic properties (Tóth et al., 2017),
- Bioclimatic (Fick and Hijmans, 2017)
- CORINE Land cover,
- the World Reference Based classification (IUSS Working Group WRB, 2014).

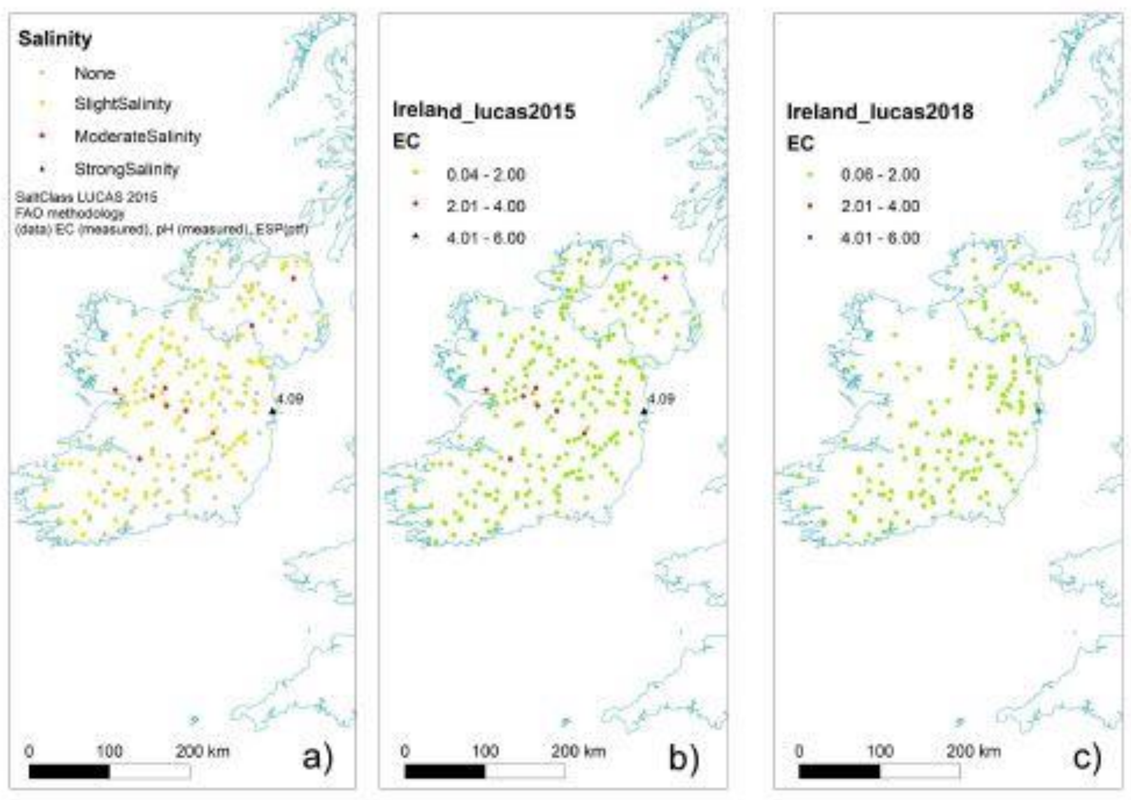
Each of the levels of CORINE and WRB reference Soil Groups (RSGs) (Commission, 2007) were binarized to carry out the classification.

METHODS



The model selected were Random Forest (RF) and Gradient boosting machine (GBM) model, there are few tuning parameters such as number of iterations, complexity of the tree, learning rate.

GBM results were evaluated using: Accuracy, Cohen's Kappa, Precision, Recall and F1 (Vermeulen and Van Niekerk, 2017).



a) EC 2015 FAO classification, b) EC 2015, c) EC 2018

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RESULTS

97.5 % of soil samples have EC below 0.75 dS m-1, and 94 % below 0.5 dS m-1, and this suggests that soils in the study area are not severely salt affected. We trained and test the model based on a random selection of (70/30) respectively and showed that the performances allowed for the detection of the most susceptible areas to salinity with an Accuracy of 0.946, Kappa, of 0.18, precision 0.95, recall 0.995 and F1 of 0.972. In particular, the model was able to identify 100% of the unaffected soil and 20%of the salt-affected. Furthermore, 50 % of (EC > 0.75 dS m-1) were identified. The list of the most important variables showed that in addition to climatic (rainfall and temperature), topographic indices, legacy soil information (WRB soil orders), were the most important covariates.

CONCLUSIONS AND FUTURE PERSPECTIVES

Annual average precipitation and saturated water content (80 % of predicted points are above the average), soil moisture of the summer season, elevation and the WRB-RSGs Gypsisols, which shows accumulation of moderately soluble salts or non-saline substances and Gleysols were the most represented WRB groups that hosts European salt affected soils.

Deepen the understanding in the Salinity mapping approaches using a large scale monitoring dataset in EU is crucial for the definition of local scale cut-off values to map land degradation.

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