

000 Classifying Soil Type Using Radar Satellite Images

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018 Abstract

019

020 The growth of the crop is dependent on soil type, apart from atmospheric
021 and geo-location characteristics. As of now, there is no direct and cost-
022 free method to measure soil property or to classify soil type. In this
023 work, we proposed a machine learning model to classify soil type using
024 Sentinel-1 satellite radar images. Further, the developed classifier
025 achieved 72.17% F1-score classifying sandy, free and clayish on a set
026 of 65003 data points collected over one year (from Oct 2018 to Sep 2019)
027 over 14 corn parcels near Ourique, Portugal.

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028 **Keywords:** Remote Sensing, Soil Electrical Conductivity, Sentinel-1,
029 Machine Learning, Random Forest

029

030 1 Introduction

031

032 Precision farming involves the collection of detailed information of mineral,
033 nutrients, water, soil texture, cation exchange capacity, drainage
034 conditions, organic matter level, salinity, and subsoil characteristics over
035 farmland [3]. Over the last few decades, many new technologies have
036 been developed for measuring soil properties, and one of such is using
037 remote sensing techniques [2].

037

038 Sentinel-1 [7] is a synthetic aperture radar instrument (SAR) satellite
039 that provides images in two different polarizations: VV (vertical transmit,
040 vertical receive) and VH (vertical transmit, horizontal receive). It consists
041 of a constellation of two satellites, Sentinel-1A and Sentinel-1B, which
042 share the same orbital plane with a 12-day revisiting period.

041

042 In precision farming, detailed information about the spatial characteristics
043 of farm operations like yield estimation, field attribute maps and
044 forecasting harvesting date are made available to the farmer. This
045 information is gathered using a wide array of electronic, mechanical and
046 chemical sensors which leads to measure and map soil and plant properties.
047 Soil Electro-Conductivity (EC) is one of the simplest, least expensive
048 soil measurements available to precision farming today [8].

047

048 EC is the ability of a material to transmit (conduct) an electrical current
049 and is usually expressed in miliSiemens/meter (mS/m). Soil EC is a
050 measurement that characterizes soil properties which, in turn, affect the
051 productivity of crops. These properties include water content, soil texture,
052 soil organic matter (OM), depth to clay layer, the capacity of cation
053 exchange (CEC), salinity, calcium and magnesium [4].

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053 The objective of the present study is to build a classification model using
054 machine learning algorithms that characterize soil types using Sentinel-
055 1 radar images.

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055 The rest of the paper is organized in the following sections: Section 2
056 introduces the data used in this work, while Section 3 describes the machine
057 learning model, the experimental setup, experiments and results. Finally,
058 Section 4 concludes the paper.

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The Electro-Conductivity value from a set of 14 parcels of corn fields

(made available by Agroinsider [1]) was used as ground data points. These

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parcels are from Alentejo region with coordinates between (37°56'29.13" N , 8°22'21.95" W) and (37°55'32.44" N, 8°21'02.23" W). Figure 1 shows the Google View image of these 14 parcels. EC value was measured at 10-meter intervals resulting in a total of 65003 points.



Figure 1: Google view images of 14 parcels

Electro-conductivity real values were discretized, leading to three types of soil: sandy, free, and clayish. Table 1 presents the information about each type: the EC values interval and the number of points.

Soil Type	Value Range	Count
Sandy	$EC < 10mS/m$	24195
Free	$10mS/m \leq EC \leq 25mS/m$	31141
Clayish	$EC > 25mS/m$	9667

Table 1: Soil type information.

For each data point, along with the EC value, the respective latitude and longitude were also noted. With the collected coordinates, the corresponding values of VV and VH from the radar images were taken.

This radar data was collected from October 2018 to September 2019, the time span of one agricultural year. Since the Sentinel-1 revisiting time is 6 days, it resulted in a set of 60 pairs of values for each EC point measured. In this way, each soil point is characterized by 122 attributes: the soil type plus latitude, longitude and 60×2 values of the radar images (60 dates and two polarizations: VV, VH). But latitude and longitude are not used as a parameter value in the ML algorithm.

Figure 2 represents the corresponding radar image for October 8, 2018 with VH polarization. And the variation of VH and VV value for one agriculture year (From Oct 2018 to Sep 2019) is shown in Figure 3.

3 Machine Learning Models

Three machine learning algorithms have been used to build classification models:

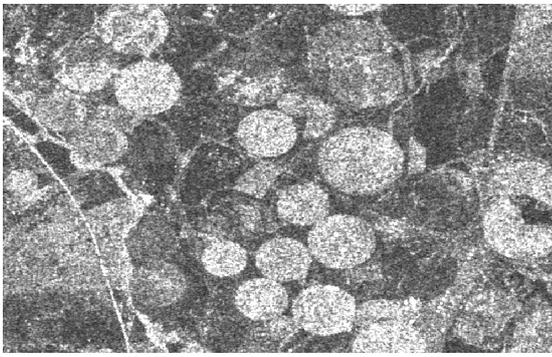


Figure 2: VH polarized radar image on 6th October 2018

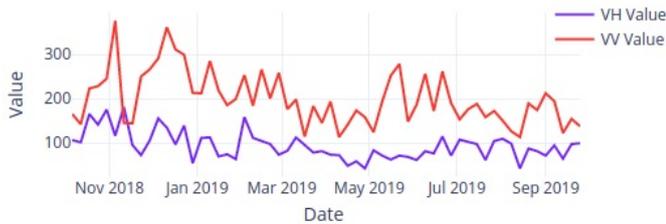


Figure 3: Variation of VH and VV values over a year in a specific point.

- Support Vector Machines (SVM) with a linear kernel.
- Random Forest (RF), a set of decision trees built from bootstrap samples of the training set where the candidate split in the learning process, is chosen from a random subset of the features.
- Extra Trees (ET), another ensemble classifier of decision trees, differs from RF in two points: each tree is trained using the whole learning sample and the top-down splitting in the tree learner is randomized.

3.1 Experimental Setup

A stratified train-test split was done over the dataset, with 80% for training (52002 samples) and 20% for testing (13001 samples).

We used Scikit-learn library [6] and RandomizedSearchCV [5] approach with 5-folds cross-validation to fine-tune the algorithms over micro-F1 measure. Parameters that produces the best results were: $nestimators = 189$, $max_features = sqrt$, $max_depth = 32$, $min_samples_split = 2$, $bootstrap = False$, $min_samples_leaf = 1$, and $criterion = gini$.

3.2 Experiments and Results

In order to evaluate the performance of the algorithms in this problem as well as the most relevant set of attributes, several experiments were carried out in a total of 153:

1. Algorithms: SVM, RF, ET
2. Time interval
 - (a) 12 months
 - (b) 3 months (Oct – Dec, Jan – Mar, Apr – Jun, Jul – Sep)
 - (c) 1 month (Oct, Nov, Dec, Jan, Feb, Mar, Apr Sep)
3. Polarization: VV, VH, VV + VH

These preliminary results made it possible to draw the following conclusions:

- Data set of 12 months time interval shows better results in performance measures: precision, recall and F1-Score.
- Compared to the other shorter intervals, performance increase between 2% to 3% in the F1-score measure, when compared to the results obtained with the April-June interval. The April-June interval presents the 2nd best F1-score values.
- The performance measure using only one of the polarization is similar. But some are gain (between 2% and 7% in the F1-score measure) when using both polarizations.
- Random Forest present the outperform than others based on the performance measures.

Table 2 details the results using Random Forest for the time span of 12 months. It presenting the best results in the three performance measures. So from 12 months time interval, several conclusions can be drawn from

Soil Type	Precision (%)	Recall (%)	F1-Score (%)
Sandy	79.70	70.15	74.62
Free	68.25	84.76	75.62
Clayish	80.17	41.21	54.44

Table 2: Performance of the Random Forest model over the test set.

the results:

1. it is possible to observe that the model behaves reasonably for sandy and free soils; precision is about 10% higher for sandy soils (almost 80%) but, on the other hand, free soils present 15% higher recall (about 85%);
2. concerning clayish soils, a high precision (about 80%) is obtained at the expense of a significantly low recall (about 41%); this difference affects F1-score, which fails to reach 55%, while for other types of soil the value is around 75%;

4 Conclusions and Future Work

This work presents a machine learning model to classify soil type using Sentinel-1 satellite images. The developed model, using Random Forests, is able to achieve 74.62%, 75.62% and 54.44% F1-score for sandy, free and clayish soils, respectively.

In future, to improve the results of this work, we will enlarge the dataset with more parcels having different crops, including more features from radar like the angle of incidence and timing for example.

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