Classifying Soil Type Using Radar Satellite Images

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Motivation and Objectives

⇒ Some crops struggle to grow and survive in certain types of soil
⇒ Soil needs (water and others) also depend on type of soil
⇒ Detect soil type from radar satellite imagery to help farmers increase crop yield

Sentinel-1

⇒ Sentinel-1 [3] is a synthetic aperture radar instrument (SAR)
⇒ Composed of a constellation of two satellites: Sentinel-1A and Sentinel-1B
⇒ Provides images in two different polarizations
→ VV (vertical transmit, vertical receive)
→ VH (vertical transmit, horizontal receive)

Soil electrical conductivity (EC)

⇒ EC is the ability of a material to transmit (conduct) an electrical current
⇒ Soil EC is a measurement that characterizes soil properties
⇒ Important indicator of soil health
⇒ One of the simplest, least expensive soil measurements available to precision farming [4]

Original data

⇒ Parcels are from Alentejo region
⇒ 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: Google view images of 14 parcels

⇒ EC value from a set of 14 parcels of corn fields (made available by Agroinsider [1])
⇒ Total points 65003 and three types of soil

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

Radar data

⇒ Data collected from October 2018 to September 2019, the time span of one agricultural year
⇒ Total 60 Days, Used dual polarization data: VH, VV

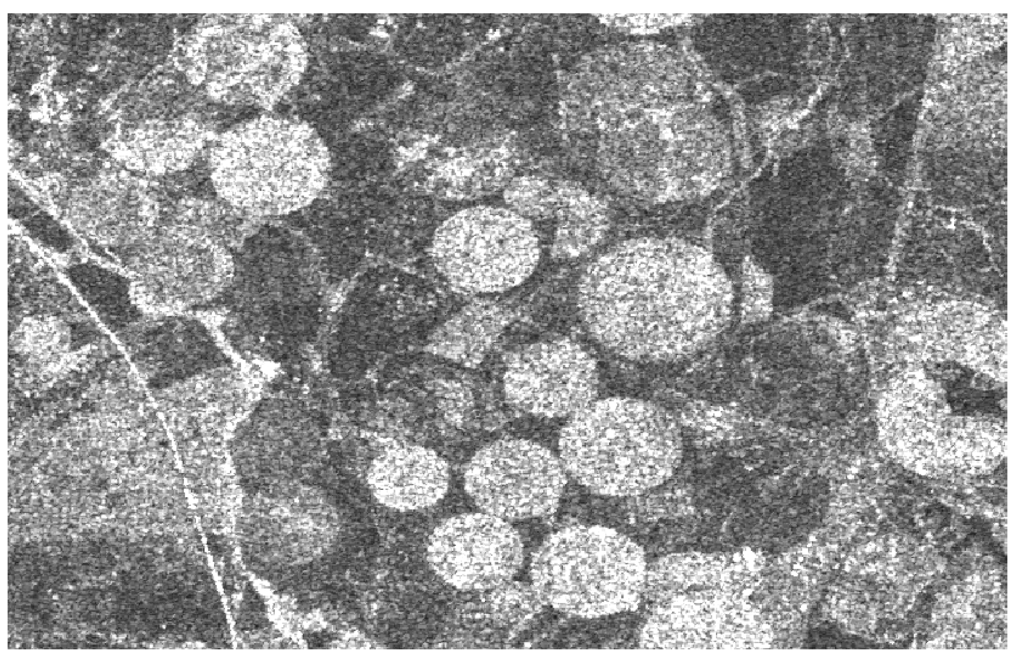

Figure 2: VH polarized radar image on 6^{th} October 2018

Machine Learning Methods

Three machine learning algorithms used to build models:

1. Support Vector Machines (SVM)
2. Random Forest (RF
3. Extra Trees (ET)

Experimental Setup

⇒ A stratified train-test split was done over the dataset
⇒ 80% for training (52002 samples) and 20% for testing (13001 samples)
⇒ Total 120 Features are used
⇒ Class (Clayish, Free, Sandy)
⇒ Used Scikit-learn library [2] and RandomizedSearchCV approach with 5-folds cross-validation

Experiments

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, May, Jun, Jul, Aug, Sep)
3. Polarization: VV, VH, VV + VH

Results

Preliminary results made draw the following conclusions

⇒ Data set of 12 months time interval shows better results base on precision, recall and F1-Score
⇒ Compared to the shorter intervals, performance increase between 2% to 3% in the F1-score
⇒ The April-June interval presents the 2nd best F1-score values
⇒ The performance measure using only one of the polarization is similar
⇒ Random Forest present the outperform than others based on the performance measures

From 12 months time interval, several conclusions can be drawn from the results:

⇒ The model behaves reasonably for sandy and free soils
→ Precision is about 10% higher for sandy soils (almost 80%)
→ Free soils present 15% higher recall (about 85%)

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.

⇒ Clayish soils, a high precision (about 80%) is obtained at the expense of a significantly low recall

Conclusions and Future Work

⇒ Presents a machine learning model to classify soil type using Sentinel-1
⇒ Random Forests achieve 74.62%, 75.62% and 54.44% F1-score for sandy, free and clayish soils
⇒ Enlarge the dataset with more parcels having different crops
⇒ Improve the ML model
⇒ Add more feature value from radar like angle of incidence, timing

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