Soil Texture Classification and Spatial Mapping Using Field Samples and World Soil Grid Data

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1 Introduction

Soil texture, defined by the relative proportions of sand, silt, and clay, is a fundamental property that influences water retention, nutrient availability, erosion susceptibility, and overall soil fertility (Daniels 2016). Understanding the spatial distribution of soil texture is essential for applications in agriculture, land management, hydrology, and environmental modeling. Field-based soil sampling provides precise measurements at specific locations but is typically limited in spatial coverage due to time, labor, and cost constraints (McBratney, Mendonça Santos, and Minasny 2003). On the other hand, global soil datasets, such as the World Soil Grid (WSG), provide spatially continuous estimates of soil properties at continental to global scales (Hengl et al. 2017). While useful for broad-scale analyses, these datasets may not accurately capture fine-scale variability present in local landscapes.

Integrating field-measured soil data with global soil grids, combined with spatial interpolation techniques such as Inverse Distance Weighting (IDW) and Kriging, allows researchers to generate detailed maps of soil texture and identify patterns of spatial heterogeneity (Li et al. 2011). Such integration improves the reliability of soil property assessments and supports decision-making in precision agriculture and environmental management. The present study focuses on classifying soil texture from field samples using the USDA soil texture triangle, generating spatially continuous interpolated maps, and comparing these results with World Soil Grid estimates. The analysis aims to highlight areas of agreement and discrepancy between local measurements and global predictions, thereby providing a more comprehensive understanding of soil texture variability in the study area.

1.1 Research Question

How do soil texture classes derived from field-measured soil samples differ from those estimated by the World Soil Grid, and what spatial patterns emerge when using interpolation techniques (Kriging & IDW) in R?

1.2 Hypothesis

Field-derived soil texture classes will show finer spatial variation than World Soil Grid predictions, with higher disagreement in areas of micro-scale heterogeneity.

1.3 Objective

To classify soil texture using the USDA texture triangle, map spatial variability using interpolation techniques, and compare results with World Soil Grid data.

2 Data Sources

1. **Field Soil Data**
   - Sand (%), Silt (%), Clay (%)
   - Coordinates (WGS84)
   - Format: CSV / XLSX
2. **World Soil Grid (ISRIC)**
   - Sand, Silt, Clay (5-15 cm depth)
   - Resolution: 250 m
   - Format: GeoTIFF
3. **Study Area**
   - Jaranwala (Pakistan) area shapefile defining the project boundary

3 Analysis

3.1 Requirements

The following R packages are required to run the SCaM (Soil Classification and Mapping) workflow. Install them before executing any scripts.

```
library (tidyverse)    # Data manipulation and visualization
library (readxl)       # Excel input
library (soiltexture)  # USDA texture classification
library (sf)           # Simple features (spatial)
library (sp)           # Spatial classes
library (gstat)        # Variography and kriging
library (raster)       # Raster processing
library (terra)        # Modern raster + vector handling
library (geodata)      # Downloads SoilGrids layers
library (ggplot2)      # Plotting (explicitly used)
library (patchwork)    # Combine plots
library (ggspatial)    # Spatial map annotations
```

3.2 Data Cleaning

The data cleaning process begins by reading raw soil texture data from an Excel file. Column names are renamed to uppercase for clarity, and missing values in SAND, SILT, and CLAY are removed. The data is then validated to ensure the sum of SAND, SILT, and CLAY equals 100%, before saving the cleaned data for further analysis.

```r
# 1. Read raw data
soil <- read_xlsx("Data/Raw/Soil_Water_Data.xlsx")
print(soil)

# 2. Columns rename for clarity
soil <- soil %>%
  rename(SAND = `Sand_%`, SILT = `Silt_%`, CLAY = `Clay_%`)

# 3. Missing values removal
soil <- soil %>%
  filter(!is.na(SAND) & !is.na(SILT) & !is.na(CLAY))

# 4. Validation of sum of soil texture components
soil <- soil %>%
  mutate(total = SAND + SILT + CLAY) %>%
  filter(total == 100 )

# 5. Save cleaned & seperated soil texture data
ST.data <- soil %>% select(Address_code, X_Coordinates, Y_Coordinates,
                           SAND, SILT, CLAY)
write_csv(ST.data, "Data/Processed/Soil_Data_Cleaned.csv")
```

3.3 Soil Texture Classification

The soil texture classification is visualized using the USDA Soil Texture Triangle, which categorizes soil based on the proportions of sand, silt, and clay. After processing the cleaned data and assigning a texture class to each sample, the soil data is plotted on the triangle (Figure 1). The plot visually represents the classification of soil texture, with each sample color-coded based on its texture class. The resulting figure is saved as a high-resolution PNG for further considrations.

```r
# 1. Read processed data
soil_data <- read.csv("Data/Processed/Soil_Data_Cleaned.csv")

# 2. Get ISSS/USDA/FAO texture matrix
```

```r
tex_matrix <- TT.points.in.classes(tri.data = soil_data[
  c("SAND", "SILT", "CLAY")], class.sys = "USDA.TT")
print(tex_matrix)

# 3. Convert matrix (0/1) to a single texture class column
soil_data$Texture_Class <- apply(tex_matrix, 1, function(row)
  {classes <- names(row)[row == 1]; if (length(classes) == 0)
    return(NA); classes[1]})
SoilTC <- soil_data %>% select(Address_code, SAND, SILT, CLAY, Texture_Class)
print(SoilTC)
write.csv(SoilTC, "A:/Class_Assignments/SCaM/Outputs/Tables/Soiltexc.csv")

# 4. Soil Texture Triangle

png("A:/Class_Assignments/SCaM/Outputs/Figures/Soil_Texture_Triangle.png",
     width = 2000, height = 1800, res = 300)

par(family = "serif")

classes <- unique(soil_data$Texture_Class)
classes <- classes[!is.na(classes)]

palette_colors <- rainbow(length(classes))
names(palette_colors) <- classes

TT.plot(class.sys = "USDA.TT",  main = "USDA Soil Texture Classification",
  cex.lab = 1.1, cex.axis = 1.0, cex.main = 1.25, frame.bg.col = "white")

TT.points(tri.data = soil_data, geo = TT.geo.get("USDA.TT"),
  col = palette_colors[soil_data$Texture_Class], pch = 19, cex = 1.2)

legend("topleft", inset = c(1.04, 0.06), legend = classes,
       col = palette_colors[classes], title = "Classes", title.cex = 1.0,
       title.font = 2, pch = 19, pt.cex = 1.0, cex = 0.9, bty = "o")

dev.off()
```

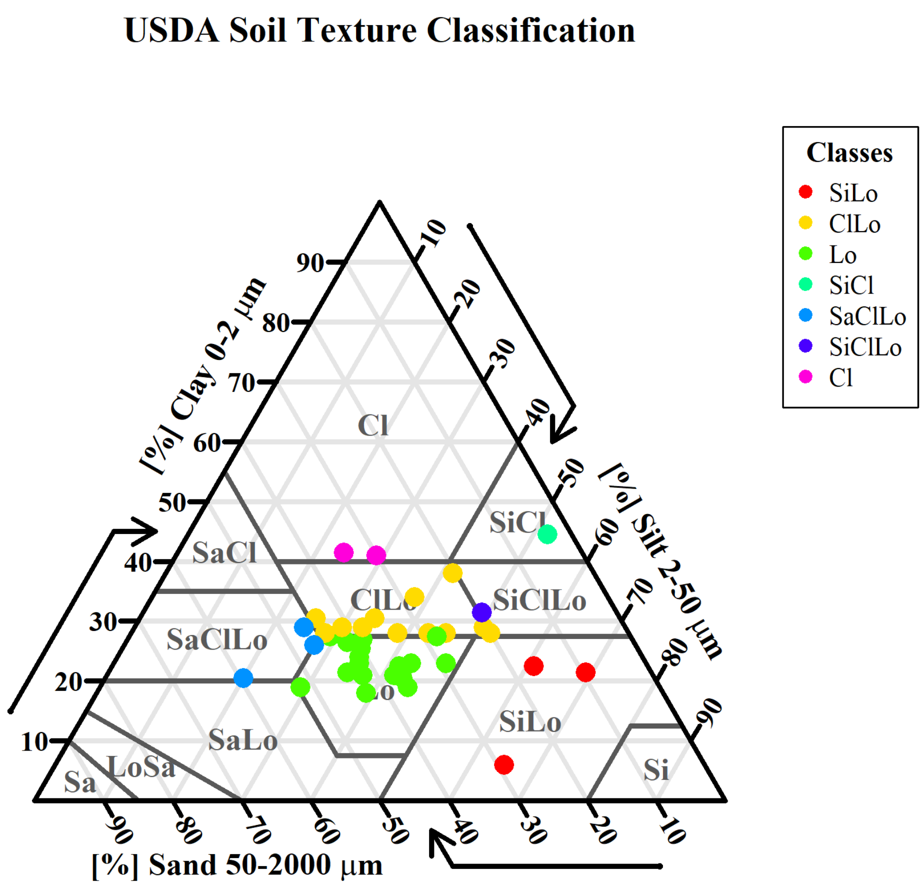

Figure 1: USDA Soil Texture Triangle showing the classification of soil texture based on the proportions of sand, silt, and clay.

3.4 Soil Texture Mapping

3.4.1 Kriging Interpolation

TO BE CONTINUED

References

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