Mapping Soil Organic Carbon at a Farm Level Using Random Forests

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Introduction

Soils are the largest terrestrial carbon sink (Stockmann et al. 2013).

Soil organic matter is responsible for soil health and quality which promotes the storage of carbon within soils (Liu et al. 2006).

Soil organic carbon is the carbon captured within soils.

This carbon storage is essential for the abatement of anthropogenic emissions, whilst improving productivity of agricultural land.

Project Rationale

The Australian Government has developed a carbon credits scheme offering agricultural landholders financial incentives to increase carbon sequestration in their soils (Australian Government 2021). To measure these changes for correct compensation, traditional lab based soil samples are undertaken due to their high accuracy. However these measurements are cost and time intensive (Grimm et al. 2008).

To improve the efficiency of data collection, an alternative sampling strategy has to be found, to minimise cost and time whilst maintaining accuracy.

The optimal sampling strategy is achieved through representative sampling, where land is divided into sections (strata) based on the predicted soil organic carbon content. This aims to reduce variability of soil organic carbon across the strata, thus reducing sample size, cost, and time of sampling, whilst maintaining accuracy (Goidts et al. 2009). The aim for this study is to determine the optimal trade offs as shown in figure 1.

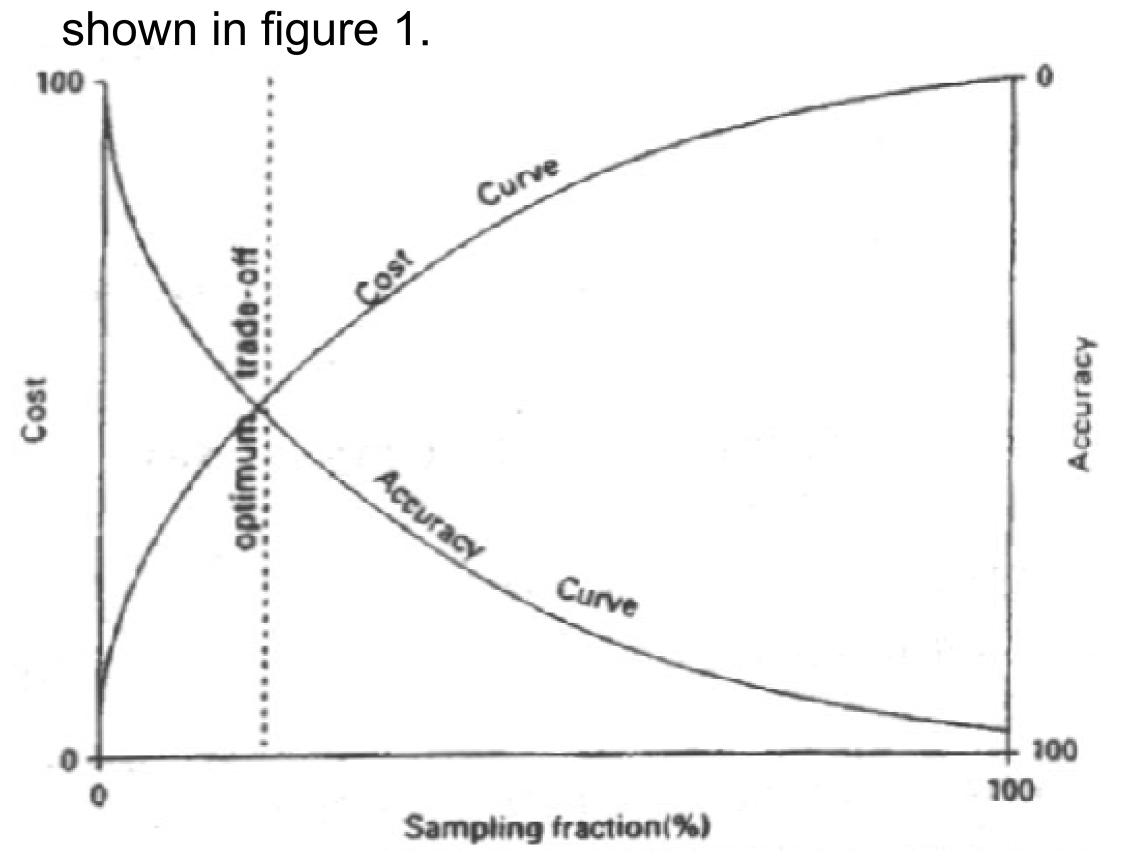


Figure 1: Finding the optimal sampling strategy amidst trade offs (Reinke 2022)

Figure 2: Investigation of the improved agricultural practices (Addinsall 2023)

Research Aims

- Determine what spatial variables influence the distribution of soil organic carbon
- Create a random forests machine learning model to predict what variables result in similar soil organic carbon content
- Evaluate sampling techniques that minimises cost and time, yet is accurate at representing soil organic carbon

Table 1: Type of Variables Affecting Soil Organic Carbon (Xiong et al. 2014)

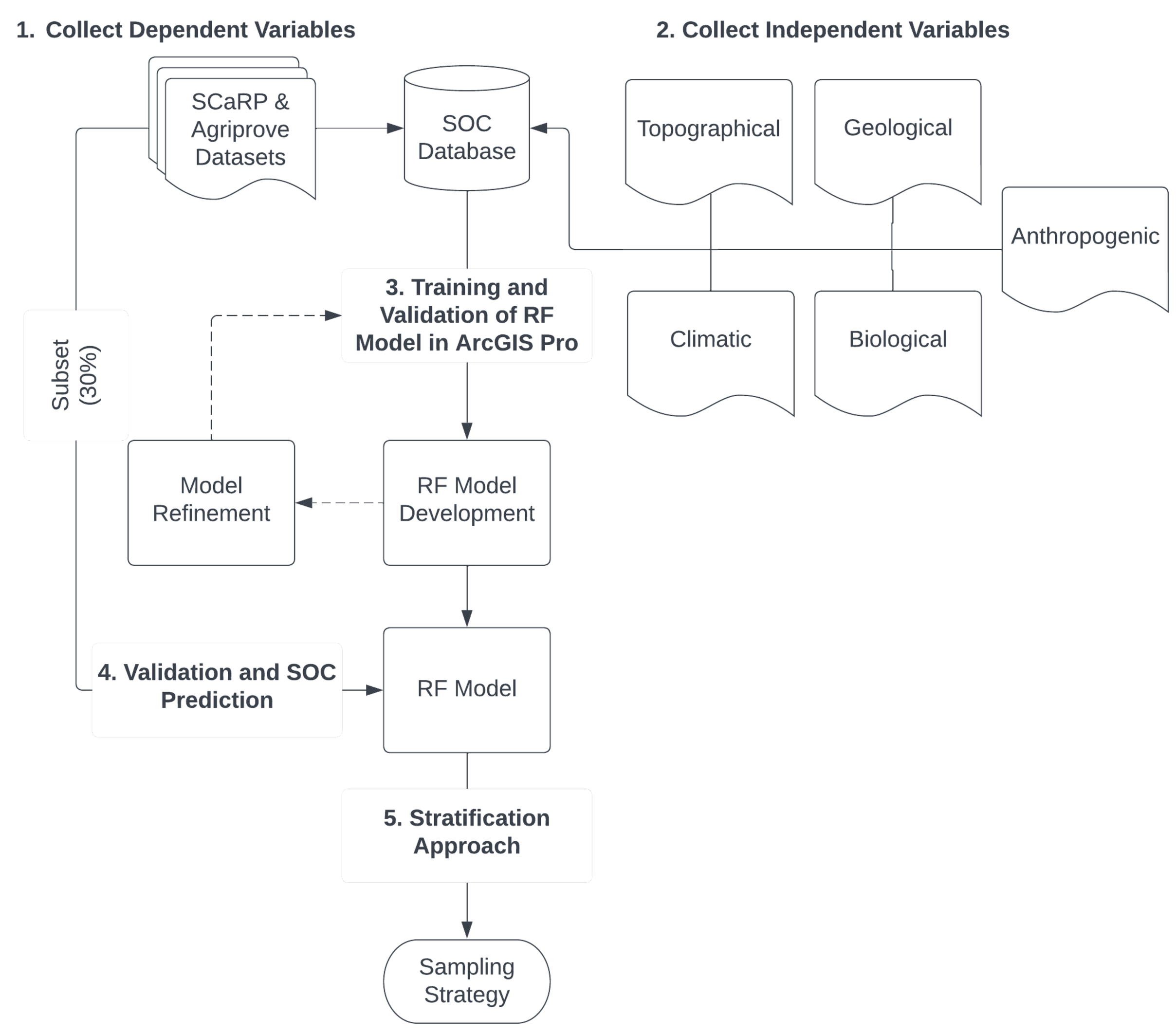
Variables	Examples
Topographical	Elevation, Slope, Aspect, Curvature, Flow Accumulation
Geological	Soil Texture, Bare Soil Index
Biological	Soil Classification, Vegetation Cover, NDVI
Climatic	Precipitation, Solar Radiation, Temperature
Anthropogenic	Land Management Practices, Land Use & Land Use Change, Infrastructure

Literature Review

Analysis of literature has highlighted several improvements that will strengthen the project methodology:

- Random forests is a suitable machine learning model for the study. Calculates variable importance and prediction of soil organic carbon distribution (Grimm et al. 2008).
- RF model paired with kriging can further improve the model accuracy (Tziachris et al. 2019).
- Increase variety of independent variables (e.g. table 1). Adopts a more holistic approach – potential to discover complex environmental processes. Collinearity between variables has to be evaluated (Xiong et al. 2014).
- Sentinel 2 data is suitable for predicting soil organic carbon variation within a field scale (Castaldi et al.,2019)

Method



Next Steps

- Literature review
- Source relevant datasets based on variable selection

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