LAND SUITABILITY ANALYSIS FOR OLIVE AND MAIZE CROP IN RAINFED AGROFORESTRY SYSTEM USING MACHINE LEARNING ALGORITHM

By

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‘Dedicated to my Parents and Grandparent.’

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Asif Hayat

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Acronyms	Meanings
LULC	Land use land cover
OC	Soil organic carbon
ML	Machine Learning
FAO	Food and Agriculture Organization of united nations
RF	Random forest
SVM	Support Vector Machine
WOL	Weighted Overlay
Elev	Elevation
VD	Valley Depth
Flow_Ac	Flow Accumulation
NDVI	Normalized Difference Vegetative Index
BI	Brightness Index
Text	Soil texture
ATGC	Annual temperature of the Growing Cycle
RFGC	Rainfall of the Growing Cycle
EVI	Enhance vegetive index
Plan_C	Plane Curvature
MRTF	Multi-resolution Ridge top Flatness
LS_factor	Land surface Factor
Long_C	Longitudinal Curvature
EC	Electrical Conductivity
DEM	Digital elevation model
S1	Highly suitable class
S2	Moderately suitable class
S3	Marginally suitable class
N2	Permanently Non-suitable class

ABSTRACT

The demand for edible oil is on the rise due to an increase in the population and affordability all over the world. But such an increase in the demand for a nation like Pakistan is a big problem by inducing pressure on the import bill and increasing the trade deficit. In our study, we focus on land suitability analysis of olive and maize crops in an Agroforestry system based on the Food and Agriculture Organization (FAO) “land suitability assessment framework” by using machine learning and traditional technique. The soil, climatic and topographic data were collected in district Dir Lower of Khyber Pakhtunkhwa to identify suitable areas for the agroforestry system of olive and maize crops in the rainfed agriculture areas. after determining the land suitability classes for the agroforestry system of olive and maize crops, they were classified and maps were produced through a machine learning algorithm of (RF, SVM) and by weighted overlay technique. The ML-based random forest (RF) gives overall accuracy and kappa index of (0.94, 0.90) for olive and (0.94, 0.91) for maize while the support vector machine (SVM) gives the overall accuracy and kappa index of (0.92, 0.88) for olive and (0.93, 0.90) for maize. On the other hand, the weighted overlay (WOL) technique gives the overall accuracy and kappa index of (0.89,0.85) for olive and (0.93, 0.87) for the maize land suitability classes. The traditional technique o WOL doesn’t predict the permanently non-suitable class for the maize while the ML-based technique did it. The maps produced by the two different techniques depict clear and prominent differences.

Chapter 1

INTRODUCTION

Agroforestry systems are land management strategies in which trees and agricultural crops are grown alongside deliberately. As a result, combining trees, crops, or livestock to promote diversity, efficiency, revenue growth, and sustainable development. As a result, agroforestry systems provide a more sustainable option to crop varieties that are biologically simplified or have low diversity. Agroforestry systems are also suitable for revitalizing degraded land in both temperate and tropical ecoregions. Enhanced soil fertility from organic matter contribution from trees and crops leads to higher crop production, having a positive outlook on food security and soil conservation. Agroforestry systems' tree and soil components can also act as protracted carbon sinks, helping to mitigate climate change. The United Nations Food and Agriculture Organization (UN-FAO) proposed agroforestry practices for food security in 2013, and there is a need for developing nations to integrate agroforestry into their national agricultural and food security policies. Agroforestry systems seem to be interesting because they have the potential to reduce the requirement for deforestation in tropical regions. It was projected that one hectare of sustainable agroforestry output might avoid up to twenty hectares of deforestation. Agroforestry systems offer environmental advantages in addition to improving soil fertility and crop output. Which include minimized nutrients leaching and soil depletion, nutrient cycle stability, weed, and insect control, increased soil water availability, and increased biological diversity. Agroforestry creates a more varied farming system, lowering the financial risk associated with the production of different goods. This also contributes to the growth of rural livelihood (Oelbermann, 2017).

Worldwide, forest ecosystems are diminishing and falling in health owing to a variety of biotic and abiotic influences. Pakistan's forest ecosystems are even worse, and the country is facing a dilemma as its rising population (> 208 million) puts increasing strain on the country's food security and forest products. Proper food security policies that boost productivity and financial stability. It is necessary to enhance environmental protection while maintaining societal acceptability. Agroforestry, an existing land management system in Pakistan, provides a chance to achieve these objectives. Trees plantation on private lands ensures unambiguous ownership of any timber, and well-managed z practices have the potential to promote agriculture while also reducing wood shortages. In Pakistan, substantial extension works have been undertaken to develop and encourage novel agroforestry practices (Baig et al. 2020)

1.1 Types of Agroforestry system

There are three types of agroforestry systems.

Agrislivicultural system is that agroforestry technique in which woody perennial trees are planted along with Agricultural Crops deliberately. e.g. Alley cropping and home gardens (FAO, 2015). Silvopastoral system is that agroforestry technique in which woody perennial trees are planted alongside the grazing animals on rangelands and pastures (FAO, 2015). Agrosylvopastoral system is on the other hand combination of trees, crops, and animals on the same land management unit (FAO 2015).

1.2 Land use Landcover

Agriculture is the backbone of Pakistan's economy. It accounts for more than a quarter of the gross domestic product (GDP) and employs 50% of the existing workforce. It nourishes the entire rural and urban communities and is the most important source of Export revenue. Agriculture is the primary industry and an important pillar of our GDP.

A bush is a perennial shrub with some stems sprouting from the ground and no single trunk, neither of which is dominant and is normally less than 3 m in height. A shrub or bush may be distinguished from a tree by its many stems and lesser height, which is usually less than 3 m.

The woodland/Forest covering area extends approximately 4.55 million ha, accounting for 5.1 percent of the country's total land area. High hill forests, which are mostly natural and coniferous, may be found in the northern region of Pakistan. Moist temperate, dry temperate, subtropical Chir pine and subalpine forest types can be found there. They are indeed the major supply of timber and cover around 54 percent of the forest area. These woodlands are extremely important in terms of water supply down the streams. The second biggest and most important forest type is subtropical broad-leaved evergreen, which spans around 1.109 million hectares. This forest type is mostly found on the lower slopes and foothills of the Himalayas in the northern areas, Suleman Ranges in Baluchistan, Kala-Chitta Range in Punjab.

Glacier is the large body of ice present on high altitudes above the mountain and adjacent valleys in the northern areas of Pakistan like in the Malakand division, and Hazara Division of Khyber Pakhtunkhwa province, and in GB and Azad Kashmir. These Glaciers are the main source of Freshwater, hydro energy, and irrigation systems down the stream.

Wasteland or Barren land are those lands where cultivation and growing of any type of crop are not possible. Usually, wastelands have thin soil, more sand, and rocks.it constitutes sand dunes, beaches, dry salt ranges, and exposed rocks.

Settlements are groups of homes that create a community or a site where a community lives to develop a new area or colony, whereas a fruit orchard is a plot of ground where organic goods such as fruits or nut trees are grown and established. Finally, water bodies include streams, rivers, lakes, and the ocean, among others.

1.3 Background information

Over a quarter of the global population is dependent on forest products for a living, and about 1.2 billion people around the globe use trees on farmland to create food and income. Pakistan, like several other nations, is dealing with a variety of forest-related concerns, such as climate change, diminishing water quality, and rising costs for wood. Pakistan aspires to achieve the objective of higher socioeconomic growth, as well as water, food, energy, and environmental protection while avoiding overexploitation of the forest and Ecosystem.

While on the other hand being an agricultural-based economy Pakistan still spends a lot of its foreign exchange reserve on imports of edible oils and other food items. Edible oil and oilseeds are one of Pakistan's most important food and feed imports. Imports of edible oil are expected to reach a new high of 3.55 million metric tonnes (MMT) in 2020/21, representing a 5% increase compared to the last financial year. Increased imports of oilseeds indicate the rising significance of oilseed-based feeding in the poultry and cattle industry, as well as increased local oil output.

Olive is a suitable oilseed crop grown in dry and semi-arid regions around the globe. Because of its medicinal and nutritional properties, it's been grown for millennia. Lots of wild olive trees may be found throughout Pakistan. The viability of olive cultivation is mostly limited to arid, hilly regions of the country. Many problems, including seedling supply, a lack of high-quality genetic material, a poor success rate of grafting, and a lack of knowledge about financial value, all lead to the country's decreasing production and new plantations. Sunflower, mustard, peanut, and maize are favored for oil extraction while not being able to satisfy rising demand. Water availability for Farmland has decreased in recent decades, increasing sensitivity to environmental pressures, notably drought. Olive plantation can assist in overcoming these issues because it can be grown on low fertility soils, in dry locations, and needs minimal water to accomplish its growth and development. Furthermore, it protects the earth's delicate natural resources and is a major supplier of oil rich in essential fats. The country's tropical and subtropical environment is ideal for olive farming (Ali, 2015). The country's tropical environment is ideal for olive plantations. therefore, proper research is required for the identification of suitable areas for the Agroforestry system of olive and maize crops being oil-producing crops.

1.4 Objectives

Area suitability Analysis for the Agroforestry system of olive and maize crops using:

1. Machine learning Algorithms (RF and SVM),
2. Traditional method and
3. Comparisons of the two methods.

1.5 Literature review

Agroforestry systems are traditional land-use practices that have been and continue to exist across Europe. They are land-use systems that are intentionally controlled and consist of two primary components: trees/shrubs and an agricultural crop (which might alternatively be grassland). Agroforestry systems may be established on a temporal and geographic scale for a farmer to apply various agroforestry activities. Because the human impact on the environment is very vital in Europe and has taken place for a long time, there are various types of agroforestry practices in Europe such as silvoarable, forest farming, riparian buffer strips, Silvopastoral, and improved fallow and multipurpose trees (Losada et al. 2009). while impoverished nations, including Pakistan, utilize agroforestry which determines the socioeconomic effects on the life of local households. The main benefit of Agroforestry is a reduction in soil loss (Luqman et al. 2018).

Now due to the current climate change scenarios, food security threatens the developing nations specifically and the developed countries generally so the Agroforestry system can be used as mitigation for all these challenges (Mbow et al. 2014). To acknowledge such environmental issues a study was carried out for Land suitability analysis which is a part of determining the long-term viability of land use.

Land suitability can only be accomplished by identifying natural and cultural potential and selecting a suitable land use concerning the ecological structure. Land suitability analysis of Gökçeada was carried out in this study using Geographical Information Systems (GIS) and McHarg methodologies (Cengiz et al. 2013). In another study Spatial analysis of geographic information system (GIS) and analytical hierarchy process (AHP) were used to assess land suitability in Gonbad-e-Kavous township for rainfed barley agriculture. To do this, the agroecological needs of the crop were first identified using scientific resources. Following that, thematic requirement maps were produced. Annual, fall, spring, and May Rainfall data were examined, as were mean, minimum, and maximum temperatures, germination temperature, the maximum temperature in heading and grain filling stages, slope percent, elevation, slope aspect, OM, pH, and EC. Then, each layer was divided into four categories (S1 class, S2 class, S3 class, N class) (Azizi et al. 2017). Now, this land suitability classification is based on the FAO Land evaluation framework which is a set of ideas and concepts that may be used to build local, national, or regional land suitability evaluation systems. The land suitability evaluation methodology is predicated on the notion that land may be classified into multiple categories, each of which corresponds to a distinctive potential for a certain use. The following categories are widely used: highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable (N). These categories, also known as suitability classes can be split further. Suitability is determined by matching land traits or attributes to the needs of certain land use (FAO 1976). According to the study of (C SYS, 1993), the parametric method was used for the land evaluation in which they classify the soil and climatic parameter based on the growth requirement of each crop. Each of the classes has its limitation and rating scale. Then Kriging interpolation is used which is a popular method for mapping soil characteristics in the analysis and interpretation of soil spatial variation. The quality of mapping may have an impact on the efficacy of site-specific management. Existing soil maps that indicate sudden changes at the boundary between distinct soil types might give significant categorical information for analyzing variance in soil attributes (Liu et al. 2006). (Hengl et al. 2008) uses the Saga GIS to prepare the auxiliary data from dem, and Indices from satellite imagery for his model. Then (Kursa et al. 2010) in his article covers the R package Boruta, which uses a new feature selection approach to locate all important variables. The algorithm is built as a wrapper for the Random Forest classification technique. It repeatedly eliminates variables that are statistically proven to be less meaningful than random probes.

Machine learning algorithms are now days used very frequently for analyzing land suitability and many other research areas due to their performance and robustness and decrease in human involvement in evaluating the data and improving models' accuracy. Machine learning algorithms like Random Forest, SVM, XGboost, CARET, etc. were used in many studies for the land suitability classification. According to (Ismayilova et al. 2020) Land suitability analysis for potential restoration sites, using the machine learning technique Random Forest (RF) was performed for the first time in his study, which aimed to assess the use of RF for a suitability analysis of Alvar grassland. Another study (Taghizadeh et al. 2020) classify the land suitability for Wheat and barley crop in Kurdistan province Iran based on the FAO land evaluation Framework by Using machine learning algorithm i.e Random Forest (RF) and support vector machine (SVM) in Which the RF classification outperforms the SVM classification results. In another study, a dataset-based land suitability classification is addressed. It is done using a newly proposed ensemble classifier generation technique referred to as RotBoost, which is constructed by combining Rotation Forest and AdaBoost, and it is known to be the first time that RotBoost has been applied for suitability classification. The experiments conducted with the study area, Shaver plain, lies in the north of

Khuzestan province, southwest of Iran. It should be noted that suitability classes for the input data were calculated according to the FAO method. This provides positive evidence for the utility of machine learning methods in land suitability classification, especially MCS methods. The results demonstrate that RotBoost can generate ensemble classifiers with significantly higher prediction accuracy than either Rotation Forest or AdaBoost, which is about 99% and 88.5%, using two different performance evaluation measures (Mokarram et al. 2015). Farmers need to know whether their land is suited for the plants they wish to cultivate. A growing number of studies have employed land use data-based machine learning algorithms for effective land suitability mapping. That technique is based on the premise, but no research has rigorously evaluated the premise that farmers are growing their crops in favorable regions (Moller et al. 2021).

1.6 Soil data collection

To generate the land suitability maps of the study area we required information about the physical and chemical properties of soil. which was obtained through the soil sampling of the area. As we implement the machine learning algorithm for the classification of the imagery so there should be a large quantity of data for that. The data should be collected in such a way so that it could represent the soil profile of the area more accurately.

1.7 Environmental Parameters

The environment affects the growth and survival of vegetation up to a great extent. so decadal information about the temperature and Rainfall is also necessary for the preparation of the suitability maps. Which can be collected from various data providers.

1.8 Auxiliary data

Additional information such as the topographic properties of the area can be generated from the digital elevation model (DEM). Which has a great influence on the vegetation of an area in the form of soil formation, water supply, nutrient availability, and much more.

1.9 Satellite Imagery of Sentinel 2

In cooperation with the European Space Agency (ESA) launched a multispectral sensor, Sentinel-2 was launched in June 2015 under the Global Environments Monitoring and security Program (GMES) (EO, 2016). The imagery contains a 10m, 20m, and 60m spatial resolution with a swath width of 290 km. There are additional 13 spectral bands for a single sensor with a 10-day review time (SIC, 2016). With the exception of thermal bands, Landsat 8 bands are comparable. They are freely accessed from the USGS website. For numerous applications such as forests and vegetation, spatial planning monitoring, water management, agro-environmental monitoring, and natural habitat, satellite imaging of sentinal-2 might be employed (Drusch et al. 2012).

Chapter 2

MATERIAL AND METHODS

2.1 Study Area

Dir lower is a district in the Khyber Pakhtunkhwa province of Pakistan as shown in (Figure 2.1). It has a total area of 1582 km^2. Swat district at the east, Malakand district at the south, District Bajaur at the southwest, and Dir upper at the North. the land use land cover of the area is comprised of agricultural land, forest area, built-up area, barren land. Most of the agricultural area of the district is rainfed, while irrigated agriculture is present along the river punjkora and some big streams in the valley. there are several mountains but with 8500 ft elevation from sea level, Laram top is the highest mountain in the district.

2.1.1 Climate and Topography

The mean annual temperature is about 16 °C. The mean annual rainfall is about 796 mm. the driest month is October with 18 mm and the wettest month is July with 113 mm average rainfall. The hottest month is June in which the maximum temperature reaches up to 38 °C while the coldest month of the year is January with a minimum temperature of -3 °C and a maximum temperature of 16 °C. The slope in the area varies from 0-5 % in the plan areas, to moderate slopes from 6-15 %, and steep slope in the uphill. The elevation ranges from 567 up to 3307 meters with numerous trophic characters such as valley, ridge, and hill shade. Frost usually occurs in December and January. Based on climate and elevation the forest types of Dir lower are comprised of subtropical broad-leaved and evergreen forest in the plain areas to subtropical Chir pine and moist temperate forest in the uphills at high altitudes.

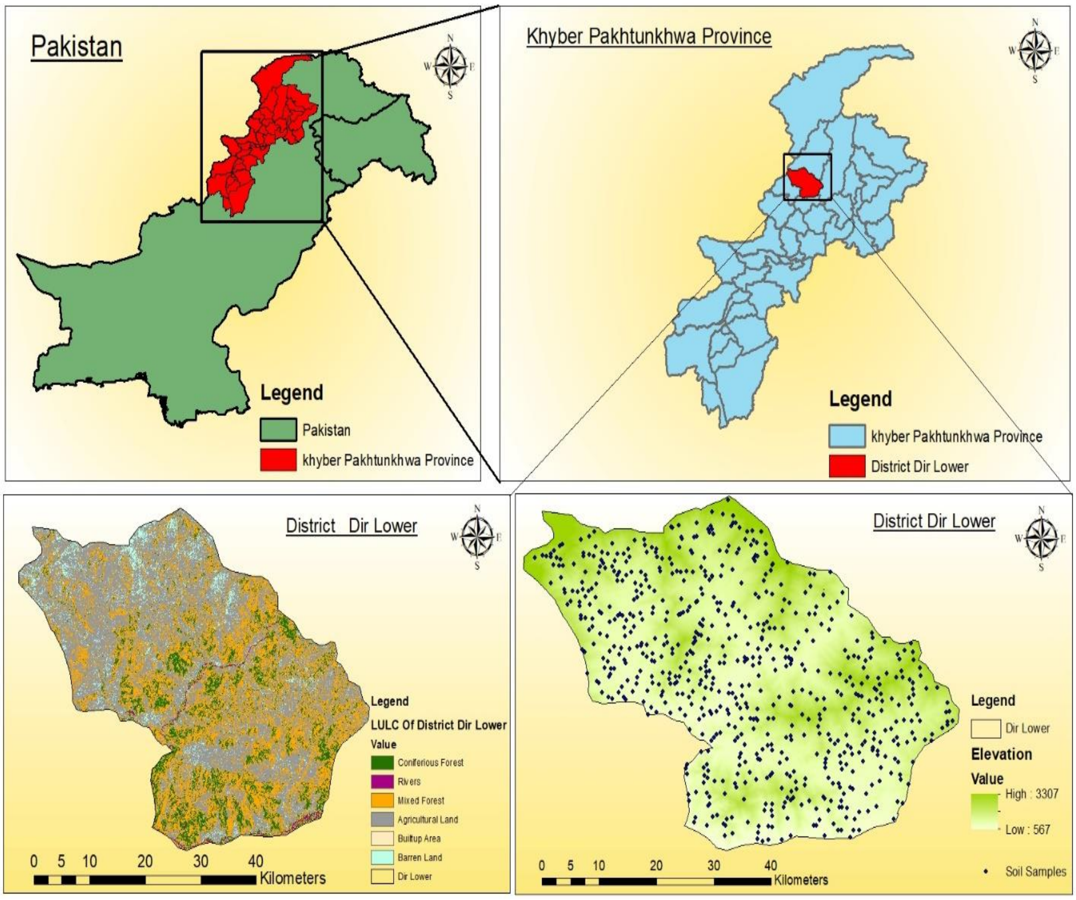

Figure 1. Showing the Location Map along with soil samples.

2.1.2 Land Use Landcover

The LULC of the area is comprised of the forest area (coniferous forest, subtropical broad-leaved forest), Agriculture land (Rainfed and irrigated), River (punjkora, swat), Built-up area, Barren lands.

2.2 Materials

2.2.1 Instruments used/satellite Imagery

To collect the soil samples in the area various instruments were used as shown in table 2.1. satellite imagery of sentinel 2A was used to take random samples in the agricultural land.

2.2.2 Software and Tools

A number of tools and software were used for the processing and analysis of the data acquired from different sources. Those tools and software are given in table 2.2.

2.3 Methodology

2.3.1 Methods

The research was carried out in several steps. The step-by-step process is explained below and the methodology flow chart is shown in (figure 2.2):

Step 1: This step consists of field data collection of soil samples through random Sampling. The soil samples were taken through a soil auger and the location of each soil sample was recorded in a handheld Global positioning system (GPS) and a total of 701 soil profile samples was collected. The soil samples were collected at various depths from 15cm to 100 cm. these soil samples were analyzed in the lab for the various chemical and physical properties i.e. soil PH, $CaCO_3$ %, OC, electrical conductivity, soil texture. While the slope percentage in the area was obtained from the Digital elevation model. The climatic data i.e temperature and rainfall data were retrieved from the Climate change portal of the world bank from the year 1981 to 2020 for Six locations in and around the study area.

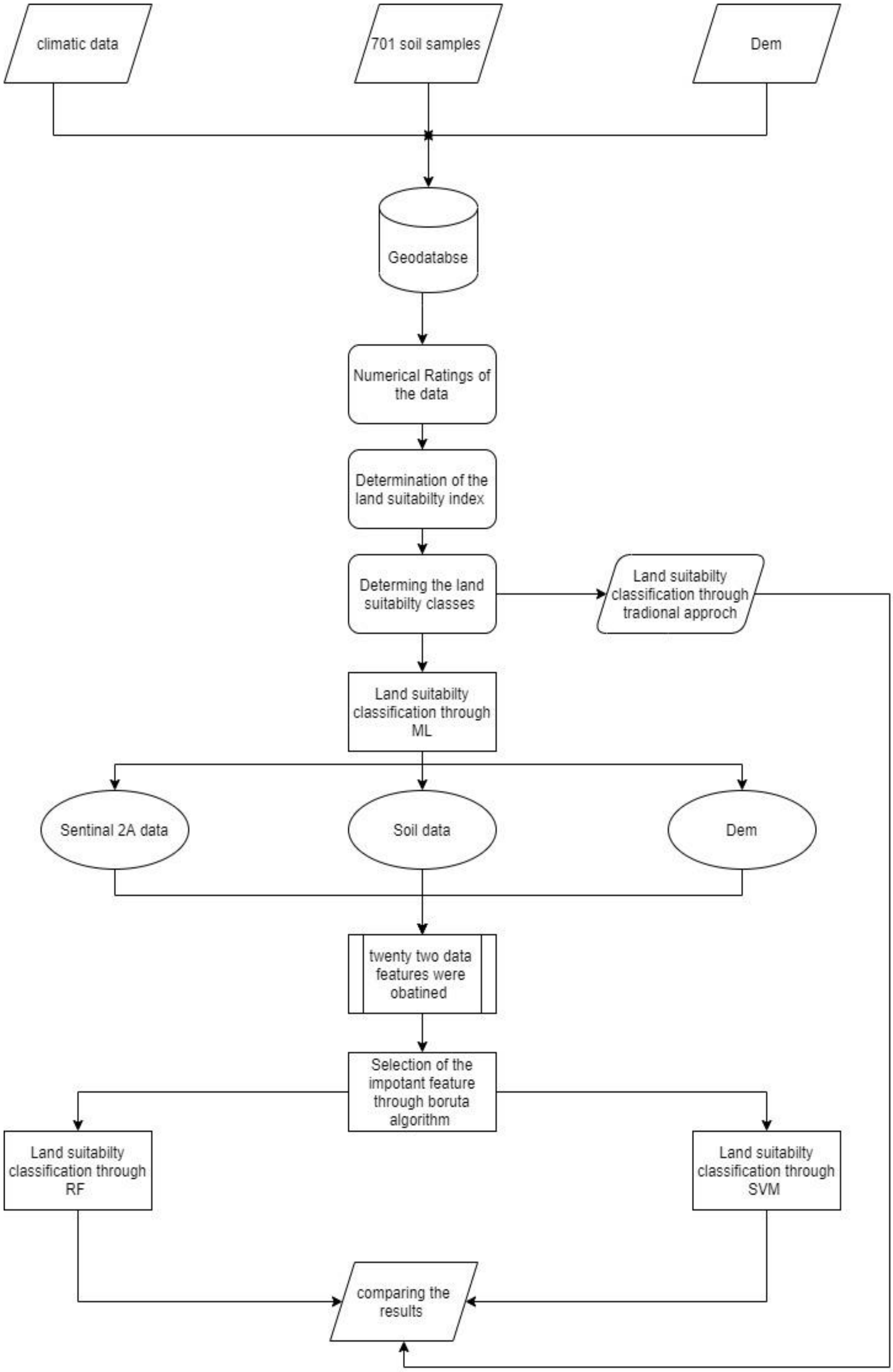

Figure 2.2 Research methodology flow chart.

Step 2: Then in the second step the data were interpolated through the inverse distance weighted technique. After that, the calculation of numerical ratings for soil, terrain, and climatic data was carried out which is used for determining the land suitability index for the agroforestry system of olive and maize crops in the rainfed areas. Then the soil properties along with climatic data and slope were classified based on the parametric equation (C SYS 1993). The land suitability classes are highly suitable, moderately suitable, marginally suitable, temporarily not suitable, and permanently not suitable (S1, S2, S3, N1, N2).

Equation 2.1 Parametric Equation;

$$I_L = \text{Rmi}\sqrt{\frac{A}{100} + \frac{B}{100} + \frac{C}{100}} \ldots \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

Step 3: in this step the index data, were used for the classification of the suitability classes. Which were carried out through the weighted overlay technique (traditional approach) and then by machine learning algorithm (RF, SVM) which is a supervised classification technique.

Step 4: In this step, we check out the performance of each algorithm based on their overall accuracy and kappa index. And the comparison of the traditional method ML-based classification

2.3.2 Familiarization with Equipment

It is done before the field activity in the study area. It is very important to know about the proper usage of the equipment and remove all the instrumental errors before data collection if found any.

2.3.3 Sampling Design

Random sampling was carried out in the study area for the collection of the soil samples at various depths with the help of soil Auger. The random sample gives an equal chance for the soil profile to be selected throughout the study area and gives a more realistic picture of the soil profile.

Table 2.1 list of the equipment and their uses

Equipment	Uses
Soil Auger	Soil samples extraction
Gamin GPS	Navigation
pH electrode	Soil pH
EC meter	Electrical conductivity
Hydrometer	Soil texture

Table 2.2 list of software/tools and their uses

Software/ Tools	Uses
ArcMap	For random sampling, LULC, slope
SAGA GIS	For the creation of various topographic features from the Dem
R studio	For Boruta algorithm
Microsoft excel	Data compilation and statistical analysis
ArcGIS pro	For classification of the image based on support vector machine and random forest algorithms.
Microsoft Excel	For the identification of soil texture class

2.4 Field Data Collection

For this study, Random sampling was carried out and a total of 701 soil samples were collected at various depths all over the study area. The location of each soil sample was recorded in the Garmin GPS. Each of the soil samples was packed in a plastic bag, each weighing about 500 mg.

2.5 Soil Sampling

The soil samples were collected from the study area by using Arc GIS sampling tools on the map and then by using GPS those samples were collected from the exact points. and send to the soil science laboratory in the agriculture department of Tarnab farm Khyber Pakhtunkhwa for identification of chemical and physical properties of the soil. then the IDW interpolation technique was utilized and final maps of each soil property were obtained.

2.5.1 Use of ArcGIS for soil Sampling

Soil samples must be gathered in the district Dir lower area; thus, we'll need a shapefile of the region. DIVA-GIS provided this information. Random sampling is used in the ArcGIS software to generate samples throughout the study area. These points were navigated by GPS in the field and thus soil samples were collected

2.5.2 Lab Analysis

- **Wet combustion method**

The wet combustion method is consisting of Walkley-Black, Mebius, and Colorimetric methods but we use the Walkley-Black method for the determination of the Organic carbon percentage in our soil samples. In this process, 1 gram of air-dried and sieved soil is added to a 500 ml conical flask. After that 5 ml, $K_2Cr_2O_7$ was added to a conical flask and stir it well then add 10 ml of H_2SO_4 into the flask and left for 30 minutes undisturbed. Add 100 ml of distilled water, 10 ml of 85% concentrated H_3PO_4, add 2-3 drops of 0.5% di-phenyl amine indicator into the flask. Titration is carried out with 0.5 N ferrous ammonium sulfate, note down the initial burette reading. The color changes from violet-blue to dark green then stop titration also note down the final burette reading. At the end perform the blank test and the ferrous sulphate values were found by subtracting samples from blank.

Equation 2.2 estimation of carbon contents through wet combustion;

$$\text{Carbon Content} = \frac{(B-S)\ \text{N of Ferrous ammonium sulphate} \times \text{meq. Wt. of C}}{\text{Weight of soil (1g)}} \times 100$$

Where:

B = ml of (Fe $(NH_4)_2(SO_4)$) Solution used to blank titrate

S = ml of (Fe $(NH_4)_2(SO_4)$) solution used to sample titrate

Convert total organic matter into carbon content using the conversion factor 1.724 (Walkley, 1947)

- **Determination of Soil pH**

The pH of the soil sample is measured by taking 25 gm of crushed and sieved soil, putting them in a beaker, and adding distilled water to prepare a saturated soil water slurry, stirring it well. Then dip the glass electrode of the pH meter into the beaker containing the soil water slurry and the results of ph will appear on the digital screen of the pH meter

- **Determination of soil texture**

The soil texture is identified with the help of the hydrometer method. In this method, the oven-dried at 105 °C for six hours, crushed and sieved through < 2 mm mesh, soil sample of about 50 gm were put into 200 ml gauge bottle/ container and then add 100 mL of hexametaphosphate (HMP) solution, and then place under a shaker for about 16 hrs. after that transfer the suspension to sedimentation cylinder and add deionized water to make a 1-liter final volume then rest the suspension to get equilibrium at room temperature for 2 hours. Dislodge sediment from cylinder bottom by inserting plunger and carefully mixing materials Add two or three smooth stokes at the end to complete the stirring. As an alternative, you can stop the cylinder and shake it from end to end for 1 minute instead. Add 2 mL of amyl alcohol to a suspension that has foamed up on the surface. Assemble a blank solution and measure the hydrometer reading and to nearest ± 0.5 g L^{-1}. After 30 seconds, gently lower the hydrometer into the suspension, take a measurement after 40 seconds, and note "R sand" to the closest 0.5 g L-1. Gently clean the hydrometer, wash it, and dry it. After 6 hours, take the temperature of the suspension and round it up to the nearest 1°C. Determine the settling time for the 2.0 µm size fraction using the temperature correction values in Table 2.4 Reinsert the hydrometer gently and obtain a reading, recording it as "R clay" to the closest 0.5 g L^{-1} based on the time since the start of the settlement. Rehash the operation with a blank solution, finding the hydrometer measurement and recording it as "RC2" to the closest 0.5 g L^{-1} (Gavlak et al. 2005). the taken by each soil texture at a given temperature of the solution is shown in table 2.3.

Calculations;

1. Sand % = ((oven dry soil mass) – (Rsand – RC1))/(oven dry soil mass) × 100
2. Clay % = ((Rclay-RC2)/ (oven dry soil mass) × 100
3. Silt % = 100 – (sand%+clay%)

- **Determination of CaCo3 %**

As shown in Table 2.4 in this test, the soil is dried at room temperature for about a week. Add 5 gm of soil in Petry dash and add 10 drops of distilled water to wet the soil. Then by using Eyedropper add white vinegar to the soil at an increment of 10 drops at a time and stir it properly also note down the number of drops added.

Table 2.3. Temperature °C settling time for clay (hr/min).

Temperature (°C)	**Time (min)**
18	8:09
19	7:57
20	7:45
21	7:35
22	7:24
23	7:13
24	7:03
25	6:53
26	6:44
27	6:35
28	6:27

Table 2.4. Estimating soil $CaCO_3$ %) with vinegar test.

Total Drops for one cap of soil (1 cap= 5 gm)	**$CaCO_3$ (%)**
<10	<2
40-70	5
100-150	10
200-230	20
410-650	40

The addition of the vinegar is stopped when the strong bubbles became weak after stirring. Let the mixture rest for five minutes before continuing. Add ten more drops and mix it well and again give rest for one minute. If a few bubbles are released, stop adding the vinegar and sum the total drops used (Zhu et al. 2020).

♦ **Determination of soil Electrical Conductivity**

An EC meter is made up of two components: a measuring cup and the meter itself. The steps for doing an EC measurement are as follows

(i) The cup must be clean properly to avoid any errors and get accurate results.
(ii) Fill the measuring cup halfway with the soil water slurry.
(iii) Switch on the electrical conductivity meter.
(iv) Allow the EC meter electrodes to rest in the measuring jug for a few minutes.
(v) Record the values.
(vi) Switch off the EC meter and wash the measuring jug with distilled water.

2.6 Satellite Data

For the preparation of the auxiliary data which was incorporated with the soil, climatic data we use satellite imagery of sentinel-2A of the year September 2020 because of free from cloud cover and maize crop were also at its peak growth stage and Dem data of 12 m spatial resolution. The satellite imagery of sentinel 2A was downloaded from the United States Geological Survey Earth Explorer website (Earthexplorer.usgs.gov) having 10 m spatial resolution. While the Dem was downloaded from the Alaska Satellite Facility (asf.alaska.edu)

- **Sentinel-2A**

The Sentinel 2A has a total number of 13 spectral bands as shown in table.2.

2.7 Sentinel-2A Preprocessing/ Radiometric Correction

The preprocessing of the sentinel-2A imagery includes the extracting of the study area from the image tile which is about 100×100 km^2. In our study, four tiles intersect each other in our study area. so, at first, we mosaic the images and then extract the area that lies in between our boundary shapefile. After that radiometric correction of the sentinel-2A optical image was carried out to enhance its quality by using arc map 10.8. the reason for doing this was to reduce the atmospheric and sun angle effects (Baillarin et al. 2012).

2.8 Preparation of Indices from Sentinel-2A Optical Imagery

The indices were generated from the sentinel-2A spectral bands by Arc GIS Pro using the indices tools and raster calculator. Following are Indices Which Were derived from the sentinel-2A imagery.

i.Normalized Difference Vegetative Index (NDVI)

NDVI is a widely used vegetative index for the prediction of crop growth, its health, and land suitability evaluation (Purnamasari et al. 2019). The past studies indicate a prominent correlation of the NDVI with land suitability prediction.

Equation 2.3 Formula of NDVI:

$$\text{NDVI} = \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}} \quad \textbf{2.3}$$

ii. Soil adjusted vegetative index (SAVI)

The Soil-Adjusted Vegetation Index (SAVI) technique is a vegetation index that uses a soil-brightness adjustment factor to try to reduce soil brightness effects. This is commonly employed in dry locations with minimal vegetative cover, and it produces values ranging from -1.0 to 1.0.it is used along with NDVI for suitability analysis of land for various crops in the previous studies (Habibie et al. 2021)

Equation 2.4 Formula of SAVI

$$\text{SAVI}= \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}+\text{L}} \times (1+L) \quad \textbf{2.4}$$

Where L = amount of green vegetation cover

Table 2.5 lists sentinel-2A bands and their properties.

Sentinel-2A bands	Central Wavelength (µm)	Spatial Resolution (m)
Band 1- Coastal aerosol	0.443	60
Band 2- Blue	0.490	10
Band 3- Green	0.560	10
Band 4- Red	0.665	10
Band 5- Vegetation Red	0.705	20
Edge		
Band 6- Vegetation Red	0.740	20
Edge		
Band 7- Vegetation Red	0.783	10
Edge		
Band 8-NIR	0.842	20
Band 8A–vegetation Red	0.865	
Edge		
Band 9- Water vapour	0.945	60
Band 10- SWIR– Cirrus	1.375	60
Band 11- SWIR	1.610	20
Band 12- SWIR	2.190	20

Source: (hatarilabs 2017)

iii. Enhanced vegetation index (EVI)

The Enhanced Vegetation Index (EVI) is a vegetation index that takes into consideration atmospheric effects as well as vegetation background signals. It is almost the same as NDVI but less susceptible to the noise, and also doesn't get saturated as when observing a location with thick vegetative cover as NDVI does due to which it is also known as an improved version of NDVI (Jiang et al. 2008).

Equation 2.5 Formula for EVI

$$\text{EVI} = 2.5 \times \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + 6 \times \text{Red} - 7.5 \times \text{Blue} + 1)} \quad \text{……………….....}\mathbf{2.5}$$

iv. Brightness index (BI)

The indicators of soil brightness index are based on the brightness of the soil, soil humidity and salt content have a direct correlation to soil brightness. In previous research, it is also used for the detection of soil moisture, salts, and organic matter contents which are present on the surface of the soil (Marques et al. 2020).

Equation 2.6 Formula for BI;

$$\text{BI} = \frac{\sqrt{R^2 + G^2}}{2} \text{…..........……….}\mathbf{2.6}$$

2.9 Auxiliary data prepared from the Digital Elevation Model

The topographic data which is retrieved from the Dem was also used as an auxiliary for the prediction of the land suitability classification. These topographic features were generated in SAGA GIS software by using DEM of spatial resolution of 12 meters which was then registered with satellite indices and soil properties map of 10 ×10-meter spatial resolution. That topographic feature includes slope, Valley Depth (VD), Cross-sectional curvature (CSC), Elevation (Elev), Flow Accumulation (Flow. AC), Plane curvature (plan_C), Multiresolution valley bottom flatness (MRVBF), multiresolution ridge top Flatness (MRTF), Longitudinal Curvature (long_C), and Aspect.

Chapter 3

RESULTS AND DISCUSSIONS

3.1 Summary Statistics

Table 3.1 depicts the descriptive statistics of the soil characteristics in the research area. The average electrical conductivity (EC) was 0.22 dSm^{-1}, with a range of 0.03 to 0.68 dSm^{-1}, and a standard deviation of ± 0.14, indicating that the electrical conductivity is low. The average pH is 7.83, which ranged between 6.40 to 8.70, and the standard deviation± 0.47, indicating that the soil in the studied region is calcareous. The variation of organic carbon is 0.32 percent to 0.59 percent, with an average of 0.45 percent, and a standard deviation of ± 0.06, indicating that soil is very poor in organic carbon content. With depth, the SOC showed a declining tendency. The calcium carbonate values varied from 0.03 percent to 0.68 percent over the research region, with an average of 0.22 percent. The major soil texture classes in the study area include loamy, silty loam, and sandy loam. The coefficients of variation EC, $CaCO_3$, clay, and sand were high based on a general assessment of the coefficient of variation or CV value, indicating a significant variation across the research area (Wilding 1985). The significant variance in EC and CaCO3 clay and sand was primarily attributable to topographic and parent material heterogeneity. Some soil characteristics like Silt have a moderate coefficient of variation and the ph and organic carbon of the soil has a low coefficient of variation. So, the soil characteristics in the examined soil have a wide range of values.

Table 3.2 illustrates the correlation coefficient for various soil physicochemical properties. A negative significant ($p \leq 0.01$) correlation coefficient ($r = 0.31$) found between the pH and EC. The correlation between the CaCO3 and OC was positively significant ($p \leq 0.01$) correlation ($r = 0.26$). The correlation between CaC03 and the pH is negativity significant ($p \leq 0.01$) correlation ($r = 0.19$). Correlation coefficient

Table 3.1 shows the descriptive statistics of soil properties.

Soil properties	Minimum	Maximum	Mean	C.V	S. D
pH	6.40	8.70	7.83	6.02	0.47
EC dsm^{-1}	0.03	0.68	0.22	64.21	0.14
$CaCO_3$ %	0.03	0.68	0.22	64.22	0.14
OC %	0.32	0.59	0.45	12.61	0.06
Clay %	2.00	42.00	18.48	41.87	7.74
Silt %	2.00	64.00	41.89	23.36	9.79
Sand %	6.00	84.00	39.63	38.70	15.34

The coefficient of variation (C.V) is a statistical index of the spread of the data points around the mean. The standard deviation (S.D) must always be the deviation from the mean

Table 3.2 shows the correlation coefficient matrix of soil properties n= 701

	Clay	Silt	Sand	pH	EC	$CaCO_3$	OC
Clay	1.00						
Silt	0.53**	1.00					
Sand	-0.84	-0.90	1.00				
pH	-0.42	-0.30	0.41*	1.00			
EC	0.40*	0.25*	-0.36	-0.31	1.00		
$CaCO_3$	0.01	0.02	-0.02	-0.19	0.27*	1.00	
OC	-0.39	-0.24	0.35*	0.18*	-0.02	0.26*	1.00

** significance at 1% probability
*Significance at 0.5% probability

between pH and OC is positively significant ($p \leq 0.01$) correlation ($r= 0.17$). the correlation between clay and silt is positively significant ($p \leq 0.01$) correlation ($r = 0.53$) while the rest is negatively correlated. The correlation between EC, clay and silt were statically significant ($p \leq 0.05$) correlation ($r=0.40$) and ($r=0.25$) respectively. While with the sand it is negatively correlated.

3.2 Selection of the important features

The relative importance of the auxiliary data along with the soil properties and climatic features for the prediction of the land suitability classes. For this purpose, the important feature selection algorithm also known as the Boruta algorithm was implemented in the R statistical package. The name of the Boruta was derived from a demon in Slavic mythology who dwelled in Pine Forests.

The Boruta algorithm is a wrapper algorithm around the Random Forest algorithm (RF) (Kursa and Rudnicki 2010). The algorithm performs several iterations and shuffling of the original data to pick up all the important features which are present in our data. The results from our data confirm the importance of twenty and twenty-one features out of twenty-two (slope, VD, CSC, Elev, Flow. AC, Plan_C, BI, SAVI, NDVI, EVI, MRVBF, LS_factor, MRTF, long_C, Aspect, RFGC, pH, EC, $CaCO_3$, ATGC, OC) for the land suitability classification of olive and maize respectively as shown in Fig 3.1 and 3.2. the relative importance is based on the Z score ($Z \geq 1$) of each variable which is present on the y-axis and the Variable is plotted on the X-axis. The blue box represents the shadow variables. In RF, the data is allocated randomization, and shuffling copies of all attributes are produced as shadow features. It was assessed if a genuine soil parameter had a sufficiently high score than its shadow feature at each iteration.

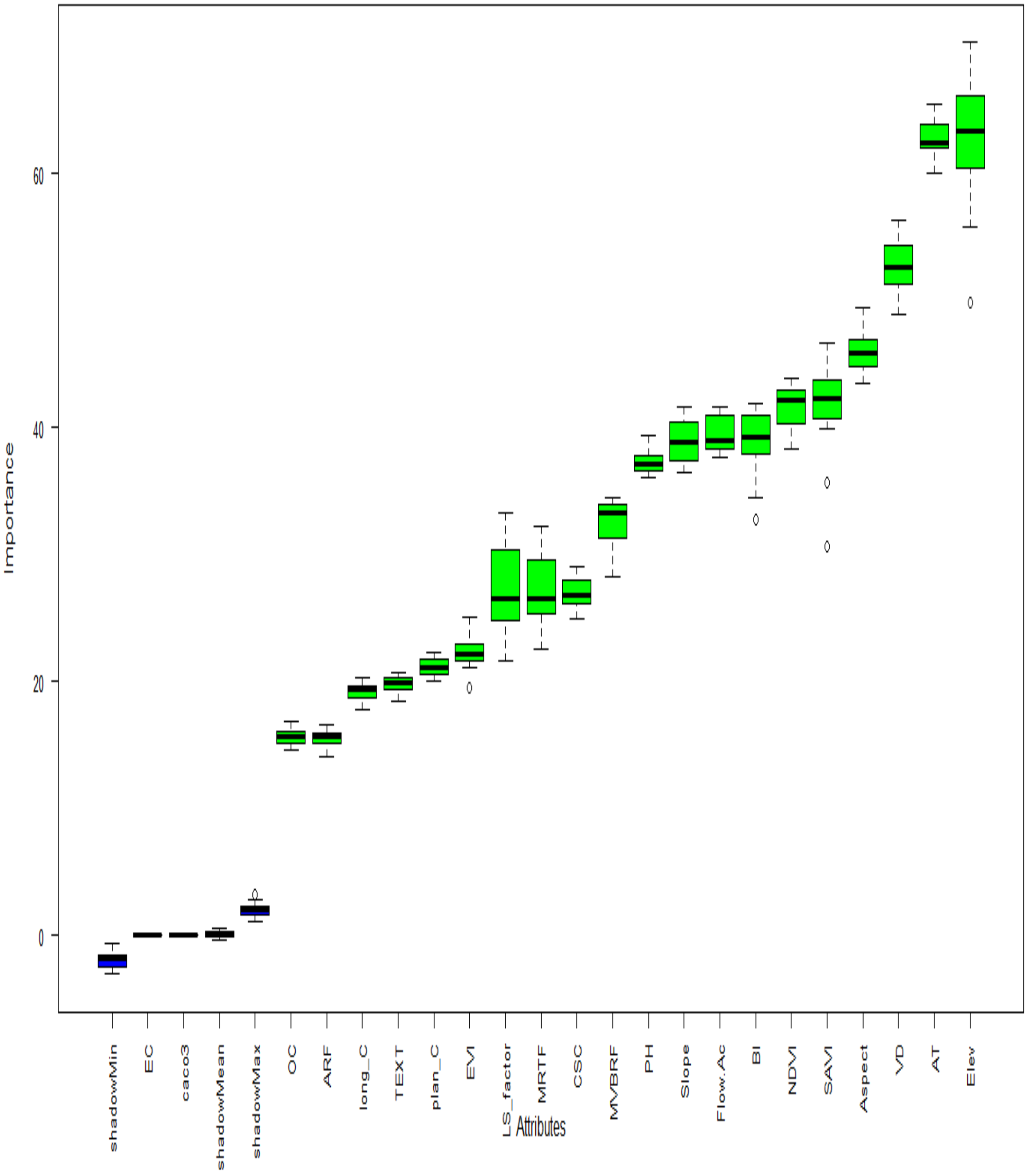

Figure 3. 1. shows the selection of important features through the Boruta Algorithm for olive, based on the physicochemical properties of the soil, climatic and topographic features. (Green boxes represent the important feature for the land suitability classification, blue represents the shuffle attributes while the red boxes represent the rejected ones.); (x-axis soil, climatic and topographic features; y-axis = importance of parameter in Z-score).

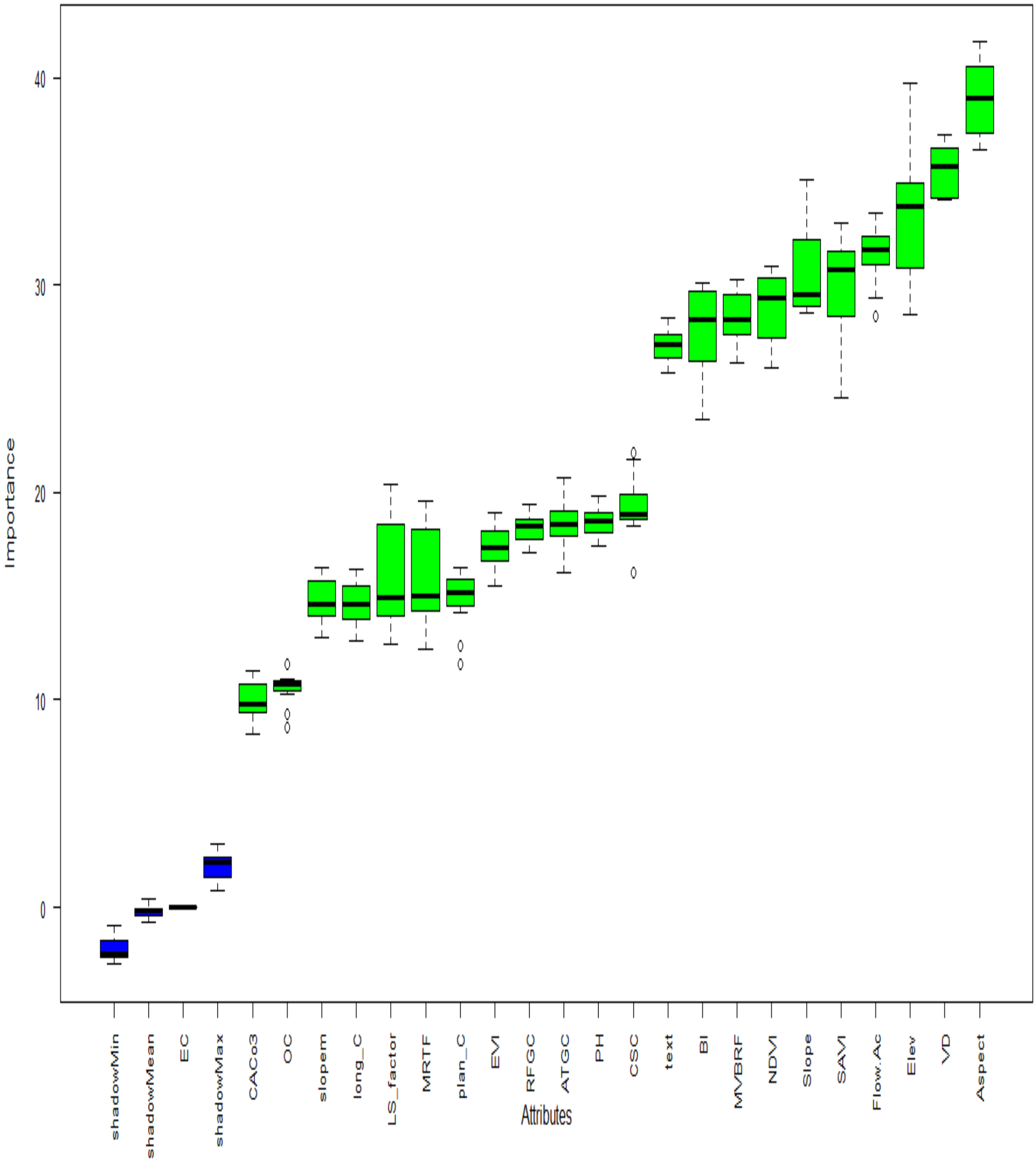

Figure 3. 2. shows the selection of important features through the Boruta Algorithm for Maize. based on the physicochemical properties of the soil, climatic and topographic features. (Green boxes represent the important feature for the land suitability classification, blue represents the shuffle attributes while the red boxes represent the rejected ones.); (x-axis = soil, climatic and topographic features; y-axis = importance of parameter in Z-score).

The higher Z-score of a feature represents the significant ($p \le 0.05$) importance. In perspective of determining land suitability classes for Rainfed olive by employing Boruta Algorithm, The Elevation (70%), AT (65%), Valley depth (56 %), Aspect (49 %), SAVI (47%), NDVI (44 %), BI (42 %), Flow_Ac (41%), Slope (42 %), pH (39 %), MrVBF (34 %), CSC (29%), EC and $CaCO_3$ has Z score of (0%) and hence get rejected. The important feature for the land suitability classification of maize crop were Aspect (42 %), VD (37 %), Elevation (39 %), Flow_Ac (33 %), SAVI (33 %), Slope (35 %), NDVI (31 %), MrVBF (30 %), BI (30 %), Soil texture (28 %), CSC (22 %), pH (20 %), ATGC (21 %), RFGC (19 %), EVI (19 %), plan_C (16 %) MrRTF (20 %), LS_factor (20 %), long_C (16 %), OC (12 %), $CaCO_3$ (11 %), and the relative importance of EC (0 %) and get rejected. The greater relative importance of auxiliary data retrieved from the digital elevation model (DEM) for the prediction of land suitability classes indicates the influence of topography. Most of those mechanisms involved in soil development are influenced by topography.

Many of the previous researches have indicated that topography has a significant influence on soil characteristics. (Nabiollahi et al. 2018) found that the average soil loss rates for the slope class >10% were substantially different and greater than other slope classes. In contrast, they discovered that the average soil quality in the >10% slope class was the lowest when related to other slope classes.

Other scientific investigations of the soil have demonstrated similar findings. (Nabiollahi et al. 2019) utilize a digital soil mapping method to analyze the spatial variability of soil organic carbon under land-use change scenarios in western Iran, and found that the most important auxiliary variables were TWI, MrRTF, MrVBF, NDVI index, Band 3 and Band 4 of Landsat 8 ETM.(Dang et al. 2019) Also Within Sapa county of northern Vietnam, used a hybrid neural-fuzzy framework to map suitable areas and discovered that the most significant environmental parameters were slope, elevation, length of flow, the ratio of evapotranspiration to precipitation, soil erosion, sediment retention, and water yield. (Moore et al. 2013) in his study identifies the effects of topographic features like slope, Elevation, aspect on the distribution and growth of the autumn olive in a managed forest landscape. Similarly (Miao et al. 2006) in their research work shows the importance of various topographic features and soil physiochemical properties which influence the maize crop yield and quality.

3.3 Land suitability classification through ML

Several machine learning algorithms were developed for the supervised classification of digital imagery. But we implemented two machine learning algorithms, Random Forest and Support vector machine based on their robustness and classification accuracy. The results of both the algorithms were based on the kappa index and overall accuracy for both the models summarized in table 3.3. The overall accuracy and kappa index of RF for predicting the land suitability classes For Maize and olive are (0.94, 0.91) and (0.94, 0.90) respectively, was higher than the overall Accuracy and kappa index of SVM for predicting the land suitability classes for the maize and olive are (0.93, 0.90) and (0.92, 0.88). As defined by (Sasikala et al. 2017, Chang et al. 2019) the values of the kappa index and overall accuracy of the RF and SVM ML algorithms for evaluating land suitability classes of rain-fed olive and maize crop show a strong and moderate capability to assess land suitability classes. In the perspective of prediction capability, the RF model scored well statistically. Its features include the capability to identify nonlinear relations with both categorical and continuous predictor variables (Liaw and Wiener 2002) with less bias and variance (Prasad et al. 2006). The RF model is regarded as a powerful modeling method for estimating land suitability classes because it is very resilient to predictor's noise, (ii) it exhibits no overfitting, (iii) it generates assumptions with low bias and variance, (iv) it

3.4 Land suitability classes

The classes which are obtained through this research work for the rainfed Agroforestry system of olive and maize crops are discussed in detail in the following sections.

3.4.1 Highly suitable class (S1)

The land suitability classification for the agroforestry system of olive and maize crops was done with two main techniques i.e., ML-based and with the weighted overlay which is a traditional method. The degree of limitation on the rating scale for the S2 class ranges between

85-100 (C SYS 1993). The area of the S1 class obtained through the ML method of RF, SVM for the olive, ranged between 5% and 9% while thorough the traditional method it is about 2 % of the total study area. The area which is classified under S1 class for the maize crop through ML technique of RF, SVM for maize, ranged between 6% and 7% respectively while through the traditional method the 21% of the total area. The area (ha) of each class is shown in table 3.4 which was classified through ML-based and traditional techniques. These lands have ideal features such as a low slope, with almost no chance of soil erosion, adequate yearly precipitation, and appropriate seasonally and monthly rainfall totals and optimal temperatures were also available in the growth phases of the Agroforestry system of olive and maize crops in the rain-fed area. The soil texture classes (sandy loam, silty loam, clay loam, silty clay loam, loamy sand, and loam) all range in the highly suitable class, the soil Ph values of the area are also in optimal range only the organic carbon is low from its optimal range in the S1 class for the olive plants which can be enhanced by adding farmyard manure and organic manure. The water scarcity in the initial growth stages in June for the maize crops can be overcome by irrigation especially in the flowering stages. (Pilevar et al. 2020) In 5474.27 hectares of saline and calcareous soils in semi-arid regions east of Iran, integrated fuzzy, AHP, and GIS approaches were utilized to estimate land suitability for rain-fed wheat and maize production. Their findings showed that 14.68 percent (803.75 ha), 78.23 percent (4282.53 ha), and 7.08 percent (387.99 ha) of the investigated region were highly (S1), moderately (S2), and marginally (S3) suitable for rain-fed wheat cultivation. Furthermore, 2.75 percent (150.52 ha), 61.51 percent (3366.99 ha), and 35.74 percent (1956.76 ha) of the area, respectively, were very, moderately, and marginally suitable for maize cultivation.

3.4.2 Moderately Suitable Class (S2)

The degree of limitation on the rating scale for the S2 class ranges between 60-85(C SYS 1993). The area of the S2 class classified through the ML approach of RF, SVM, and the traditional approach for the olive is about 21%, 21%, and 57%, similarly, the area which is obtained for the maize crop through RF, SVM, and through the traditional technique of Weighted overlay are 34%, 49%, and 63% respectively. The area has a certain limitation of slope, elevation, organic content in the soil, while the soil texture is good for the olive but has few limitations for the maize crop. The rainfall and temperature have also certain limitations during the phenotypic growth stages in May to June for the maize while the olive require less water so they survived well in such conditions. The water scarcity will be improved by providing irrigation before the monsoon. The pH of the soil has also certain limitations and is therefore classified in the S2 class.

3.4.3 Marginally suitable area (S3)

For the marginally suitable class (S3) the degree of limitation on the rating scale ranges between 40-60 (C SYS 1993). The area classified under the S3 class through the RF, SVM, and through the traditional method of weighted overlay for the olive is about 56%, 51%, and 16% respectively of the total area. Similarly, the area determined for the maize crop through RF, SVM, and weighted overlay technique is about 40%, 27%, and 16%. The degree of limitation of the soil physicochemical properties the topographic feature and the climatic parameters are poorer than that of the S2 class and hence the chances of the survival and the potential production of the agroforestry system of olive and maize crop will be less than S2 class. Some of the soil contents like pH and soil organic carbon content can be improved by organic farmyard manure and by adding lime (McCauley et al. 2009). While fewer rainfall requirements can be improved by the water harvesting technique cause the area of S3 class slopes is steep and the area is mostly present on the high elevation where general irrigation is not possible during the dry season.

3.4.4 permanently non-suitable (N2)

For the permanently non-suitable class N2, the degree of limitation on the rating scale ranges between 0-25 (C SYS 1993). The area classified under the N2 class by ML method of RF, SVM, and through weighted overlay for the olive is 18%, 19%, and 2% respectively. While the area classified through the ML and weighted overly for maize is 20%, 17%, and less than 0% respectively of the total study area. The area has very high steep slopes, a high level of pH, and temperature and rainfall discrepancies. This area also has some mining activities for marbles and crushing plants which deteriorate the soil properties of the area and hence are not suitable for the agroforestry system of olive and maize crops. these areas cannot be improved by Agricultural improvement techniques. The area in ha is shown in table 3.4.

Table 3.3. Error criteria for an estimation of land suitability class (RF: random forest; SVM: support vector machine; WOL: weighted overlay) based on 10-fold cross-validation.

	Kappa Index		Overall Accuracy	
ML and traditional Techniques	**Rainfed olive**	**Rainfed maize**	**Rainfed olive**	**Rainfed maize**
RF	0.90	0.91	0.94	0.94
SVM	0.88	0.90	0.92	0.93
WOL	0.87	0.85	0.91	0.87

Table 3.4. Area in a hectare of the study area for the Land suitability classes of the Agroforestry system of olive and maize crop.

Land suitability class	ML-Based technique				Traditional technique	
	RF olive	**SVM Olive**	**RF Maize**	**SVM Maize**	**WOL olive**	**WOL Maize**
	Area (ha)	**Area (ha)**	**Area (ha)**	**Area (ha)**	**Area (ha)**	**Area (ha)**
Highly suitable (S1)	9567.1	14924.6	10673.9	11543.7	36167.4	43756.2
Moderately suitable (S2)	36171	36131.1	60336.7	85835.7	110835	99480.5
Marginally suitable (S3)	97488.5	90146.1	70366.1	48525.9	28134.8	29171
Permanently non-suitable (N2)	32165.4	34165.4	34006.1	29480.3	302.2	3002.07

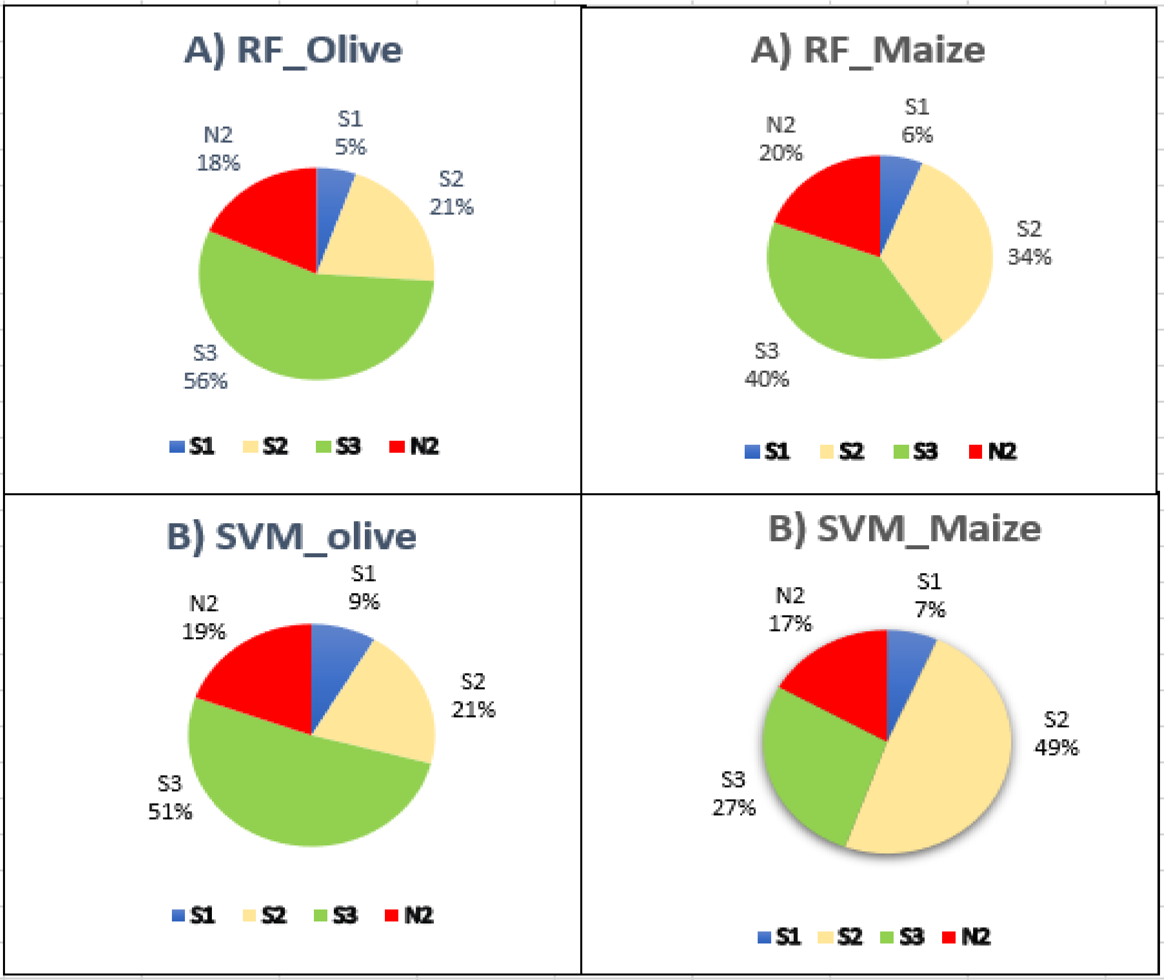

Figure 3. 3 Pie Chart representing the percentages of Area classified through ML Algorithms (A) Random Forest (RF) and (B) Support vector machine (SVM).

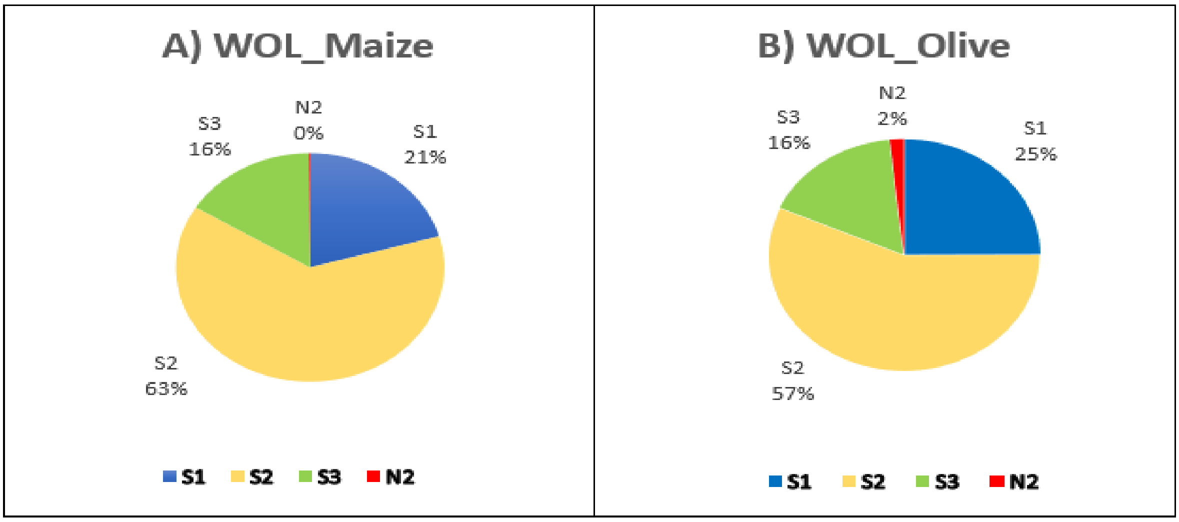

Figure 3. 4 Pie chart representing the percentages of Area classified through Traditional method of weighted overlay (WOL) (A) Maize and (B) Olive.

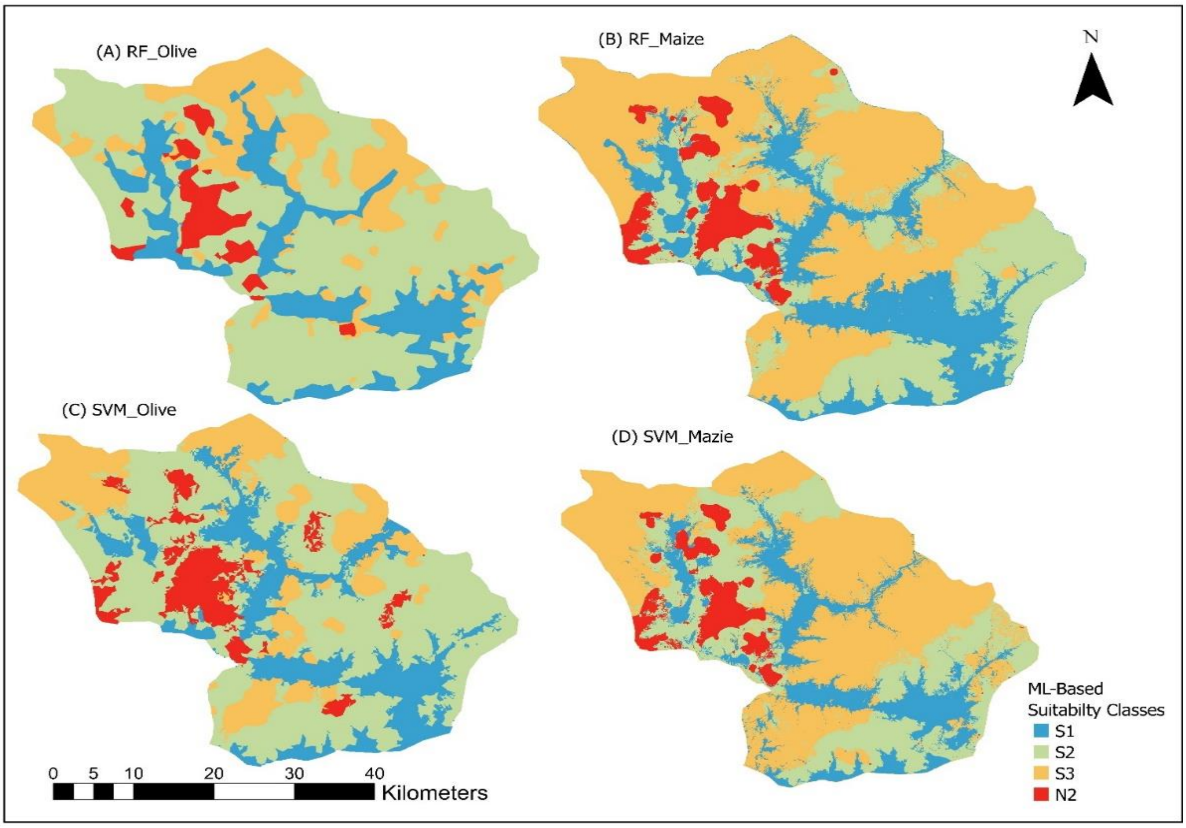

Figure 3. 5 shows the land suitability classes for agroforestry system of Olive and Maize crop through Machine Learning Algorithms (A) Random Forest for Olive (B) Maize (C) Support vector machine for Olive (D) Maize.

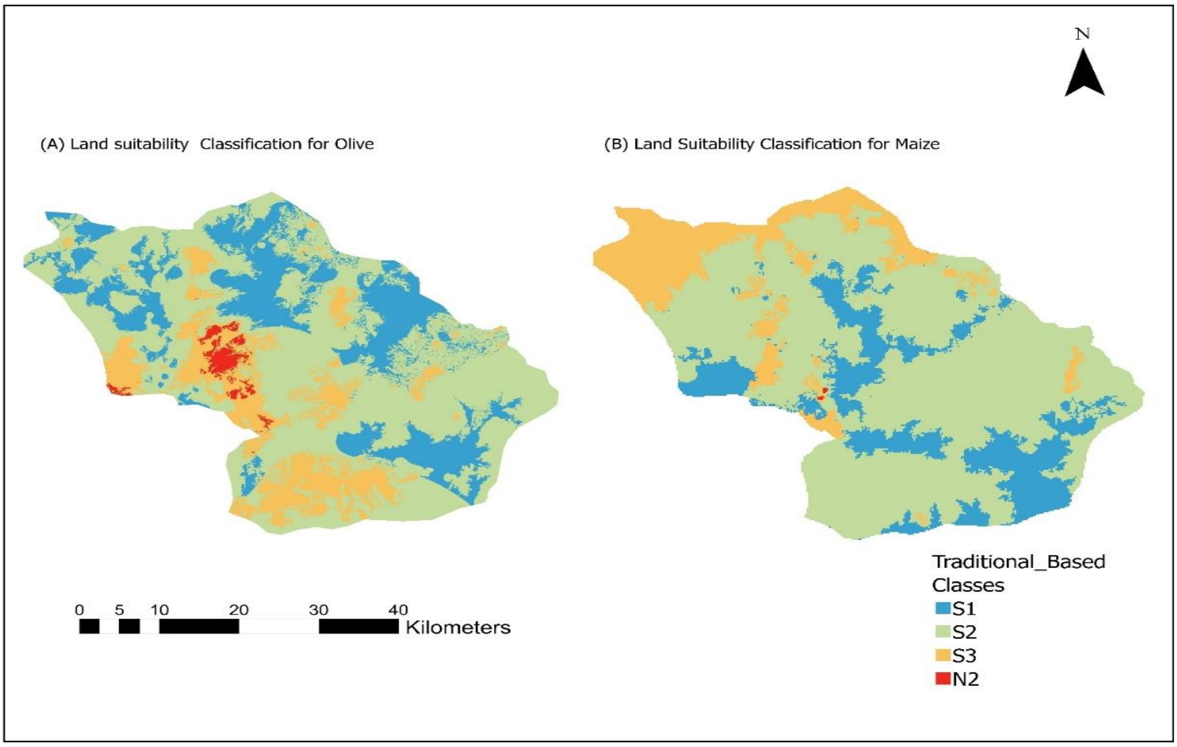

Figure 3. 6 shows the Land suitability classes for the Agroforestry system of olive and maize crops through the traditional weighted overlay technique.

Chapter 4

CONCLUSION AND RECOMMENDATIONS

4.1 Conclusions

The land suitability analysis was carried out in the Rain-fed area of the District Dir Lower, Khyber Pakhtunkhwa province, Pakistan. The land suitability classes were defined on the FAO land suitability Framework, by using the parametric method. Then we use two mapping methods for the classification of the Study Area. One is the Machine learning algorithms of Random Forest and Support vector machine while the second approach is through the Traditional method of the weighted overlay. The Elevation, Valley depth, Aspect, SAVI, NDVI, BI, Flow_Ac, MrVBF, CSC, MrRTF, LS_factor, EVI, Plan_C, and long_C, were the most important factor from the Auxiliary data which were used for the prediction of the Land suitability classes for the Agroforestry system of olive and maize crop in the rain-fed area. Based on the kappa index and the overall Accuracy, RF performs better than the SVM model, and hence it is concluded that RF is the best model for predicting the land suitability classes for the Agroforestry system of olive and maize crops. RF offers numerous benefits over other statistical modeling techniques and is regarded as an effective modeling tool for determining land suitability classes. RF offers numerous benefits over other statistical modeling techniques and is regarded as an effective modeling tool for classifying land suitability. When conventional and ML-based techniques were compared, the ML-based technique detected more areas of the N2 and S3 classes and fewer areas of the S1 and S2 classes than the traditional method. The traditional method is time-consuming and expensive while the ML-based method of mapping, on the other hand, is less affected by these restrictions and is preferable for dealing with the typical land suitability evaluation study. This is especially true in a data-poor country like Pakistan, where soil data is limited.

As a result, machine learning and ancillary data may be an appealing technique for extensive land suitability analysis. In general, the research areas demonstrated that it was highly favorable for the agroforestry system of olive and maize owing to fewer rainfall restrictions during the blooming stage of maize in the early developmental stage of maize, fewer slopes in the plan, with favorable pH, and soil texture class. while the organic matter is lower in the area. As a result, land improvement activities like farmyard manure should be applied to enhance the growth of the vegetation, supplementary irrigation, and gravel gathering are required to improve the suitability of the study area for maize crops and boost its yield. This research provides valuable knowledge that may be used to measure the impact of management strategies in Khyber Pakhtunkhwa and other similar areas.

4.2 Recommendations for further research

As soil data is scarce in our country on such a large scale. But to improve the classification results more data about the flooding drainage, coarse fragments (%), soil depth, Gypsum (%), apparent cation exchange capacity, and base saturation (%) of the soil were also be determined. Which is an expansive and time-consuming activity and requires sufficient funds.

While on the other hand, the satellite imagery of sentinel 2 is of moderate resolution, in which some bands are of 10 m spatial resolution and some are of 20 m spatial resolution. When they get resampled and bring down all the bands to the 10 m spatial resolution, they lose their accuracy, and hence the indices get affected, which are generated from it. Therefore, high spatial resolution imagery is recommended for further studies.

In Pakistan, the land units are small in size and the farmer wants to get more benefits out of it with less investment so this study can help for the selection of specific crops and multipurpose trees for a specific site. In the future, the same study can be applied to a different area with a different Agroforestry system having different compositions of tree species and crops.

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APPENDICES

Appendix-1. Results of the soil samples, clay, silt, sand, soil texture, pH, Electrical conductivity (EC), $CaCO_3$, Organic Carbon (OC).

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
1	28	46	26	clay loam	7.40	0.31	7.50	0.49
2	30	40	30	clay loam	7.40	0.21	8.75	0.53
3	28	48	24	clay loam	7.80	0.47	8.75	0.49
4	30	46	24	clay loam	7.60	0.46	8.75	0.53
5	32	48	20	clay loam	7.80	0.46	7.75	0.51
6	28	40	32	clay loam	7.70	0.44	9.25	0.49
7	30	48	22	clay loam	7.50	0.52	8.25	0.45
8	28	48	24	clay loam	7.20	0.41	7.75	0.45
9	32	46	22	clay loam	7.00	0.58	7.50	0.45
10	34	46	20	clay loam	7.50	0.35	5.75	0.44
11	32	38	30	clay loam	7.70	0.41	9.00	0.45
12	36	30	34	clay loam	7.60	0.41	8.75	0.45
13	34	38	28	clay loam	7.70	0.32	8.25	0.45
14	30	48	22	clay loam	7.70	0.32	8.50	0.45
15	28	48	24	clay loam	7.70	0.10	8.25	0.45
16	32	42	26	clay loam	7.50	0.31	7.75	0.45
17	34	32	34	clay loam	7.70	0.32	7.25	0.45
18	28	42	30	clay loam	7.60	0.34	9.00	0.43
19	30	36	34	clay loam	7.60	0.46	10.00	0.45
20	32	44	24	clay loam	7.70	0.52	8.25	0.45
21	34	38	28	clay loam	7.70	0.40	7.50	0.45
22	28	50	22	clay loam	7.60	0.37	8.75	0.43
23	30	50	20	clay loam	7.70	0.33	7.25	0.43
24	28	50	22	clay loam	7.70	0.35	8.75	0.43
25	28	46	26	clay loam	7.60	0.37	8.75	0.43
26	28	46	26	clay loam	7.10	0.25	8.50	0.43
27	28	48	24	clay loam	7.50	0.38	8.50	0.43
28	28	44	28	clay loam	7.50	0.38	7.50	0.43
29	30	46	24	clay loam	7.60	0.44	9.00	0.43
30	34	38	28	clay loam	7.50	0.31	7.00	0.43
31	28	50	22	clay loam	7.60	0.30	8.25	0.43
32	34	46	20	clay loam	7.40	0.36	7.75	0.43
33	28	46	26	clay loam	5.60	0.13	7.00	0.40
34	28	44	28	clay loam	4.80	0.13	7.00	0.40
35	30	48	22	clay loam	5.00	0.13	7.00	0.43
36	28	48	24	clay loam	7.90	0.10	6.25	0.43
37	32	42	26	clay loam	8.20	0.20	6.25	0.40
38	30	44	26	clay loam	8.20	0.22	6.75	0.40
39	28	48	24	clay loam	8.10	0.20	7.50	0.37
40	28	42	30	clay loam	8.00	0.11	8.25	0.37
41	28	46	26	clay loam	7.50	0.04	8.50	0.40
42	28	44	28	clay loam	8.30	0.14	7.50	0.37

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
43	30	48	22	clay loam	7.60	0.10	8.00	0.36
44	28	48	24	clay loam	7.30	0.17	6.25	0.41
45	28	44	28	clay loam	8.40	0.22	6.25	0.37
46	28	44	28	clay loam	8.40	0.18	6.75	0.37
47	30	44	26	clay loam	8.00	0.12	6.25	0.37
48	28	50	22	clay loam	8.00	0.18	7.50	0.37
49	28	46	26	clay loam	8.00	0.12	7.50	0.39
50	28	46	26	clay loam	5.60	0.13	7.00	0.40
51	28	44	28	clay loam	6.80	0.13	7.00	0.36
52	30	48	22	clay loam	6.50	0.13	7.00	0.32
53	12	46	42	Loam	8.40	0.09	6.25	0.53
54	8	42	50	Loam	8.20	0.08	5.50	0.45
55	10	42	48	Loam	8.30	0.06	8.75	0.53
56	8	46	46	Loam	8.00	0.10	8.75	0.53
57	12	46	42	Loam	8.20	0.10	8.75	0.53
58	16	42	42	Loam	8.20	0.10	8.75	0.45
59	14	38	48	Loam	8.20	0.12	8.75	0.53
60	11	44	45	Loam	8.00	0.22	9.00	0.53
61	12	44	44	Loam	8.40	0.18	8.70	0.45
62	14	46	40	Loam	8.10	0.10	7.50	0.53
63	12	46	42	Loam	8.50	0.12	5.50	0.53
64	8	42	50	Loam	8.00	0.12	8.50	0.53
65	6	48	46	Loam	8.50	0.09	6.25	0.53
66	14	44	42	Loam	7.90	0.07	8.50	0.53
67	12	48	40	Loam	8.00	0.11	10.00	0.45
68	8	42	50	Loam	8.50	0.10	9.00	0.45
69	12	46	42	Loam	7.90	0.09	6.25	0.45
70	8	48	44	Loam	8.10	0.10	8.75	0.43
71	14	44	42	Loam	8.80	0.04	6.25	0.53
72	14	40	46	Loam	8.80	0.44	7.50	0.49
73	16	32	52	Loam	8.30	0.12	8.75	0.49
74	12	46	42	Loam	8.70	0.16	8.50	0.53
75	16	40	44	Loam	8.60	0.15	6.25	0.53
76	8	40	52	Loam	6.90	0.08	8.25	0.53
77	18	48	34	Loam	8.20	0.54	8.75	0.53
78	14	46	40	Loam	8.30	0.16	8.25	0.53
79	16	34	50	Loam	8.50	0.49	6.25	0.53
80	12	40	48	Loam	8.10	0.14	8.50	0.49
81	18	42	40	Loam	8.40	0.12	7.50	0.53
82	10	40	50	Loam	8.20	0.13	6.25	0.53
83	14	42	44	Loam	8.20	0.22	7.50	0.53
84	8	40	52	Loam	8.30	0.29	7.00	0.53
85	14	46	40	Loam	8.40	0.28	8.50	0.59

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
86	16	46	38	Loam	7.90	0.12	6.25	0.53
87	16	46	38	Loam	8.00	0.18	7.50	0.49
88	8	46	46	Loam	8.50	0.11	6.25	0.49
89	16	42	42	Loam	8.00	0.13	6.00	0.59
90	8	44	48	Loam	8.10	0.10	8.50	0.53
91	10	38	52	Loam	8.10	0.08	8.75	0.59
92	14	48	38	Loam	8.60	0.10	6.25	0.36
93	16	42	42	Loam	7.30	0.03	6.25	0.49
94	12	42	46	Loam	7.00	0.09	7.50	0.59
95	12	46	42	Loam	7.90	0.05	6.25	0.49
96	12	44	44	Loam	8.10	0.07	8.75	0.49
97	14	46	40	Loam	8.30	0.10	6.25	0.49
98	10	42	48	Loam	8.20	0.08	5.75	0.49
99	10	44	46	Loam	8.30	0.07	8.50	0.49
100	16	48	36	Loam	8.00	0.10	6.25	0.49
101	20	48	32	Loam	8.20	0.06	5.50	0.49
102	14	44	42	Loam	8.40	0.05	8.50	0.49
103	10	40	50	Loam	8.10	0.03	7.50	0.49
104	18	30	52	Loam	8.20	0.06	8.25	0.49
105	16	46	38	Loam	8.20	0.27	8.25	0.49
106	14	34	52	Loam	8.20	0.33	8.75	0.53
107	8	42	50	Loam	8.10	0.28	8.25	0.49
108	18	40	42	Loam	8.00	0.40	5.75	0.47
109	18	30	52	Loam	8.00	0.22	8.50	0.49
110	16	40	44	Loam	8.10	0.09	8.75	0.49
111	16	44	40	Loam	8.10	0.14	5.75	0.49
112	10	48	42	Loam	8.00	0.18	6.50	0.49
113	18	42	40	Loam	7.30	0.11	8.25	0.49
114	8	42	50	Loam	8.20	0.15	8.75	0.49
115	18	42	40	Loam	8.30	0.11	7.50	0.49
116	8	46	46	Loam	8.20	0.09	5.75	0.49
117	16	46	38	Loam	8.30	0.09	8.50	0.49
118	14	44	42	Loam	8.40	0.12	8.75	0.47
119	10	48	42	Loam	8.10	0.09	6.00	0.49
120	14	38	48	Loam	7.10	0.04	6.25	0.49
121	8	40	52	Loam	8.40	0.11	8.75	0.49
122	12	44	44	Loam	8.30	0.09	8.50	0.49
123	14	48	38	Loam	8.50	0.10	5.75	0.45
124	12	42	46	Loam	8.10	0.14	5.75	0.49
125	14	44	42	Loam	8.40	0.10	8.75	0.36
126	12	48	40	Loam	8.20	0.09	7.50	0.53
127	16	38	46	Loam	7.60	0.10	5.75	0.37
128	16	48	36	Loam	8.50	0.13	6.00	0.49

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
129	20	46	34	Loam	7.40	0.34	6.75	0.51
130	18	44	38	Loam	7.50	0.36	7.75	0.47
131	14	44	42	Loam	7.50	0.39	9.00	0.45
132	16	40	44	Loam	7.00	0.41	7.50	0.47
133	20	48	32	Loam	7.60	0.31	7.75	0.51
134	22	48	30	Loam	7.60	0.39	6.75	0.49
135	20	46	34	Loam	7.50	0.32	8.75	0.47
136	18	44	38	Loam	7.40	0.22	8.25	0.45
137	22	42	36	Loam	7.70	0.45	7.50	0.49
138	16	42	42	Loam	7.40	0.45	8.50	0.49
139	22	38	40	Loam	7.80	0.46	7.75	0.49
140	24	42	34	Loam	7.60	0.45	7.50	0.49
141	16	46	38	Loam	7.40	0.44	7.75	0.53
142	22	48	30	Loam	7.60	0.46	8.50	0.49
143	24	48	28	Loam	6.90	0.14	8.75	0.48
144	22	40	38	Loam	7.30	0.17	9.00	0.47
145	40	48	12	Loam	6.90	0.14	6.75	0.51
146	26	42	32	Loam	7.30	0.47	8.25	0.47
147	22	44	34	Loam	7.80	0.50	9.25	0.47
148	26	36	38	Loam	7.60	0.46	8.25	0.49
149	24	46	30	Loam	7.10	0.49	9.00	0.45
150	18	44	38	Loam	8.10	0.47	8.00	0.45
151	20	46	34	Loam	7.70	0.45	9.25	0.49
152	16	40	44	Loam	7.30	0.44	7.50	0.45
153	18	40	42	Loam	7.70	0.48	7.00	0.47
154	18	44	38	Loam	7.30	0.44	8.75	0.45
155	20	48	32	Loam	7.60	0.47	7.25	0.45
156	22	36	42	Loam	7.70	0.39	7.75	0.45
157	20	44	36	Loam	7.80	0.35	7.50	0.45
158	18	42	40	Loam	7.80	0.45	7.25	0.49
159	20	42	38	Loam	7.80	0.40	7.75	0.45
160	24	42	34	Loam	7.90	0.38	8.75	0.47
161	28	36	36	Loam	7.80	0.35	9.00	0.45
162	26	46	28	Loam	7.70	0.34	8.75	0.45
163	20	42	38	Loam	7.00	0.40	8.75	0.45
164	16	40	44	Loam	6.90	0.45	8.50	0.45
165	24	46	30	Loam	7.10	0.43	8.25	0.45
166	22	48	30	Loam	7.40	0.40	7.50	0.44
167	18	48	34	Loam	7.20	0.43	8.50	0.47
168	20	42	38	Loam	7.20	0.45	8.75	0.44
169	16	40	44	Loam	7.20	0.38	8.50	0.45
170	26	38	36	Loam	7.60	0.48	8.75	0.40
171	24	32	44	Loam	7.70	0.38	7.50	0.49

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
172	22	40	38	Loam	7.70	0.44	8.75	0.45
173	24	40	36	Loam	7.60	0.33	8.50	0.43
174	20	42	38	Loam	7.50	0.32	8.25	0.43
175	26	48	26	Loam	7.70	0.31	7.75	0.43
176	20	46	34	Loam	7.80	0.34	7.25	0.43
177	22	46	32	Loam	7.70	0.36	7.50	0.43
178	24	48	28	Loam	7.80	0.37	8.50	0.45
179	22	48	30	Loam	7.80	0.51	7.25	0.43
180	17	47	36	Loam	8.00	0.52	7.50	0.43
181	18	46	36	Loam	7.80	0.11	8.50	0.43
182	16	44	40	Loam	7.70	0.54	8.75	0.43
183	20	42	38	Loam	7.40	0.33	8.50	0.43
184	24	48	28	Loam	7.10	0.24	9.25	0.43
185	22	42	36	Loam	7.30	0.25	9.50	0.43
186	20	36	44	Loam	7.50	0.25	9.50	0.43
187	26	40	34	Loam	7.50	0.25	7.50	0.43
188	16	48	36	Loam	7.50	0.31	9.50	0.43
189	20	42	38	Loam	7.50	0.22	8.75	0.43
190	18	40	42	Loam	7.30	0.25	9.25	0.43
191	22	44	34	Loam	7.40	0.24	9.00	0.43
192	24	48	28	Loam	7.30	0.26	8.75	0.43
193	16	40	44	Loam	7.60	0.37	8.25	0.43
194	18	34	48	Loam	7.70	0.45	8.75	0.43
195	18	40	42	Loam	7.60	0.37	7.50	0.43
196	22	46	32	Loam	7.40	0.22	7.75	0.43
197	18	46	36	Loam	7.50	0.31	8.75	0.43
198	26	48	26	Loam	8.10	0.49	7.00	0.43
199	20	42	38	Loam	7.60	0.40	8.25	0.43
200	20	48	32	Loam	7.10	0.10	9.00	0.43
201	18	42	40	Loam	6.80	0.11	8.50	0.43
202	20	36	44	Loam	7.50	0.27	9.25	0.43
203	18	36	46	Loam	7.80	0.30	9.25	0.43
204	24	42	34	Loam	7.10	1.32	5.75	0.43
205	22	48	30	Loam	7.50	0.33	6.25	0.43
206	20	44	36	Loam	6.70	0.31	8.50	0.43
207	20	40	40	Loam	7.30	0.23	7.50	0.41
208	24	46	30	Loam	7.60	0.36	7.75	0.43
209	18	40	42	Loam	7.60	0.30	8.50	0.43
210	16	40	44	Loam	7.70	0.27	8.25	0.43
211	20	44	36	Loam	7.60	0.29	5.75	0.43
212	22	48	30	Loam	7.60	0.27	7.25	0.43
213	18	40	42	Loam	7.60	0.28	8.50	0.41
214	24	44	32	Loam	7.70	0.26	8.75	0.41

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
215	14	46	40	Loam	7.70	1.76	7.50	0.41
216	16	36	48	Loam	7.60	50.00	5.75	0.41
217	20	42	38	Loam	7.60	0.41	8.50	0.43
218	22	44	34	Loam	7.70	0.37	7.75	0.41
219	14	40	46	Loam	8.00	0.32	8.25	0.41
220	18	42	40	Loam	7.50	0.44	9.25	0.41
221	16	42	42	Loam	7.70	0.36	8.50	0.41
222	16	40	44	Loam	7.70	0.33	6.75	0.41
223	20	44	36	Loam	7.60	0.82	7.75	0.41
224	18	42	40	Loam	7.40	0.36	8.75	0.41
225	16	38	46	Loam	7.70	1.88	7.25	0.41
226	14	38	48	Loam	7.40	0.33	8.50	0.40
227	16	40	44	Loam	7.30	0.56	10.00	0.40
228	18	46	36	Loam	7.70	0.35	9.25	0.40
229	26	48	26	Loam	8.00	0.14	6.00	0.43
230	22	44	34	Loam	8.00	0.11	7.00	0.40
231	26	44	30	Loam	6.60	0.16	6.00	0.40
232	18	42	40	Loam	6.50	0.17	6.75	0.40
233	20	44	36	Loam	6.50	0.15	6.00	0.40
234	22	48	30	Loam	6.50	0.15	6.50	0.40
235	26	42	32	Loam	6.50	0.13	7.50	0.40
236	22	38	40	Loam	6.20	0.13	6.00	0.40
237	18	40	42	Loam	5.90	0.18	6.50	0.43
238	16	40	44	Loam	6.80	0.15	7.00	0.41
239	20	46	34	Loam	6.30	0.11	6.75	0.40
240	24	44	32	Loam	6.30	0.10	6.00	0.43
241	20	42	38	Loam	6.50	0.12	6.25	0.43
242	18	42	40	Loam	8.40	0.17	5.75	0.43
243	22	44	34	Loam	7.80	0.11	6.25	0.40
244	24	46	30	Loam	8.10	0.12	7.50	0.40
245	26	48	26	Loam	8.20	0.14	6.00	0.40
246	22	46	32	Loam	8.00	0.14	5.75	0.40
247	24	50	26	Loam	8.10	0.16	5.25	0.43
248	20	48	32	Loam	8.20	0.13	6.75	0.40
249	20	48	32	Loam	8.20	0.18	5.75	0.40
250	18	46	36	Loam	8.10	0.14	7.50	0.43
251	16	42	42	Loam	8.10	0.17	6.25	0.43
252	20	46	34	Loam	7.80	0.11	6.50	0.41
253	22	40	38	Loam	8.10	0.12	6.50	0.37
254	18	36	46	Loam	7.60	0.10	7.50	0.37
255	20	46	34	Loam	7.90	0.14	6.25	0.40
256	16	46	38	Loam	7.80	0.12	5.50	0.43
257	22	38	40	Loam	8.00	0.17	6.00	0.40

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
258	26	38	36	Loam	8.20	0.13	6.25	0.43
259	20	40	40	Loam	7.80	0.10	6.75	0.37
260	16	38	46	Loam	8.10	0.12	6.25	0.37
261	18	40	42	Loam	8.00	0.14	7.50	0.43
262	20	36	44	Loam	8.40	0.17	6.00	0.40
263	24	36	40	Loam	8.20	0.12	6.00	0.37
264	22	46	32	Loam	7.90	0.10	6.25	0.40
265	26	44	30	Loam	8.00	0.13	5.50	0.43
266	24	44	32	Loam	8.10	0.18	6.00	0.37
267	22	38	40	Loam	8.20	0.15	7.50	0.41
268	18	40	42	Loam	8.00	0.12	6.75	0.40
269	20	46	34	Loam	8.40	0.18	6.25	0.37
270	24	46	30	Loam	8.20	0.16	6.75	0.40
271	22	46	32	Loam	8.20	0.17	7.50	0.40
272	20	44	36	Loam	8.00	0.12	6.00	0.43
273	24	42	34	Loam	8.30	0.16	6.75	0.40
274	20	42	38	Loam	8.50	0.20	6.50	0.40
275	22	48	30	Loam	8.20	0.22	6.25	0.41
276	18	42	40	Loam	8.10	0.19	6.25	0.43
277	20	38	42	Loam	8.20	0.16	6.50	0.40
278	14	42	44	Loam	7.20	0.13	7.50	0.43
279	18	44	38	Loam	7.60	0.16	7.25	0.37
280	16	42	42	Loam	7.20	0.17	6.00	0.43
281	18	46	36	Loam	9.10	0.18	8.50	0.40
282	12	42	46	Loam	7.80	0.17	9.00	0.37
283	16	46	38	Loam	7.10	0.55	8.75	0.40
284	22	42	36	Loam	6.90	0.14	8.25	0.40
285	12	44	44	Loam	7.80	0.18	8.00	0.37
286	10	45	45	Loam	7.10	0.12	7.75	0.40
287	18	46	36	Loam	8.10	0.42	8.75	0.37
288	16	42	42	Loam	7.50	0.38	7.50	0.40
289	12	42	46	Loam	7.60	0.38	5.75	0.37
290	18	46	36	Loam	7.70	0.48	7.00	0.37
291	19	42	39	Loam	7.70	0.45	8.70	0.37
292	18	44	38	Loam	6.80	0.47	9.00	0.40
293	13	46	41	Loam	7.70	0.42	8.50	0.37
294	18	40	42	Loam	7.90	0.10	8.75	0.40
295	20	40	40	Loam	7.00	0.08	9.00	0.37
296	24	44	32	Loam	6.90	0.03	9.25	0.37
297	26	36	38	Loam	6.30	0.07	8.50	0.42
298	26	40	34	Loam	8.10	0.10	7.25	0.37
299	16	38	46	Loam	7.40	0.04	8.50	0.37
300	16	40	44	Loam	7.00	0.16	7.75	0.37

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
301	22	46	32	Loam	6.90	0.09	7.25	0.37
302	19	45	36	Loam	7.10	0.10	8.50	0.36
303	20	44	36	Loam	7.30	0.06	9.00	0.40
304	22	48	30	Loam	6.00	0.08	8.75	0.36
305	20	38	42	Loam	7.80	0.09	9.00	0.37
306	24	42	34	Loam	8.00	0.10	8.25	0.40
307	16	38	46	Loam	7.50	0.06	8.50	0.37
308	22	40	38	Loam	8.40	0.14	6.25	0.36
309	24	48	28	Loam	7.60	0.30	6.50	0.37
310	20	44	36	Loam	7.70	0.27	7.00	0.40
311	22	48	30	Loam	7.60	0.23	6.00	0.41
312	18	42	40	Loam	8.00	0.20	5.75	0.36
313	16	40	44	Loam	7.90	0.28	6.75	0.40
314	14	44	42	Loam	8.00	0.19	7.00	0.41
315	20	42	38	Loam	7.70	0.28	7.50	0.40
316	12	42	46	Loam	8.10	0.27	6.75	0.40
317	18	40	42	Loam	8.40	0.22	6.25	0.40
318	38	42	20	Loam	8.30	0.17	6.50	0.40
319	20	36	44	Loam	8.50	0.20	6.75	0.37
320	24	40	36	Loam	8.00	0.12	6.50	0.40
321	26	40	34	Loam	7.80	0.10	6.50	0.41
322	24	46	30	Loam	7.60	0.15	6.25	0.40
323	22	42	36	Loam	8.20	0.22	7.00	0.37
324	18	38	44	Loam	8.30	0.20	7.50	0.40
325	16	44	40	Loam	8.00	0.14	7.75	0.40
326	14	40	46	Loam	8.10	0.10	6.25	0.41
327	20	38	42	Loam	8.20	0.16	6.00	0.37
328	12	38	50	Loam	8.00	0.18	6.25	0.40
329	20	42	38	Loam	8.20	0.13	7.00	0.36
330	26	48	26	Loam	7.80	0.22	6.50	0.37
331	20	34	46	Loam	8.00	0.11	6.75	0.43
332	18	40	42	Loam	7.80	0.10	7.50	0.41
333	20	44	36	Loam	7.70	0.13	7.00	0.40
334	18	38	44	Loam	8.00	0.13	7.50	0.37
335	22	48	30	Loam	7.80	0.11	7.75	0.36
336	24	42	34	Loam	8.00	0.20	6.50	0.40
337	18	44	38	Loam	7.80	0.22	6.00	0.40
338	16	42	42	Loam	8.00	0.23	6.50	0.40
339	18	46	36	Loam	7.80	0.22	7.00	0.40
340	12	42	46	Loam	8.00	0.11	6.50	0.36
341	16	46	38	Loam	7.70	0.19	6.75	0.36
342	20	46	34	Loam	8.10	0.18	6.75	0.40
343	24	44	32	Loam	7.80	0.30	6.50	0.36

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
344	18	40	42	Loam	7.90	0.22	7.00	0.37
345	22	44	34	Loam	7.80	0.11	6.25	0.37
346	24	48	28	Loam	7.60	0.10	6.00	0.40
347	16	40	44	Loam	8.00	0.15	7.00	0.40
348	18	34	48	Loam	8.20	0.12	7.50	0.40
349	18	40	42	Loam	8.00	0.14	7.00	0.36
350	22	46	32	Loam	8.40	0.18	6.25	0.40
351	18	46	36	Loam	8.30	0.16	6.75	0.37
352	26	48	26	Loam	8.10	0.11	6.00	0.41
353	20	42	38	Loam	8.00	0.10	6.50	0.40
354	22	46	32	Loam	8.30	0.16	6.50	0.41
355	24	42	34	Loam	8.00	0.12	6.75	0.37
356	16	42	42	Loam	8.20	0.15	7.00	0.40
357	20	44	36	Loam	7.90	0.14	7.50	0.37
358	18	38	44	Loam	8.10	0.12	6.25	0.41
359	20	40	40	Loam	8.30	0.20	6.75	0.40
360	14	38	48	Loam	8.40	0.18	6.50	0.37
361	22	42	36	Loam	8.50	0.16	6.50	0.37
362	24	38	38	Loam	8.20	0.14	7.00	0.37
363	22	42	36	Loam	8.20	0.22	7.50	0.40
364	20	48	32	Loam	8.00	0.10	7.75	0.41
365	26	46	28	Loam	7.60	0.12	7.00	0.37
366	14	44	42	Loam	8.00	0.14	6.25	0.41
367	16	40	44	Loam	8.30	0.16	6.50	0.40
368	18	42	40	Loam	8.50	0.18	6.25	0.37
369	26	38	36	Loam	8.20	0.12	6.50	0.37
370	16	36	48	Loam	8.00	0.14	7.00	0.37
371	16	40	44	Loam	8.20	0.16	5.75	0.40
372	18	34	48	Loam	8.00	0.13	7.00	0.37
373	24	48	28	Loam	7.80	0.12	6.50	0.41
374	26	48	26	Loam	7.70	0.10	6.25	0.40
375	14	48	38	Loam	8.00	0.13	6.00	0.36
376	18	40	42	Loam	7.80	0.10	6.50	0.36
377	20	44	36	Loam	7.80	0.11	6.75	0.36
378	22	38	40	Loam	7.70	0.10	6.50	0.40
379	24	42	34	Loam	8.10	0.17	6.25	0.41
380	26	46	28	Loam	8.20	0.13	6.50	0.40
381	18	36	46	Loam	8.00	0.20	6.75	0.36
382	20	38	42	Loam	8.20	0.40	7.00	0.36
383	22	42	36	Loam	8.30	0.30	6.50	0.37
384	20	40	40	Loam	8.10	0.27	7.00	0.40
385	18	38	44	Loam	8.40	0.24	6.25	0.37
386	16	36	48	Loam	8.50	0.22	6.75	0.41
387	22	42	36	Loam	8.20	0.19	6.50	0.40

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
388	26	46	28	Loam	8.70	0.24	6.00	0.41
389	18	46	36	Loam	8.20	0.23	6.25	0.32
390	16	42	42	Loam	8.40	0.33	7.50	0.40
391	14	38	48	Loam	8.80	0.22	6.00	0.37
392	18	38	44	Loam	8.10	0.19	6.25	0.40
393	20	40	40	Loam	8.40	0.44	6.75	0.40
394	24	42	34	Loam	8.10	0.28	6.50	0.37
395	22	40	38	Loam	8.50	0.23	6.50	0.41
396	20	48	32	Loam	8.40	0.15	7.75	0.37
397	26	46	28	Loam	8.10	0.18	6.75	0.40
398	16	48	36	Loam	7.70	0.10	6.00	0.37
399	20	42	38	Loam	7.80	0.16	6.25	0.40
400	26	48	26	Loam	8.00	0.14	6.00	0.40
401	22	44	34	Loam	8.00	0.11	7.00	0.40
402	26	44	30	Loam	6.60	0.16	6.00	0.37
403	18	42	40	Loam	6.50	0.17	6.75	0.36
404	20	44	36	Loam	6.50	0.15	6.00	0.32
405	22	48	30	Loam	6.50	0.15	6.50	0.32
406	26	42	32	Loam	6.00	0.13	7.50	0.37
407	22	38	40	Loam	6.20	0.13	6.00	0.40
408	18	40	42	Loam	6.90	0.18	6.50	0.40
409	19	43	38	Loam	5.80	0.15	7.00	0.39
410	20	46	34	Loam	6.30	0.11	6.75	0.36
411	24	44	32	Loam	5.30	0.10	6.00	0.37
412	20	42	38	Loam	5.50	0.12	6.25	0.36
413	18	42	40	Loam	8.40	0.17	5.75	0.33
414	22	44	34	Loam	7.80	0.11	6.25	0.40
415	24	46	30	Loam	8.10	0.12	7.50	0.36
416	26	48	26	Loam	8.20	0.14	6.00	0.40
417	22	46	32	Loam	8.00	0.14	5.75	0.37
418	24	50	26	Loam	8.10	0.16	5.25	0.37
419	20	48	32	Loam	8.20	0.13	6.75	0.40
420	20	48	32	Loam	8.20	0.18	5.75	0.32
421	18	46	36	Loam	8.10	0.14	7.50	0.40
422	16	42	42	Loam	8.10	0.17	6.25	0.37
423	6	16	78	Loamy sand	8.50	0.22	5.75	0.49
424	4	14	82	Loamy sand	8.30	0.14	7.50	0.55
425	4	20	76	loamy sand	8.40	0.11	8.75	0.49
426	2	24	74	Loamy sand	8.30	0.11	8.75	0.45
427	14	2	84	Loamy sand	7.80	0.37	8.25	0.53
428	4	20	76	Loamy sand	8.30	0.18	8.75	0.53
429	2	22	76	Loamy sand	8.40	0.14	7.50	0.45
430	2	16	82	Loamy sand	8.20	0.11	5.75	0.53

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
431	4	16	80	Loamy sand	8.30	0.11	5.50	0.49
432	4	16	80	Loamy sand	7.80	0.06	8.25	0.53
433	4	16	80	Loamy sand	8.00	0.08	8.75	0.45
434	6	16	78	Loamy sand	8.20	0.29	8.25	0.45
435	4	22	74	Loamy sand	8.40	0.13	5.75	0.49
436	10	22	68	Sandy loam	8.30	0.10	6.25	0.53
437	8	30	62	Sandy loam	8.30	0.12	6.75	0.45
438	8	24	68	Sandy loam	8.50	0.08	8.75	0.53
439	10	18	72	Sandy loam	8.60	0.07	8.50	0.53
440	8	22	70	Sandy loam	8.40	0.09	5.75	0.45
441	8	30	62	Sandy loam	8.50	0.12	8.25	0.49
442	12	18	70	Sandy loam	8.50	0.10	9.25	0.47
443	8	14	78	Sandy loam	8.30	0.09	6.75	0.53
444	8	20	72	Sandy loam	8.20	0.12	6.25	0.53
445	10	32	58	Sandy loam	8.00	0.10	8.75	0.53
446	8	40	52	Sandy loam	8.20	0.08	8.50	0.53
447	8	20	72	Sandy loam	8.10	0.13	5.75	0.53
448	6	28	66	Sandy loam	8.10	0.12	6.25	0.53
449	6	24	70	Sandy loam	8.20	0.14	6.25	0.53
450	8	20	72	Sandy loam	8.20	0.14	7.50	0.45
451	14	24	62	Sandy loam	8.20	0.12	8.50	0.53
452	8	16	76	Sandy loam	8.50	0.17	8.75	0.53
453	4	26	70	Sandy loam	8.20	0.12	7.50	0.53
454	2	28	70	Sandy loam	8.20	0.19	8.50	0.47
455	4	24	72	Sandy loam	8.30	0.15	6.25	0.53
456	10	12	78	Sandy loam	8.20	0.18	8.75	0.45
457	6	18	76	Sandy loam	8.10	0.05	8.50	0.53
458	6	18	76	Sandy loam	8.70	0.08	9.00	0.53
459	8	16	76	Sandy loam	8.30	0.08	8.25	0.53
460	12	22	66	Sandy loam	8.20	0.10	8.50	0.53
461	10	26	64	Sandy loam	8.40	0.08	9.25	0.53
462	10	20	70	Sandy loam	8.30	0.10	8.25	0.53
463	12	28	60	Sandy loam	8.10	0.10	7.50	0.53
464	8	28	64	Sandy loam	8.20	0.05	6.25	0.53
465	6	26	68	Sandy loam	7.60	0.06	10.00	0.49
466	10	32	58	Sandy loam	7.80	0.14	8.25	0.45
467	14	32	54	Sandy loam	8.10	0.06	10.00	0.53
468	6	32	62	Sandy loam	8.40	0.06	8.50	0.53
469	8	38	54	Sandy loam	8.20	0.11	6.25	0.53
470	6	18	76	Sandy loam	8.20	0.16	7.50	0.49
471	8	18	74	Sandy loam	7.60	0.07	6.25	0.45
472	6	34	60	Sandy loam	8.00	0.19	8.50	0.53
473	8	40	52	Sandy loam	8.50	0.08	6.25	0.53

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
474	6	32	62	Sandy loam	8.30	0.07	8.75	0.49
475	4	42	54	Sandy loam	8.10	0.11	8.20	0.53
476	6	26	68	Sandy loam	7.60	0.08	5.70	0.53
477	12	30	58	Sandy loam	7.20	0.13	7.50	0.53
478	16	36	48	Sandy loam	8.00	0.20	8.50	0.49
479	6	44	50	Sandy loam	8.20	0.13	7.50	0.49
480	4	34	62	Sandy loam	7.60	0.10	6.25	0.53
481	8	38	54	Sandy loam	8.50	0.05	5.50	0.53
482	6	18	76	Sandy loam	8.30	0.09	8.70	0.53
483	8	22	70	Sandy loam	8.00	0.06	8.50	0.49
484	6	38	56	Sandy loam	8.10	0.08	8.50	0.53
485	6	34	60	Sandy loam	7.90	0.14	9.00	0.53
486	6	46	48	Sandy loam	8.00	0.09	6.25	0.49
487	8	30	62	Sandy loam	8.20	0.12	8.75	0.53
488	14	32	54	Sandy loam	8.40	0.07	8.50	0.49
489	12	14	74	Sandy loam	7.80	0.14	6.25	0.49
490	6	22	72	Sandy loam	7.70	0.15	6.50	0.51
491	6	36	58	Sandy loam	8.40	0.14	10.00	0.49
492	8	24	68	Sandy loam	7.90	0.14	8.75	0.53
493	10	28	62	Sandy loam	8.20	0.17	8.25	0.49
494	6	22	72	Sandy loam	8.70	0.15	7.50	0.49
495	12	34	54	Sandy loam	8.40	0.06	7.00	0.49
496	12	34	54	Sandy loam	8.20	0.13	6.25	0.43
497	10	28	62	Sandy loam	8.30	0.20	7.50	0.41
498	14	32	54	Sandy loam	8.70	0.12	6.00	0.49
499	12	34	54	Sandy loam	8.10	0.56	6.25	0.53
500	14	26	60	Sandy loam	7.90	0.11	7.50	0.45
501	10	24	66	sandy loam	8.00	0.09	8.75	0.47
502	8	20	72	sandy loam	8.00	0.08	7.50	0.59
503	8	36	56	sandy loam	8.20	0.16	6.25	0.49
504	8	38	54	sandy loam	8.20	0.15	8.75	0.59
505	8	26	66	sandy loam	7.70	0.34	8.75	0.53
506	14	30	56	sandy loam	8.30	0.04	6.25	0.59
507	10	38	52	sandy loam	7.90	0.05	8.50	0.49
508	12	28	60	sandy loam	8.30	0.08	8.75	0.45
509	8	28	64	sandy loam	7.60	0.04	8.50	0.59
510	10	38	52	sandy loam	7.40	0.10	7.50	0.53
511	10	26	64	sandy loam	8.20	0.12	5.75	0.49
512	6	40	54	sandy loam	8.10	0.16	8.75	0.49
513	12	24	64	Sandy loam	8.40	0.12	7.50	0.59
514	10	36	54	Sandy loam	7.30	0.05	6.25	0.49
515	8	22	70	Sandy loam	7.30	0.03	8.25	0.59
516	6	30	64	Sandy loam	7.20	0.07	7.50	0.49

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
517	8	38	54	Sandy loam	8.10	0.04	8.25	0.59
518	8	34	58	Sandy loam	7.90	0.11	8.75	0.53
519	14	16	70	Sandy loam	8.00	0.04	8.75	0.49
520	18	10	72	Sandy loam	8.40	0.10	8.75	0.49
521	12	36	52	Sandy loam	7.80	0.70	6.25	0.49
522	18	20	62	Sandy loam	8.30	0.43	8.75	0.53
523	10	30	60	Sandy loam	8.00	0.15	5.75	0.49
524	12	22	66	Sandy loam	8.20	0.13	5.50	0.53
525	8	24	68	Sandy loam	7.80	0.37	8.75	0.49
526	8	20	72	Sandy loam	8.10	0.26	8.50	0.53
527	18	16	66	Sandy loam	8.20	0.33	6.25	0.49
528	8	26	66	Sandy loam	8.10	0.26	5.75	0.53
529	10	24	66	Sandy loam	8.00	0.23	8.25	0.49
530	18	16	66	Sandy loam	8.20	0.31	5.50	0.49
531	8	30	62	Sandy loam	8.10	0.41	7.75	0.49
532	8	32	60	Sandy loam	8.00	0.23	7.50	0.49
533	12	30	58	Sandy loam	7.90	0.32	8.75	0.49
534	14	20	66	Sandy loam	8.30	0.25	6.25	0.49
535	10	14	76	Sandy loam	8.10	0.10	5.75	0.49
536	4	28	68	Sandy loam	8.00	0.09	8.50	0.49
537	6	38	56	Sandy loam	8.20	0.09	8.50	0.49
538	12	34	54	Sandy loam	8.30	0.14	5.75	0.49
539	10	24	66	Sandy loam	8.40	0.10	8.75	0.49
540	8	34	58	Sandy loam	8.20	0.10	7.50	0.49
541	6	36	58	Sandy loam	8.20	0.08	8.50	0.40
542	10	30	60	Sandy loam	8.30	0.12	8.00	0.49
543	14	30	56	Sandy loam	8.40	0.11	6.25	0.47
544	10	30	60	Sandy loam	8.10	0.09	7.50	0.43
545	8	30	62	Sandy loam	8.20	0.12	8.00	0.49
546	6	22	72	Sandy loam	8.40	0.14	9.25	0.49
547	8	22	70	Sandy loam	8.10	0.16	6.25	0.47
548	12	36	52	sandy loam	7.50	0.60	7.50	0.41
549	14	32	54	sandy loam	7.60	0.37	7.00	0.41
550	12	30	58	sandy loam	7.60	0.48	8.75	0.40
551	14	32	54	sandy loam	7.40	0.13	5.75	0.37
552	12	34	54	sandy loam	7.70	0.09	6.75	0.40
553	14	32	54	sandy loam	7.80	0.12	6.25	0.37
554	28	58	14	silty clay loam	7.60	0.31	7.50	0.49
555	36	54	10	silty clay loam	6.90	0.20	7.50	0.53
556	28	60	12	silty clay loam	6.90	0.18	7.75	0.49
557	40	54	6	silty clay loam	6.40	0.32	8.50	0.51
558	32	48	20	silty clay loam	7.20	0.18	8.75	0.47
559	28	54	18	silty clay loam	7.60	0.10	6.25	0.53

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
560	30	56	14	silty clay loam	7.60	0.20	8.75	0.49
561	30	58	12	silty clay loam	7.80	0.21	8.25	0.47
562	36	54	10	silty clay loam	7.00	0.18	8.50	0.49
563	42	50	8	silty clay loam	7.50	0.10	8.75	0.47
564	28	56	16	silty clay loam	7.60	0.49	8.25	0.45
565	20	58	22	silty clay loam	7.20	0.45	8.50	0.49
566	30	52	18	silty clay loam	7.30	0.39	9.25	0.47
567	28	58	14	silty clay loam	7.00	0.58	8.75	0.51
568	28	54	18	silty clay loam	7.10	0.60	8.75	0.51
569	36	54	10	silty clay loam	7.00	0.57	8.50	0.47
570	38	56	6	silty clay loam	7.60	0.53	8.25	0.47
571	34	54	12	silty clay loam	7.80	0.50	9.25	0.51
572	40	52	8	silty clay loam	7.70	0.47	7.75	0.51
573	30	56	14	silty clay loam	7.50	0.43	7.50	0.47
574	28	52	20	silty clay loam	7.70	0.41	8.75	0.47
575	30	54	16	silty clay loam	7.80	0.42	10.00	0.47
576	34	54	12	silty clay loam	7.80	0.35	9.00	0.45
577	36	50	14	silty clay loam	7.70	0.34	8.50	0.49
578	34	48	18	silty clay loam	6.90	0.51	8.50	0.45
579	30	56	14	silty clay loam	8.00	0.60	8.25	0.45
580	36	54	10	silty clay loam	7.40	0.45	8.75	0.45
581	36	48	16	silty clay loam	7.70	0.32	7.50	0.45
582	34	48	18	silty clay loam	7.70	0.32	8.75	0.45
583	36	46	18	silty clay loam	8.20	0.34	7.75	0.45
584	32	46	22	silty clay loam	7.70	0.46	8.50	0.43
585	32	50	18	silty clay loam	7.60	0.32	5.75	0.43
586	30	52	18	silty clay loam	5.80	0.10	6.00	0.40
587	26	50	24	silty clay loam	6.50	0.11	7.50	0.40
588	30	54	16	silty clay loam	8.10	0.18	6.25	0.37
589	30	50	20	silty clay loam	8.00	0.12	6.50	0.43
590	30	52	18	silty clay loam	5.80	0.10	6.00	0.36
591	26	50	24	silty clay loam	5.90	0.11	7.50	0.32
592	14	50	36	Silty loam	8.20	0.13	5.75	0.47
593	10	58	32	Silty loam	8.10	0.14	8.75	0.49
594	16	58	26	Silty loam	8.50	0.16	5.75	0.53
595	12	58	30	Silty loam	8.30	0.10	8.75	0.49
596	8	40	52	Silty loam	8.40	0.15	7.50	0.53
597	10	48	42	Silty loam	8.20	0.12	7.00	0.49
598	14	40	46	Silty loam	8.40	0.14	8.75	0.45
599	8	26	66	Silty loam	8.20	0.11	8.50	0.47
600	16	22	62	Silty loam	8.30	0.08	5.75	0.53
601	18	32	50	Silty loam	8.20	0.11	5.75	0.49
602	10	36	54	Silty loam	8.30	0.10	6.25	0.45

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
603	8	26	66	Silty loam	8.40	0.09	7.50	0.53
604	6	56	38	Silty loam	8.30	0.09	6.25	0.49
605	4	50	46	Silty loam	8.30	0.09	8.50	0.49
606	4	54	42	Silty loam	8.30	0.12	6.25	0.47
607	18	50	32	Silty loam	7.90	0.10	9.00	0.49
608	8	60	32	Silty loam	8.00	0.07	8.25	0.53
609	16	52	32	Silty loam	8.40	0.09	8.00	0.53
610	8	56	36	Silty loam	7.80	0.18	6.25	0.49
611	10	50	40	Silty loam	8.10	0.13	7.50	0.49
612	16	50	34	Silty loam	8.60	0.11	8.00	0.53
613	18	50	32	Silty Loam	8.70	0.04	7.75	0.53
614	12	54	34	Silty Loam	7.90	0.22	8.75	0.49
615	10	50	40	Silty Loam	7.70	0.14	8.75	0.59
616	16	50	34	Silty loam	8.20	0.03	7.50	0.49
617	16	58	26	Silty loam	8.00	0.08	7.50	0.49
618	18	56	26	Silty loam	8.20	0.05	6.25	0.49
619	12	60	28	Silty loam	7.20	0.15	8.25	0.49
620	14	50	36	Silty loam	8.20	0.16	8.75	0.49
621	14	52	34	Silty loam	8.10	0.21	8.75	0.49
622	10	54	36	Silty loam	8.20	0.12	8.50	0.49
623	12	56	32	Silty loam	8.50	0.15	6.25	0.49
624	14	58	28	Silty loam	8.60	0.21	7.50	0.49
625	4	54	42	Silty loam	8.50	0.11	8.50	0.49
626	6	58	36	Silty loam	8.20	0.11	10.00	0.49
627	10	50	40	Silty loam	8.20	0.12	5.75	0.47
628	18	56	26	Silty loam	8.20	0.14	6.25	0.49
629	12	60	28	Silty loam	8.30	0.09	8.50	0.36
630	24	54	22	Silty loam	7.60	0.28	8.75	0.53
631	18	52	30	Silty loam	6.80	0.25	7.50	0.49
632	22	52	26	Silty loam	6.90	0.29	8.50	0.53
633	20	50	30	Silty loam	7.50	0.35	8.75	0.47
634	24	58	18	Silty loam	7.60	0.35	7.00	0.47
635	24	56	20	Silty loam	7.40	0.32	8.75	0.49
636	22	50	28	Silty loam	7.60	0.32	7.50	0.47
637	26	52	22	Silty loam	7.50	0.30	8.75	0.49
638	16	54	30	Silty loam	7.40	0.30	6.75	0.45
639	22	54	24	Silty loam	7.50	0.31	8.75	0.49
640	26	56	18	Silty loam	7.60	0.31	7.00	0.45
641	24	60	16	Silty loam	7.30	0.31	8.75	0.49
642	26	52	22	silty loam	8.00	0.30	7.75	0.49
643	16	50	34	Silty loam	7.40	0.45	8.75	0.47
644	26	50	24	Silty loam	7.70	0.48	8.50	0.45
645	24	56	20	Silty loam	7.60	0.48	9.00	0.49

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
646	30	56	14	Silty loam	7.70	0.45	7.50	0.47
647	26	58	16	Silty loam	7.60	0.46	7.75	0.45
648	26	52	22	Silty loam	7.50	0.16	10.00	0.45
649	20	52	28	Silty loam	6.70	0.16	8.75	0.45
650	24	54	22	Silty loam	7.30	0.13	7.75	0.47
651	16	50	34	Silty loam	7.80	0.12	7.75	0.47
652	22	60	18	Silty loam	7.50	0.18	6.25	0.49
653	18	58	24	Silty loam	7.60	0.22	6.75	0.49
654	16	64	20	Silty loam	6.70	0.17	8.75	0.53
655	26	54	20	Silty loam	7.80	0.11	7.75	0.45
656	24	52	24	Silty loam	7.40	0.37	7.50	0.47
657	20	50	30	Silty loam	7.40	0.48	6.00	0.49
658	22	50	28	Silty loam	7.50	0.38	5.75	0.47
659	26	54	20	Silty loam	7.20	0.48	8.50	0.47
660	32	50	18	Silty loam	7.80	0.45	8.75	0.47
661	22	50	28	Silty loam	7.30	0.50	8.50	0.47
662	20	58	22	Silty loam	6.80	0.57	9.75	0.47
663	26	54	20	Silty loam	7.60	0.46	7.50	0.47
664	24	54	22	Silty loam	7.80	0.44	7.00	0.45
665	22	54	24	Silty loam	7.80	0.44	7.75	0.49
666	20	52	28	Silty loam	7.70	0.43	8.50	0.45
667	22	52	26	Silty loam	7.50	0.42	8.75	0.45
668	24	52	24	Silty loam	8.20	0.41	8.50	0.45
669	24	50	26	Silty loam	7.20	0.38	9.25	0.49
670	24	58	18	Silty loam	6.70	0.52	8.50	0.45
671	26	50	24	Silty loam	7.20	0.42	8.25	0.45
672	40	52	8	Silty loam	7.20	0.45	8.75	0.45
673	26	60	14	Silty loam	7.50	0.58	8.50	0.45
674	24	58	18	Silty loam	7.80	0.52	7.50	0.45
675	22	62	16	Silty loam	7.20	0.45	8.75	0.45
676	26	50	24	Silty loam	7.20	0.45	9.00	0.44
677	26	50	24	Silty loam	7.80	0.32	7.25	0.43
678	26	56	18	Silty loam	7.70	0.36	7.00	0.43
679	18	50	32	Silty loam	8.00	0.45	7.50	0.43
680	18	56	26	Silty loam	7.40	0.28	8.75	0.45
681	18	50	32	Silty loam	7.50	0.30	8.25	0.43
682	24	52	24	Silty loam	7.60	0.48	8.75	0.43
683	24	56	20	Silty loam	8.20	0.10	6.25	0.40
684	22	54	24	Silty loam	8.20	0.12	6.25	0.43
685	22	52	26	Silty loam	8.00	0.22	6.50	0.40
686	22	52	26	Silty loam	7.80	0.15	7.00	0.40
687	22	52	26	Silty loam	8.10	0.14	7.00	0.43
688	26	52	22	Silty loam	8.40	0.22	7.00	0.40
689	20	50	30	Silty loam	6.90	0.20	9.00	0.37

Continue

S.no	Clay (%)	Silt (%)	Sand (%)	Texture class	pH	EC (dsm^{-1})	$CaCO_3$ (%)	Organic carbon (%)
690	20	50	30	Silty loam	8.00	0.22	7.50	0.41
691	26	50	24	Silty loam	8.00	0.23	6.25	0.36
692	18	50	32	Silty loam	7.50	0.14	7.00	0.37
693	24	52	24	Silty loam	8.20	0.15	7.50	0.37
694	24	50	26	Silty loam	7.80	0.23	5.75	0.40
695	18	50	32	Silty loam	8.10	0.13	6.75	0.36
696	24	56	20	Silty loam	8.20	0.10	6.25	0.37
697	22	54	24	Silty loam	8.20	0.12	6.25	0.36
698	22	52	26	Silty loam	8.00	0.22	6.50	0.36
699	22	52	26	Silty loam	7.80	0.15	7.00	0.40
700	40	36	24	clay	7.60	0.44	7.50	0.47
701	22	34	44	clay	7.60	0.40	8.75	0.43