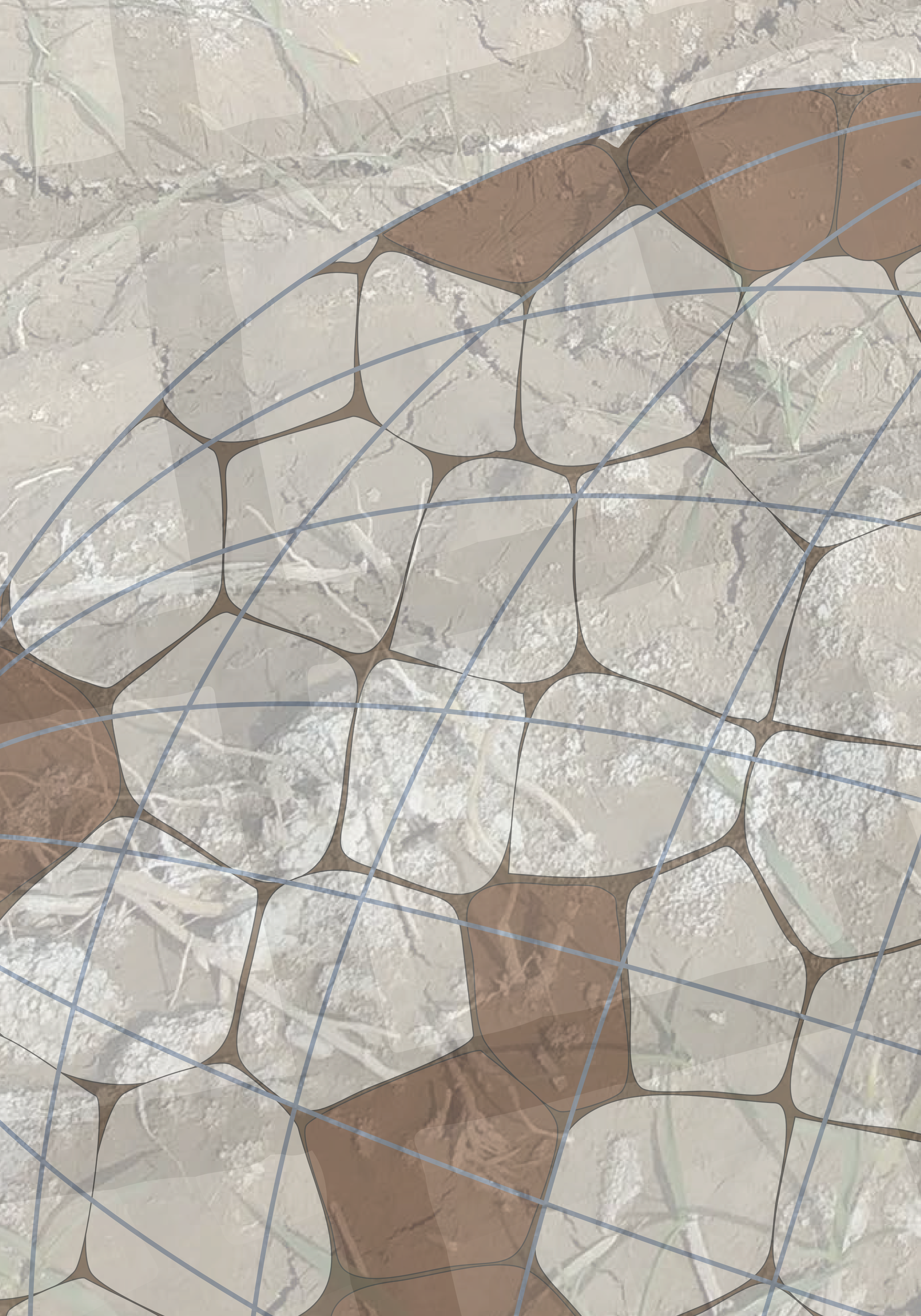
Food and Agriculture Organization of the United Nations

MAPPING OF SALT-AFFECTED SOILS

Technical manual

GLOBAL SOIL PARTNERSHIP



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FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS

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Mapping of salt-affected soils:

Technical manual

Salt-affected soils such as saline or sodic soils are distributed in all continents at various levels of problem intensity. They are soils with high amounts of soluble salts and/or sodium ions. An updated information of their distribution and drivers is a first step towards their sustainable management. This book provides technical guidelines and approach for developing a harmonized multiscale soil information of salt-affected soils. The book is organized into three sections covering seven chapters. The sections are sequentially arranged but independently designed to benefit focused readership who may want to go straight to any section. Section 1 gives the background information. It has three chapters covering existing literature on the characteristics and mapping methods for salt problems in the soil. It is intended to illustrate the basic concepts, linkage of the characteristics of salt-affected soils with input data requirements for their mapping, existing classification methods, and global distribution of these soils. Section 2 covers the methodological procedures for developing multiscale spatial information of salt-affected soils. It has two chapters describing requirements, input data preparation, and the procedural steps for developing spatial information of salt-affected soils. It outlines how data from different sources and characteristics are harmonized and integrated to produce information of salt-affected soils. Section 3 covers information sharing and resources mobilization when developing information on salt-affected soils. It gives the guidelines for preparing spatial maps and steps for value-addition to benefit end-users of the information. It also contains a generic training program for building technical capacity for mapping salt-affected soils. This program also serves as one of the steps for harmonizing product development in multiscale mapping activities.

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List of Abbreviations and acronyms

ADR	Amplitude Domain Reflectometry
ASAL	Arid and Semi-Arid Land
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very-High-Resolution Radiometer
BI	Brightness Index
CRSI	Canopy Response Salinity Index
CRS	Coordinate Reference System
CSV	Comma Separated Values
DEM	Digital Elevation Model
EC	Electrical Conductivity
ER	Electrical Resistivity
EMI	Electromagnetic Induction
EOLSS	Encyclopedia of Life Support Systems
ESA	European Space Agency
ESP	Exchangeable Sodium Percent
ESPG	European Petroleum Survey Group
FAO	Food and Agriculture Organization of the United Nations
FDR	Frequency Domain Reflectometry
GIS	Geographic Information System
GLS	Global Land Survey
GLOSIS	Global Soil Information System
GLOVIS	Global Visualization
GSOCmap	Global Soil Organic Carbon Stock Map
GSP	Global Soil Partnership
GSSmap	Global Soil Salinity Map
HWSD	Harmonized World Soil Database
IPR	Intellectual Property Rights
ITPS	Inter-governmental Technical panel on Soils
ME	Mean Error
MC	Monte Carlo
MLD	Minimum Legible Distance
MODIS	Moderate Resolution Imaging Spectroradiometer
NIR	Near Infrared
NDSI	Normalized Difference Salinity Index
NDVI	Normalized Difference Vegetation Index
NRCS	Natural Resources Conservation Service
NSE	Nash-Sutcliff coefficient of Efficiency
NSI	Normalized Salinity Index
OC	Organic carbon

OLI	Operational Land Imager
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
SR	Salinity Ratio
SAR	Sodium Adsorption ratio
SAVI	Salinity Adjusted Vegetation Index
SDF	Soil Data Facility
SDI	Spatial Data Infrastructure
SI	Salinity Index
SIOR	Sodium –Ion Ratio
SWIR	Shortwave Infrared
TCP	Technical Cooperation Project
TDR	Time Domain Reflectometry
TDS	Total Dissolved Solids
TDI	Total Dissolved Ions
TSS	Total Soluble Salt
UAV	Unmanned Aerial Vehicle
UNESCO	United Nations Educational, Scientific and Cultural Organization
USDA	United States Department of Agriculture
USGS	United States Geological Survey
VSSI	Vegetation Soil Salinity Index
WoSIS	World Soil Information Service

List of symbols and notations

EC_{SE}	Electrical conductivity of saturated soil paste extract
EC_S	Electrical conductivity of soil-water solution
EC_a	Electrical conductivity of the bulk soil in-situ
g/l	Grams per litre
pH	Soil reaction (acidity or alkalinity)
MOD9A1	MODIS notation for land surface reflectance category of 8-day composite images
CLORP	Climate, Organism, Relief and Parent materials
Ls	slope-length factor
cnbl	channel network to basin level
loncurve	longitudinal curvature
BBlue	Blue band
BGreen	Green band
Bred	Red band
BIRed	Infrared band
swir	shortwave band
lcover	Land cover

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Executive Summary

Background

Salt-affected soils are soils with high amounts of soluble salts and/or sodium ions. The first global distribution of these soils was first estimated in the late 1970s at about 1 billion hectares. Since then, there has been inconsistent updates of the global distribution. Recent literature at the global scale mostly use data that was collected in the late 1970s and still portray global distribution of affected areas at about 1 billion hectares. Evidently, a new update is necessary to improve knowledge of the status and actual distribution of salt-affected soils. Part of the reason for the inconsistent global update is due to unclear coordination for periodic data collection and harmonized data collection protocols to support it. The Global Soil Partnership (GSP) of the Food and Agriculture Organization (FAO) is leading global mobilization to kickstart information update from the country to global level. The GPS's bottom-up approach is underpinned by the twin need to support countries to update their national information and to contribute to the update of global information of salt-affected soils. One of the challenges with this approach is the potential uncertainties due to differences in datasets and approaches by countries. The focus of this book is to provide guidelines for harmonizing input data and approaches for mapping salt-affected soils at all levels of information update.

Developing spatial information of salt-affected soils

Many methods exist in the literature for mapping salt-affected soils. They include methods based on soil-type maps integrated with expert opinions, remote sensing applications and soil indicator-based method. The requirements, limitations and example applications of these methods have been highlighted in this book. Prominence has been given to the indicator-based approach for mapping salt-affected soils because 1) the method is amenable to country-level harmonization of procedures, 2) it develops information of both salt-affected soils and soil properties related to salt problems, 3) the method is able to quantify mapping accuracy and uncertainty, 4) quantifies horizontal and vertical information. The description of its methodological steps has been illustrated using case-study test data from Northern Sudan and minimum requirement for input data, computer, and software. The intention is to present the steps as clearly and repeatable as possible to enable implementation with own datasets.

Resource mobilization

Developing information and updating the status of salt-affected soils is resource-intensive and should be properly planned. This book has dedicated the last two chapters for resources mobilization to build national information on salt-affected soils. It outlines key areas of focus for resource mobilization and steps for building technical resources to develop a harmonized database for assessing salt-affected soils. It also discusses steps for enriching spatial maps through value addition to improve their information resource.

SECTION ONE: BACKGROUND INFORMATION

This section gives the background information related to the global mobilization to provide mapping of salt-affected soils. It also covers a brief literature review on the characteristics, distribution, indicators and drivers, and mapping and classification methods for these soils. The section is intended to illustrate the relationship between the characteristics of these soils and input data requirement for their mapping and classification.

1 Introduction

Salt-affected soils are soils with high amounts of soluble salts and/or sodium ions. The salts hold water in the soil at high osmotic potential, which limit easy exchange of water and nutrients with the plant roots. Consequently, they retard growth and development of many plants. Their global distribution was first estimated in the late 1970s at about 1 billion hectares (Szabolcs, 1979; Abrol et al., 1988). Since then, there has been inconsistent updates of their distribution. Recent literature at the global scale mostly use data that was collected in the late 1970s and portray global distribution of affected areas at about 1 billion hectares (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2008; Wicke et al., 2011; Ivushkin et al., 2019). A new update is necessary to improve knowledge of the status and actual distribution of salt-affected soils.

Salt-affected soils have significant impacts on the environment, water, and agriculture. They negatively influence agriculture productivity and quality of soil and surface water but also have significant economic potential if they are properly managed (Wicke et al., 2011). An improved knowledge of their distribution, characteristics, and trend is necessary for sustainable management and economic exploitation. The current lack of consistent information update of salt-affected soils is hampering policy developments to support management and alternative uses of these soils. In 2018, the Global Soil Partnership (GSP) Plenary Assembly deliberated on the global information gap for salt-affected soils and requested for global mobilization to update the information (GSP-FAO, 2018). Following the request, GSP conducted a survey among member countries as a first step to gain understanding of the status of salt problems and identify areas to focus on when mobilizing for information update. The survey revealed that more than 70% of the countries have varied aspects of salt problems and data for mapping salt-affected soils (Figure 1.1). However, most of the datasets are old and need updating.

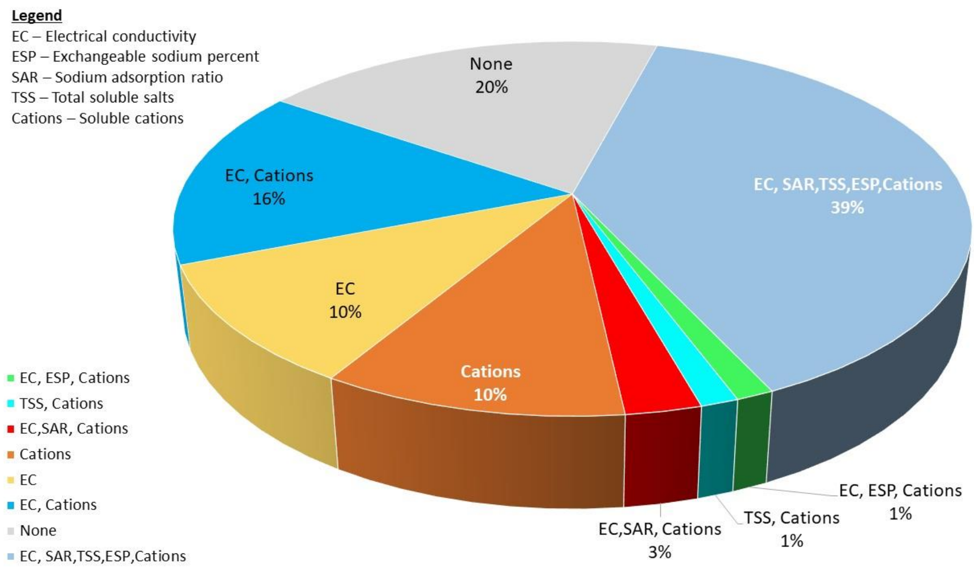

Figure 1.1: Survey results on country-level data availability for mapping salt-affected soils

In this manual, the GSP global mobilization approach is used to develop information update of salt-affected soils. The approach is a country-driven process where countries (partners) develop and contribute global soil information but retain the copyright of the contributed soil data (Figure 1.2). The process is globally coordinated by GSP in collaboration with International Network of Soil Information Institutions (INSII) and focal persons (FP) in each country. The whole process is supported with technical documents developed by the technical bodies within GSP such as Pillar four Working Group (P4WG) and Intergovernmental Technical Panel on Soils (ITPS) (FAO and ITPS, 2018). This manual is part of the technical documents for supporting the global mapping of salt-affected soils (Figure 1.2).

One of the challenges in updating global information using the approach in Figure 1.2, is the potential uncertainties due to differences in datasets and approaches by countries. There are many methods and indicators in the literature which countries can use in mapping and classifying salt-affected soils. Unless the country data and methods are harmonized, the contributions can be disorganized and result into uncertain global map of salt-affected soils. The focus of the present manual is to provide guidelines for harmonizing input data and approaches for mapping salt-affected soils. The book puts emphasis on popularly used soil indicators for diagnosing salt problems in the soils (Figure 1.1) and a harmonization protocol for all contributing countries.

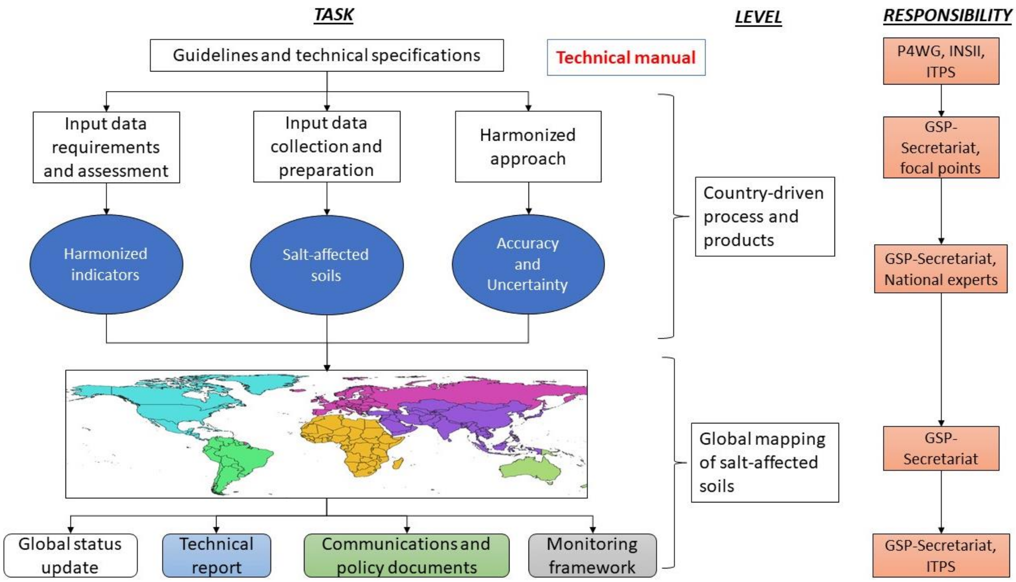

Figure 1.2: Country-driven framework for global mapping of salt-affected soils

1.1 Presentation

This book is organized into three sections covering seven chapters. The sections are sequentially arranged but independently designed to benefit focused readership who may want to go straight to any section. Section 1 gives the background information, Section 2 covers the methodological procedures for developing multiscale spatial maps of salt-affected soils, and section3 outlines the steps for information sharing and resources mobilization (Table 1.1). Section 1 has three chapters that gives brief literature review on the characteristics of salt-affected soils and methods for their mapping. The section is intended to provide readers with basic concepts linking the characteristics of salt-affected soils with data requirements for mapping and classifying these soils. It also discusses the mapping methods and existing information on the global distribution of salt-affected soils. Section 2 describes the procedural steps for developing maps of salt-affected soils (Table 1.1). Section 3 outlines the requirements and procedures for information sharing and resource mobilization for developing or monitoring salt-affected soils.

Table 1.1: Book presentation

<table>
<tr><th colspan="2">Main areas</th><th colspan="2">Description</th><th>Book chapter</th></tr>
<tr><td rowspan="4">Section 1</td><td rowspan="4">Background</td><td colspan="2">Introduction</td><td>Chapter 1</td></tr>
<tr><td colspan="2">Characteristics of salt-affected soils</td><td rowspan="2">Chapter 2</td></tr>
<tr><td colspan="2">Global information of salt-affected soils</td></tr>
<tr><td colspan="2">Methods for mapping salt-affected soils</td><td>Chapter 3</td></tr>
<tr><td rowspan="5">Section 2</td><td rowspan="5">Systematic procedures for mapping salt-affected soils</td><td rowspan="2">Assessment requirements</td><td>Input data assessment</td><td rowspan="2">Chapter 4</td></tr>
<tr><td>Software and computer requirements</td></tr>
<tr><td colspan="2">Step 1: Data preparation and harmonization</td><td rowspan="3">Chapter 5</td></tr>
<tr><td colspan="2">Step 2: Spatial modelling, validation, and uncertainty assessment</td></tr>
<tr><td colspan="2">Step 3: Classification and map update</td></tr>
<tr><td rowspan="4">Section 3</td><td rowspan="2">Information sharing</td><td colspan="2">Product specification</td><td rowspan="2">Chapter 6</td></tr>
<tr><td colspan="2">Data sharing requirements</td></tr>
<tr><td rowspan="2">Resources mobilization</td><td colspan="2">Resources mobilization</td><td rowspan="2">Chapter 7</td></tr>
<tr><td colspan="2">Capacity development program</td></tr>
</table>

1.2 References

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2 Characteristics of salt-affected soils

2.1 Genesis of salt-affected soils

The minerals responsible for salt problems in the soil originate from diverse sources and gradually accumulate to contribute to the formation of salt-affected soils. Many models exist in the literature for describing the salt accumulation and evolution of these soils. They can be grouped into two broad categories (Figure 2.1): one involving climatic interactions with soil and water (Miller and Brierley, 2011) and the other describing direct deposit of the salt particles into the soil (Abou-Baker and El-Dardiry, 2015; Daliakopoulos et al., 2016).

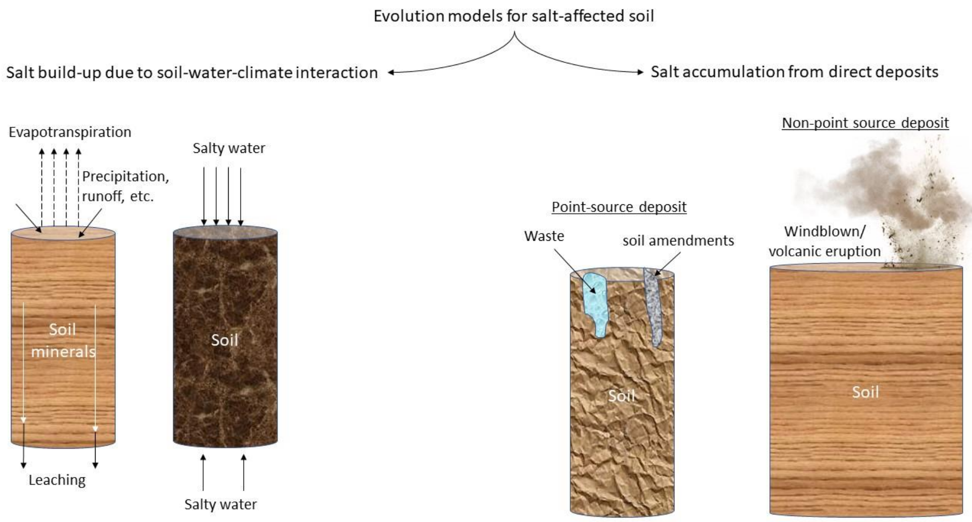

Figure 2.1: Genetic pathways for development of salt-affected soils

2.1.1 Soils-water-climate interaction model

This model was first proposed by Gedroiz (Kelly and Brown, 1934) and described the evolution of salt-affected soils along the trajectory of gradual changes of the characteristics of soluble salts. It postulated that salt-affected soils develop when dissolved minerals in water accumulate and change status as water is moved from the soil. Soluble salts are deposited in the soil when water evaporates and gradually accumulate with time to form saline soils. Sodic soils then develop when the soluble salts are leached and/or when divalent cations are precipitated out of the exchange complex followed by the corresponding increase in sodium ions. If leaching is insufficient, the salt-affected soils remain predominantly saline (FAO, 1984). Further types of sodic soils (e.g. solodized sodic soils) are formed when sodium ions move out of the exchange complex and are replaced by hydrogen ions (Miller and Pawluk, 1994). This genetic evolution is common in arid and semiarid areas where evaporative demand is high during certain times of the year.

Salt-affected soils also develop when salts accumulate due to repeated direct contact of soil with salty water. In this case, the type of salt-affected soils is particularly influenced by the dominant soluble salts in the salty water (Munn and Boehm, 1983). The model describing this genetic pathway is common in the coastal areas and in areas with salty and high groundwater table. The model also explains the development of certain types of salt-affected soils or ion-specific salinity in areas subjected to wastewater irrigation (Jalali et al., 2008).

2.1.2 Direct deposit model

In this model, salt accumulation in the soil is facilitated by the repeated deposition of salt particles or solutions in the soil. There are two types of this model: point-source and non-point source deposits (Figure 2.1). Point-source depositions introduce localized salt accumulation, which gradually spread to other areas or down the soil profile by action of runoff, leaching, tillage, etc. Non-point deposits occur when windblown salt particles or volcanic eruptions settle on the soil. Alternate layers of the deposits may be buried and contribute to accumulation of salts in the soil profile. This model also explains the development of salt-affected soils due to geologic marine incursions (Schofield et al., 2001).

2.2 Characteristics

The dominant cations in salt-affected soils are Sodium (Na^{+}), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Potassium (K^{+}) and dominant anions are Chloride (Cl^{-}), Sulphate ($S0_4^{-2}$), Carbonate ($C0_2^{-2}$), Bicarbonate ($HC0_3^{-}$) and Nitrates ($N0_3^{-}$) (Richards, 1954). Salt-affected soils with high amounts of sodium ions are known as sodic soils. High content of sodium ions in these soils cause dispersion of clay and organic matter, which settle on the surfaces of soil particles to give them a brownish black appearance. This black appearance is the reason for the name "black alkali soils" in reference to sodic soils (Richards, 1954). When the dispersed clay settles in between soil particles, they plug the matric spaces and block water infiltration. Consequently, sodic soils tend to remain waterlogged for extended period after rainfall or irrigation. In some instances, dispersed humus and clay may be leached down the soil profile and portray clay accumulation and decrease in texture down the profile (Sparks, 2003; Krasilnikov et al., 2013).

High content of sodium ions has been used as an indicator for identifying sodic soils. According to Richards (1954), sodium occupies more than 15% of the soil's cation exchange capacity (CEC) in sodic soils. This observation has led to the use of Exchangeable Sodium Percent (ESP) ≥ 15 as a diagnostic indicator for sodic soils. In addition, since sodic soils are low in total salt but high in exchangeable sodium, the ratio of sodium ions to the sum of major anions has been shown to be more than 1 in sodic soils (Chhabra, 2005). Figure 2.2 gives an illustration of the characteristics of sodic soils.

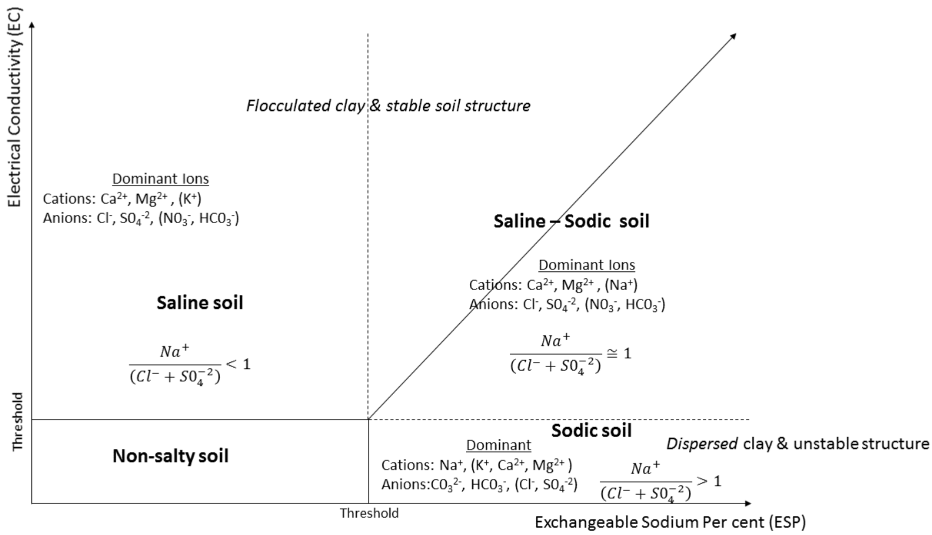

Figure 2.2: Graphical illustration of characteristics of salt-affected soils

Salt-affected soils with high contents of soluble salts and low sodium ions in the exchange complex are often identified as saline soils. Due to their low content of exchangeable sodium ions, saline soils have low ESP and the ratio between sodium ions and sum of major anions is less than 1 (Figure 2.2). Preponderance of chloride and sulphate ions give saline soils a brownish white appearance. Hence, they are sometimes referred to as white alkali soils.

Saline soils with significant proportions of calcium ions have good soil structure. Calcium ions have high flocculation power in the soil (Sumner and Naidu, 1998; Rangesamy and Marchuk, 2011). Therefore, their presence in soil tends to promote clay flocculation and particle aggregation. Some saline soils have gypsum (calcium sulphate) and lime (calcium and magnesium carbonate) (Skarie et al., 1987).

Salt-affected soils with high content of soluble ions and appreciable amount of sodium ions are known as saline-sodic soils. When sodium salts in these soils hydrolyse, the pH of the soil increases and the soil changes to sodic soils. In this regard, saline-sodic soils are sometimes referred to as saline-soils capable of alkaline hydrolysis (Chhabra, 2005). When the soluble salts remain high in the saline-sodic soils, the characteristics of the soils are like those of the saline soils. When the concentration of the soluble salts is lowered and the sodium salts hydrolyse, then the characteristics of the soils change to those of sodic soils.

Richard (1954) used measurable soil properties to further quantify characteristics of salt-affected soils (Table 2.1). These characteristics have been widely applied for general classification of salt-affected soils (Chhabra, 2005; Zaman et al., 2018).

Table 2.1: Characteristics of salt-affected soils

Soil property	**Unit/Symbol**	**Type of salt-affected soil**		
		Saline	**Saline-sodic**	**Sodic**
Electrical conductivity	EC_e (dS/m)	> 4	> 4	< 4
Exchangeable sodium Percent	ESP	< 15	> 15	> 15
pH	-	< 8.5	< 8.5	> 8.5
Sodium adsorption ratio	SAR	< 13	> 13	> 13

2.3 Indicators for assessing salt-affected soils

Indicators of salt-affected soils are features that identify the status or occurrence of the soils. In this book, they have been divided into three categories: quantitative soil properties, qualitative soil surface/profile properties, and vegetation characteristics.

Quantitative soil indicators are measurable soil properties related to salt problems in the soil such as concentration of soluble ions or exchangeable sodium ions, soil pH, etc. Integral soil indicators representing overall concentration of soil salts are also often used. These indicators include electrical conductivity (EC), total soluble salts (TSS), total dissolved solids (TDS), total soluble cations (TSC), resistivity etc. (Abrol et al., 1988; Zaman et al., 2018). Various levels of these indicators have been proposed in the literature for identification of the three types of salt-affected soils. A seminal work in this regard was proposed by Richard (1954) (Table 2.1). Other adjustments to the thresholds given in Table 2.1 have since been given, for example using different levels of soil pH and introduction of the ratio of soluble ions (Table 2.2). Soil spectral reflectance indices are also new indicators under development and are expected to provide diagnostic threshold for different types of salt-affected soils (Kalra and Joshi, 1994; Farifteh et al., 2008).

Table 2.2: Summary of soil properties for diagnosing salt-affected soil

Soil property		Unit/Symbol	Threshold			Reference
			Saline	Saline-sodic	Sodic	
Electrical conductivity		EC_e (dS/m)	> 4	> 4	< 4	Richards[1] (Abrol[*1])
Exchangeable sodium		ESP	< 15	> 15	> 15	
pH		-	< 8.5 (<8.2)	< 8.5(<8.2)	> 8.5(>8.2)	
Sodium adsorption ratio		SAR	< 13	> 13	> 13	
Ratio of salt ions	Sodium	$[Na^+/(Cl^-+SO_4^{-2})]$	<1	-	> 1	Choudhary[2]
	Carbonate	$[CO_3^{-2}+HCO_3^-]/(Cl^-+SO_4^{-2})$	< 1		> 1	Chhbra[3]
Salt content		TSS (mg/l)	< 2640	> 2640	< 2640	Horneck[4]
		% Soluble salt	> 0.1	>0.1	<0.1	

[1]Richards (1954); [*1]Abrol et al. (1988); [2]Choudhary and Kharche (2018); [3]Chhabra (2005); [4]Horneck et al. (2007)

Qualitative soil properties are observable features associated with certain characteristics of salt-affected soils. They include presence of crusts, qualitative diagnostic properties of natric/salic soil horizons, columnar/prismatic soil structure under dry conditions with peds covered by brownish black films (WRB, 2014; Pankova, 2015). These soil properties are mostly used to identify salt-affected soils in the field. Their aggregate evidence can be found in most soil maps with delineations of salt-affected soils (Abuelgasim and Ammad, 2019).

Salt-tolerant vegetation are dominant in salt-affected areas. Their presence is sometimes used as indicator of salt-affected soil (Bouchhima et al., 2018). An advance application of this concept is found in remote sensing of the earth surface. Many tests have revealed correlation between remote sensing indices with salt-affected soils (Gorji et al., 2019).

2.4 Drivers of salt problems in the soil

Drivers of salt problems in the soils can be grouped into two: primary and secondary drivers. Primary drivers are the natural sources of mineral elements contributing to the salt problems or the natural conditions that favor development of salt-affected soils. Secondary drivers are factors that exacerbate salt problems in the soils. They are largely associated with human intervention on the natural environment. Table 2.3 gives a summary of these drivers of salt problems in the soil.

Table 2.3: Drivers of salt problems in soil

Primary drivers	Secondary (human-induced) drivers
Salty parent materials	Irrigation application
Climate (arid and semi-arid climate)	Inappropriate fertilizer application
Groundwater	Improper waste disposal
Sea/tidal water	Inappropriate use of wastewater
Windblown salt particles	Misuse of soil amendments
Flood/runoff from salt-affected areas	Inappropriate soil-water management and land use change

2.4.1 Primary drivers

Salty parent material is a primary source of salt problems in the soil. They gradually release the mineral constituents of soil during chemical weathering, which react with air and water to produce soluble salts responsible for salt problems. These salts are laterally carried away by moving water to other sites or vertically by capillarity up the soil profile (Fanning and Fanning, 1989). Further processes such as leaching can convert the salt conditions to produce other types of salt-affected soils.

Climate is another driver of formation of salt-affected soils. In arid and semi-arid climate, the evaporative demand dries up water on the soil which leave the salt crystals on the soil surface. In addition, low rainfall in these climatic zones does not fully facilitate leaching of salts down the soil profile. The combined effects of evaporative demand and insufficient leaching cause accumulation of salts in the soil and contribute to the development of salt-affected soils (Schaetzl and Anderson, 2005).

Groundwater is another driver influencing the development of salt-affected soils. Salty groundwater rising through the soil profile by capillarity contributes the salts, which remain in the soil when the water evaporates (Rengasamy, 2006). In certain areas where salty groundwater table meets the land surface, groundwater is discharged on to the soil surface as springs and geysers. The discharged salty water gradually builds salts in the soil and contribute to the development of salt problems in the soil. Groundwater also contributes to the salt problems when its salty water is used for irrigation.

Other primary causes of salt problems in the soils are sea/tidal water interaction, windblown salt deposits, and salty runoff water. Sea/tidal water contains salt that remain on the soil after interaction with soil at the seacoast. They can also influence soil salt problems when the water is used for irrigation or if used elsewhere (such as in wastewater or sewage) but later discharged onto the soil. Interaction of windblown salt particles also introduces salts into soils. Repeated deposits of windblown salt particles can accumulate the salts and lead to the development of salt-affected soils (Yang et al., 2018). Recurrent runoff or flood water from salt-affected areas can also bring in salt, which can accumulate with time and contribute to the development of salt-affected soils (Krasilnikov et al., 2013).

2.4.2 Secondary drivers

Irrigation is the most cited secondary driver of salt problems in the soil. Irrigation water can either induce salt problems when salty water is used for irrigation or when irrigation water causes inadequate leaching of soil salts. Irrigation water can also recharge groundwater and cause it to rise and gradually introduce groundwater salts into the soil (Rietz and Haynes, 2003; Pulido-Bosch et al., 2018). Fertilized irrigation water can also introduce salts into the soil, which gradually build up with repeated application and contribute to the development of salt-affected soils.

Besides irrigation, waste and wastewater are also significant secondary drivers of salt problems in the soil. Improper management of wastewater and solid waste can contribute to the development of salt-affected soils (Piotr, 2008). Repeated disposal of waste material either directly mix with soil or contribute salty leachates into the soil, which gradually accumulate with time and lead to the formation of salt-affected soils. Use of wastewater in irrigation is also another way of inducing salt problem in the soil. Wastewaters contain mineral elements which can cause ion-specific toxicity and salinity in the soil (Muyen et al., 2011; Abd-Elwahed, 2018).

Land use/cover change is also an important secondary driver of salt-accumulation in the soil. Altering the vegetation type in certain ecosystems potentially change the plant water-use and evapotranspiration characteristics with consequences such as drying up of soil and salt build-up. Changing the vegetation types can also alter the equilibrium of groundwater table and eventually contribute to groundwater-induced salt-affected soils (Rengasamy, 2006). In the arid and semi-arid environments, declining vegetation cover has also been linked to increased exposure of soils to the risk of salinization (Perri et al., 2018).

Other secondary sources of salt problems in the soil include inappropriate fertilizer application, inadequate drainage, and misuse of soil amendments.

2.5 Classification of salt-affected soils

Salt-affected soils are classified according to the types of salt and intensity of the salt problems. Classification of the types of salt-affected soils was first proposed by Richard (1954) based on electrical conductivity (EC), pH and exchangeable sodium percent (ESP) or sodium adsorption ratio (SAR). According to this scheme, there are three types of salt-affected soils (Table 2.2):

- Saline: soils with excess soluble salts in which EC > 4 dS/m, pH < 8.5, and ESP < 15 (or SAR < 13)
- Sodic: soils with excess exchangeable sodium ions in which EC<4 dS/m, pH>8.5, and ESP>15 (SAR>13)
- Saline-sodic soils: soils with high content of soluble salts and appreciable quantity of sodium ions capable of alkaline hydrolysis. The soils have EC>4 dS/m, pH > 8.5, and ESP >15 (or SAR > 13)

Many proposals have been proposed in the literature on the limits given by Richards (1954). Abrol et al. (1988) proposed pH limit of 8.2 instead of 8.5 for the three classes of salt-affected soils. This pH value was also found satisfactory in Indian soils (Choudhary and Kharche, 2018). Szabolcs (1987) also gave a further classification of saline soils as: Gypsiferous soils, saline soils due to calcium chloride, saline soils due to soluble magnesium salts, acid sulphate soils with iron and aluminium sulphates, and potentially saline soils.

Classification of the intensity of salt problems in the soil is commonly expressed using levels of electrical conductivity and exchangeable sodium ions and on weight basis (Richard, 1954; Abrol et al., 1988; FAO, 2006; Chinese Academy of Sciences, 2001). Examples of these levels are given in Table 2.4

Table 2.4: Identifying intensity of salt problems in soil

Salinity (EC_e dS/m)			**Sodicity (ESP)**		
Intensity	FAO (2008)	Richard (1954)	Intensity	Abrol et al. (1988)	Amrhein (1996)
None	< 0.75	0 - 2	None	< 15	< 6
slight	0.75 - 2	2 - 4	Slight	15 - 30	6 - 10
Moderate	2 - 4	4 - 8	Moderate	30 - 50	10 - 15
Strong	4 - 8	8 - 16	High/Strong	50 - 70	15 - 25
Very Strong	8 - 15	> 16	Extreme/V. Strong	> 70	> 25
Extreme	> 15				
Chinese classification scheme (weight of salt per unit Kg of soil) (Chinese Academy of Sciences, 2001)					
Coastal, semi-humid, semiarid, and arid			Semi-desert and desert regions		
None	< 1.0 g/Kg		None	< 2.0 g/Kg	

Light	1 – 2 g/Kg	Light	2 – 3 g/Kg
Moderate	2 – 4 g/Kg	Moderate	3 – 5 g/Kg
Severe	4 – 6 g/Kg	Severe	5 – 10 g/Kg
Solonchak	> *6 g/Kg	Solonchak	> 10 g/Kg

Besides the classification in Table 2.4, there are some other lumped parameters that are used to assess the salinity problems. The parameters include total dissolved solids (TDS in mg/L), total soluble cations (TSC) and total soluble anions (TSA) in $mol_{(c)}$/L. There are approximations in the literature for converting these gravimetric measures into EC. For example, TDS may be approximated by multiplying EC (dS/m) by 800 for hypersaline soils and 640 for other saline soils. These are approximate guidelines since there are no exact relationships. Classification of salt intensity using gravimetric measurements has been given by Vargas et al. (2018) (Table 2.5).

The classification schemes in Table 2.4 and Table 2.5 show that there are many alternatives for identifying different levels of salt problems. They can be used at the national scale in the countries where they are popularly used.

Table 2.5: Classification of salt intensity using gravimetric measurements

Salinity classification (weight of salt per kg of soil) depending on chemistry of salts (Vargas et al., 2018)			
With predominance of chlorides $Cl^-/SO_4^{2-} > 1$, pH < 8.5		Chloride-sulphate $0.5 < Cl^-/SO_4^{2-} < 1$, pH<8.5	
None	< 1 g/kg	None	< 2 g/kg
Slight	1 – 2 g/kg	Slight	2 – 4 g/kg
Moderate	2 – 4 g/kg	Moderate	4 – 6 g/kg
Strong	4 – 8 g/kg	Strong	6 – 10 g/kg
Very strong	> 8 g/kg	Very strong	> 10 g/kg
With predominance of sulphates $Cl^-/SO_4^{2-} < 0.5$, pH < 8.5		Soda saline $HCO_3^- + CO_3^{2-} > Cl^-$, $HCO_3^- + CO_3^{2-} > SO_4^{2-}$, pH > 8.5	
None	< 3 g/kg	None	< 1 g/kg
Slight	3 – 6 g/kg	Slight	1 – 2 g/kg
Moderate	6 – 8 g/kg	Moderate	2 – 3 g/kg
Strong	8 – 15 g/kg	Strong	3 – 5 g/kg
Very strong	> 15 g/kg	Very strong	> 5 g/kg

2.6 Global distribution of salt-affected soil

Salt-affected soils are found in all continents in varying spatial proportions. The literature is replete with attempts to quantify the global distribution of these soils. Massoud (1976) and Szabolcs (1979) developed the first world map of salt-affected soils using FAO/UNESCO Soil Map of the World. They estimated salt-affected areas at about 0.9 billion hectares (Table 2.6). In 2004, Squires and Glenn (2004) published new estimates of the global distribution and placed the coverage of affected areas at 1.029 billion hectares. This estimate portrayed 40% of the global affected areas as saline and 60% as sodic soils.

Table 2.6: Global estimates of salt-affected areas

Region	**Massoud (1974) and Szabolc (1976)**	**Squires and Glenn (2004)**	**Wicke et al. (2011)**	**FAO-ITPS-GSP (2015)**
North America	15.755	15.8	84	15.8
Central America	1.965	2	5	2
South America	129.163	129.2	84	129.3
Europe (and former USSR)	50.747	-	129	30
Africa	80.438	209.6	322	209.6
North and central Asia	211.448	211.4	274	211.7
South Asia	85.108	84	52	84.1
Southeast Asia	19.983	20	6	20
Pacific	357.568	357.5	169	357.6
Global total (million Ha)	**952.175**	**1029.5**	**1125**	**1060.1**

In 2011, Wicke et al. (2011) estimated the global distribution of types and intensity of salt-affected soils based on the Harmonized World Soil Database (FAO et al., 2008). Their estimate portrayed salt-affected areas as covering 1.1 billion hectares in which 60% of the areas were saline, 26% sodic, and 14% saline-sodic (Figure 2.3). It is important to note the proportions of affected areas by types as given by Wicke et al. (2011) was the opposite (flipped) proportions given by Squires and Glenn (2004). In 2018, Joint Research Centre (JRC) developed a global map of salinization, which showed the affected areas covering 1 billion hectares (Cherlet et al., 2018).

Recently, Ivushkin et al. (2019) published another global estimate of salt-affected soils. This study used a combination of remote sensing, soil data from World Soil Information System (WoSIS, https://www.isric.org/explore/wosis) and modelling.

Their estimate also put the global distribution of salt-affected soils at about 1 billion hectares (Figure 2.3).

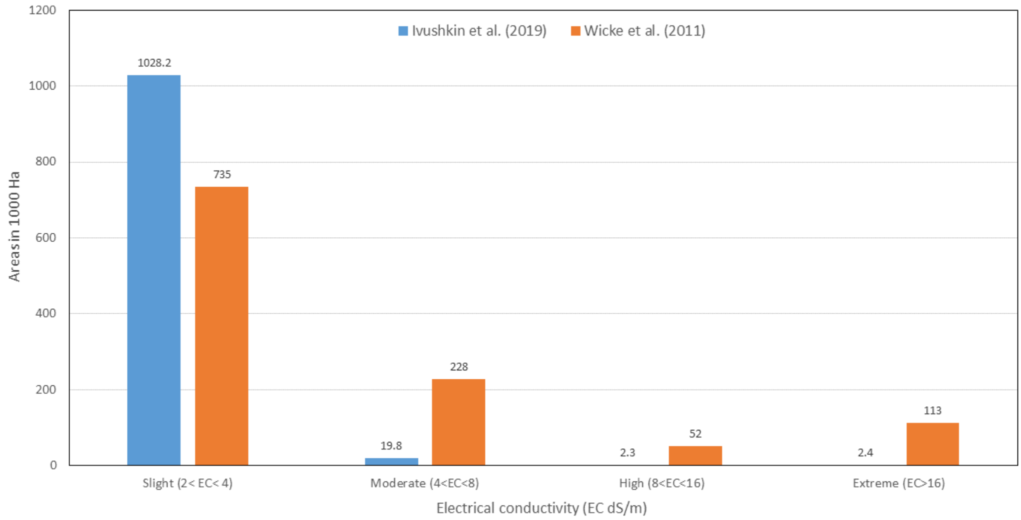

Figure 2.3: Proportion of severity of salt-affected areas of the world

Interestingly, all these global estimates have remained nearly the same at around 1 billion hectares. Possible explanations are that: 1) the overall salt-affected soil areas have not changed over the years, or 2) the input data for estimating the areas has not changed, or 3) the estimation methods have been inconsistent. There is a need for new updates to improve the global information of the status of salt-affected soils.

Although all continents have salt-affected soils, arid and semi-arid Land (ASAL) areas seem to have a higher proportion. This is attributed to the prevalently low and irregular rainfall and high evaporative demand in ASAL areas, which all together combine to accumulate salts in/on the soil (Sheng et al., 2010; Pankova and Konyushkova, 2013).

Apart from ASALs, coastline salt problems are also of significant importance. Coastline salt problems are largely due to seawater intrusion. Li et al. (2014) gave a global picture of salt-affected coastlines of the world using secondary information from the literature (Figure 2.4). Other than this preliminary work, there is no clear data or representation of the extent and severity of salt-affected coastlines of the world.

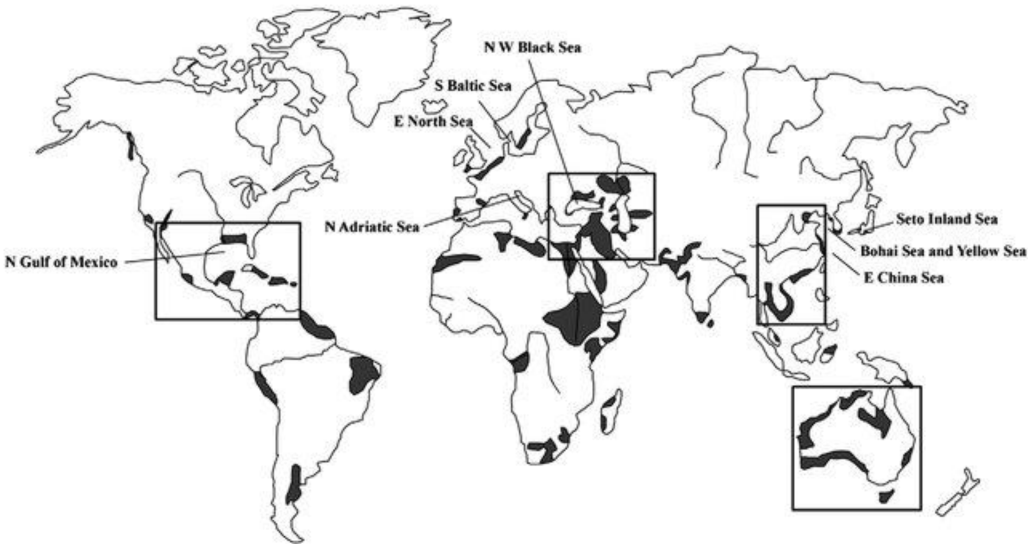

Figure 2.4: Global distribution of salt-affected coastline and river valleys (source: Li et al., 2014)

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3 Methods for mapping salt-affected soils

Maps of salt-affected soils contain spatial information of the distribution of types and intensity of salt problems in the soils. They are developed by considering the drivers, indicators, prevalence of salt-affected soils in the landscape and mapping tools and resources (Figure 3.1). Input data on the drivers and indicators provide the evidence of occurrence of salt problems in the soil. They influence the type of mapping tools for information mining and representation of the final maps. Some of the commonly used mapping tools include Geographic Information Systems (GIS), statistical modelling, stereoscopes, etc. Besides the input data and mapping tools, mapping methods are also influenced by resource requirements such as expertise, computing facility, and funding.

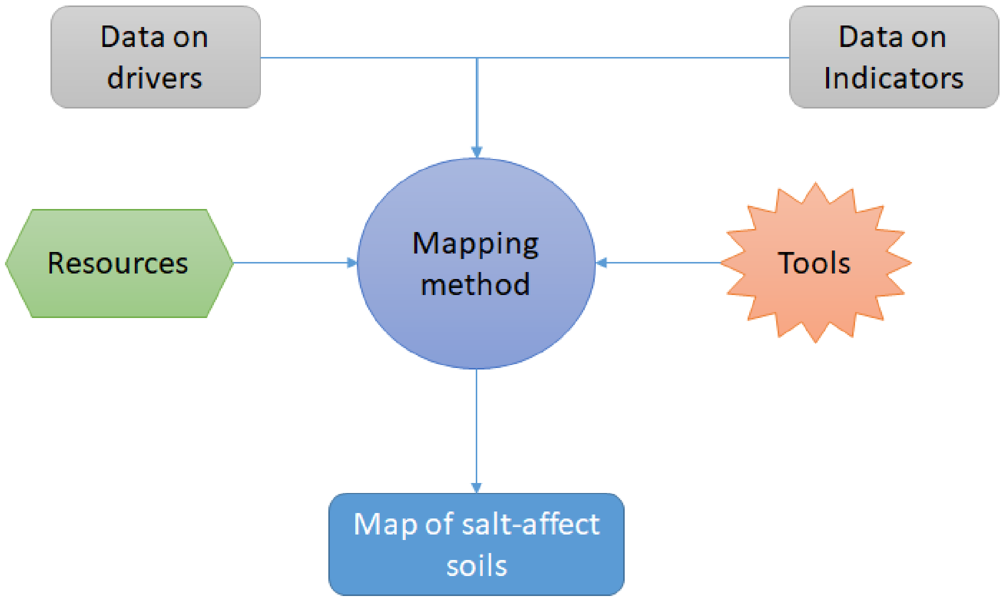

Figure 3.1: Framework for developing mapping methods for salt-affected soils

The main categories of the methods for mapping salt-affected soils are:

i. Methods based on soil maps and expert opinion
ii. Remote sensing applications
iii. Modelling of soil indicators of salt problems

This chapter elaborates on the potential and limitations of these categories of mapping methods with regards to their: 1) contribution to building integral global information of salt-affected soils, 2) ability to quantify mapping accuracy and uncertainty, and 3) flexibility for periodic information update.

3.1 Methods based on soil maps and expert opinion

Soil maps have been traditionally used to identify salt-affected soils in many territories of the world. Their application relies on identification and verification of the areas in the soil maps with designations related to salt-affected soils. A seminal work in global assessment of salt-affected soils using this approach was published by Szabolcs (1979). The publication used FAO-UNESCO soil map of the world in which the polygons with salt-affected soils were classified saline soils (solonchak and saline phases), alkali soils (solonetz and alkaline phases), and potentially salt-affected soils.

Potentially salt-affected soils were soils in areas that were not salt-affected at the time (or salt-affected to a very low degree) but could be easily become affected due to human activities. The approach given by Szabolcs (1979) also used expert opinion to identify the areas that were not very well represented in the FAO-UNESCO soil map of the world. Figure 3.2 is example output from this mapping approach.

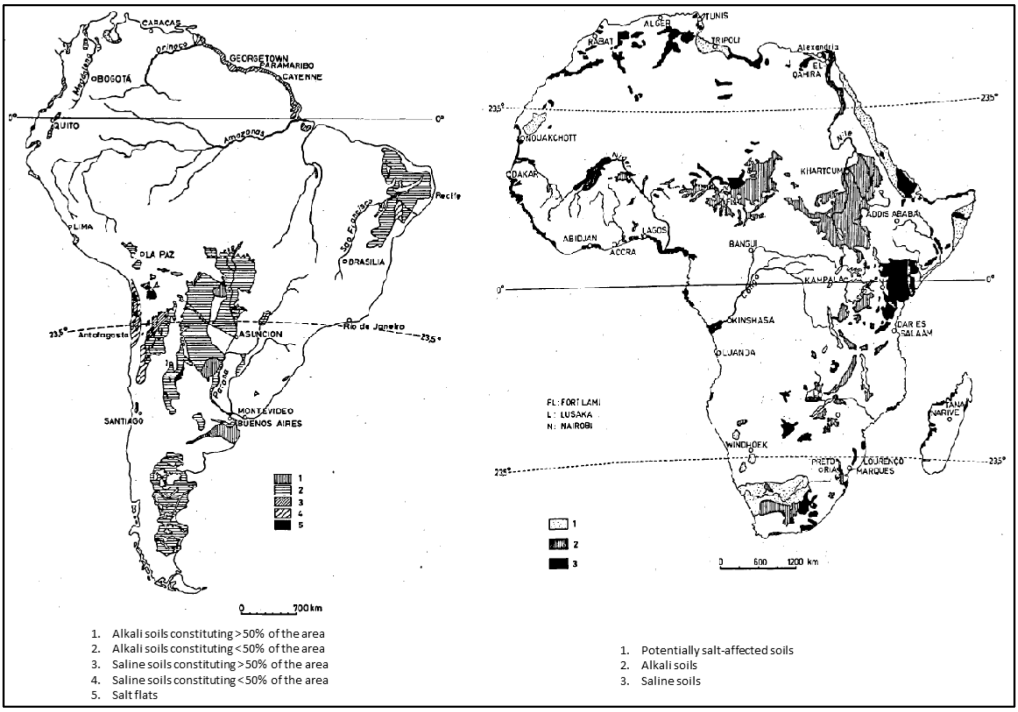

Figure 3.2: Example map of salt-affected soils (adapted from Szabolcs, 1979).

Application of soil maps to quantify areas of salt-affected soils has since been applied in various parts of the world. Examples include mapping of saline and sodic soils in the European Union (Toth et al., 2008), salt-affected soils in the European part of Russia (Khitrov et al., 2009), digital assessment of salt-affected soils in India (Mandal et al., 2011), among others.

Most applications of soil maps use the sequence of identification, verification, and quantification processes to produce the spatial information of salt-affected soils. The identification process aims at locating the soil typological/mapping units in the soil map with classified designations of salt-affected soils. The identified units are then verified with either through expert opinion or confirmatory field-sampling and testing. The confirmed areas are finally delineated and their aerial extent quantified. This sequence may be preceded with the development of a new soil map or digitalization of old maps where necessary (Kitrov et al., 2009; Mandal et al., 2011).

Although the application of soil maps to identify salt-affected soils is popular in some countries, it suffers from the lack of accuracy and uncertainty quantification of the final maps. The approach also produces maps of salt-affected soils with hard boundaries, which are arguably infrequent in most landscapes. Other soil information associated with salt-affected soils such as the distribution of electrical conductivity, pH, soluble ions, etc. may be imprecisely given or missing.

3.2 Using remote sensing application

Remote sensing application has been used in agriculture and environment for many years. The technology provides spatial and temporal information about the land cover, soil cover characteristics, climate, and atmospheric conditions, which are of importance in soil and agriculture resources management. It relies on the interaction of the electromagnetic radiations with soil and vegetation to produce characteristic signatures in the reflected radiations. The reflected signatures are then modelled to extract soil and vegetation features. Two broad categories of radiations are discernible with this technology: radiations from the sun (also called passive radiations) or radiations from the sensor (active radiation). They are further classified according to the type of sensors detecting the radiations: 1) proximal sensors, which are put on the soil surface or a few meters from the soil surface; 2) sub-atmosphere cameras, which are carried by low lying aircrafts or aerial vehicles; and 3) satellites (Figure 3.3).

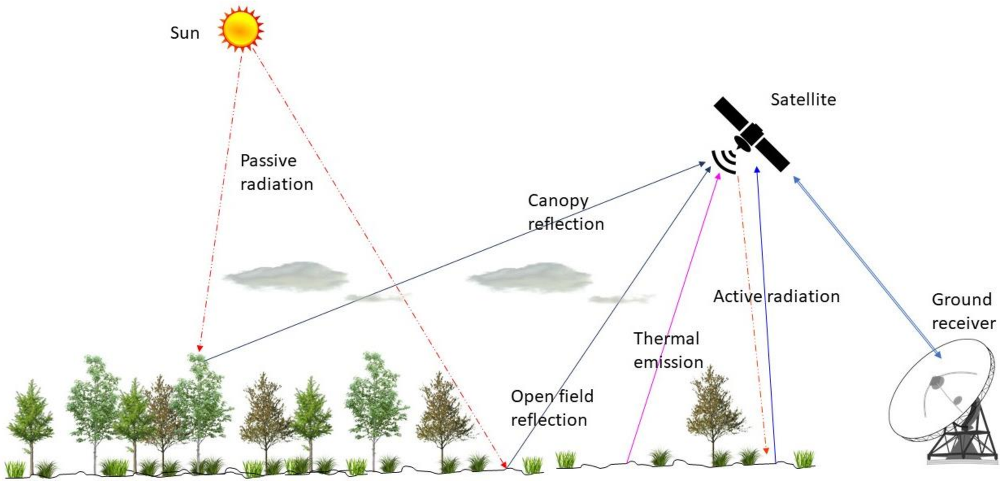

Figure 3.3: Framework for remote sensing of land surface

Remote sensing applications in mapping salt-affected soils target land surface evidence of salt problems in the soil. Examples of proximal sensors often used are electromagnetic induction (EMI), geophysical sounding, and reflectometers. These sensors are mostly used to determine bulk soil electrical conductivity (Lesch et al., 1992). Low-altitude sensors such as Unmanned Arial Vehicles (UAV) are also gaining traction in mapping salt-affected soils (Hu et al., 2019; Ivusking et al., 2019). Hu et al. (2019) tested hyperspectral camera mounted on UAV and EMI in mapping salinity and found UAV as the most promising method for high-resolution identification of soil surface salinity characteristics.

Satellite remote sensing are the most popularly used. They cover wide areas in a single scene, which is economical for large-area mapping. Moreover, most satellite images are increasingly becoming freely downloadable and gaining wide applications because of globally tested models and free processing algorithms. Their applications range from interpretation of composite images to modelling the relationships between indices of image reflectance and indicators of salt problems in the soil (Matternicht and Zinc, 2003; Gorji et al., 2019). Widely used remote sensing images for mapping soil resources are Landsat, sentinel and (Moderate Resolution Imaging Spectroradiometer (MODIS) (Table 3.1). These images are globally available for free download.

Table 3.1: Commonly used remote sensing image characteristics for mapping salt-affected soils

Band category	Bands	Landsat (OLI)	Sentinel-2	MODIS (MOD09A1)
Visible	Blue	B2*	B2	B3
	Green	B3	B3	B4
	Red	B4	B4	B1
Infrared	IR	B5	B8	B2
Shortwave Infrared (SWIR) 1	SWIR1	B6	B11	B6
Shortwave Infrared (SWIR) 2	SWIR2	B7	B12	B7
Spatial resolution (pixel size)		30 m	10 m(B2-B8) and 20m (B11-B12)	500 m

*B is notation for satellite image band

Examples of popularly used image indices in mapping salt-affected soils are normalized salinity index (NSI), salinity index (SI), soil adjusted vegetation index (SAVI), vegetation soil salinity index (VSSI), normalized difference salinity index (NDSI), normalized difference vegetation index (NDVI), salinity ratio (SR), canopy response salinity index (CRSI), and brightness index (BI) (Gorji et al., 2019). They are summarized in Table 3.2. These indices have been variously used either alone or in combination to model soil surface salinity characteristics.

Table 3.2: Examples of popular image band combinations for soil salinity mapping

Image bands*	Band ratio		Remarks
SWIR1(B6), NIR(B5), SWIR2(B7)	NSI	$NSI = \frac{B6 - B7}{B6 - B5}$	Saline: NSI > 1; Non-saline: NSI < 1
Green (B3), Red (B4)	SI1	$SI1 = \sqrt{(B4 * B3)}$	
Blue (B2), Red (B4)	SI2	$SI2 = \sqrt{(B4 * B2)}$	
Green (B3), Red (B4)	SI3	$SI3 = \sqrt{(B4^2 * B3^2)}$	
SWIR1(B6), NIR(B5),	SI4	$SI4 = \frac{B5 * B6 - B6^2}{B5}$	
Blue (B2), Red (B4)	SI5	SI5 = B2/B4	
Red(B4), NIR(B5), Green(B3)	SI6	SI6=B4*B5/B3	
NIR(B5), Red(B4)	SAVI	$SAVI = \frac{B5-B4}{(B5+B4+0.5)*1.5}$	Exponential relationship with EC_{SE}
Green(B3), Red(B4), NIR(B5)	VSSI	Vegetation Soil Salinity Index $VSSI = 2 * B3 - 5(B4 + B5)$	Exponential relationship with EC_{SE}
Red(B4), NIR(B5)	NDSI	Normalized Difference Salinity Index $NDSI = \frac{B4 - B5}{B4 + B5}$	Exponential relationship with EC_{SE}

NIR(B5), Red(B4)	NDVI	Normalized Difference Vegetation Index $$NDVI = \frac{B5 - B4}{B5 + B4}$$	Exponential relationship with EC_{SE}
Blue(B2), Green(B3), Red(B4),	SR	Salinity Ratio $$SR = \frac{B3 - B4}{B2 + B4}$$	
NIR(B5), Red(B4), Green(B3), Blue (B2)	CRSI	Canopy Response Salinity Index $$CRSI = \sqrt{\frac{B5 * B4 - B3 * B2}{B5 * B3 + B3 * B2}}$$	Power relationship with EC_{SE}
Red(B4), Green(B3), NIR(B5)	BI	Brightness Index $$BI = \sqrt{B3^2 + B4^2 + B5^2}$$	

*Band notation used are those of Landsat 8 OLI (Operational Land Imager)

Remote sensing application for mapping salt-affected soils is expedited by the availability of images and processing software. Consequently, the approach is the fastest of all the methods for mapping salt-affected soils. Its application in large areas often produce consistent maps between boundaries of countries, which minimizes the need for harmonization. Furthermore, its time-series application is potentially useful in monitoring changes in status of salt-affected soils. A recent application at the global level was demonstrated by Ivushkin et al. (2019) (Figure 3.4).

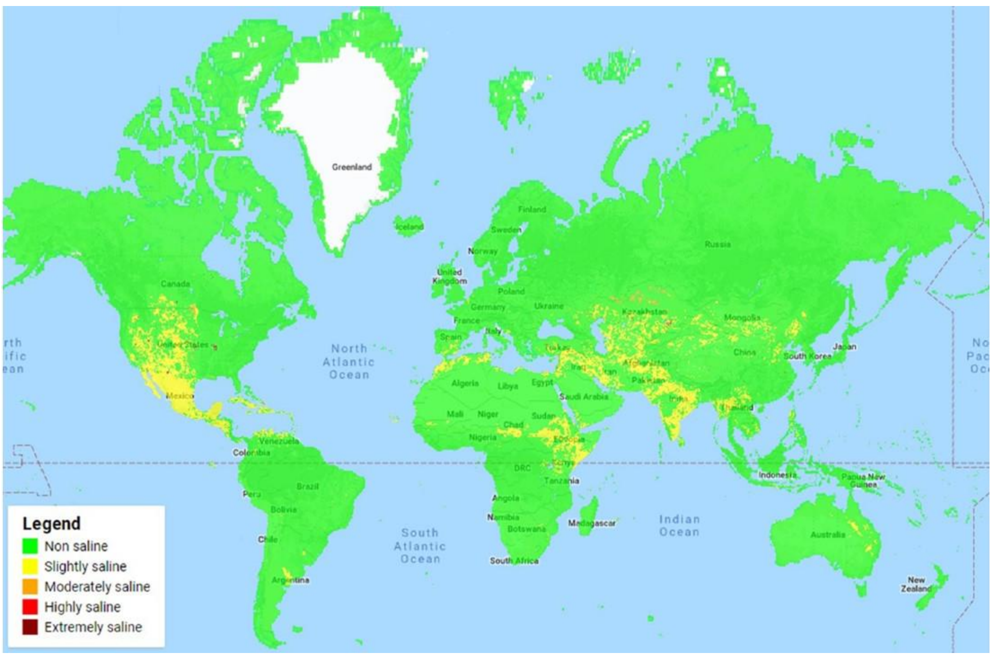

Figure 3.4: Global map of soil salinity using remote sensing applications (source: Ivushkin et al., 2019)

Despite the potential of remote sensing application, the approach is limited in detecting salt problems down the soil profile. Most remote sensing images for large-area mapping do not penetrate more than a few inches of the topsoil and only rely on the calibration models to estimate salt problems down the soil profile. These calibration models can result into spurious relationships without significance in salt dynamics in the soil (Matternicht and Zinc, 2003; Gorji et al., 2019). Some attempts have been made to overcome these limitations. Combined modelling with other spatial datasets such as climate, soil maps and vegetation cover are examples focused on performance improvements of the approach (Scudiero et al., 2019).

3.3 Methods based on soil indicators of salts

Soil indicators provide evidence of the presence of salts in the soil and occurrence of salt-affected soils. They are traditionally used in most soil classification schemes to identify the soil profiles and soil types belonging to the group of salt-affected soil (Soil Survey Staff, 1999; IUSS Working Group WRB, 2015; Craig and Hempel, 2017). Soil indicators of salt-affected soils are also used to quantify the intensity of salt problems in the soil (Table 2.4). They are also used to calibrate other methods for mapping salt-affected soils. Hence, they play a central role in assessing salt-affected soils and should therefore be the foundation for developing soil information of salt-affected soils.

Three types of applications exist in the literature for mapping salt-affected soils using soil indicators: 1) mapping the soil attributes and classifying the output maps, 2) mapping classes derived from the soil attributes, and 3) classifying calibrated maps of electromagnetic induction outputs or remote sensing images (Figure 3.5) (Triantafilis et al., 2001; Taghizadeh-Mehrjardi et al., 2019).

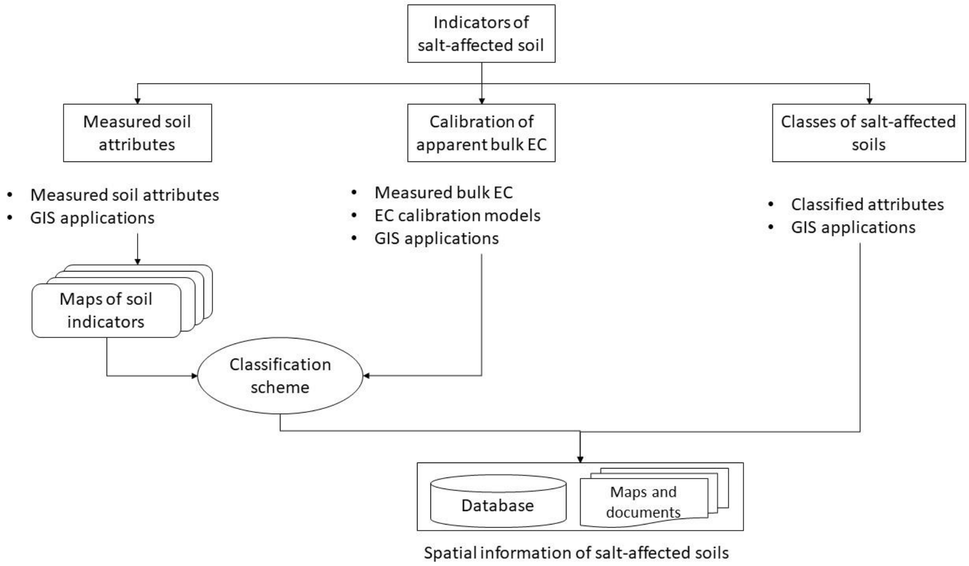

Figure 3.5: Approaches for using soil indicators in mapping salt-affected soils

Applications using calibrated models with EMI are popularly used in mapping soil salinity. In this case, EMI data are calibrated with measured EC on a select sample set and the results used to map soil salinity (Lesch et al., 1992). Farzamian et al. (2019) recently tested the efficacy of local and regional models of this approach to improve its wide adoption. Mapping approaches involving extrapolation of pre-classified classes of salt-affected soils are also available in the literature. These approaches resemble the soil-map based method except that the input data are georeferenced soil attributes. They are not very popular owing to the challenges with extrapolation of categorical attributes (Jafari et al., 2012). Classifying spatially interpolated soil attributes is also another way of mapping salt-affected soils. In this case, the georeferenced soil indicators are first interpolated then the resulting maps are classified into maps of salt-affected soils (Zurqani et al., 2018). This approach was tested by Wicke et al. (2011) to produce a global map of salt-affected soils (Figure 3.6).

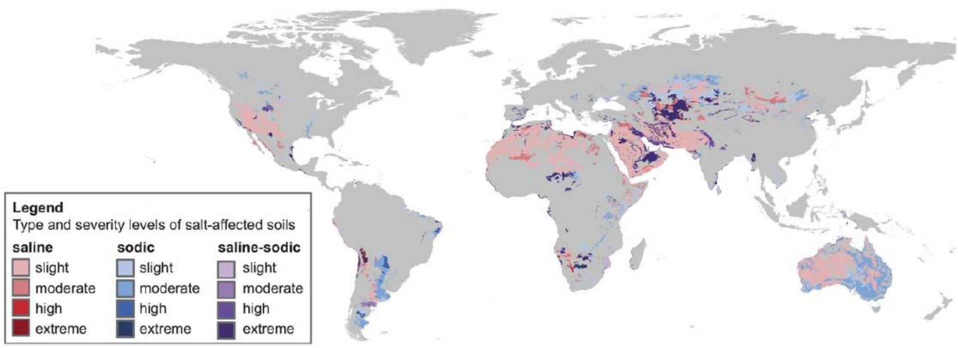

Figure 3.6: Global distribution of salt-affected soils (Source: Wicke et al., 2011)

3.4 Data requirements for mapping soil salinity

Input data for mapping salt-affected soils depends on the mapping methods. A summary of data requirements by the main categories of mapping methods is given in Table 3.3. The soil indicator-based methods are the most data demanding. At least, they require soil data on electrical conductivity (EC), pH, and exchangeable sodium percent (ESP) or sodium adsorption ratio (SAR) as recommended by FAO or USDA classification schemes for salt-affected soils.

Table 3.3: Summary data requirements for mapping salt-affected soils

Major categories of mapping methods		
Based on soil-type maps	**Based on remote sensing applications**	**Based on soil indicators**
1. Classified soil map	1. Remote sensing data/images	1. Electrical conductivity
2. Confirmatory soil data	2. Calibration soil data	2. pH
	3. Georeferenced ground control points	3. ESP or SAR
		4. Soluble ions
Ancillary data		
Land use/cover, hydrogeology, soil degradation, proximity to coastline		
Climate, relief parameters		

3.4.1 Soil data

3.4.1.1 Measured soil properties

Measured soil properties for classifying salt problems in the soil are given in Table 3.4. Soluble ions in this category include Sodium (Na^{+}), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Potassium (K^{+}), Chloride (Cl^{-}), Sulphate ($S0_4^{-2}$), Carbonate ($C0_2^{-2}$), Bicarbonate ($HC0_3^{-}$) and Nitrates ($N0_3^{-}$). They are useful in identification of the dominant salts and types of salt-affected soils. Electrical conductivity (EC), total soluble salts (TSS), total soluble cations (TSC), and total dissolved solids (TDS) are integral measures of salt concentration in the soil. This book recommends a minimum dataset for classifying salt-affected soils as EC, pH and either ESP or SAR because of the recommendations given by the popular salt classification schemes (Table 2.1).

Table 3.4: Summary soil properties for mapping salinity

Property	Notation	Units	Description	Measurement method
Electrical conductivity	EC_{SE}	dS/m	EC (SE*)	Saturated soil paste extract
	EC	dS/m	EC of soil solution	Other soil extracts (1:n mix = soil:water mix)
	EC_a	dS/m	Apparent EC	EC of bulk soil in-situ (EMI, TDR, etc.)
Salt content	TSS	mg/L	Total soluble salts	Evaporation of saturated soil paste extract
	ions	mg/L	Soluble ions	Photometry/spectrometry
Reaction	pH	-	Soil pH (water)	pH meter/ glass electrode
Ionic ratios	SAR	-	Sodium Adsorption	Ratio = sodium (Na) ions/(Mg and Ca ions)
	ESP	-	Exchangeable Sodium	Ratio = exchangeable Na/(100*CEC**)
	Sodium	-	Sodium-chloride	Ratio = Na ions/(sum of Cl and S04 ions)
	carbonate	-	Carbonate-chloride	Ratio = carbonate /(sum of Cl & $S0_4$) ions

*SE- of saturated extract; **CEC- cation exchange capacity

3.4.1.2 Bulk-soil properties and soil maps

Bulk soil properties are properties measured in the field using proximal soil sensors. They are mostly used for estimation of pH and electrical conductivity. The sensors for measuring electrical conductivity are: 1) electrical resistivity, 2) electromagnetic induction, and 3) time domain/amplitude domain/frequency domain reflectometry (TDR, ADR, FDR). They measure electrical conductivity of the bulk soil, which is also known as apparent electrical conductivity (EC_a) (Dalton and van Genuchten, 1986; Corwin and Lesch, 2005).

Field measurement of soil pH is often done using pH meters (and sometimes pH sensors). pH meters are used with samples prepared in the field. Hence, they are not really pH of the bulk soil. The sensors for bulk soil pH include field-efficient transistor (ion-selective field efficient transistor – ISFET) and conductimetric sensors, electrode sensors (Schirrmann et al., 2011).

Soil maps are ensemble of spatial information of groups (units) of soil with certain characteristics. Typical examples of soil maps are polygon maps showing dominant soil types in each polygon and thematic choropleth maps of indicators/classes of salt-affected soil types.

3.4.2 Information on soil forming factors

Soil forming factors are the parent material, land use/cover, climate, and relief. Information on the parent material is obtained from the geology map. The map should contain data on the age and type of lithology of the dominant rocks from which the soil was formed (Figure 3.7). Most geology maps are available as polygon GIS vector files.

Land cover/use information represent the biotic and anthropogenic activities influencing soil formation and secondary drivers of salt problems in the soil. Land cover/cover maps and remote sensing images are suitable sources of information of land cover/use. Examples of climate data are mean annual precipitation (rainfall, snowfall, etc.), annual minimum and maximum temperature, mean annual evapotranspiration rate, and wind speed. Freely downloadable climate data at low-resolution global scale are available at https://www.worldclim.org/ (Accessed on 31 January 2020). Digital elevation model (DEM) is the primary input data for deriving relief information. DEM can be downloadable at https://earthexplorer.usgs.gov/ accessed on 14 January 2020).

3.4.3 Other ancillary data

Other ancillary data for mapping salt-affected soils are administrative boundaries and spatial data of other drivers of salt problems in the soil (Figure 3.7). Spatial data of other drivers of salt problems are maps of hydrogeology (groundwater quality and depth to groundwater level), soil degradation, proximity to coastline, and flood-prone areas.

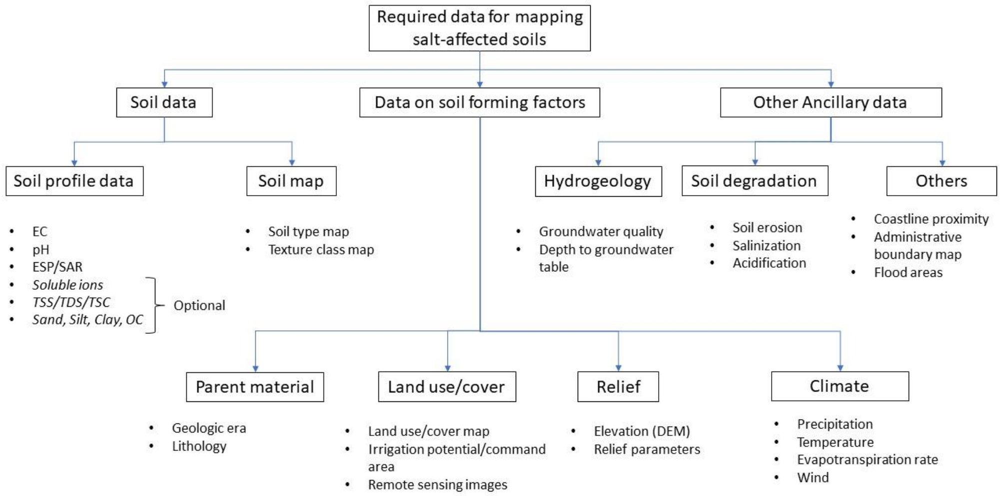

Figure 3.7: Data requirements for mapping salt-affected soils

3.4.4 Conversion models

Electrical conductivity determined on saturated soil paste extract (EC_{SE} in dS/m) is the preferred EC for classifying salt-affected soils. However, many soil laboratories don't analyse EC_{SE} due to the cumbersome laboratory procedures involved with its determination and long turn-around time for analysing many samples. Instead they use other extracts, such as from 1:5 soil:water mix (1 part of soil in 5 parts of water), 1:2.5 solutions, etc (Landon, 1984). Proposals have been made in the literature to calibrate EC determined from other soil extracts to the EC_{SE} equivalent (Hogg and Henry, 1984, Ozcan et al., 2006; Sonmez et al., 2008; Kargas et al., 2018). These proposals depend on the soil texture, organic matter content, temperature, and measured EC_S. A generic framework in these proposals for converting EC to EC_{SE} is as follows:

$$EC_{SE} = f(EC_s, texture, carbon, temperature) + \varepsilon \qquad \text{(Equation 3.1)}$$

Where EC_s is the measured EC other than from saturated soil paste extract method (EC_{SE}). Examples of models for Equation 3.1 in the literature are given in Table 3.5.

Table 3.5: Existing EC conversion models

Model name	Description	Texture class	soil:water mix	Reference
USDA	EC_{SE} = EC*3	All	1:1	Richards (1954)
	EC_{SE} = EC*5	All	1:2	
Landon	EC_{SE} = EC*2.2	All	1.1	Landon (1984)
	EC_{SE} = EC*6.4	All	1:5	
	EC_{SE} = EC*3.81	All	1:3	
Hogg	EC_{SE} = EC*1.75-0.37	All	1:1	Hogg and Henry (1984)
	EC_{SE} = EC*1.38-0.14	All	1:2	
Zhang	EC_{SE} = EC*1.79+1.46	All	1:1	Zhang et al. (2005)
Chi	EC_{SE} = EC*11.68-5.77	All	1:5	Chi and Wand (2010)
Ozcan	EC_{SE} = EC*1.93-0.57	All	1:1	Ozkan et al. (2006)
	EC_{SE} = EC*3.3-0.2	All	1:2.5	
	EC_{SE} = EC*5.97-1.17	All	1:5	
Sonmez	EC_{SE} = EC*2.72-1.27	Coarse texture	1.1	Sonmez et al. (2008)
	EC_{SE} = EC*4.33+0.17		1:2.5	
	EC_{SE} = EC*8.22-0.33		1:5	
	EC_{SE} = EC*2.15-0.44	Medium texture	1:1	
	EC_{SE} = EC*3.84+0.35		1:2.5	
	EC_{SE} = EC*7.58+0.06		1:5	
	EC_{SE} = EC*2.03-0.41	Fine texture	1:1	
	EC_{SE} = EC*3.68+0.22		1:2.5	
	EC_{SE} = EC*7.58+0.24		1:5	
FAO	EC_{SE} = f(texture, clay, carbon, EC)		varied	FAO (2006)

3.5 References

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SECTION TWO: DEVELOPMENT OF INFORMATION ON SALT-AFFECTED SOILS

This section describes the procedural steps for developing multiscale spatial information of salt-affected soils. It demonstrates how to integrate the resources (computer and software, data, and expertise) with methods to develop spatial information of salt-affected soils

4 Preparation for multiscale mapping of salt-affected soils

4.1 Requirements

Multiscale mapping of salt-affected soils requires adequate coordination and mobilization of input data, computer and software for implementing the mapping methods, and a harmonized approach that allows comparison of information in space and time. Input data requirements have been elaborated in Section 1, which gives the relationship between input data and characteristics of salt-affected soils. Mobilization of capital resources and coordination of activities are outlined in Section 3. The interaction between different aspects on input requirements for mapping salt-affected soils are illustrated in Figure 4.1

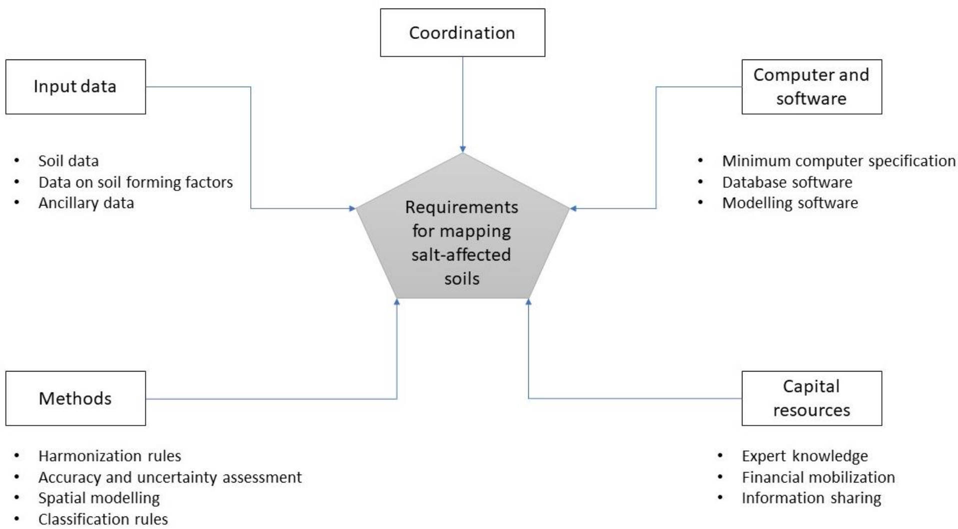


Figure 4.1: Requirements for multiscale mapping of salt-affected soils

4.1.1 Input data

Input data provide evidence of occurrence of salt-affected soils. Their characteristics influence and are also influenced by the specifications of the final outputs of the mapping exercise such as suitable soil depths, spatial resolution of the final maps, incorporation of uncertainty and accuracy assessment , and classification of the intensity of salt problems in the soil. Table 4.1 is an example summary of input data requirements for national, regional and global mapping of salt-affected soils.

Table 4.1: Minimum input data requirements for large-area mapping of salt-affected soils

Data type	Variables	Units	Main data source	Other sources	
				Name	**Format**
Georeferenced soil profile data	EC	dS/m	National data	WOSIS[1], HWSD[2]	vector point data
	pH	-			
	ESP	%			
	*Soluble ions**	*cmol/kg*			
Climate (Mean annual)	Precipitation	mm	National data	Worldclim[3]	vector point data
	Temperature	°C			
Land use/cover	cover/use types	-	National data	ESA[4]	raster image (300 m)
soil map	soil types	-		WOSIS, HWSD	vector polygon
DEM	Elevation	m	Contour map	USGS[5]	Images (15, 30, etc.)
Remote sensing land surface reflectance	Visible reflectance	-	National data	USGS	MODIS Landsat OLI Sentinel, ASTER images
	Infrared Red reflectance	-			
	Shortwave Infrared reflectance	-			
Geology	Lithology types	-	National data		
Hydrogeology*	Groundwater level	m	National data		
	Groundwater quality	-			
Soil degradation	Degradation drivers and classes		National data		

*Optional data

4.1.2 Computer and software

Computer and software are required to process the input data, implement the assessment methods, and to store and share the final spatial information. They include processing, storage, and networking facilities for developing the spatial information of salt-affected soils. Processing facility is the core component responsible for implementing the assessment methods and consist of the computer

[1]WOSIS: https://www.isric.org/explore/wosis
[2]HWSD:http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/
[3] WorldClim: https://www.worldclim.org/
[4] ESA: https://www.esa-landcover-cci.org/
[5] USGS: https://earthexplorer.usgs.gov/

processor and software. Consideration for specification of the processing facility is important since processing complexities tend to increase with increase in spatial extent and resolution of the final outputs. Storage of the input and processed data is handled by the computer storage (hardware) facility. Like the processing facility, the demand for storage facility also increases with increase in spatial extent of the target areas. The sizes of the input images and processed maps may increase from the national to global level assessment. All these considerations influence the minimum computer and software requirements for implementing multiscale mapping of salt-affected soils. The following computer specifications are suggested for national mapping of salt-affected soils:

- Enough processing memory (at least 8GB RAM)
- Fast processing capacity (at least Core i5 or equivalent)
- Enough storage capacity (at least 100 GB)

Internet connectivity is also an important aspect of the computer and software requirements. It enables access to online data repositories during data acquisition as well as during information sharing.

4.1.3 Example input data for demonstrating spatial mapping of salt-affected soils

The case study for demonstration indictor-based spatial mapping of salt-affected soil was obtained is northern Sudan. The area stretches from the Latitude 22° 13' 30.3" to 16° 30' 28.59" North and from the Longitude 32° 41' 3.55" to 25° 0' 0" East (Figure 4.2). Input soil data from this area consist of 379 profile locations which were surveyed in 2018 at various soil depths between 0 and 200 cm. The data includes EC_{SE} (dS/m), pH, ESP, soluble ions (Soluble Na^{+}, $S0_4^{2-}$, $C0_3^{2-}$, $HC0_3^{-}$, and Cl^{-}) in cmol+/kg and were determined using the saturated soil paste extract approach. This data is available at GSP-Secretariat@fao.org.

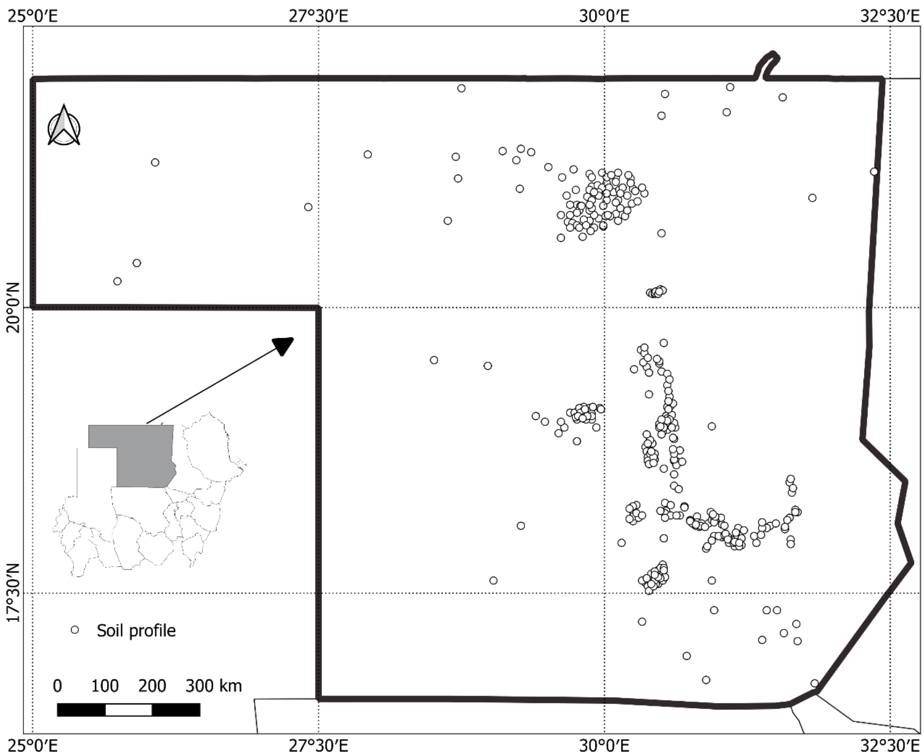


Figure 4.2: Location of soil profile information in Northern Sudan

Data on soil forming factors include multispectral remote images, remote sensing image of digital elevation model (DEM), and maps of land cover types, geology, and mean annual rainfall amount (Table 4.2). The input data also include shapefiles of the case-study boundary and major towns and raster map of aquifer types.

Table 4.2: Case-study input data from northern Sudan (source: Government of Sudan, http://susis.sd/)

Input data category	Data	Description
Soil profile data (0-200 cm soil depth)	EC_{SE}, pH, ESP and SAR Soluble (Na^+, SO_4^{2-}, CO_3^{2-}, HCO_3^-, and Cl^-)	Determined in the laboratory using saturated soil paste extract approach
Soil forming factors	Land cover	Polygon map of major cover classes

	Remote sensing images	500-m MODIS (MOD9A V6)
	Elevation (DEM)	90-m SRTM DEM
	Geology	Polygon map of lithology
	Mean annual rainfall amounts	200-m raster map of annual rainfall
Ancillary data	Boundary and major towns maps	Shapefile
	Hydrogeology map	Aquifer types

4.2 Software requirements for multiscale mapping salt-affected soils

4.2.1 GIS application requirements

GIS applications are useful in spatial data preparation and presentation of the final products to enrich the information content. Commonly used GIS applications for data preparation are:

a) **Reprojection**: This application is needed to align the coordinate system of GIS data into one uniform projection. Projections that give spatial dimensions in meters are preferred while WGS84 geographic (decimal degrees) projection is preferred for data sharing.
b) **Layer clipping**: This application helps with reducing data bulk by trimming the extent within the boundary of the area of interest.
c) **Format conversion**: This application is used to enable data exchange between different software and for data sharing. Format conversion is done to change GIS vector to raster (and vice versa) or to change between raster file types (such as from geoTiff to ASCII).
d) **Resampling**: Resampling application is needed to harmonize resolution of input layers for spatial modelling of indicators and classified map of salt-affected soils.
e) **Image correction**: Image correction is mainly applied to remote sensing images. There are two types of image correction: radiometric and geometric correction. Radiometric correction aims at converting image digital numbers (DN) to reflectance. The algorithms for radiometric corrections are usually given for each type of remote sensing mission. Geometric correction application reprojects the images to a preferred coordinate reference system (CRS) to the images.
f) **GIS database development**: This facility is required to put together a harmonized complete dataset to minimize spatial modelling errors and to ensure compatible storage for future reference or applications.

g) **Map layout**: This is the final value-addition to GIS layers to enhance communication with users of the final products of spatial information for salt-affected soils.

Most GIS software can implement the above applications. The following guidelines can be used to select a suitable GIS software to use:

- Software which accommodates a wide range of GIS file formats
- Software with many alternatives for colour pellets and symbology for map layouts
- Software with easily accessible layer view and graphical user interface functionalities
- Software which is strict with on-screen overlay of truly pixel-harmonized and georeferenced layers
- Software with versatile but easy-to-implement vector-to-raster conversion algorithms
- Software with robust modules for remote sensing applications and direct image download
- Software with vibrant and freely accessible online support
- Easily accessible software (preferably low cost or open source)

Some of the GIS software meeting the above criteria are QGIS (https://download.qgis.org/), ILWIS (https://52north.org/software/software-projects/ilwis/), gvSIG (http://www.gvsig.com/en), and SAGA (http://www.saga-gis.org/en/index.html). Other commercial GIS software such as ArcGIS, ERDAS, IDRISI, ENVI, etc. are also suitable alternatives.

4.2.2 Data harmonization requirements

Data for multiscale mapping of salt-affected soils may have variations and standards because of their sources and methods of data generation, spatial and temporal resolution, file format, and measurement units. Input data harmonization is necessary to produce compatible dataset to reduce errors in data handling and spatial modelling uncertainties. Data harmonization applications include:

a) Standardizing measurement units
b) Converting soil property values to the equivalent of a preferred measurement method
c) Harmonizing soil property values at uniform soil depth intervals

d) Transforming statistical distribution to a preferred probability distribution function
e) Harmonizing spatial resolution, projection and extent of input GIS layers for spatial modelling

In multiscale mapping of salt-affected soils, input data harmonization focuses on soil indicators and GIS spatial layers (Figure 4.3). Software requirement for data harmonization include requirements for implementing data conversion models, image correction and indices development, and harmonizing GIS layers. Statistical harmonization needs are implemented using statistical software while GIS harmonization needs are implemented using GIS software. A suitable software such as R and its contributed packages (R (https://cran.r-project.org/bin/windows/base/) may be suitable for combining statistical and GIS harmonization needs. R contributed packages include soilassessment (Omuto, 2020), raster (Hijmans, 2020), rgdal (Bivand et al., 2019), and GSIF (Hengl, 2019).

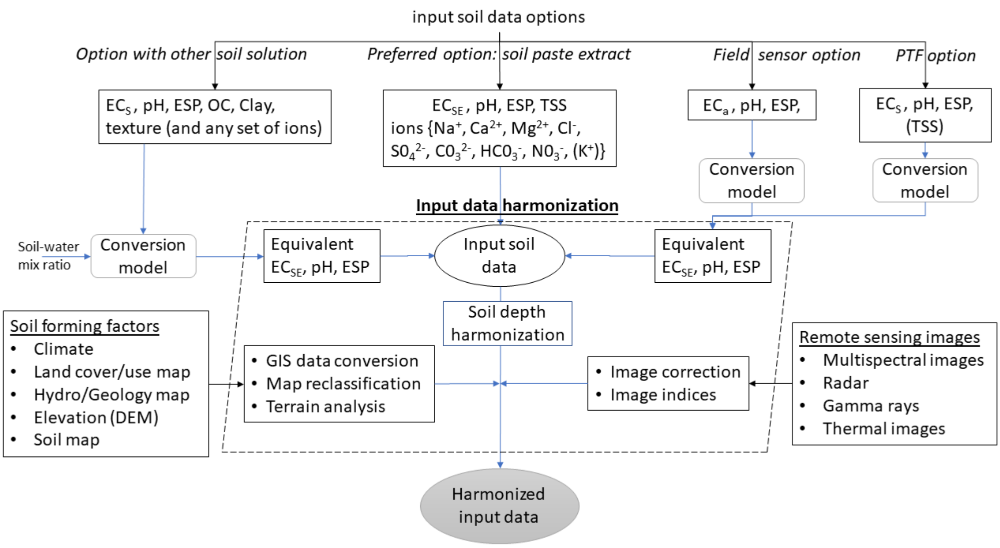


Figure 4.3: Input data harmonization for multiscale mapping of salt-affected soils

4.2.3 Spatial modelling requirements

Multiscale mapping of salt-affected soils requires spatial input data, which are combined through certain procedures to produce spatial information of the status of soil salt problems. Spatial modelling targets the development of spatial layers of input data (indicators) of salt problems and for developing classified map of salt-affected soils. The software requirements for spatial modelling are:

- Functionality for spatial prediction of numerical and categorical variables
- Functionality to estimate mapping accuracy and uncertainties
- Functionality to classify salt-affected soils

Freely downloadable R computing software adequately meets these requirements. Some of its packages are especially useful in implementing some of the above requirements. For example, the soilassessment package has functions for classifying salt-affected soils and estimating mapping accuracy and uncertainties while the caret package has functions for spatial prediction of numerical and categorical variables (Khun, 2020; Omuto, 2020).

4.3 Input data preparation for mapping salt-affected soils

Input data preparation is a necessary step in mapping salt-affected soils. It involves creation of a complete and fully harmonized database of soil profile data, GIS layers, and reference documentation.

i. Soil profile database is the database containing spreadsheet of georeferenced soil profile. The database contains information on soil depth and measured soil properties for each sampled depth, measurement units, methods used in measurements, reference laboratory, date of data acquisition, reference publication (if any), contact person, and summary metafile (text-file).
ii. GIS database is the database containing spatial GIS layers, which are layers of soil forming factors and ancillary drivers of salt problems in the soils.
iii. Document database is the database containing literature of existing information about salt-affected areas, problems, legislation, and previous attempts on solving the problem, etc.

It is important to consider standard GIS practices when preparing and GIS data handling. The practices include:

I. Rule on file path: A short pathname is preferred.

Pathname contains file locations separated by forward or backward slash "/". The number of items in a pathname, which are separated by the slash "/" should be as few as possible and containing no spaces. For example, "C:/Salinity/Input" has two slash symbols implying two folders in the pathname while "C:/Salinity/Sudan/Input" has three slash symbols for three folders in the pathname. The 3-folder pathname is longer than the 2-folder pathname.

II. Rule on file name

DO NOT create filenames or folder-names with spaces (e.g. "salt affected.shp" is not recommended). Instead use underscore or without space (e.g. "salt_affected.shp" or "saltaffected.shp" are recommended).

DO NOT start filenames with numbers, symbols, mathematical operators, full-stop and comma (e.g. ".ECtp.xls" or "+ESP.tif" or "0_30topESP.mpr" are not recommended). It is better not to use mathematical operators in filenames.

DO NOT create filenames with long names (e.g. "salt_affected_soluble_ions_sodium.csv" is not recommended)

Use informative naming style incorporating file type or projection for GIS layers (e.g. "soildata_dg.shp" or "ECtop0_30cm.tif" or "DEM90_UTM37N")

III. Rule on data archive

Separate and protect input data by placing them in input folder and write-protecting it from inadvertent overwrite. The steps shown in Figure 4.4 are useful in creating working and archiving folders and protecting archive folders. Write-protect feature for *input folder* may need to be remove when a new original data is to be added to the archive and the protection reinstated afterwards.

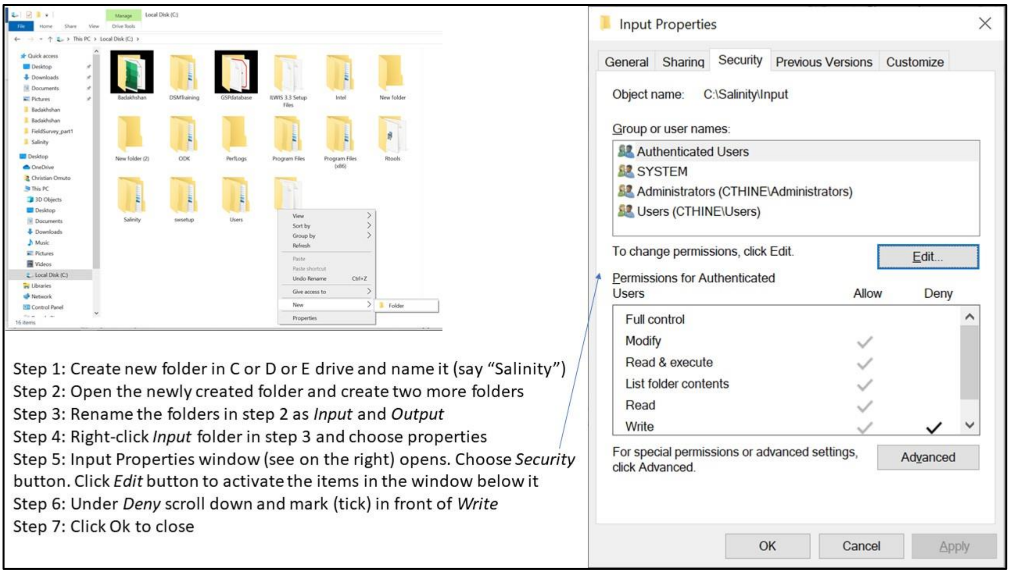


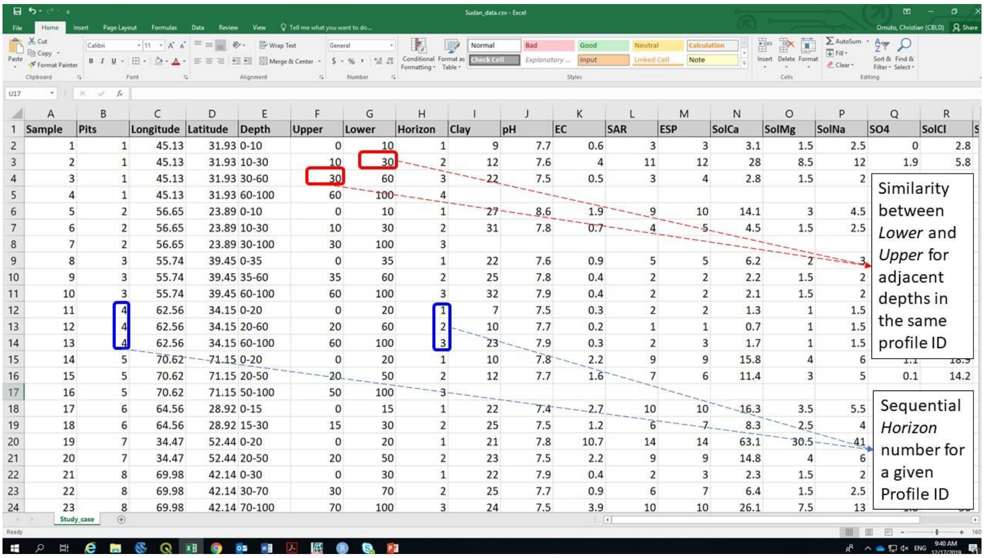
Figure 4.4: Steps for protecting folder with original data

4.3.1 Organizing spreadsheet data

A three-step approach is described for organizing and documenting spreadsheet data.

Step 1: Aligning spreadsheet data

In this step, the spreadsheet data is orderly arranged so that the data rows represent samples and columns represent variables. The samples are distinguished by sequential serial numbers. A good practice is to use the first column as the variable indexing the serial order of the samples. The other variables in the database are consecutively aligned in the columns beginning with profile ID, location description (if any), Latitude and Longitude, and sampling depth-range (Figure 4.5). The depth-range is further split into two variables: *Upper* and *Lower*. *Upper* denotes the first part of the depth-range while *Lower* denotes the last part of the depth-range. The value for *Upper* in one sample should be the same as the value for *Lower* in the preceding sample for the same profile ID (Figure 4.5). Other variables such as Depth Code (or Horizon number), soil texture components, organic carbon, pH, EC, ESP, and additional soil properties (e.g. soluble ions, exchangeable sodium ions and CEC) are also included in that order (Figure 4.5). The Depth Code (or Horizon) should have consecutive numbers beginning with 1 for the first depth to the last sampled depth/horizon in each profile. This arrangement creates repeated numbers/codes for the profile ID and Longitude and Latitude values (Figure 4.5).



	Sample	Pits	Longitude	Latitude	Depth	Upper	Lower	Horizon	Clay	pH	EC	SAR	ESP	SolCa	SolMg	SolNa	SO4	SolCl
2	1	1	45.13	31.93	0-10	0	10	1	9	7.7	0.6	3	3	3.1	1.5	2.5	0	2.8
3	2	1	45.13	31.93	10-30	10	30	2	12	7.6	4	11	12	28	8.5	12	1.9	5.8
4	3	1	45.13	31.93	30-60	30	60	3	22	7.5	0.5	3	4	2.8	1.5	2		
5	4	1	45.13	31.93	60-100	60	100	4										
6	5	2	56.65	23.89	0-10	0	10	1	27	8.6	1.9	9	10	14.1	3	4.5		
7	6	2	56.65	23.89	10-30	10	30	2	31	7.8	0.7	4	5	4.5	1.5	2.5		
8	7	2	56.65	23.89	30-100	30	100	3										
9	8	3	55.74	39.45	0-35	0	35	1	22	7.6	0.9	5	5	6.2	2	3		
10	9	3	55.74	39.45	35-60	35	60	2	25	7.8	0.4	2	2	2.2	1.5	2		
11	10	3	55.74	39.45	60-100	60	100	3	32	7.9	0.4	2	2	2.1	1.5	2		
12	11	4	62.56	34.15	0-20	0	20	1	7	7.5	0.3	2	2	1.3	1	1.5		
13	12	4	62.56	34.15	20-60	20	60	2	10	7.7	0.2	1	1	0.7	1	1.5		
14	13	4	62.56	34.15	60-100	60	100	3	23	7.9	0.3	2	3	1.7	1	1.5		
15	14	5	70.62	71.15	0-20	0	20	1	10	7.8	2.2	9	9	15.8	4	6		
16	15	5	70.62	71.15	20-50	20	50	2	12	7.7	1.6	7	6	11.4	3	5	0.1	14.2
17	16	5	70.62	71.15	50-100	50	100	3										
18	17	6	64.56	28.92	0-15	0	15	1	22	7.4	2.7	10	10	16.3	3.5	5.5		
19	18	6	64.56	28.92	15-30	15	30	2	25	7.5	1.2	6	7	8.3	2.5	4		
20	19	7	34.47	52.44	0-20	0	20	1	21	7.8	10.7	14	14	63.1	30.5	41		
21	20	7	34.47	52.44	20-50	20	50	2	23	7.5	2.2	9	9	14.8	4	6		
22	21	8	69.98	42.14	0-30	0	30	1	22	7.9	0.4	2	3	2.3	1.5	2		
23	22	8	69.98	42.14	30-70	30	70	2	25	7.7	0.9	6	7	6.4	1.5	2.5		
24	23	8	69.98	42.14	70-100	70	100	3	24	7.5	3.9	10	10	26.1	7.5	13		

Figure 4.5: Input spreadsheet data format

It is important to ensure that:

- *Upper, Lower,* and *Horizon* for each profile ID should be increasing down the soil profile
- *Latitude, Longitude* and *Profile ID* should remain constant for each Profile ID
- *Upper* is equivalent to the first part of the *Depth* range and *Lower* is the second part of *Depth*

Step 2: Saving and exporting spreadsheet data

After data organization, the spreadsheet data should be saved (preferably as comma separated values, CSV) for further alignment with other datasets (Figure 4.6).

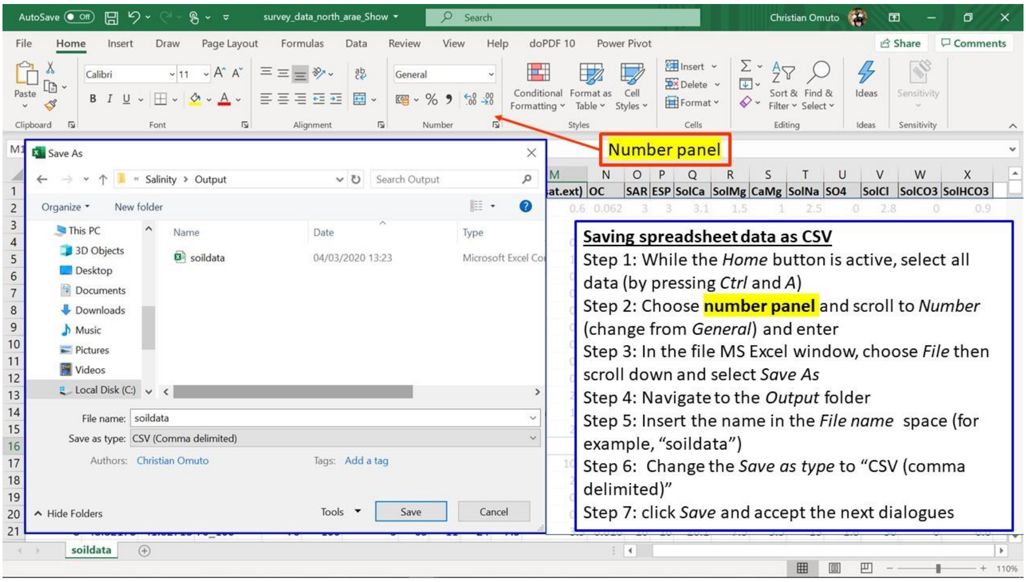


Figure 4.6: Saving spreadsheet data in MS Excel as CSV text file

Sometimes, it may be necessary to ascertain that the computer system separator is *comma* or *semi-colon* since this will influence access to the saved CSV file. The following procedure may be useful to establish the type of system separator.

1. Click on the **Start** menu.
2. Type *control panel*.
3. Click on **Control Panel (Desktop app)**.
4. Select **Clock, Language, and Region**.
5. Click **Region**.
6. Select **Additional settings** in the pop-up window.
7. Check the separator in front of **List separator**

Where necessary, change the system separator to *comma* (by following the above steps and changing to *comma* at step 7 and saving the change). If the system separator is changed after completing the steps in Figure 4.6, then the steps should be repeated.

Step 3: Documenting spreadsheet data

This last step is concerned with documenting the data. The items to document are:

- Title (short description data type – point or spatial GIS layer)
- Data type, date of data generation, number of profiles/augers
- Salinity/sodicity indicator
- Type of measurement (field or laboratory) and units of measurement
- Type of soil-water solution (soil solution extract used)
- GPS coordinate reference system (CRS)
- Reference publication/contact address
-

The following is an example of a two-column textfile/notepad for the documentation. It should be saved as data metafile alongside the CSV file in Figure 4.6.

Title:	Soil salinity measurements of North Sudan in 2018
Data type:	Point-data of soil profiles
Data date:	From January – June 2018
Profiles:	1065 auger holes (0 - 35 cm) and 897 pits (0- 200 cm)
Attributes:	EC (dS/m), pH(H_2O), ESP
Type measurements:	Laboratory (all measurements carried on saturated paste extract)
GPS co-ordinates:	WGS84 (Geographic)
Reference:	Mohamed Nuha (nuha75n@gmail.com; Ministry of Agriculture, Agriculture Research Centre, P.O. Box 126 Wad Medani, Sudan)

4.3.2 Organizing GIS layers

Organizing GIS layers starts from layer acquisition. Online repositories are available for free download of some GIS datasets such as remote sensing images, elevation, land cover/use types, soil, and climate. The link to some of these datasets is given in Table 4.1. An example of steps for GIS data download is given in Appendix A1. Downloaded data is harmonized and archived in input GIS database

4.3.3 Harmonizing input GIS layers

4.3.3.1 Harmonizing coordinate reference system

Coordinate reference system (CRS) defines the projection of a GIS layer. CRS models the Earth's surface into a 2D representation. Since the earth is not a perfect sphere, its surfaces require unique conversion models to transform the 3D landscape into 2D representation. Consequently, there are different CRS models between sets of Latitudes and Longitudes. GIS data organization endeavours to identify layers' CRS and harmonize them into one uniform projection model. Harmonized CRS is a basic core of GIS database because it allows spatial layering of different datasets either for visualization (on the screen) or for subsequent spatial modelling of salt-affected soils. *Reprojection* is the terminology often used in GIS for transforming one CRS to another. The following steps are used for reprojecting GIS layers:

1. Step 1: Identifying the final CRS to use for all GIS layers (here known as harmonized CRS)
   It is important to use WGS 84 (decimal degrees) as the harmonized CRS for all layers because it has uniform parameters throughout the world. During reprojection, this CRS is known as target CRS
2. Step 2: Note the CRS for each GIS layer and the individual need for *reprojection*. This CRS is known as source CRS during reprojection
3. Step 3: *Reproject* the layers as shown in Figure 4.7

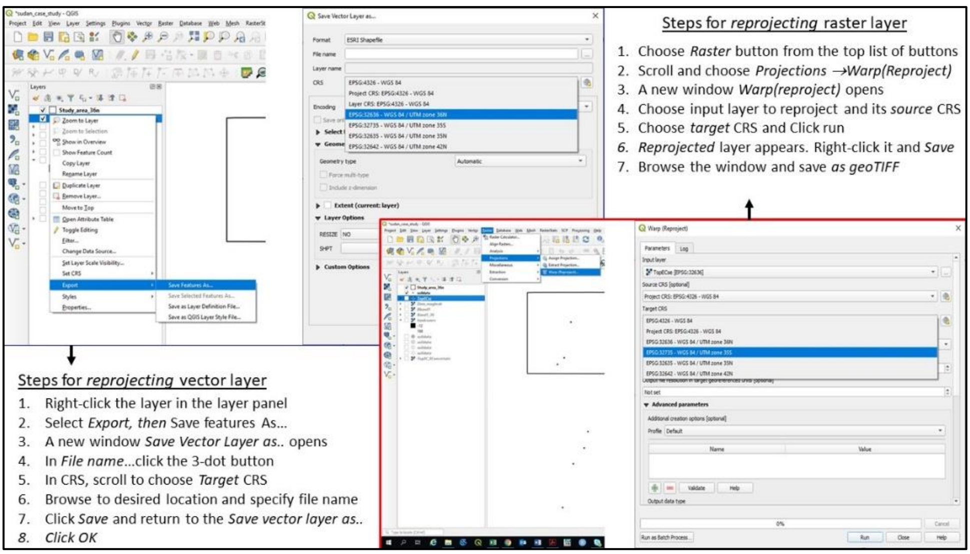


Figure 4.7: Reprojecting GIS layers in QGIS

4.3.3.2 Harmonizing layer format

Not all GIS layers are available in the preferred file format. Most soil forming factors such as soil map, geology, and land cover types are often available as polygon vector files. They need file format conversion to raster since spatial modelling is normally done on raster file formats. The process of harmonizing GIS layer formats attempts to convert vector files to raster formats. It also seeks to convert all file in the database to uniform filetypes. Vector-to-raster conversion is the GIS function for harmonizing vector polygons into raster data types.

Vector-to-raster conversion in QGIS can be implemented using modules in GRASS, SAGA, GDAL, or QGIS Raster tools. Except for SAGA, all the other modules require an attribute of unique integers designating the polygon items for vector-to-raster conversion. Nonetheless, they all produce comparable results for mapping salt-affected soils. Creating an attribute of unique integers may require additional steps that are accessible at https://docs.qgis.org/testing/en/docs/user_manual/index.html.

Some of the pre-requisite operations before vector-to-raster harmonization include projection harmonization, identification of the target polygon attribute to use in the conversion, decision on the target pixel resolution of the final raster map, and cleaning of missing entries, topology errors, and associated errors in the data entry. Figure 4.8 illustrates the steps for vector-to-raster conversion in QGIS.

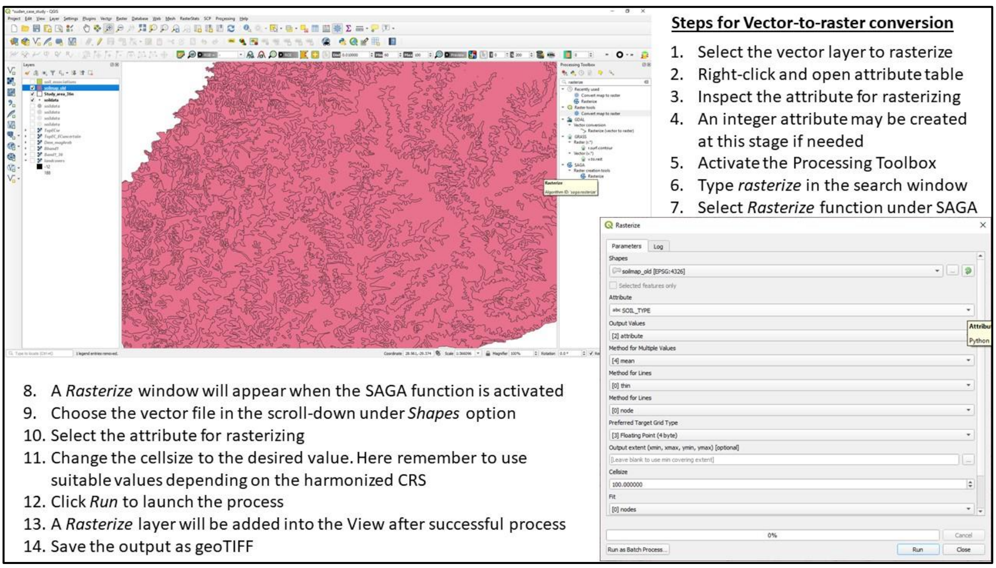


Figure 4.8: Steps for vector-to-raster conversion in QGIS

4.3.3.3 Harmonizing remote sensing images

(1) Image correction

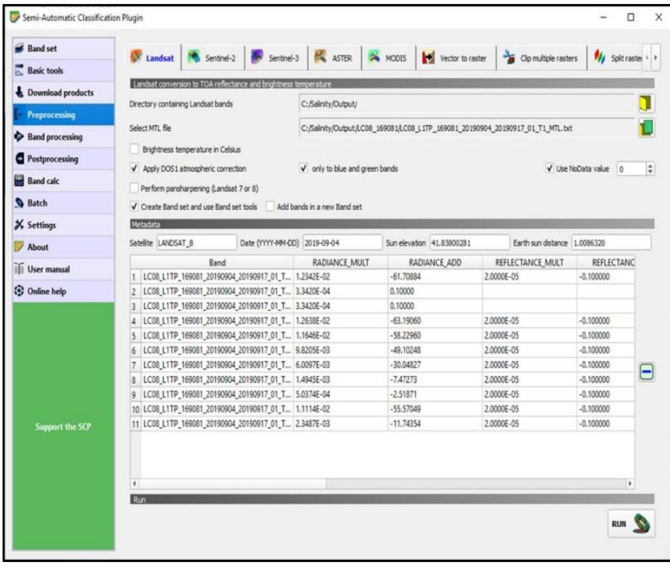
Input remote sensing images for spatial modelling of salt-affected soils come from diverse sources with different characteristics such as spatial extent, image digital numbers, CRS, and file format. They need harmonization before integration in the modelling process. Image correction is the harmonization process for aligning the characteristics of downloaded images to correspond with those of the established GIS database for mapping salt-affected soils.

a. Step 1: Unzip the downloaded images.

Most downloaded images are wrapped in compressed files such as .zip, .rar or .gz. They should be unpacked into commonly used GIS file formats such as geoTIFF, ASCII, HDF, etc. Software such as WinZip or WinRar or 7-Zip unpacks the compressed files into a preferred destination folder (such as C:/Salinity/Output). Sometimes the unpacked file may still contain compressed files and another unpacking step should be used in this regard to extract the GIS files. Different zipped files should be unzipped into different folders to avoid over-writing metafiles and for processing each file independently.

b. Step 2: Image correction

Semi-Automatic Classification Plugin (SCP) in QGIS provides a quick way for simultaneous geometric and radiometric correction of remote sensing images. The plugin has many functions for handling different types of remote sensing images such as Landsat, Sentinel-2, Sentinel-3, ASTER, MODIS, etc. Figure 4.9 illustrates how these types of images are corrected using SAC plugin in QGIS.



Steps for image correction using SAC

1. Select and set the working CRS for the QGIS window. Harmonized CRS is preferred
2. Launch the plugin
3. Select *Preprocessing* button
4. Select the image type (say Landsat)
5. In front of the *Directory containing landsat bands*: Select the folder containing the unpacked Landsat images. Each folder is processed at a time
6. Select the MTL file, which is a textfile with MTL at the end of the file name.
7. If the image type is Sentinel-2, the textfile name ends with MSI
8. Click *Run* to execute the command. A prompt for choosing the output folder comes up. The folder with the downloaded image (step 4 above) is preferred
9. If the image type is MODIS, the no need for the textfile since the information is already contained in the header-file.
10. The corrected image images will be loaded into the QGIS view window.
11. Repeat the steps for all downloaded image scenes

Figure 4.9: Image processing using semi-automatic classification plugin

c. Step 3: Combine and size Images

Downloaded images sometimes cover regions that extend outside the study area. In such cases, the images need to be clipped using the boundary layer of the study area. Besides image clipping, there are also cases where two or more remote sensing image-scenes are needed to cover the study area completely. Image mosaicking is used to join adjacent images to produce a composite image that covers the whole study area. The harmonization process endeavours to merge overlapping data and/or trim data to fit the study area.

(1) Mosaicking images

Although there are algorithms for mosaicking several bands in one-step, band-by-band mosaicking is preferred as it gives room to assess the quality of the output product. Starting with Band1, vertically overlapping images covering the country are selected and mosaicked (Figure 4.10). The process is repeated for all the bands of the selected image type. It is important to:

1) note of the image CRS and harmonized pixel size for the resultant mosaicked image
2) select a suitable choice of name for each mosaicked image band (say *Mosaic1* for band 1)

3) identify the need for further clipping of the final mosaicked bands to trim them to the study area.

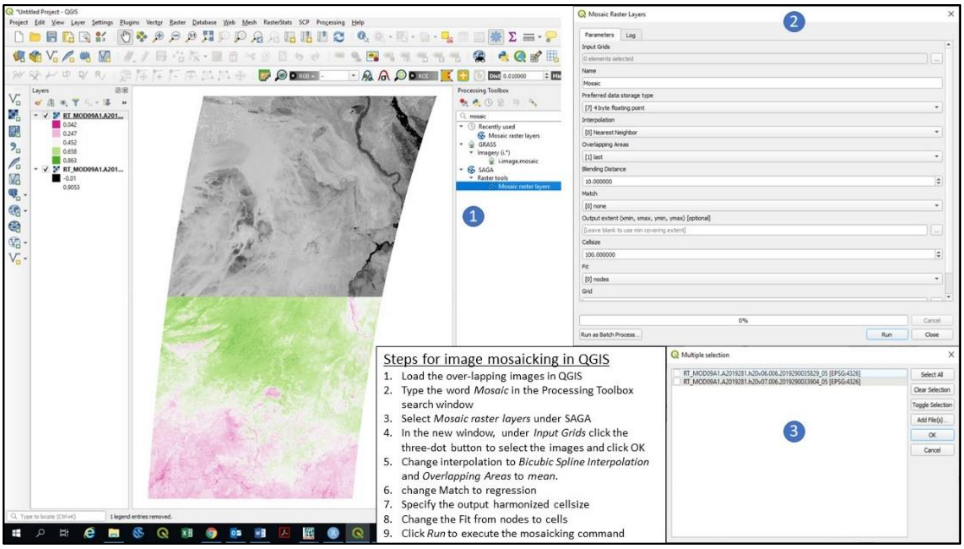


Figure 4.10: Mosaicking remote sensing images

(2) Image trimming

Image trimming/clipping/masking produces reduced data size and customizes products to the area of interest. The steps for image clipping are illustrated in Figure 4.11.

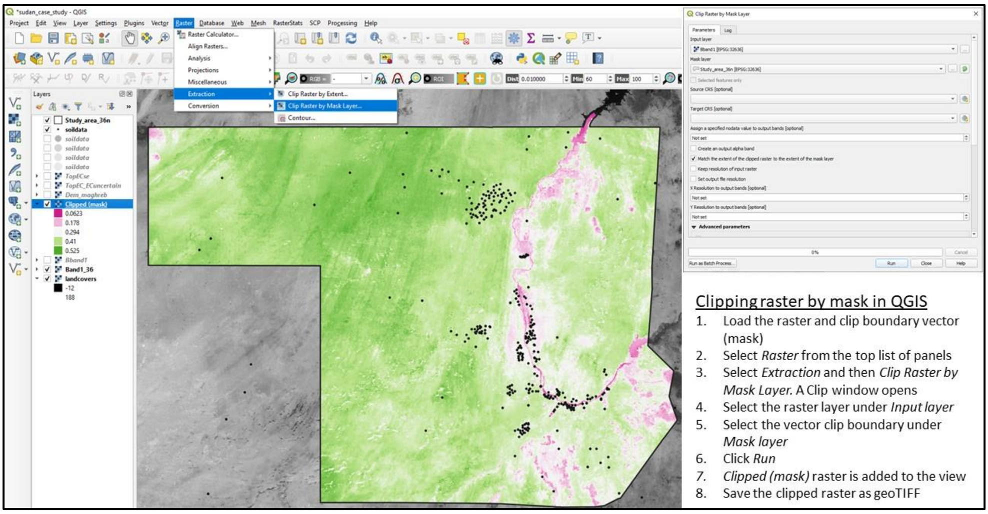


Figure 4.11: Image clipping using QGIS

4.3.3.4 Harmonizing relief data

Relief data is processed to produce a set of terrain parameters influencing the distribution of salt-affected soils. The literature categorizes terrain parameters as either primary or secondary attributes (Wilson and Gallant, 2000). Primary attributes are derived from the altitude and directional location of the topographic surface. They include slope, aspect, curvature, flow accumulation and up-slope flow contributing area. Secondary attributes are obtained from the altitude and derivatives of the primary attributes. They depict surface characteristics regarding water distribution and light reflection and include indices such as topographic wetness index, compound topographic index, stream power index, etc. (Li et al., 2005).

Elevation map is the primary input for extracting terrain parameters. Where necessary, depressionless elevation is first developed to improve the quality of the derived parameters (Weibel and Heller, 1991). SAGA software has a module for simultaneous derivation of 14 terrain parameters from DEM input. Its implementation steps are given in Figure 4.13.

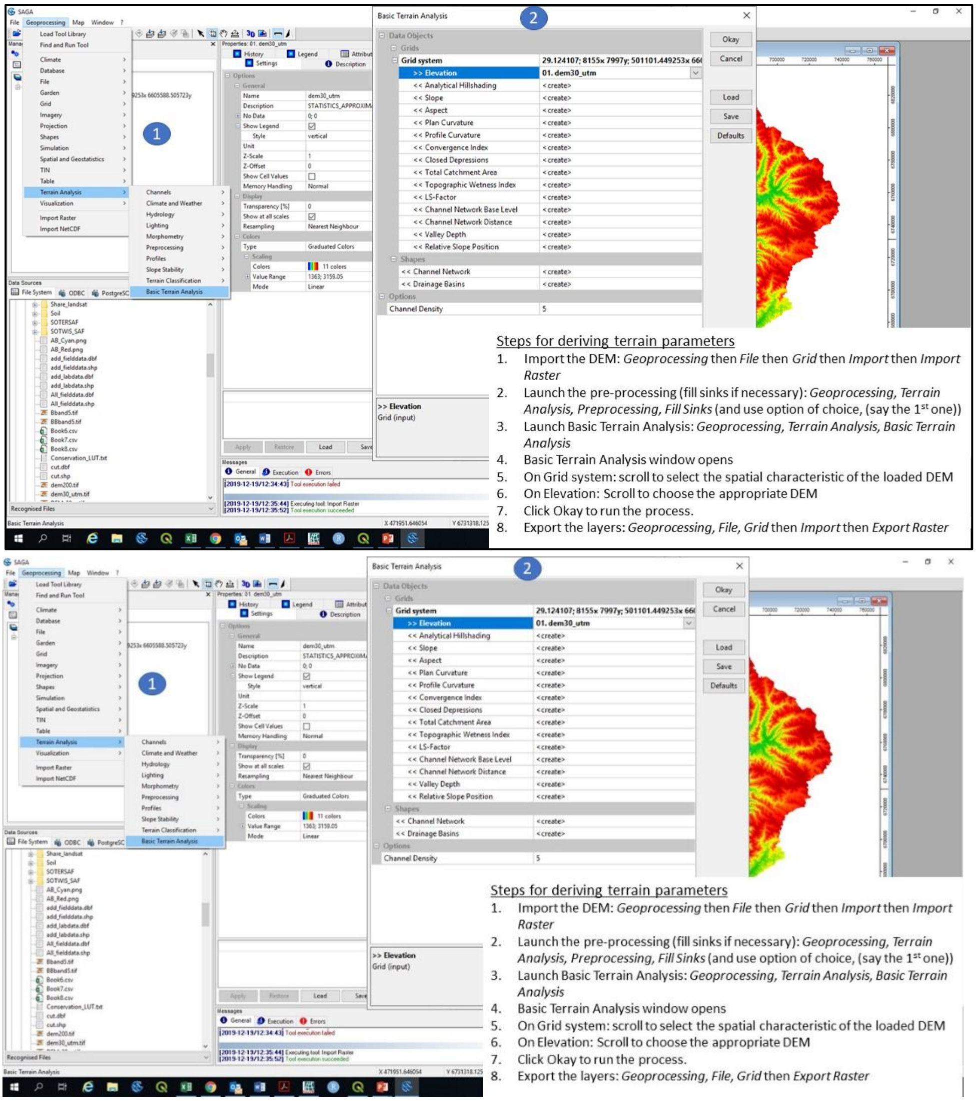


Figure 4.13: Steps for digital terrain analysis in SAGA

At least two primary and two secondary terrain parameters are adequate for modelling salt-affected soils. This book proposes slope, longitudinal curvature, LS-factor, Channel Network Base Level, and Valley Depth as the terrain parameters for mapping salt-affected soils.

4.3.4 Input GIS database

Properly established and complete GIS database has many advantages in data management, spatial modelling and as organized baseline for future monitoring activities. GIS database for multiscale mapping of salt-affected soils comprise harmonized input data, documentation (metadata) of the input data, and methods and software for data access and preparation (Figure 4.14). The database is the backbone for spatial information of salt-affected soils and should therefore be properly established and standardized to improve efficiency in information update, access, and data sharing.

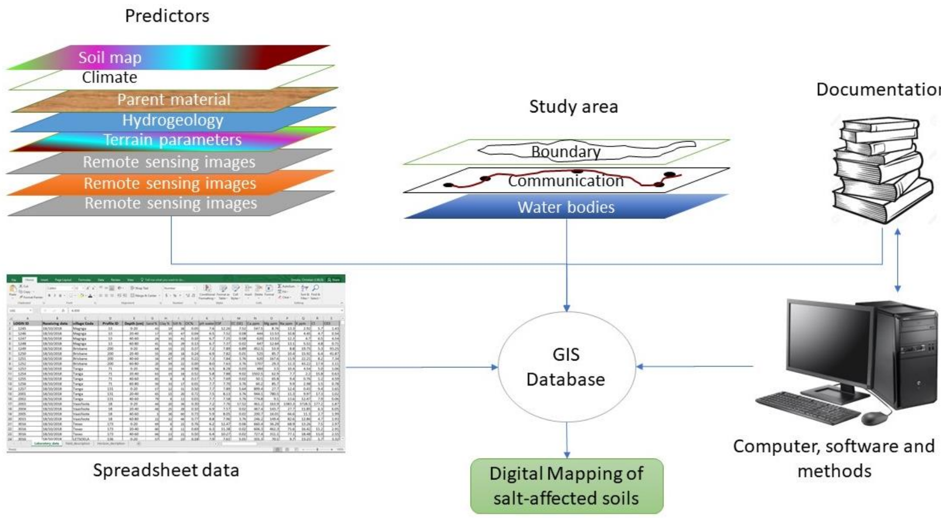


Figure 4.14: Development of GIS database for mapping salt-affected soil

Some of the desired GIS database characteristics for mapping salt-affected soils re:

- The database should have representative data (raster layers) of soil forming factors, ancillary information on other drivers of salt problems in the soil (such as groundwater and irrigation command areas), and soil indicators of salt-affected soils
- All methods for data transformation and metadata should be documented
- All input (un-processed) data should be archived in secured *input* folder and protected from inadvertent data modification. The processed data should be saved in the *Output* folder, which should also be the *working directory*.
- All GIS raster files should be harmonized to a common CRS and pixel resolution

ILWIS map-list is a suitable facility for ensuring that all harmonized raster layers have uniform CRS and pixel resolution. Unlike other GIS software which can allow (force) on-screen overlay even for different layer characteristics, ILWIS never overlay non-harmonized layers. In addition, it can also facilitate multivariate statistics and harmonization of statistical distribution of the layers. Figure 4.15 gives the steps for creating a map-list of harmonized raster layers.

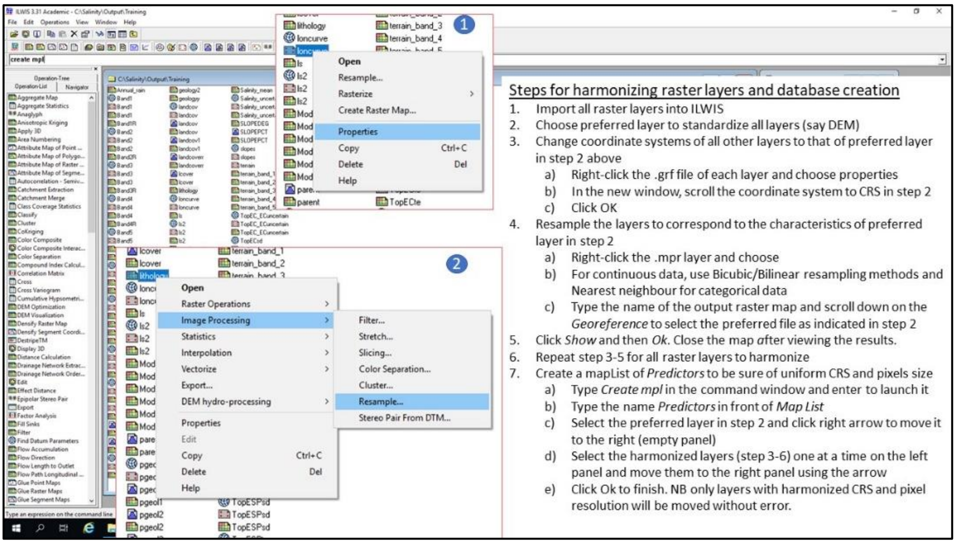


Figure 4.15: Creating spatially harmonized GIS database in ILWIS

The final GIS database should have:

1. Spreadsheet soil data. It should contain at least the following variables: Sample, Pits, Longitude, Latitude, Depth, Upper, Lower, Horizon, EC, pH, ESP
2. GIS layers. This data should have the following minimum layers
    a. Relief parameters: Elevation (denoted as dem), slope (slope), slope-length factor (ls), channel network to basin level (cnbl), longitudinal curvature (loncurve), and valley depth (valley)
    b. Remote sensing image bands: Blue band (BBlue), Green band (BGreen), Red band (Bred), Infrared band (BIRed), shortwave band 1(swir1), and shortwave band 2 (swir2)
    c. Land cover (lcover)
    d. Climate: rainfall (rain), maximum temperature (maxtempr), and minimum temperature (mintempr)

e. Geology (geology)
f. Hydrogeology (pgeology)
g. Soil map (soilmap)
h. Erosion (erosion)

4.4 References

1. Bivand R, Keitt T, Rowlingson B, Pebesma E. 2019. rgdal: Bindings for the 'Geospatial' Data Abstraction Library. https://cran.r-project.org/web/packages/rgdal/index.html
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5 Country-driven global mapping approach

5.1 Background

The country-driven approach for mapping salt-affected soils is based on indicator mapping backed by drivers of salt-affected soils and models for classification of the salt problems. The approach integrates and borrows from the potential of other mapping methods. It also offers quantification of mapping accuracy and uncertainty, which are increasingly accepted by the soil science community as a standard practice. It also facilitates building of spatial information on indicators and drivers besides information on the status of salt-affected soils at multiple scales. However, these advantages come at the price of data demand. Some of the required input data such as soil indicators (ESP and Soluble ions) may not be readily available in many territories.

The country-driven global mapping is a three-step approach anchored on input data harmonization, spatial modelling of input soil indicators using spatial predictors, and classification of salt-affected soils (Figure 5.1).

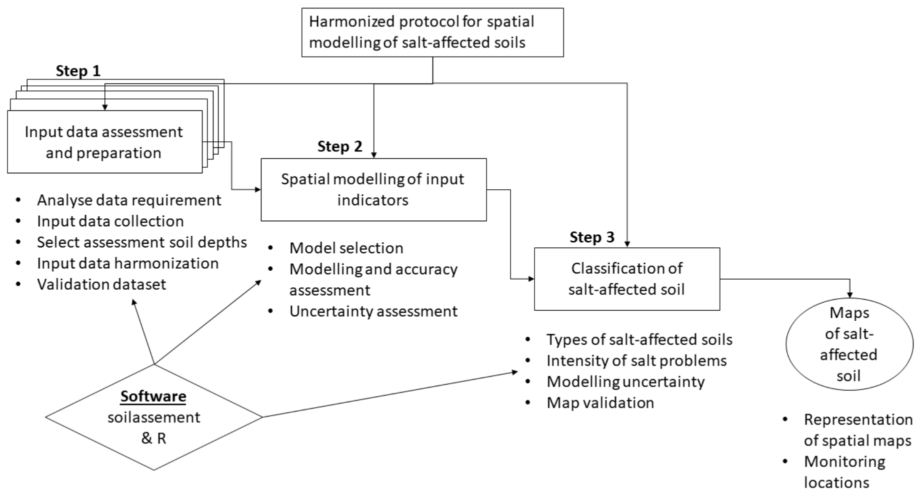


Figure 5.1: Multiscale approach for national mapping salt-affected soils based on indicator maps

The approach puts emphasis on measured soil data (EC, pH, and ESP) as the primary soil indicators for classifying salt-affected soils. These input soil data are spatially modelled to produce maps of soil indicators of salt-affected soils. Appropriate classification schemes are selected to classify the indicator maps into maps of salt-affected soils (Figure 5.1).

R software and its contributed packages are the principal software for implementing the country-driven global mapping protocol. A summary of the key packages for implementing various steps of the protocol is given in Table 5.1. RStudio software (https://rstudio.com/products/rstudio/download/) is used as an integrated development environment to support implementation of the packages in R.

Table 5.1: R packages and their application in multiscale mapping of salt-affected soils

Mapping protocol application area	Package	Package reference
Text editor (for scripting and documentation)	RStudio (as an integrated development environment and not as a package)	RStudio Team (2015)
Input data import and export (including GIS data analysis)	rgdal	Bivand et al. (2019)
	raster	Hijman (2020)
	sp	Pebesma and Bivand (2020)
Harmonization	soilassessment	Omuto (2020)
	GSIF	Hengl (2019)
	car	Fox et al. (2020)
Spatial modelling (including uncertainty and accuracy assessment)	Caret	Khun (2020)
	soilassessment	Omuto (2020)
	sp	Pebesma and Bivand (2020)
Classification of salt problems	soilassessment	Omuto (2020)

These packages and their dependencies are installed using the following commands in R

```
>install.packages(c("raster", "sp", ”rgdal”, ”car”, “carData”, ”dplyr”, ”spacetime”, ”gstat”, ”automap”, ”randomForest”, “fitdistrplus”, “e1071”, “caret”, “soilassessment”, “soiltexture”, “GSIF”, “aqp”, “plyr”, “Hmisc”, “corrplot”, “factoextra”, “spup”, “purrr”, “lattice”, “ncf”, “npsurv”, “lsei”, “qrnn”, “nnet”, “mda”, “RColorBrewer”, “vcd”, “readxls”,”maptools”,”neuralnet”,”psych”))
```

```
>library(sp); library(foreign); library(rgdal); library(car);library(carData); library(maptools)
```

library(spacetime); library(gstat); library(automap);library(randomForest);library(fitdistrplus); library(e1071); library(caret); library(raster); library(soilassessment); library(soiltexture); library(GSIF); library(aqp); library(plyr); library(Hmisc); library(corrplot); library(factoextra) library(spup); library(purrr); library(lattice);library(ncf);library(npsurv); library(lsei); library(nnet); library(class); library(mda); library(RColorBrewer); library(vcd); library(grid); library(neuralnet);library(readxl); library(psych);library(qrnn); library(dplyr)

It is important to note the following points when implementing the mapping protocol in Figure 5.1 in R.

- R is a case-sensitive scripting software. More than 90% of its commands are scripted in a text-editor and executed by running the line/script
- Hash (#) denotes the beginning of a comment and is not executed by the software. Consequently, it can be used to insert comments in a line. All comments after hash (#) are colored green (like green traffic light) implying "pass" without execution.
- Errors and warnings are given in red, while functions and number are given in blue and commands and variables are given in black.
- When using RStudio text-editor, four panes are available in which the top left pane is the text editing window, top right pane is for data environment, bottom right pane is for display and help, and the bottom left is the console for executing the scripts
- Implemented scripts and reports (warning or errors) are shown in the console pane
- Some commands may run for some time and patience is recommended to enable the software to progress to completion. During such time, a red icon will be shown at the top left corner of the console pane

5.2 Step 1: Input data harmonization

Input data harmonization at this point is carried out to: 1) harmonize soil indicators to those of saturated soil paste extract, 2) harmonize statistical distribution to normal distribution, and 3) harmonize soil depths at the interval of 0-30 cm, 30-100 cm, and 100-200 cm (and more depending on soil depths). These harmonization steps compliment those that were done during input data preparation.

5.2.1 Harmonizing GIS layers

 # Step 1-1: Import the data

Begin by setting the working directory. This is a recommendation building on the previous database development in which the input processed data were saved in the output folder (c:/salinity/output) in Section 4.3.4.

```
> setwd("C:/Salinity/Output") # Setting the working directory
> soil=readOGR(".","soildata") # Importing soildata.shp as shapefile
```

Spreadsheet data can also be imported directly as excel data or CSV using appropriate commands such as soil = read_xlsx ("soildata.xlsx") for importing MS Excel or soil=read.csv("soildata.csv",header=T) for importing CSV filetype. GIS rater files are imported using either *readGDAL* or *raster* functions. Both functions accept many GIS raster file format such as geoTIF, ILWIS, ASCII, etc. When using the *readGDAL* function, the first instance is used to create a stack space for subsequent layers. Hence, it does not have "$" sign at the end of *predictors* and does not have *"$band1"* at the end of the import line. The function is unique since (1) it does not accept import and stack of layers of different dimensions in terms of spatial extent and pixel sizes and (2) it automatically creates a stack (here known as predictors) for input GIS layers. Subsequently, it is a preferred function for ensuring input data conformity. If the *raster* function is used, it may be necessary to resample the layers in case of possible differences in dimensions that may later introduce modelling errors. All imported input GIS layers should be named accordingly (dem, slope, ls, loncurve, cnbl, valley, rain, lcover, geology, pgeology, BBlue, BGreen, BRed, BIRed, swir1, swir2, etc.)

```
> predictors=readGDAL("dem.tif")
> predictors$slope=readGDAL("SLOPE.mpr")$band1
> predictors$ls=readGDAL("ls.asc")$band1
> predictors$valley=readGDAL("valley.mpr")$band1
> predictors$geology=readGDAL("geology.mpr")$band1
```

….

```
> predictors$BBlue=readGDAL("BBlue.mpr")$band1
> predictors$swir1=readGDAL("swir1.asc")$band1
> predictors$swir2=readGDAL("swir2.tif")$band1


> predictors$dem=predictors$band1 # for replacing the first layer
> predictors$band1=NULL # for removing replaced layer
```

```
# Step 1-2: Check the data for unique values and remove where possible
```

```
> summary(predictors)
#  Object of class SpatialGridDataFrame
```

```
#  Coordinates:
#          min     max
#  x  -75674.99  417325
#  y 1883692.11 2443692
#  Is projected: TRUE
#  proj4string :
#  [+proj=utm +zone=36 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +t
owgs84=0,0,0]
#  Grid attributes:
#    cellcentre.offset cellsize cells.dim
#  x            -75176 997.9757       494
#  y           1884191 998.2175       561
#  Data attributes:
#       dem            loncurve                 ls               cnbl
#  Min.   : 176.0   Min.    :-1.000e-07   Min.   :0.000002   Min.   :1
78.6
# 1st Qu.: 292.5   1st Qu.:-1.000e-07   1st Qu.:0.011727   1st Qu.:27
9.4
# Median : 342.9   Median :-1.000e-07   Median :0.033486   Median :32
6.9
# Mean   : 349.7   Mean   : 1.170e-06   Mean   :0.053562   Mean   :33
2.3
# 3rd Qu.: 399.1   3rd Qu.: 1.149e-06   3rd Qu.:0.062155   3rd Qu.:38
0.0
# Max.   :1064.6   Max.   : 3.295e-04   Max.   :7.043770   Max.   :57
1.0
#  ………….
#      swir1            swir2             BBlue             BGreen
# Min.   :0.008162   Min.   :0.002062   Min.   :0.009072   Min.   :0.
01625
# 1st Qu.:0.554471   1st Qu.:0.533823   1st Qu.:0.426480   1st Qu.:0.
11551
# Median :0.625109   Median :0.603396   Median :0.476060   Median :0.
13294
# Mean   :0.604679   Mean   :0.582251   Mean   :0.462953   Mean   :0.
13189
# 3rd Qu.:0.676205   3rd Qu.:0.650973   3rd Qu.:0.516825   3rd Qu.:0.
15002
# Max.   :0.868268   Max.   :0.838160   Max.   :0.679898   Max.   :0.
22036
```

 # Remove NAs in case they occur due to data clipping

```
> predictors$slope=ifelse(is.na(predictors$slope),mean(!is.na(predict
ors$slope)),predictors$slope)
```

Statistical distribution of the GIS layers may also need to be checked if it requires harmonization. The histogram function (*hist*) is used to facilitate visual assessment for skew and need for normalization. In the case-study sample dataset, slope and rainfall layers showed skewed distribution and are normalized with square root and log-transformation, respectively. Other transformation models can be tested for other datasets.

 # Check for frequency distribution of the GIS layers

```
>
hist(predictors@data[,c("dem","slope","loncurve","cnbl","valley","lcover","rain", "geology","pgeology")])
```

 # Step 1-3: Derive the remote sensing indices

Remote sensing image indices in Table 3.1 related to surface features/evidence of salt problems are determine using *imageIndices* function in the *soilassessment* package. It uses seven bands of the input remote sensing data, which should now be in the *predictors* stack of layers. They are specified in the script using the "*$*" symbol with the predictors.

```
> predictors$SI1=imageIndices(predictors$BBlue,predictors$BGreen,predictors$BRed,predictors$BIRed,predictors$swir1,predictors$swir2,"SI1")

#    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#  0.03426 0.16152 0.18227 0.17972 0.20203 0.28645


> predictors$SI2=imageIndices(predictors$BBlue,predictors$BGreen,predictors$BRed,predictors$BIRed,predictors$swir1,predictors$swir2,"SI2");summary(predictors$SI2)
#    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
#  0.02974 0.31104 0.34469 0.33663 0.37158 0.50973
```

…………

 # Continue to complete all 13 image indices (see appendix A and Table 3.1).

```
> predictors$BI=imageIndices(predictors$BBlue,predictors$BGreen,predictors$BRed,predictors$BIRed,predictors$swir1,predictors$swir2,"BI");summary(predictors$BI)
#    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
# 0.1113  0.5757  0.6454  0.6302  0.7039  0.9405
```

Any NAs produced during the calculation of the image indices can also be removed using the command in *Step 1-2*. Altogether, there are at least 13 layers of image indices produced. This number can be reduced using multivariate principal component analysis (PCA). The next step assesses statistical distribution of the image indices and harmonizes them to normal distribution, which is a prerequisite for PCA data reduction.

 # Step 1-4: assess statistical distribution and harmonize where necessary

```
> hist(predictors@data[,24:29]) # Figure 5.2
> summary(predictors$SI6)
#     Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
#  0.003647 0.940943 1.129692 1.068303 1.232106 1.663694

> predictors$BI=sqrt(predictors$BI)
> hist(predictors$BI)
```

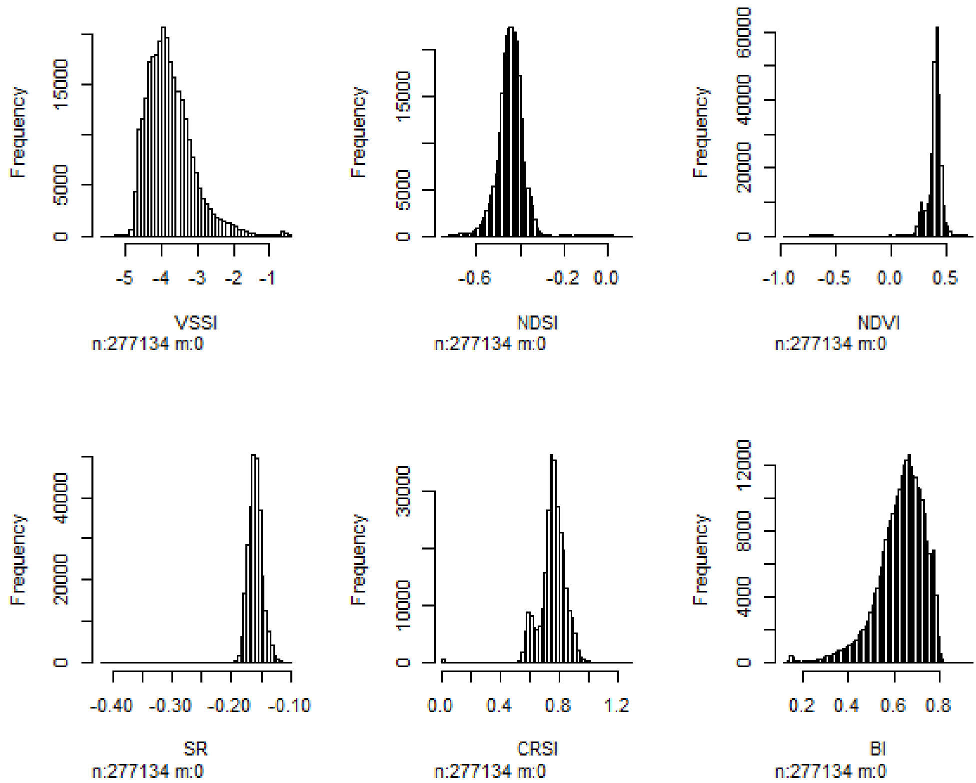


Figure 5.2: Empirical statistical distribution of image indices from Sudanese case-study dataset

VSSI and BI image indices showed slight skew. Test with square-root transformation was found to adequately normalize the data. Although the transformation model is arbitrarily tested at this stage, it is better to use robust models such as the Box-Cox transformation (Box and Cox, 1964).

 # Step 1-5: Perform PCA and select the first PCs accounting for over 95% of the image indices' variation

After normalizing the image indices, they are selected and converted into data-frame to enable determination of correlation and principal component analysis. Afterwards, the selected PCs are converted back to the raster stack.

 # Extract the image layers

```
> predicters=predictors@data[,c("SI1","SI2","SI3","SI4","SI5","SI6","SAVI","VSSI","NDSI","NDVI","SR","CRSI", "BI")]
> soil.cor=cor(predicters)
> corrplot(soil.cor,method="number",number.cex = 0.8) # Figure 5.3a
> pca<-prcomp(predicters[], scale=TRUE)
```

```
> fviz_eig(pca) # Figure 5.3b
```

The correlation plot (Figure 5.3b) shows the correlation between image indices. For example, SI1 and SI2 have a Pearson correlation index equal to 86%. PCA examines these correlations and determines the principal axes where data are highly correlated. These axes are also known as principal component (or dimensions in Figure 5.3b). Figure 5.3 is important in guiding the choice of PCs to represent the entire (13) layers of image indices.

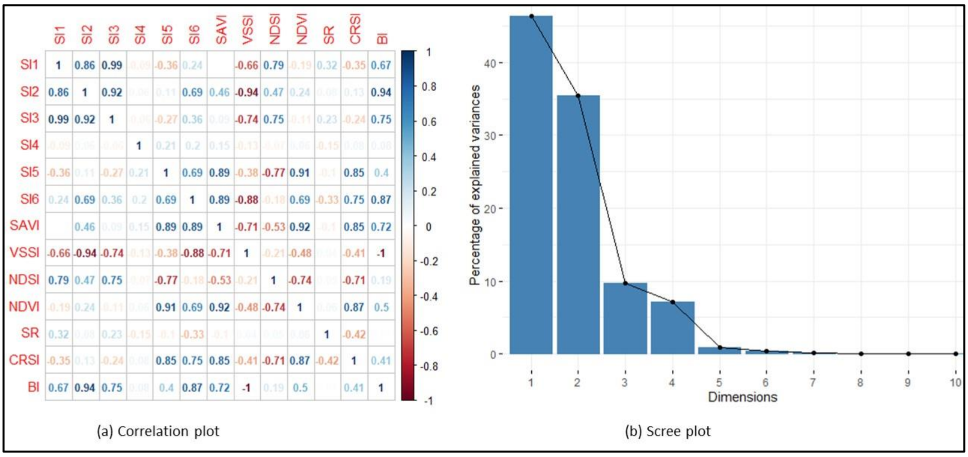


Figure 5.3: Correlation of image indices and scree plot of their principal component

In Figure 5.3b, cumulative sum of the first 4 PCs (Dimensions) add up to more than 95% explained variation in the overall 13 layers of the image indices. Hence, the first 4 PCs can adequately represent the 13 image indices. This approach can be used on any set of image indices to select the appropriate number of PCs to reduce the data bulk.

 # Return the selected PCs to the raster stack to complete the harmonization process

```
> Pred.pcs<-predict(pca,predicters[])
> predictors@data$PCA1=Pred.pcs[,1]
> predictors@data$PCA2=Pred.pcs[,2]
> predictors@data$PCA3=Pred.pcs[,3]
> predictors@data$PCA4=Pred.pcs[,4]
```

5.2.2 Harmonization of input soil data

 # Step 1-6a: Harmonize input indicator measurements to those for saturated soil paste extract

Many methods can be used to determine EC. They include (1) use of saturated soil paste extract, (2) using other soil extracts, (3) using pedotransfer models from other soil properties, or (4) electromagnetic induction. Harmonization seeks to standardize methods 2 to 4 to the equivalent values in method 1, since popular classification schemes use values obtained by method 1.

(1) Example harmonization using known models in Table 3.5 (in Chapter3)

#Step 1-6b: Load the library and import the soil data

NB: This part is for the purposes of illustrating the steps for harmonizing EC. The case-study data indeed contains EC as obtained by the method of saturated soil paste extract and do not need harmonization. A quick look at the data structure is necessary to establish availability and format for target variables (EC, texture components, and organic carbon). The *str* function extracts the data structure.

```
> str(soil)
```

```
'data.frame':192 obs. of  14 variables:
 $ Sample   : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Pits     : int  1 1 2 3 4 5 6 6 7 8 ...
 $ Longitude: num  62.2 62.2 62.2 62.2 62.2 ...
 $ Latitude : num  30.2 30.2 30.2 30.2 30.2 ...
 $ Upper    : int  0 20 0 0 0 0 0 40 0 0 ...
 $ Lower    : int  20 100 30 30 30 30 40 100 30 40 ...
 $ Horizon  : Factor w/ 2 levels "A","B": 1 2 1 1 1 1 1 2 1 1 ...
 $ EC        : num   1.16 1.63 0.499 0.295 0.161 0.8 1.85 0.938 0.167
0.141 ...
 $ PH       : num  8.3 8.71 8.64 8.72 9.14 8.6 8.86 8.95 8.83 9.45 ...
 $ ESP      : num  3.61 7.16 2.76 2.26 1.56 ...
 $ Sand     : num  51 45.2 45.2 55.2 67.2 43.2 45.2 49.2 49.2 85.2 ...
 $ Silt     : num  38 44 39 32 20 44 39 36 31 2 ...
 $ Clay     : num  11 10.8 15.8 12.8 12.8 12.8 15.8 14.8 19.8 12.8 ...
 $ OC        : num  0.21 0.32 0.24 0.66 0.23 0.36 0.17 0.05 1.37 0.12
...
```

The data seems to have the required variables for harmonizing EC values. The first step in the harmonization is to derive the soil textural classes. The functions for deriving the soil textural classes do not accept NAs in the data. Hence, they must be clearly checked and removed from the list of variables containing the textural components. This is done by first creating a dummy column to sum the texture components and using this dummy to choose only data-entries without missing entries (i.e. *NA*). In the case-study dataset, the texture components appear in variables number 11 (Sand), 12 (Silt) and 13 (Clay) (Note that there are 14 variables all together).

#Step 1-6c: Check for missing data and select only complete dataset

```
>          variable.names(soil[11]);         variable.names(soil[12]);
variable.names(soil[13]);
> soil$dummy= rowSums(soil[, 11:13])
> soil1=subset(soil,!is.na(soil$dummy))
> soil1$dummy=NULL # remove the dummy
> soil0=data.frame(soil1)
```

#Step 1-6c: Create and code the texture classes

```
> SSCP=soil0[,c("Clay","Silt","Sand")]
> names(SSCP) = c('CLAY', 'SILT', 'SAND')
> SSCP = round(SSCP, 2)
> SSCP_norm = TT.normalise.sum(tri.data = SSCP[,1:3], residuals = T)
> colnames(SSCP_norm)[1:3] = paste0(colnames(SSCP_norm)[1:3],"_nm")
> SSCP = cbind(SSCP, round(SSCP_norm, 2))
>
SSCP$CLAY=SSCP$CLAY_nm;SSCP$SILT=SSCP$SILT_nm;SSCP$SAND=SSCP$SAND_nm
> rm(SSCP_norm)
> soil0=cbind(soil0,"TEXCLASS" =TT.points.in.classes(tri.data =SSCP[,
   c('CLAY',  'SILT',   'SAND')],class.sys = "USDA.TT",        PiC.type
   = "t",collapse  = ', '))
> soil0$TEXCLASS=as.factor(soil0$TEXCLASS)
> soil0$TEXCLASS1=as.numeric(soil0$TEXCLASS)
> summary(soil0$TEXCLASS)
> rm(SSCP)
> soil0$TEXCLASS=car::recode(soil0$TEXCLASS,"'Lo, SiLo'='SiLo'") #
Here, the double classes are changed one at a time
> summary(soil0$TEXCLASS)
      Cl        Lo  Lo, SiLo      LoSa    SaClLo      SaLo      SiLo
       2        51         2         9         1       104        22

> soil0$TEXCLASS1=dplyr::recode(soil0$TEXCLASS,Cl=1, ClLo =7, Lo=11,
   LoSa=10, Sa=12, SaCl=8, SaClLo=9,SaLo=5,
   SiCl=2,SiClLo=3,SiLo=4,Si=6,CS=13,MS=14,HCL=16,FS=15)
> summary(soil0$TEXCLASS1)
  Min.    1st Qu.   Median     Mean    3rd Qu.     Max.
  1.000   5.000     5.000        6.691    11.000       11.000

> soil1=soil0
```

#Step 1-6d: EC harmonization

It is important to note again that the sample case-study variables were determined on saturated soil paste extract. Hence, the examples for harmonization given here are for the purpose of demonstrating script implementation. Suppose the EC was determined from 1:1 soil extract, then the following script is used to harmonize the EC values.

```
>
soil1$ECse1=ECconversion1(soil1$EC,soil1$OC,soil1$Clay,soil1$texture1
,"1:1","FAO")
> summary(soil1$ECse1)
```

```
  Min.  1st Qu.   Median     Mean   3rd Qu.     Max.     NA's
0.4912   2.0461   4.0769  10.5302   9.8501  108.8235        1
```

(2) Example harmonization using pedotransfer function

#Step 1-6e: EC harmonization

Pedo-transfer function (PTF) is a function for estimating soil property by utilizing functional relationship between this property (known as a target variable, such as EC_{SE}) and other easy-to-measure soil variables such as texture, carbon, etc. Suppose a few samples have EC_{SE} measurements, then a PTF is built between EC_{SE} and the other soil properties. The PTF function is stored and later used to estimate EC_{SE} for all (or future) samples in the study area. The *soilassessment* package has *pedoTransfer* function for building PTF. This function provides for alternative models such as linear, random forest, support vector machine, neural networks, etc. for modelling the relationship between the target soil variable and its predictors. The first term in the *pedoTransfer* function specifies the preferred model such as *randomforest*, *svm*, *neuralnetwork*, *linear*, etc. The second term specifies the dataframe containing the calibration dataset. This dataframe should not have *NAs* in any of the variables for developing the pedotransfer model. The last terms are unlimited list of predictor variables, which are separated by comma. Their names should be like the variable names in the dataframe.

```
> soil2 =soil1[sample(nrow(soil1)), ][1:(floor((nrow(soil1)/4)*1)), ]
> soil2=subset(soil2,!is.na(soil2$ECse))
> EC.ptf= pedoTrasnfer("randomforest",soil2,ECse,Sand,OC,Clay)
> soil1$ECpf=predict(EC.ptf, newdata=soil1) #to attach the harmonized
ECSE equivalent
> plot(soil1$ECse,soil1$ ECpf)
> abline(a=0,b=1,lty=20, col="black")
```

(3) Example harmonization of apparent electrical conductivity of bulk soil

#Step 1-6f: EC Harmonization

Apparent electrical conductivity of bulk soil (EC_a) is measured in the field using proximal sensors such as EMI. It's possible to obtain many sampled data points with this EC measurement approach owing to its rapid nature. However, the measured ECa values need calibration with measured EC_{SE} to harmonize them. The harmonization is a two-step process in which the calibration model is first build between selected samples with EC_a and EC_{SE} and then the model applied to the remaining EC_a to estimate the equivalent EC_{SE}. In the *soilassessment* package, the function *ECconversion3* facilitates this kind of harmonization. The following scripts demonstrate how to use *ECconversion3* to harmonize ECa with EC_{SE}. A scatterplot of

ECa with EC_{SE} is important in guiding the choice for the link model. In the given example, a power relationship is assumed as the link model between EC_a and EC_{SE} (Figure 5.4). Other link options such as linear, exponential, logarithmic, etc. are also provided in the *ECconversion3* (Omuto, 2020).

```
> plot(ECse~ECa,soil2) # To choose a suitable predictive model #(Figure 5.4)
> EC3.ml=nls(EC~ECconversion3(ECa,A,B,"power"), start=c(A=0.1, B=0.8), data=soil2)
> soil$ECse3=ECconversion3(soil$EC, coef(EC3.ml)[1], coef(EC3.ml)[2],"power")
```

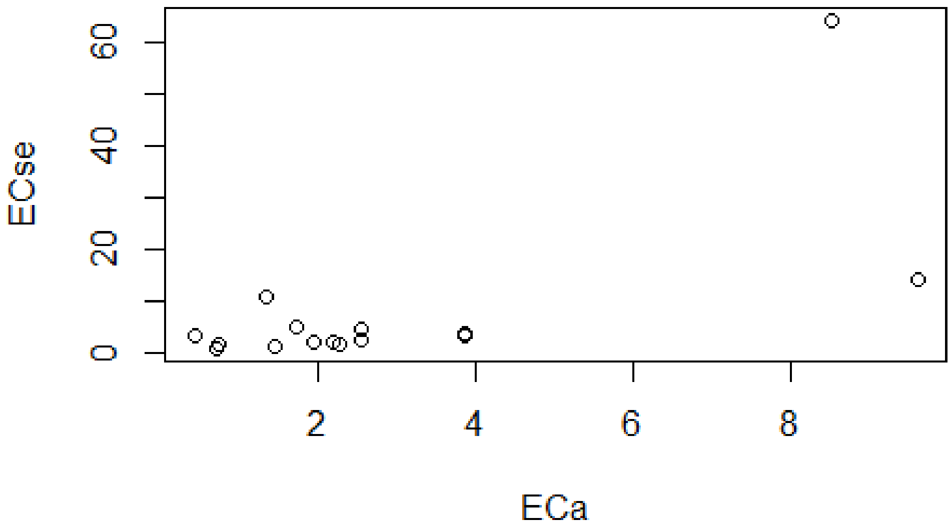


Figure 5.4: Graphical illustration of relationship between apparent and measured EC

#Step 1-7: Harmonizing soil depths

Soil depth harmonization aims at developing soil information for uniform depth throughout the soil data. Uniform depth facilitates comparison of salt problems down the profile and horizontally across the landscape. This harmonization is achieved with the depth-integrating spline approach (Bishop et al., 1999). The tool for implementing the approach is contained in the *GSIF* package (Hengl, 2019).

```
> lon=soil1$Longitude
> lat=soil1$Latitude
> id=soil1$Pits
> top=soil1$Upper
>  bottom=soil1$Lower
> horizon=soil1$Horizon
> ECdp=soil1$EC
> prof1=join(data.frame(id,top,bottom, ECdp, horizon),data.frame(id,l
on,lat),type="inner")
Joining by: id
> depths(prof1)=id~top+bottom
Warning message:
converting IDs from factor to character
> site(prof1)=~lon+lat
> coordinates(prof1) = ~lon+lat
> proj4string(prof1)=CRS("+proj=longlat +datum=WGS84 +no_defs")
> depth.s = mpspline(prof1, var.name= "ECdp", lam=0.8,d = t(c(0,30,10
0,150)))
Fitting mass preserving splines per profile...

   |================================================================|
100%
> plot(prof1, color= "ECdp", name="horizon",color.palette = rev(brewe
r.pal(8, 'Accent')),par=c(cex.lab=2.0)) #Figure 5.5
```

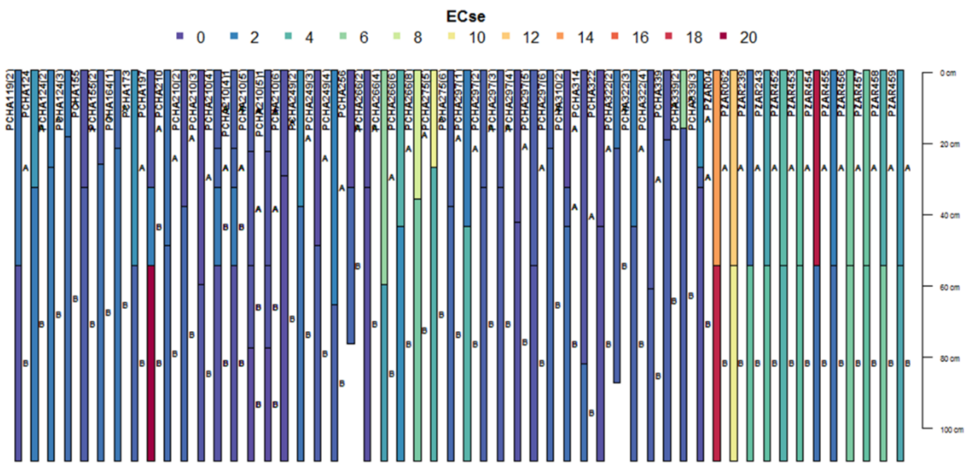


Figure 5.5: Example depth harmonization for EC_{se}

#Step 1-8: Extract the depth-harmonized soil data and re-project

```
> soilhrmdepths=data.frame(depth.s$idcol, depth.s$var.std, check.name
s = TRUE)
> soil2=merge(soil1,soilhrmdepths,by=intersect(names(soil1),names(soi
lhrmdepths)),by.x="Pits",by.y="depth.s.idcol",all=TRUE)
```

```
> coordinates(soil2)=~Longitude+Latitude
> proj4string(soil2)=CRS("+proj=longlat +datum=WGS84")#Attach CRS to
the data
```

#Harmonize CRS and ensure use of the correct +proj and +zone for the study area

```
> soil1=spTransform(soil2,CRS("+proj=utm +zone=36 +ellps=WGS84 +units
=m +no_defs"))
> soil1=soil2
> hist(soil1$EC)
> soil1=subset(soil1,!is.na(soil1$EC))
> bubble(soil1,"X0.30.cm", main="Harmonized EC (0-30 cm)") #Figure 5.
6
```

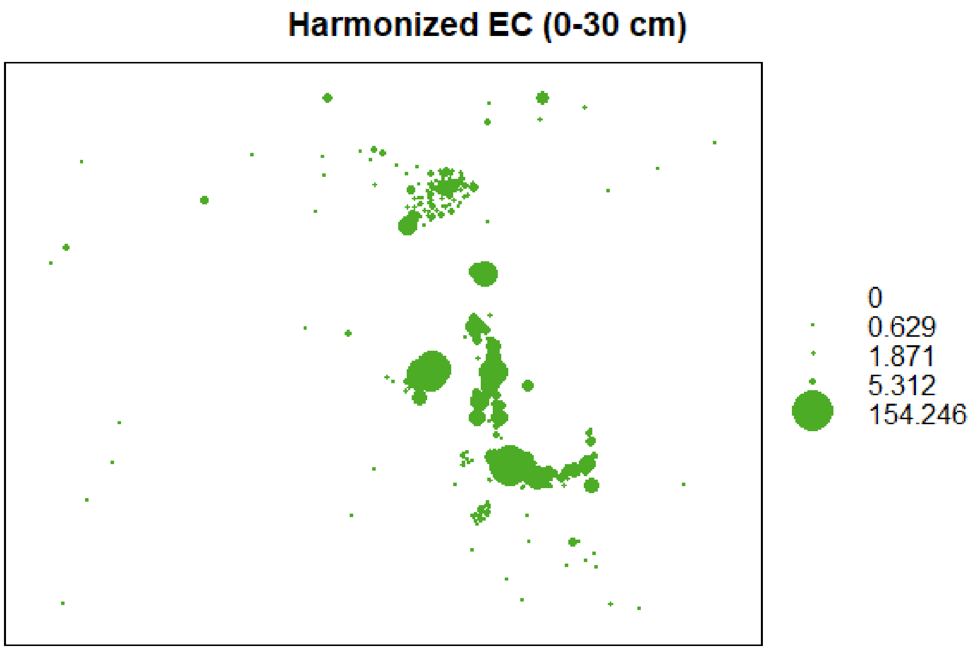


Figure 5.6: Bubble plot for top 0-30cm harmonized EC

#Step 1-9: Harmonization of statistical distribution

This harmonization is done to transform the frequency distribution to normal distribution. Frequency transformation to normal distribution is optional for spatial modelling algorithms. If it's chosen, then the empirical distribution is first established through histogram analysis and transformation implemented if the distribution is found to be skewed. *hist* function is used to extract and plot the histogram. Box-Cox (1964) transformation is preferred. The following scripts illustrate the steps for transforming statistical distribution. Summary distribution is first obtained to establish if there are zeros, *NAs*, or negative values. It is desirable to remove them before implementing Box-Cox transformation.

```
> summary(soil1$X0.30.cm)
   Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
 0.0000   0.6291   1.8709   6.6812   5.3121 154.2463 

> soil1$dummy=(soil1$EC)+0.001 # add "+0.001" if minimum X0.30.cm is zero
> hist(soil1$dummy, main="Frequency distribution (before transformation)", xlab="Harmonized EC (dS/m)")
> soil1$Tran=(soil1$dummy^(as.numeric(car::powerTransform(soil1$dummy, family ="bcPower")["lambda"]))-1)/(as.numeric(car::powerTransform(soil1$dummy, family ="bcPower")["lambda"]))
> hist(soil1$Tran, main="Frequency distribution (after transformation)",xlab="Harmonized EC (dS/m)")
```

Histogram plot of the empirical distributions before and after transformation are given in Figure 5.7.

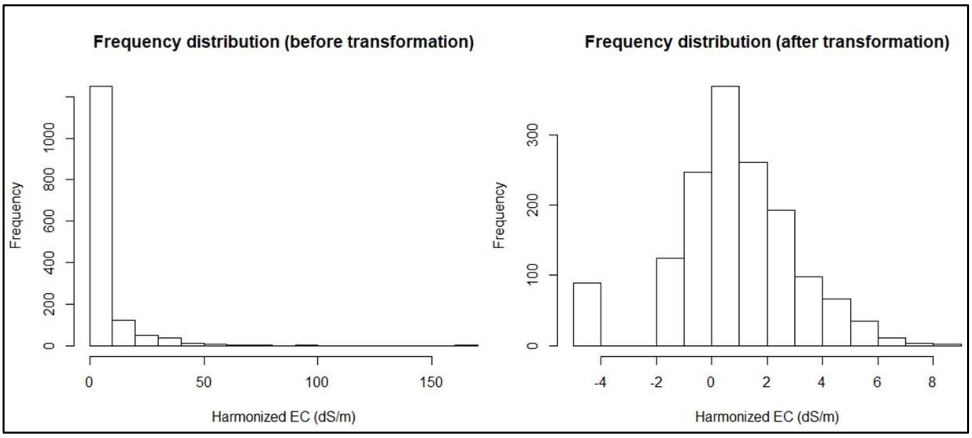


Figure 5.7: Frequency distribution before and after EC transformation

5.3 Step 2: Spatial modelling of indicators

Spatial modelling of indicators of salt-affected soils is based on the digital soil mapping (DSM) concept. In this concept, a relationship is built between the soil indicators of salt problems and spatial predictors (GIS layers of drivers and indicators of salt problems and soil forming factors). This approach enables quantification of:

1. Spatial information of indicators of salt-affected soils (EC, pH, ESP) and different soil depths
2. Mapping uncertainties and accuracy
3. Spatial information of classes and intensity of salt problems

5.3.1 Choosing suitable model

DSM approach proposes a mathematical relationship between the target soil variable and its predictors (or representation of soil forming factors). This relationship is popularly known as the SCORPAN model (McBratney et al., 2003):

$$Target\ soil\ variable = f(S, C, O, R, P, A, N) + error \quad (5.1)$$

where *S* is the soil component (such as soil map), *C* is climate, *O* is organism, *R* is relief, *P* is parent material, *A* is the Age(time), *N* is the spatial coordinates, *error* is the error term, and *f* is the link function of the relationship between the predictors and the target soil variable. Popular models often used to represent *f* are linear, random-forest, support-vector machine, mixed-effects, regression kriging, etc. The *soilassessment* package provides *regmodelSuit* function for guiding the choice of the appropriate model for mapping soil variables. It tests different models and returns the top nine models using RMSE, ME, NSE and r^2. Lowest root mean-square error (RMSE), highest r^2, lowest mean error (ME), highest Nash-Sutcliff coefficient of efficiency (NSE) are then used as the guiding criteria for choosing the suitable model (Holst and Thyregod, 1999; Gupta and Kling, 2011).

$$RMSE = \sqrt{\frac{1}{n}(y_o - y_m)^2} \quad (5.2)$$

$$ME = (y_o - y_m)/n \quad (5.3)$$

$$NSE = 1 - \frac{(y_o - y_m)^2}{(y_o - \bar{y})^2} \quad (5.4)$$

where harmonized value is y_o, y_m is the modelled value, and the mean value is $\bar{y}$.

An initial step for spatial modelling is to build the model in a calibration dataset and then testing the model using an independent dataset. This calls for the establishment of calibration and validation datasets. These datasets should have well aligned soil properties (indicators) and spatial predictors at each georeferenced sampling point.

Pixel value extraction of GIS layers (predictors) using point data (soil1) is a suitable method for developing either the calibration or validation datasets.

#Step 2-1: Extract pixel values of predictors and attach to the soil sampling points

 # First check for similarity in coordinate reference system – crs and then extract the predictors

```
> crs(predictors); crs(soil1)
CRS arguments:
 +proj=utm +zone=36 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towg
s84=0,0,0
CRS arguments:
 +proj=utm +zone=36 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towg
s84=0,0,0
```

It's important to ensure that the CRS for predictors and soil database are the same before starting pixel extraction

#Then extract the pixel values for all predictors into the soildata dataframe

```
> {predictors.ov=over(soil1, predictors)
+   soil1$dem=predictors.ov$dem
+   soil1$slope=predictors.ov$slope
+   soil1$cnbl=predictors.ov$cnbl
+   soil1$ls=predictors.ov$ls
+   soil1$valley=predictors.ov$valley
+   soil1$loncurve=predictors.ov$loncurve
+   soil1$lcover=predictors.ov$lcover
+   soil1$rain=predictors.ov$rain
+   soil1$pgeology=predictors.ov$pgeology
+   soil1$geology=predictors.ov$geology
+   soil1$PCA1=predictors.ov$PCA1
+   soil1$PCA2=predictors.ov$PCA2
+   soil1$PCA3=predictors.ov$PCA3
+   soil1$PCA4=predictors.ov$PCA4
+ }
```

#Step 2-2: Establish suitable DSM model

```
> summary(soil1)
Object of class SpatialPointsDataFrame
Coordinates:
                min     max
Longitude -261790.8  497928
Latitude  1841020.7 2430061
Is projected: TRUE
proj4string :
[+proj=utm +zone=36 +datum=WGS84 +units=m +no_defs +ellps=WGS84
+towgs84=0,0,0]
Number of points: 1498
Data attributes:
      Pits          Sample          Upper            Lower            H
orizon
 292    :   8   1      :   1   Min.   :  0.00   Min.   :  2.00   Min.
:1.000
 280    :   7   10     :   1   1st Qu.:  0.00   1st Qu.: 30.00   1st
Qu.:1.000
```

```
 293     :   7   100     :   1   Median : 30.00   Median : 64.00   Medi
an :2.500
 327     :   7   1000    :   1   Mean   : 42.56   Mean   : 75.37   Mean
:2.692
 372     :   7   1001    :   1   3rd Qu.: 70.00   3rd Qu.:110.00   3rd
Qu.:4.000
 378     :   7   1002    :   1   Max.   :210.00   Max.   :300.00   Max.
:8.000
………
       ls               valley            loncurve          lcover
 Min.   :0.00051   Min.   :  0.7306   Min.   :0e+00   Min.   :  2.0
 1st Qu.:0.00129   1st Qu.: 30.1037   1st Qu.:0e+00   1st Qu.:178.0
 Median :0.00219   Median : 43.0999   Median :0e+00   Median :178.0
 Mean   :0.02028   Mean   : 44.6613   Mean   :0e+00   Mean   :155.5
 3rd Qu.:0.02821   3rd Qu.: 62.2221   3rd Qu.:0e+00   3rd Qu.:178.0
 Max.   :0.44952   Max.   :105.7522   Max.   :1e-05   Max.   :188.0
 NA's   :4         NA's   :4          NA's   :4       NA's   :4
```

The NAs appearing in the data need to be removed (or investigated).

```
> soil1=subset(soil1,!is.na(soil1$dem))
> soil11a=soil1@data[,c("Tran","dem","slope","ls","cnbl","loncurve","
valley","rain","lcover","pgeology","geology","PCA1","PCA2","PCA3","PC
A4")]
> regmodelSuit(soil11a,Tran,dem,geology,pgeology,slope,rain,loncurve,
cnbl,valley,lcover,ls,PCA1,PCA2,PCA3, PCA4)
  |===================================================================
======| 100%
                       ME      RMSE        R2         NSE
Linear           1.37034834 1.8129133 0.1320264 -4.45424486
RandomForest     0.24614749 0.4291176 0.9623631  0.99707891
SVM              1.34745209 1.8212570 0.1357457 -4.44014767
BayesianGLM      1.36669809 1.8051662 0.1399516 -4.55079779
BaggedCART       0.88676091 1.1705841 0.7018074  0.44302759
Cubist           0.07851255 0.2744213 0.9753726  1.00000000
CART             1.40147986 1.8274332 0.1320797 -4.56273851
Ranger           0.26852953 0.4205875 0.9655103  0.99702690
QuantRandForest  0.04923343 0.2855093 0.9761419  1.00000000
QuantNeuralNT    1.16162791 1.7075411 0.2582558  0.07778314
```

The above results depict *quantum regression random forest* and *cubist* models as suitable for modelling the 0-30cm EC_{se} using the given spatial predictors in the case-study test data.

5.3.2 Model building and testing

Statistical model building and testing strategies recommend independent datasets for model building and for model testing. These datasets should ideally be sampled with focus for model building and testing. In the absence of independently sampled dataset for either model building (calibration) or testing (validation), data-splitting strategy is often used. Data-splitting strategy randomly (or stratified randomly) splits the data into two parts. One part is held as calibration and the other as validation. The validation dataset is used for accuracy assessment. The indices for reporting modelling accuracy include RMSE, ME, r^2, NSE, and a graphical plot of the modelled versus harmonized values. Data-splitting may be arbitrarily chosen according to or depending on the data-size.

#Step 2-3: Model building and testing

```
> {soil4=as.data.frame(soil1)
+   bound <- floor((nrow(soil4)/4)*3)
+   soil3 <- soil4[sample(nrow(soil4)), ]
+   df.traina <- soil3[1:bound, ]
+   df.testa <- soil3[(bound+1):nrow(soil3), ]}

> rf.ec=train(Tran~(slope+rain+loncurve+ls+cnbl+valley+lcover+dem+PCA
1+PCA2+PCA3+PCA4+PCA5),  data = df.traina,  method = "qrf", trControl
=trainControl( method = "cv",number=5,returnResamp = "all",savePredic
tions = TRUE, search = "random",verboseIter = FALSE))

# Show the prediction interval
> df.testa$Strain=predict(rf.ec,newdata=df.testa)
> hist(df.testa$Strain,xlab="Box-Cox Transformed ECse (0-30cm)", main
=NULL)
> abline(v = quantile(df.testa$Strain, probs = c(0.05, 0.95)),lty = 5
, col = "red")
```

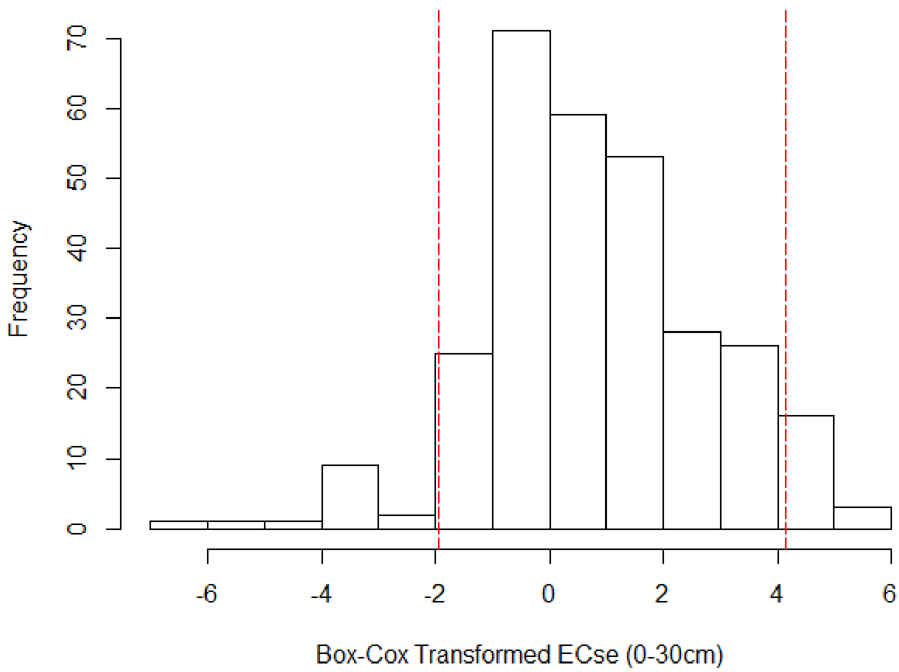


Figure 5.8: Graphical plot of frequency distribution with prediction limits at 95% confidence interval

Prediction limits on the Box-Cox transformed values at 95% confidence interval are given in Figure 5.8. It shows the interval around the mean of 0.77 as [-2, 4.1].

#Step 2-4: Accuracy assessment

```
> cor(df.testa$Strain,df.testa$dummy)^2
[1] 0.9950319
> {plot(df.testa$Strain~df.testa$dummy, xlab="Measured ECse",ylab="Mo
delled ECse", main="Accuracy assessment on hold-out samples")
+   abline(a=0,b=1,lty=20, col="blue")} # Figure 5.9
```

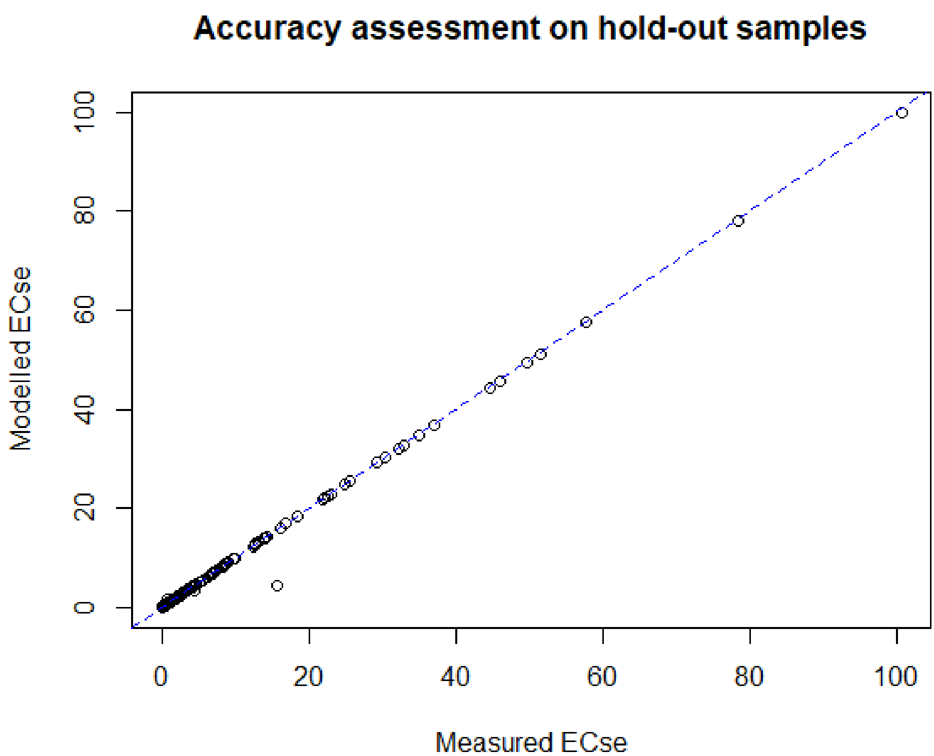


Figure 5.9: Graphical plot of predicted versus measured EC

```
> Bias=mean(df.testa$Strain-df.testa$dummy,na.rm=TRUE)
> RMSE=sqrt(sum(df.testa$Strain-df.testa$dummy,na.rm=TRUE)^2/length((
df.testa$Strain-df.testa$dummy)))
> Rsquared=cor(df.testa$Strain,df.testa$dummy)^2
> NSE=1-sum(df.testa$Strain-df.testa$dummy,na.rm=TRUE)^2/sum((df.test
a$Strain-mean(df.testa$dummy,na.rm=TRUE))^2,na.rm=TRUE)
> statia=data.frame(Bias,RMSE,Rsquared,NSE);View(statia)
> write.csv(statia,file = "ECO_30_validmodel_stats.csv")
```

```
> statia
        Bias     RMSE  Rsquared       NSE
1 -0.1019564 1.751158 0.9950319 0.982046
```

5.3.3 Spatial prediction and uncertainty assessment

The model can now be used to produce spatial prediction of the target variable (EC in this case) in the whole study area. A summary of the predicted and validation data can also be compared to give indication of the prediction ranges.

#Step 2-3: Use the developed model to predict the map of EC

```
> lmbda1=(as.numeric(powerTransform(soil1$dummy, family ="bcPower")["
lambda"]))
> predictors$ECte=predicta(rf.ec,predictors)
> coordinates(df.testa)=~Longitude+Latitude
> proj4string(df.testa)=CRS("+proj=utm +zone=36 +datum=WGS84 +units=m
+no_defs +ellps=WGS84 +towgs84=0,0,0") # Make sure to use correct CRS
> predicters.ov1=over(df.testa, predictors)
> df.testa$Predre=predicters.ov1$ECse
> cor(df.testa$dummy,df.testa$Predre)^2
[1] 0.9978655
```

#Compare the spatial prediction and validation dataset

```
> featureRep(predictors["ECse"],df.testa) #Figure 5.10

        Two-sample Kolmogorov-Smirnov test

data:  dist.histbb$left and dist.histbb$right
D = 0.52174, p-value = 0.003819
alternative hypothesis: two-sided

> summary(predictors$ECse);summary(df.testa$dummy)
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
  0.00007   0.48810   1.17487   1.51685   1.61781 112.74435
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
  0.00048   0.59755   1.71126   6.60388   5.05220 113.50941
```

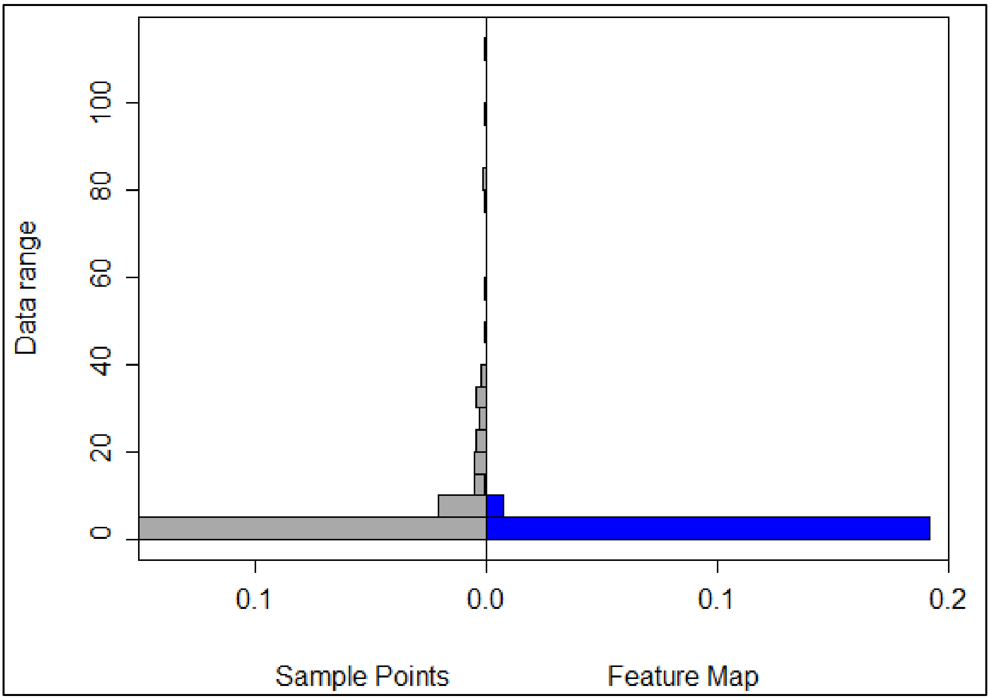


Figure 5:10: Representativeness of validation (sample points) EC ranges in prediction map (feature map)

The feature representation in Figure 5.10 shows how well the range of measured EC (validation EC) are contained in the prediction map. In the case-study sample, high EC (>40 dS/m) seem to have been poorly captured in the prediction map. The x-axis shows the frequency (probability density) of occurrence of data (EC) values in y-axis. Poor representation of the high (EC > 40) implies model uncertainty for high EC values. This will be further investigated when uncertainties are produced.

#Step 2-4: Export the output

```
writeGDAL(predictors["ECse"], drivername = "GTiff", "Top0_30ECse.tif")
```

#Step 2-5: Uncertainty assessment

The general spatial model for digital soil mapping is generally given as

$$y = f(X) + \varepsilon \quad (5.5)$$

where y is the target soil variable to be mapped, X is a vector of spatial predictors (controlling factors of causes or drives for salt problems), ε is the error term, and f is the link function between the target soil variable and its drivers/forming factors. The nature of f is unknown and is approximated by mathematical models. These model approximations, denoted as $\hat{f}$, give estimates of y which are also denoted as ŷ. The difference between y and $\hat{y}$ is the uncertain quantity.

$$\hat{y} = \hat{f}(X) \quad (5.6)$$

$$y - \hat{y} = [f(X) + \varepsilon] - \hat{f}(X)$$

$$= \left[f(x) - \hat{f}(X)\right] + \varepsilon \quad (5.7)$$

In this Book, the uncertain quantity is estimated using prediction width at 95% confidence interval. *predUncertain* function in *soilassessment* package is used to extract the uncertainty by bootstrap approach (Efron, 1992). The inputs for the function are a list of predictors, input soil indicator, and the chosen link model (which is taken from the suitable model for map development in Section 5.3.1).

#Step 2-6: Uncertainty assessment

```
> soil6a=soil1[,c("Tran")]
> predictors6a=predictors[c("dem","slope","cnbl","lcover","loncurve",
"rain","pgeology","geology","ls","valley","PCA1","PCA2","PCA3","PCA4"
,"PCA5")]

> pred_uncerta=predUncertain(soil6a,predictors6a,3,95,"qrandomforest"
)
  |===================================================================
====| 100%


> spplot(pred_uncerta, "pred_width", scales = list(draw = TRUE),col.r
egions=heat.colors(20,rev = TRUE)) + spplot(df.testa,"dummy",pch=3,ce
x=0.4) #Figure 6.11
```

#Step 2-7: Exporting the uncertainty maps

```
> ECO_30_uncertain=(pred_uncerta$pred_width*lmbda1+1)^(1/lmbda1)
> writeRaster(ECO_30_uncertain, filename="ECO_30_uncertain.tif",forma
t="GTiff")
```

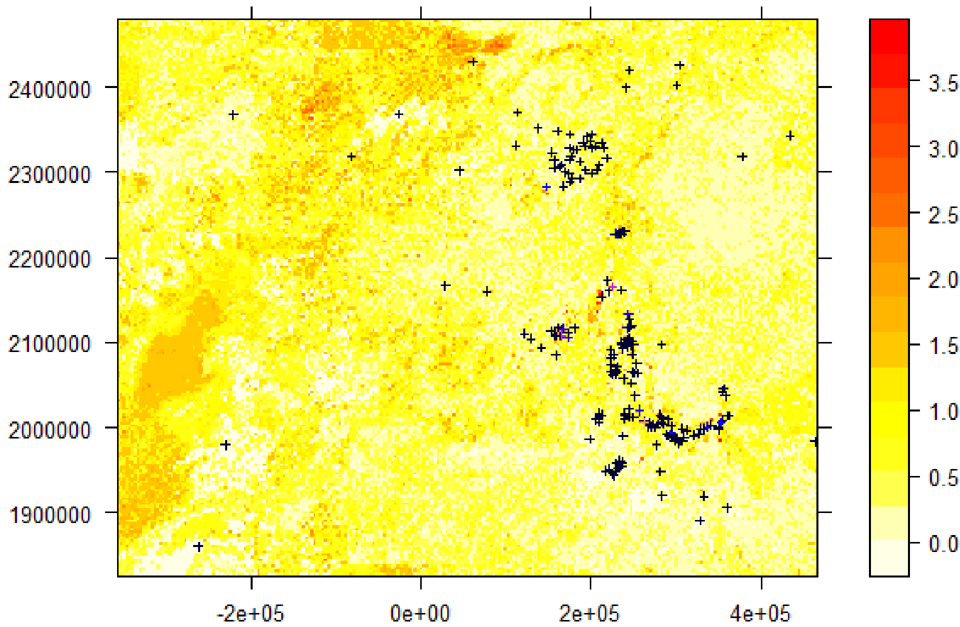


Figure 5.11: Spatial prediction width at 95% confidence interval and overlay of validation points

The steps for spatial modelling of EC should be repeated for pH, ESP and soluble ions for 30-100 cm soil depths. Altogether, the final products form the spatial information of indicators of salt-affected soils at 0-30 cm and 30-100 cm soil depths.

5.4 Part 3: Spatial modelling of salt-affected soils

5.4.1 Spatial modelling of salt-affected soils

This section describes the approach for spatial modelling of salt-affected soils based on input maps of soil indicators of salt problems. It is the final step of the multiscale approach in Figure 5.1. Spatial modelling approach for salt-affected soils is focused on:

1) Classification of salt-affected areas
2) Identification of intensity of the salt problems
3) Assessment of uncertainty in developing maps of salt-affected soils

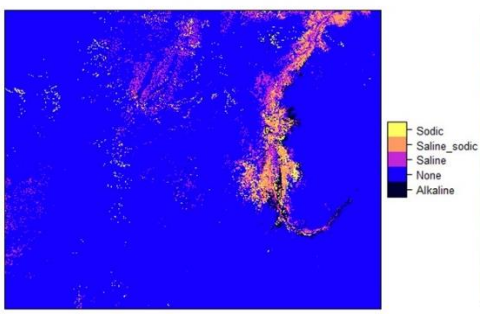
The mathematical model for classifying salt-affected soils is given here as

$$salt = g(EC, pH, ESP) + error \quad (5.8)$$

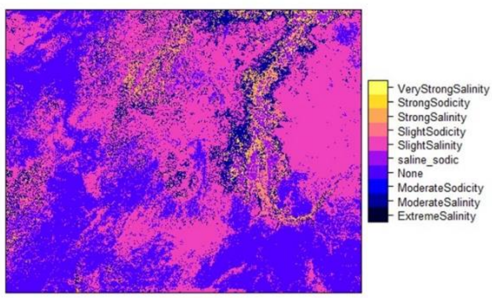
where *salt* is the class of type or intensity of the salt problems and *error* is the difference between the actual and modelled values classes. Proposed estimations for the model *g* in the literature are given in Table 2.4 and Table 2.5. The *soilassessment* package contains the functions *saltClass, saltSeverity* and *saltRating* for implementing these models. The input data for *saltClass* and *saltSeverity* functions are the three soil indicators, EC, pH, and ESP. *saltRating* functions give the major classes of salt-affected soils using EC and pH only. It's an approximation for indicative classes which need improvement with data from sodium salts. The input data for classifying salt-affected soils can be point-data in a spreadsheet dataframe or raster maps.

#Step 3-1: Classifying types of salt-affected soils

```
> predictors$salty=saltClass(predictors$ECse,predictors$PH,predictors
$ESP,"FAO")
> summary(predictors$salty)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   1.000   1.000   1.151   1.000   5.000

> predictors$saltiness=classCode(predictors$salty,"saltclass")
> spplot(predictors["salty"])
> spplot(predictors["saltiness"]) # Figure 5.12a

> predictors$Salt_affected=saltSeverity(predictors$ECse,predictors$PH
,predictors$ESP,"FAO")
> predictors$saltaffectedness=classCode(predictors$Salt_affected,"sal
tseverity")
> spplot(predictors["saltaffectedness"]) # Figure 5.12b
```



(a) Major categories of salt-affected soils



(a) Intensity classes of salt-affected soils

Figure 5.12: Maps of salt-affected soils (0-30 cm)

The final maps in Figure 5.12 are exported as a GIS file format for use with other GIS software (such as QGIS) or for data sharing. Since the export function does not work with factors /character values, the salt classes in the maps are first converted into numeric map-values and then exported. A look-up table (LUT) is necessary to help identify the classes and the unique numeric codes generated for each map-value. The LUT is exported as a text-file.

 # Step 3-2: Exporting the maps

```
> predictors$Saltclass=as.numeric(predictors$saltaffectedness)
> salinity_LUT30=classLUT(predictors["saltaffectedness"],"saltseverit
y")

  |==================================================================
=====| 100%
> writeGDAL(predictors["Saltclass"], drivername = "GTiff", "Top0_30sa
ltaffected.tif")
> write.table(salinity_LUT30,file = "saltaffected_LUT30.txt",row.name
s = FALSE)
```

5.4.2 Accuracy assessment

Accuracy of classified salt-affected map is assessed using confusion matrix. In this strategy holdout samples are independently classified in terms of types and severity of salt problems in the soil. Classification of the holdout samples should follow the same procedure of harmonization as other input data (that is, harmonization of input indicators and depths 0-30 and 30-100 cm). These classes are then compared to the pixel-extracted classes from the classified maps. The Kappa index is a suitable indicator for reporting the accuracy.

#Step 3-2: Import and classify validation dataset

```
> soilv=readOGR(".","validation_harmonized")
> soilv=subset(soilv,soilv$Horizon==1)
> soilv$salt_affected1=saltSeverity(soilv$EC,soilv$pH,soilv$ESP,"FAO"
)
> summary(soilv$salt_affected1)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    3.0     6.0     8.0     8.5    11.5    15.0 

> soilv$saltaffectedness1=classCode(soilv$salt_affected1,"saltseverit
y")
> summary(soilv$saltaffectedness1)

 ExtremeSalinity ModerateSalinity ModerateSodicity             None 
               3               10                1               18 
    saline_sodic   SlightSalinity   SlightSodicity   StrongSalinity 
```

12 13 16 5

After classifying the validation dataset, the dataset is used to extract pixel values of the classified map and compared with the classified validation.

#Step 3-3: Extract the salt classes from the map using the validation samples

```
> soilv=subset(soilv,!is.na(soilv$saltaffectedness1))
> predictors.ovv=over(soilv, predictors)
> soilv$salt_affected=predictors.ovv$Salt_affected
> soilv$saltaffectedness=predictors.ovv$saltaffectedness
```

 # Check the summary of extracted classified pixels

```
> summary(soilv$salt_affected)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  3.000   6.000   8.000   7.808  10.000  14.000 
> summary(soilv$saltaffectedness)
   ExtremeSalinity   ModerateSalinity   ModerateSodicity 
None 
                 1                  7                  0 
14 
      saline_sodic     SlightSalinity     SlightSodicity     StrongSa
linity 
                18                 15                 11 
10 
    StrongSodicity VeryStrongSalinity 
                 0                  2 
```

A visual comparison shows that the validation datasets had points classified as extremely saline soil, but the map reported only one pixel. Similarly, three points in the validation datasets had strong salinity class while the map had 10 pixels with strong salinity classes. A graphical plot of the comparison (confusion matrix) gives a clear picture of the accuracy (Figure 5.13).

 # Plot the confusion matrix and determine the Kappa index

```
> agreementplot(confusion(soilv$salt_affected, soilv$salt_affected1),
main = "Accuracy assessment",xlab = "Class codes in holdout samples",
ylab = "Class codes in map")
> Kappa(confusion(soilv$salt_affected, soilv$salt_affected1))
            value     ASE     z  Pr(>|z|)
Unweighted 0.4211 0.06384 6.597 4.208e-11
Weighted   0.4780 0.07792 6.135 8.525e-10
```

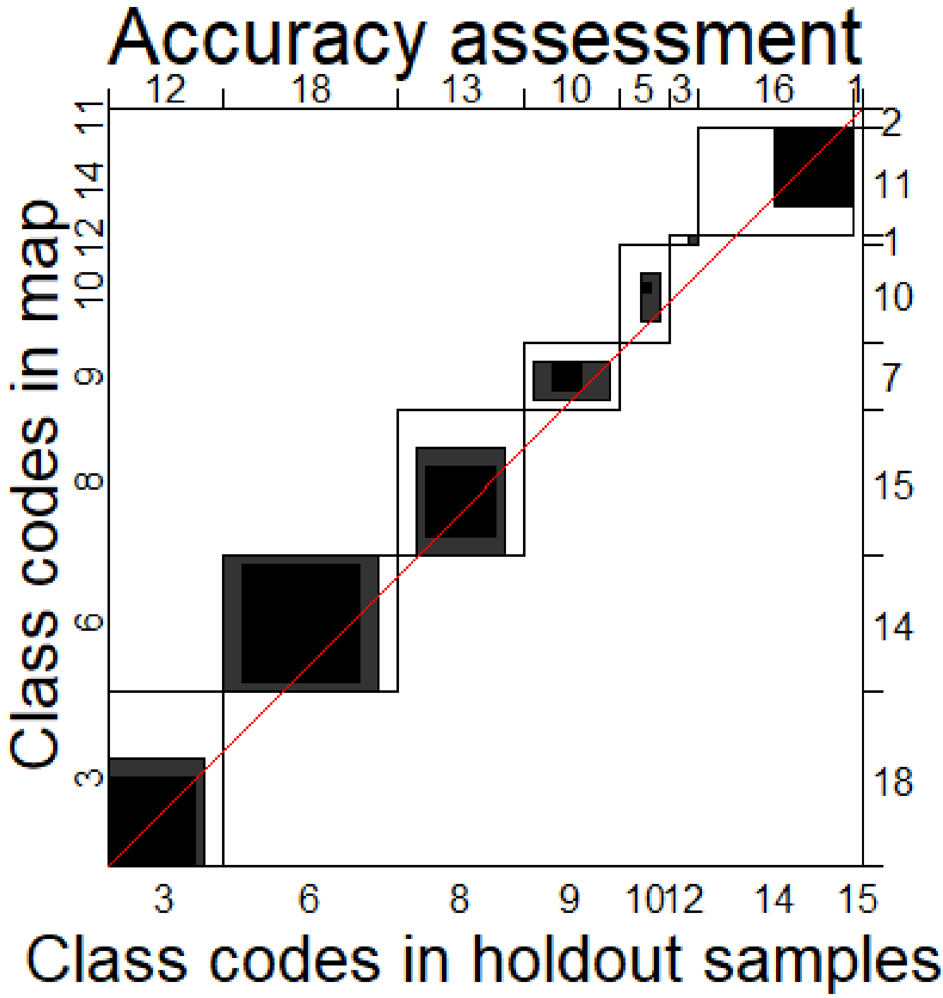


Figure 5.13: Graphical illustration of classification accuracy for salt-affected soils

5.4.3 Uncertainty assessment

Uncertainty assessment in salt-affected modelling is conceived as estimating uncertainties contributed by input data modelling and uncertainties from the salt-classification model. The Monte Carlo uncertainty propagation approach is used to model both input data uncertainty and classification model uncertainty (Sawicka et al., 2018). This is a three-step approach involving input parameter specification, development of marginal and joint distributions, and simulations for uncertainty propagation (Figure 5.14). Input parameter specifications comprise definition of the salt-classification model (Equation 5.8) and spatial distribution of mean and variance of the input variables. Spatial distribution of mean and variance are used to train the MC simulations at a set number of simulations/realizations. Usually, MC simulations are more accurate with a higher number of realizations. However, this may cost the analysis computing time for large datasets. A trade-off is necessary to safeguard suitable accuracy while at the same time incurring moderate computing time. A value of 100 is suggested for modelling salt-affected soils.

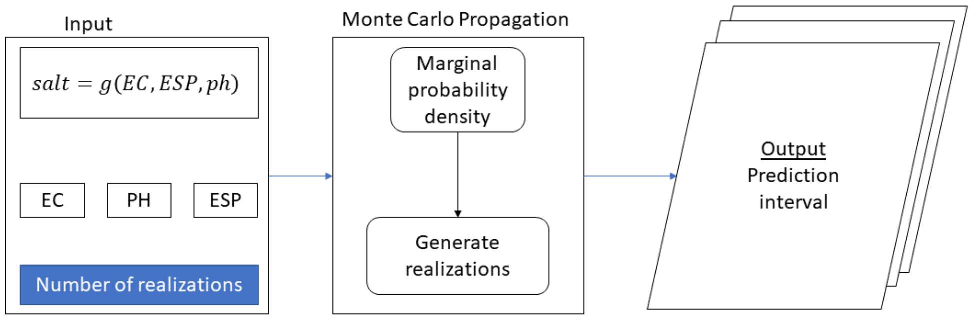


Figure 5.14: Monte Carlo uncertainty estimation process

Development of marginal density functions uses statistical distribution parameters and correlation models (crm). Examples of statistical distribution parameters, which depend on the type of distribution, are the mean($\bar{x}$) and standard variation (s) for normal distribution or the scale (λ) and rate (α) for gamma distribution.

The following steps describes the process for preparing the input indicator maps into raster file format, since the modules for uncertainty assessment were developed for the raster file format. The input maps are further converted into spatialPixelsDataFrame to facilitate mathematical operations on dataframes. It is important to check the probability distributions of the input data using the histogram function. Although MC simulations in Figure 5.14 are not strict on the type of the distribution, normal distribution is easy to sample. It's therefore recommended that normalized distributions be established from the input maps.

#Step 3-4: Convert the input layers into raster files

```
> EC=raster(predictors["ECse"]);names(EC)=c("EC"); EC1=as(EC,"SpatialPixelsDataFrame")
> PH=raster(predictors["PH"]); names(PH)=c("PH"); PH1=as(PH,"SpatialPixelsDataFrame")
> ESP=raster(predictors["ESP"]);names(EC)=c("ESP");ESP1=as(ESP,"SpatialPixelsDataFrame")
>
```

```
> ECte=raster(predictors["ECte"]);ECsd=pred_uncerta$pred_sd; names(EC
sd)=c("ECsd")
> PHde=raster(predictors["PHt"]);PHsd=pred_uncertb$pred_sd; names(PHs
d)=c("PHsd")
> ESPt=raster(predictors["ESPt"]);ESPsd=pred_uncertc$pred_sd; names(E
SPsd)=c("ESPsd")
```

 # Obtain sample spatial autocorrelation (Figure 5.15)

```
> b=nrow(EC1)
> c=trunc(0.01*b)
> jj=EC1[sample(b,c),]
> vrm=autofitVariogram(EC~1,jj)

> plot(vrm)#Note the spatial correlation model and the value of Range
parameter
> acf((EC1$EC)) ##Also not the acf0 (at lag 0)
> EC_crm <- makeCRM(acf0 = 0.85, range = 20000, model = "Sph")
> plot(EC_crm, main = "EC correlogram")
```

The above correlation functions are repeated for all input soil indicators for 0-30 cm and 30-100 cm.

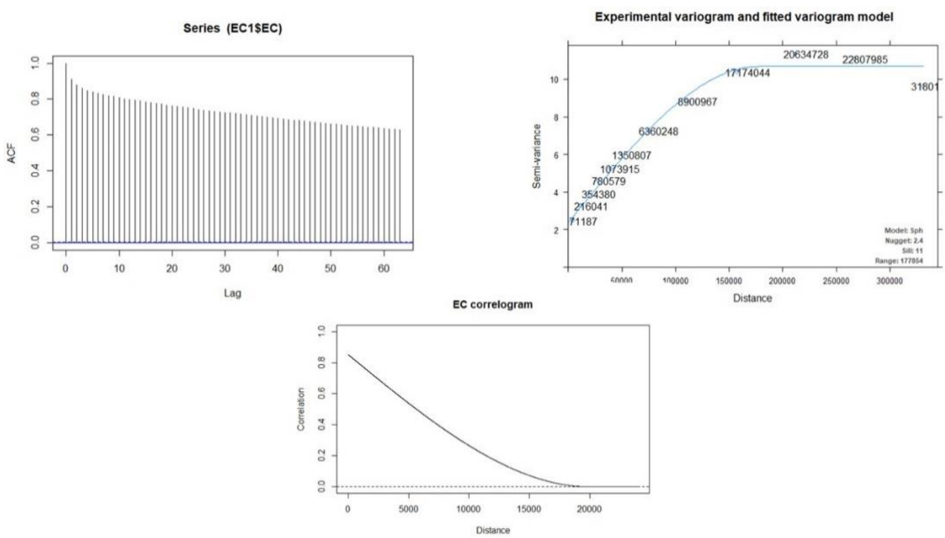


Figure 5.15: Correlation functions for EC (0-30 cm)

#Step 3-5: Develop input marginal and joint multivariate uncertainty models for defining MC models

```
> EC_UM=defineUM(distribution="norm",distr_param = c(ECte,ECsd),crm =
EC_crm,id = "EC")
> PH_UM=defineUM(distribution ="norm",distr_param =c(PHde,PHsd),crm =
PH_crm,id = "PH")
> ESP_UM=defineUM(distribution="norm",distr_param=c(ESPt,ESPsd),crm=E
SP_crm,id= "ESP")
> class(EC_UM);class(PH_UM);class(ESP_UM)
[1] "MarginalNumericSpatial"
```

```
[1] "MarginalNumericSpatial"
[1] "MarginalNumericSpatial"
```

#Get the correlation values and use them in defining the Monte Carlo Uncertainty Mode (MUM)

```
> cor(values(ECte),values(PHde)); cor(values(ECte),values(ESPt)); cor
(values(PHde),values(ESPt))
[1] 0.5511048
[1] 0.3204495
[1] 0.2859129

> salinityMUM = defineMUM(UMlist = list(EC_UM, PH_UM, ESP_UM),
  cormatrix = matrix(c(1, cor(values(ECte),values(PHde)),
  cor(values(ECte),values(ESPt)), cor(values(ECte), values(PHde)), 1,
  cor(values(PHde), values(ESPt)), cor(values(ECte), values(ESPt)),
  cor(values(PHde), values(ESPt)),1), nrow = 3, ncol = 3))

> class(salinityMUM)
[1] "JointNumericSpatial"
```

Possible realizations are now developed after setting the Monte Carlo Uncertainty models (MUM). 100 level is set for simulating the MC simulations.

#Step 3-6: Create MC realizations from the distributions

```
> MC <- 100
> input_sample = genSample(UMobject = salinityMUM, n = MC, samplemeth
od = "ugs",  nmax = 20, asList = FALSE)
Linear Model of Coregionalization found. Good.
[using unconditional Gaussian cosimulation]
```

 # Compute input sample statistics

```
> EC_sample = input_sample[[1:MC]]
> PH_sample = input_sample[[(MC+1):(2*MC)]]
> ESP_sample = input_sample[[(2*MC+1):(3*MC)]]
> EC_sample_mean <- mean(EC_sample)
> PH_sample_mean <- mean(PH_sample)
> ESP_sample_mean <- mean(ESP_sample)

> EC_sample_sd <- calc(EC_sample, fun = sd)
> PH_sample_sd <- calc(PH_sample, fun = sd)
> ESP_sample_sd <- calc(ESP_sample, fun = sd)
```

#Plot the realizations

```
> par(mfrow=c(2,2),mar = c(1, 1, 2, 2), mgp = c(1.7, 0.5, 0), oma = c
(0, 0, 0, 1),
+      las = 1, cex.main = 1, tcl = -0.2, cex.axis = 0.8, cex.lab = 0.
8)
> plot(EC_sample_mean, main = "Mean of ECt realizations", xaxt = "n",
yaxt = "n")
> plot(PH_sample_mean, main = "Mean of PHt realizations", xaxt = "n",
yaxt = "n")
```

```
> plot(ESP_sample_mean, main = "Mean of ESPt realizations", xaxt = "n
", yaxt = "n")
```

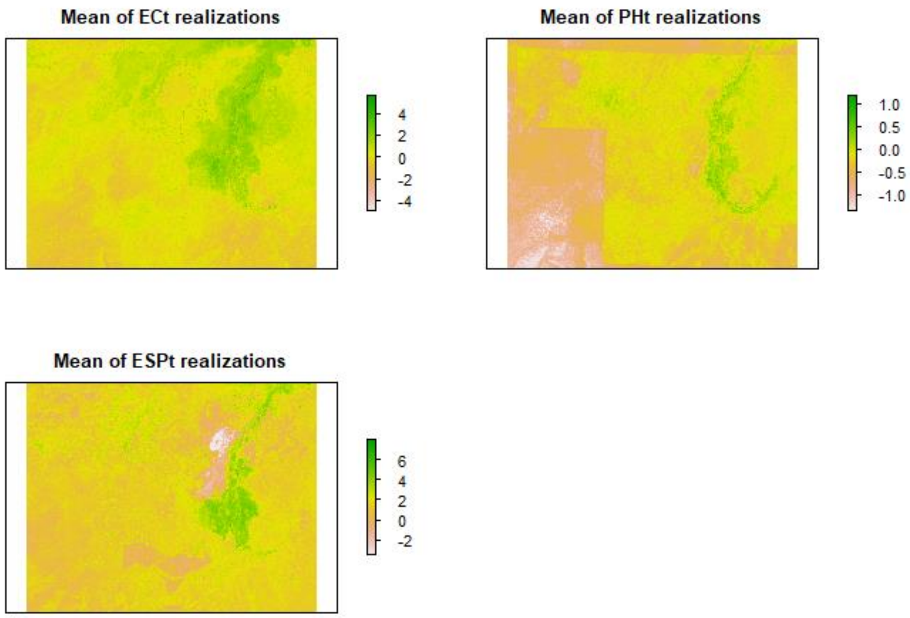


Figure 5.16: Simulated realizations of normalized input soil indicators

Note that the MC simulations were done on the normalized input soil indicators. It's possible to sample from non-normalized data. However, a harmonized statistical distribution is use in this book.

#Step 3-7: Uncertainty propagation through the classification model

The uncertainty propagation model is used to determine how uncertainties in input soil indicators propagate through the classification model into the final classified map.

```
> Salinity_model_raster <- function (EC1,PH1,ESP1){
+   ww=EC1
+   ww=raster(ww)
+   ww$salt=saltSeverity(values(EC1),values(PH1),values(ESP1),"FAO")
+   ww=ww$salt; names(ww)=c("salt")
+   ww
+ }

> v <- list()
> v[[1]] = map(1:100, function(x){input_sample[[x]]})
> v[[2]] = map(101:200, function(x){input_sample[[x]]})
> v[[3]] = map(201:300, function(x){input_sample[[x]]})
> input_sample=v
> salinity_sample=propagate(realizations=input_sample,model=Salinity_
model_raster,n=MC)
```

#Determine the uncertainty in final classified map

```
> samplelist <- list()
> samplelist [[1]] = map(1:100, function(x){input_sample[[x]]})
> samplelist [[2]] = map(101:200, function(x){input_sample[[x]]})
> samplelist [[3]] = map(201:300, function(x){input_sample[[x]]})
> input_sample= samplelist
> salinity_sample = propagate(realizations = input_sample, model =
Salinity_model_raster, n = MC)

> salinity_sample <- raster::stack(salinity_sample)
>         names(salinity_sample)          <-          paste("salt.",
c(1:nlayers(salinity_sample)), sep = "")
> salinity_freq = modal(salinity_sample, freq=TRUE)
> salinity_prop = salinity_fre/100
> salinity_SErr = sqrt(salinity_prop*(1-salinity_prop)/100)
> CL=0.95
> z_star=round(qnorm((1-CL)/2,lower.tail=F),digits = 2)
> salinity_MErr=z_star*salinity_SErr
```

The final output is exported to a GIS file format for map layout development (Figure 5.17).

```
>
writeRaster(salinity_MErr,filename="Salinity_ME.tif",format="GTiff")
```

Overall classification accuracy of salt-affected topsoils (0-30 cm) was 65%. These soils covered more than 82% of the topsoils in the case-study area (Figure 5.17). Northwest of the area had slight to moderately saline topsoil with pockets of overlying saline-sodic and slightly sodic topsoils. Topsoil salinity seems to be predominant in the eastern side towards the Red Sea. Topsoil sodicity seems to be concentrated along the River Nile (Figure 5.17).

The above steps for developing maps of salt-affected soils and associated uncertainty maps should be repeated for 30-100 cm soil depths.

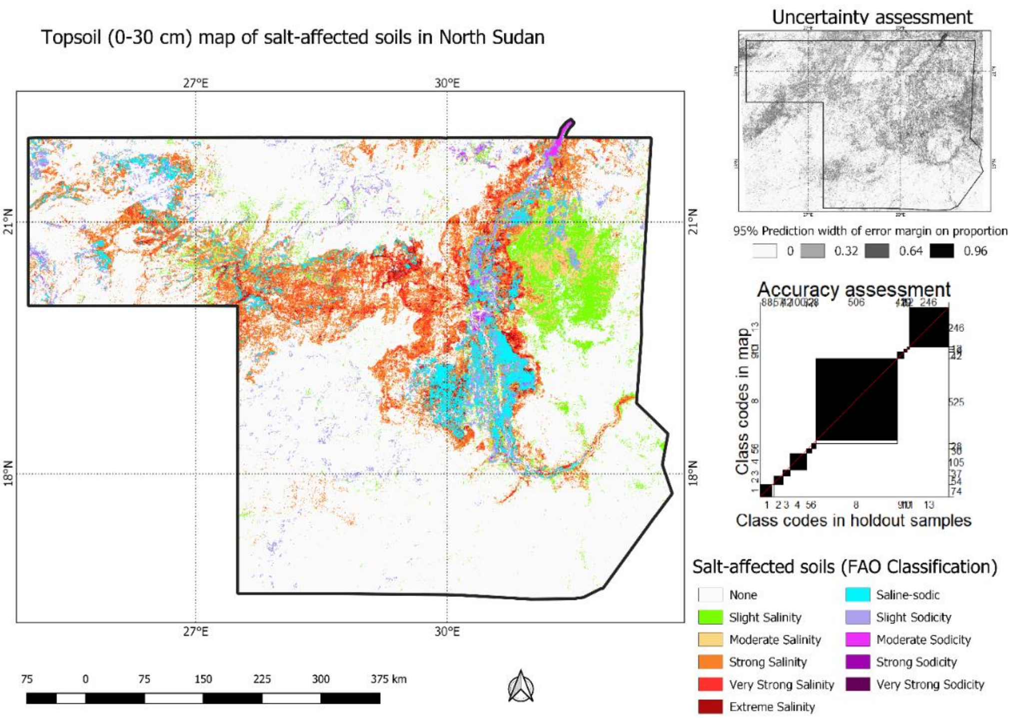


Figure 5.17: Map of salt-affected topsoil (0-30 cm) in study area

5.5 Map update

5.5.1 Update needs assessment

Salt problem in the soil is a dynamic phenomenon owing to the changing characteristics of its drivers. It is therefore expected that maps of salt-affected soils will also change with time. Furthermore, the spatial coverage of measured soil indicators is not always exhaustive owing to sampling limitations. Altogether, these factors emphasize the need for planning for updates. The following factors need consideration when planning update for salt-affected soil maps:

a) Need to update the age of input data used in developing the current map
b) Need for additional data collection to cover areas with high uncertainties in the current map
c) Need for field surveys to monitor hot-spot areas in terms of salt problems
d) Budget to cover the update cost
e) Update focus (e.g. for prevention or control of salt problems, database management, etc.)

5.5.2 Sampling for monitoring and gap filling

One of the points to consider when planning information update is the number of locations to visit and the geographic areas to prioritize. The number of locations is determined using a simple expression such as

$$samples = Area * \left(\frac{1}{4*w*pixel}\right)^2 \quad (5.9)$$

where *pixel* is the pixel size of the map, *Area* is the area of target site to be sampled in m^2, and *w* is the number of soil forming factors data for mapping, which is obtained from the Jenny's soil forming factors model (*Cl,O,R,P*). The maximum possible number of soil-forming factors (*w*) is 5 (Jenny's factors and Soil) irrespective of number of layers in each factor while the minimum number is 1. Equation (5.9) is based on the minimum legible distance (MLD) concept in soil mapping (USDA-NRCS, 1999).

The number of samples from Equation (5.9) can be allocated to the target area using available sampling protocols such as Latin hypercube sampling, random sampling, stratified random sampling (Sheikholeslami and Razavi, 2017). The function *surveyPoints* in the *soilassessment* package, which uses stratified random sampling is used to implement the sample allocation. The inputs for this function are:

- the map to sample,
- number of CLORP layers used in developing the map,
- the class in the map to sample, and the proportion of all statistically possible sample-size to target.

#Step 4-1: Identifying areas to target with update

 # Get the summary of classes to target

```
> predictors$saltaffectedness=classCode(predictors$Salt_affected,"sal
tseverity")
> hist(predictors$Salt_affected, main = "Topsoil salt-affected classe
s ", xlab="Codes for salt-affected classes")
```

#Convert the summary into a dataframe for determining the proportions of each class

```
> salts=predictors["saltaffectedness"]; salts=as(salts,"SpatialPixels
DataFrame")
> salts=predictors["saltaffectedness"]; salts=as(salts,"SpatialPixels
DataFrame")
> salty=as.data.frame(salts)
> salty1=data.frame(count(salty$saltaffectedness))
> colnames(salty1)=c("Saltclass","Cases")
> salty1$Props=round(salty1$Cases/sum(salty1$Cases)*100,1)
> barchart(Saltclass~Props, data=salty1, xlab="Proportion (%)")
```

The bar plot shows the proportions of study areas dominated by the salt intensity classes. After choosing the preferred class to update, then sample points are selected and distributed in the identified class.

#Step 4-2: Create number of update locations and display in the map

```
> predictors$Saltclass=as.numeric(predictors$saltaffectedness)
> salinity_LUT30=classLUT(predictors["saltaffectedness"],"saltseverit
y")
  |==================================================================
=========| 100%
> salt_affected_class=5
> clorp_factors=5
> survey=surveyPoints(soilsample,clorp_factors,salt_affected_class,10
)
> length(survey$new)

[1] 33
> spplot(soilsample, scales=list(draw=TRUE),sp.layout=list("sp.points
",survey,pch=8,col="cyan")) # Figure 5.18
> writeOGR(survey,".","SurveyPointsClass5",driver = "ESRI Shapefile")
```

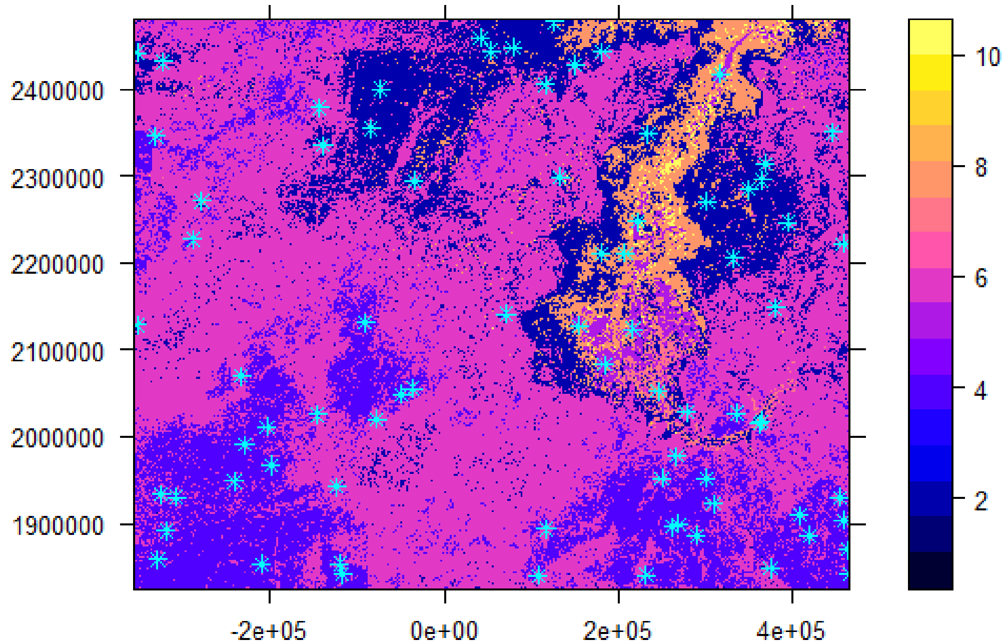


Figure 5.18: Number and placement of samples for updating

5.6 References

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SECTION THREE: INFORMATION SHARING AND RESOURCES MOBILIZATION

This section outlines the requirements and procedures for information sharing and resource mobilization for developing or monitoring salt-affected soils.

6 Product documentation and information sharing

6.1 Product documentation

Maps of salt-affected soils are useful spatial information depicting the status of salt problems in the mapped area. They are much more useful when shared with stakeholders with interest in management or alternative use of these soils. Map documentation adds value to the spatial information. Map documentation is done through: 1) cartographics of map elements during map development, 2) map metadata accompanying the maps, and 3) map publication in platforms such as the country soil information system, journals, etc.

6.1.1 Cartographics of map elements

Elements in a map layout are objects that help users of the map to visually connect the spatial relationship in the map product. Unlike other documents that are separate from the map, map elements are integral with the map. Key elements of a map are data, legend, title, compass, scale, citation, longitude and latitude grid lines, inset, acknowledgements, and year of publication and data age. These elements should be included during map layout development.

Map data are derived from the GIS layers that produced the map. Levels of EC or ESP are examples of map data in the map of types of salt-affected soils. Map data are the central information carried by the map. Their clear representation is the first step towards conveying the intended spatial information of the maps. Buckley (2012) outlined the following five principles generally considered important when making a good map: good visual contrast, legibility, figure-ground orientation, hierarchical organization, and balance.

Good visual contrast enhances aesthetic appeal of the map and helps readers to identify the distinction between different levels of the map data. In mapping salt-affected soils, good visual contrast is achieved by using distinct colour symbology for different types and intensity of salt problems in the soil. Figure 6.1 is an example of colour symbology for different classes of salt problems in the soil.

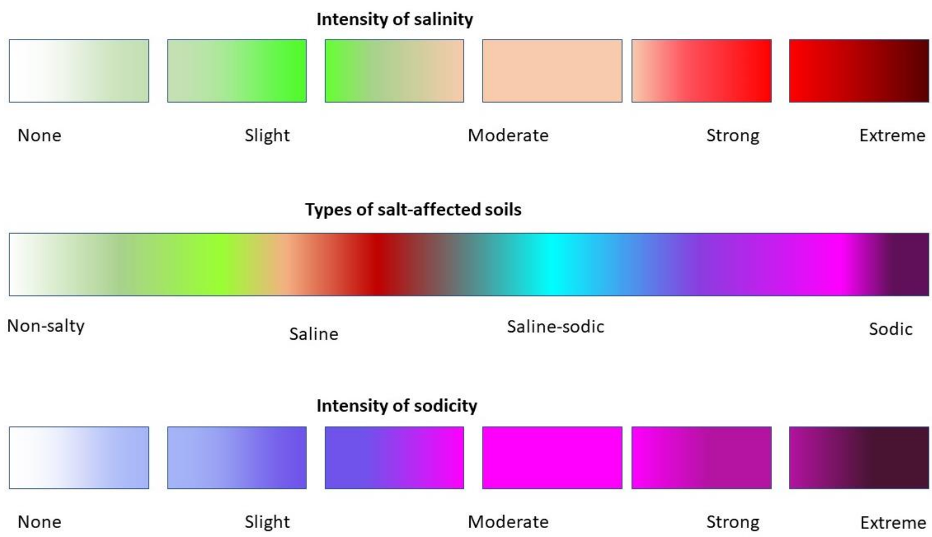


Figure 6.1: Representing salinity in maps

Legibility concerns map presentation to allow easy reading and understanding of its message by the users. Legibility focuses on the map elements and labelling. The elements of the map need to be clearly visible and easily convey the intended map message. Labelling and texts in the map play a crucial role in map legibility. They are used to convey intellectual hierarchy, that is, ranking of the importance of what is labelled. An example of intellectual hierarchy is in the case of labelling boundaries where use of uppercase letters is preferred for international country names, bold lowercase letters for higher administrative units within a country, and so on. In general, the legibility principle emphasizes on using big and bold labelling styles for high hierarchy and decreasing text font and style with lower hierarchy. Legibility principle also emphasizes on the following when labelling:

- To avoid (or minimize) text rotation (up-side down, except for left and right grid labels)
- To avoid (or minimize) mixing font types in a labelling hierarchy
- To separate rank categories by changing the font size by 2
- Use colour deep blue for water bodies
- Separate map of salt-affected soils and uncertainty maps for clarity (Figure 6.2)
- Always spell-check the labels
- A good visual balance in map legibility including:
    - The size, pattern and colour of the symbols

- Visual hierarchy of the symbols and elements
- Location of the map elements with respect to each other and visual centre of the map
- Including graticule and neat line

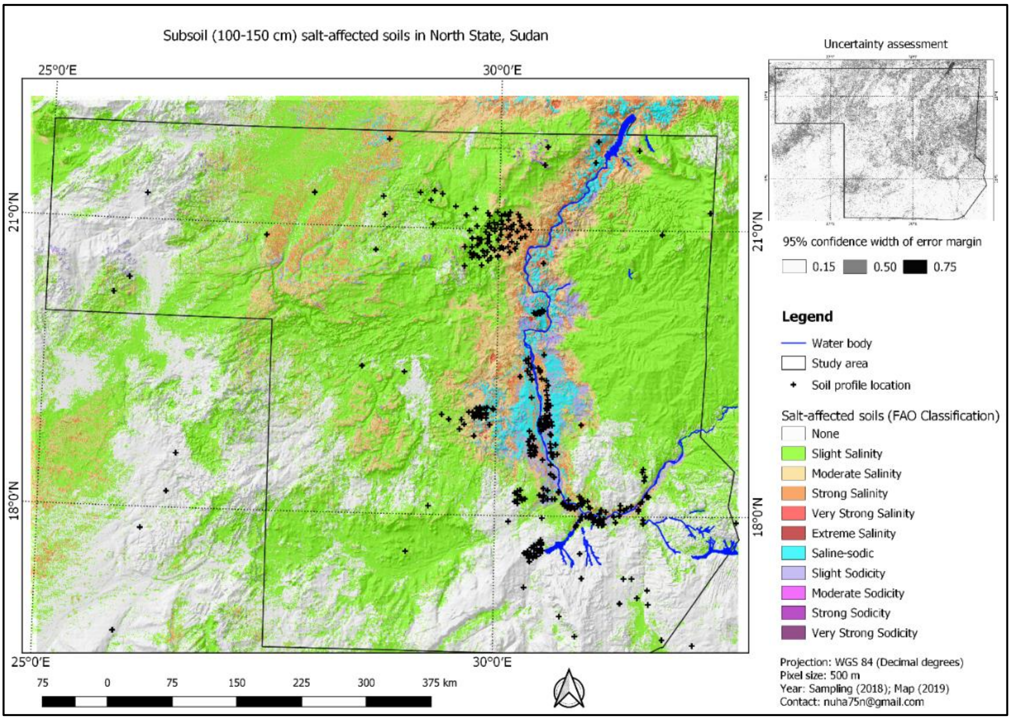
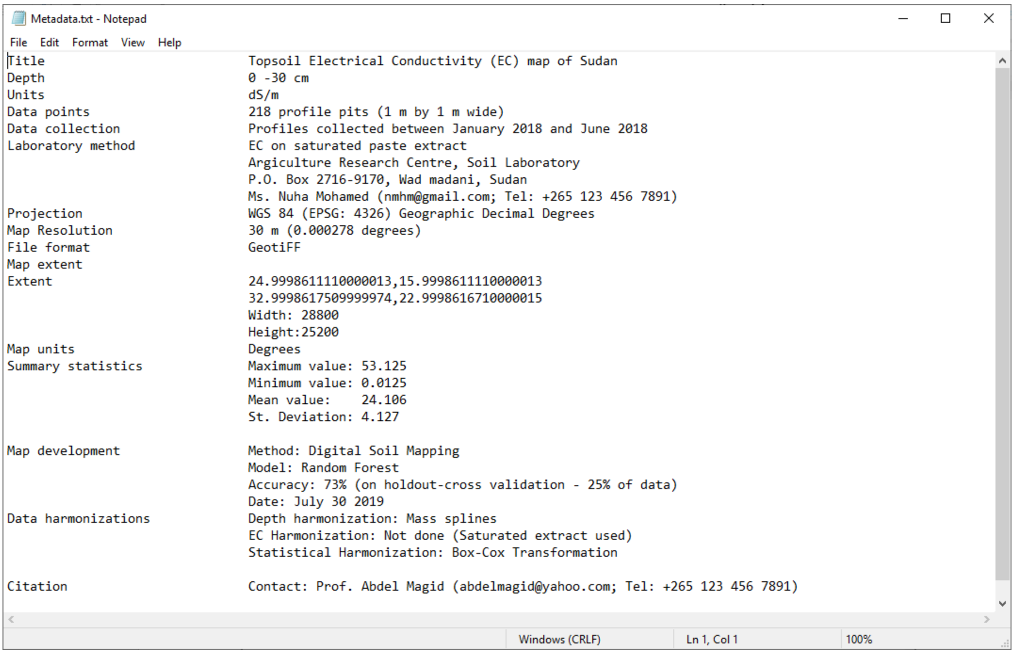


Figure 6.2: Example documentation in map layout

Background orientation convey the landscape feel of the map. They pin the user's perspective to specific areas in the map. Examples of background orientation includes hillshade, whitewash, drop shadow, and feathering, among others. In mapping salt-affected soils, background orientation enhances areas with certain salt levels and convey visual relationships to the underlying landscape drivers of the salt levels (Figure 6.2).

6.1.2 Map metafile

A metafile is the file containing map metadata. Metadata is the data about data or simply information about data (*métadonnée* in French). It gives a summary of the map content, data used and methods for creating the map, date of publication and other relevant information. It is normally a two-column textfile, which is convertible to xml file when necessary (Figure 6.3).



```
Title                        Topsoil Electrical Conductivity (EC) map of Sudan
Depth                        0 -30 cm
Units                        dS/m
Data points                  218 profile pits (1 m by 1 m wide)
Data collection              Profiles collected between January 2018 and June 2018
Laboratory method            EC on saturated paste extract
                             Argiculture Research Centre, Soil Laboratory
                             P.O. Box 2716-9170, Wad madani, Sudan
                             Ms. Nuha Mohamed (nmhm@gmail.com; Tel: +265 123 456 7891)
Projection                   WGS 84 (EPSG: 4326) Geographic Decimal Degrees
Map Resolution               30 m (0.000278 degrees)
File format                  GeotiFF
Map extent
Extent                       24.9998611110000013,15.9998611110000013
                             32.9998617509999974,22.9998616710000015
                             Width: 28800
                             Height:25200
Map units                    Degrees
Summary statistics           Maximum value: 53.125
                             Minimum value: 0.0125
                             Mean value:    24.106
                             St. Deviation: 4.127

Map development              Method: Digital Soil Mapping
                             Model: Random Forest
                             Accuracy: 73% (on holdout-cross validation - 25% of data)
                             Date: July 30 2019
Data harmonizations          Depth harmonization: Mass splines
                             EC Harmonization: Not done (Saturated extract used)
                             Statistical Harmonization: Box-Cox Transformation

Citation                     Contact: Prof. Abdel Magid (abdelmagid@yahoo.com; Tel: +265 123 456 7891)
```

Figure 6.3: Example metafile containing map metadata

6.2 Information sharing

Planning information sharing is important in order to deliver useful and impact-oriented information. The following three aspects need consideration when planning information share for salt-affected soils (Figure 6.4):

- Identification of the key issues driving information sharing
- Technical specification to harmonize information from different areas/sources
- Identification of the platform for information sharing

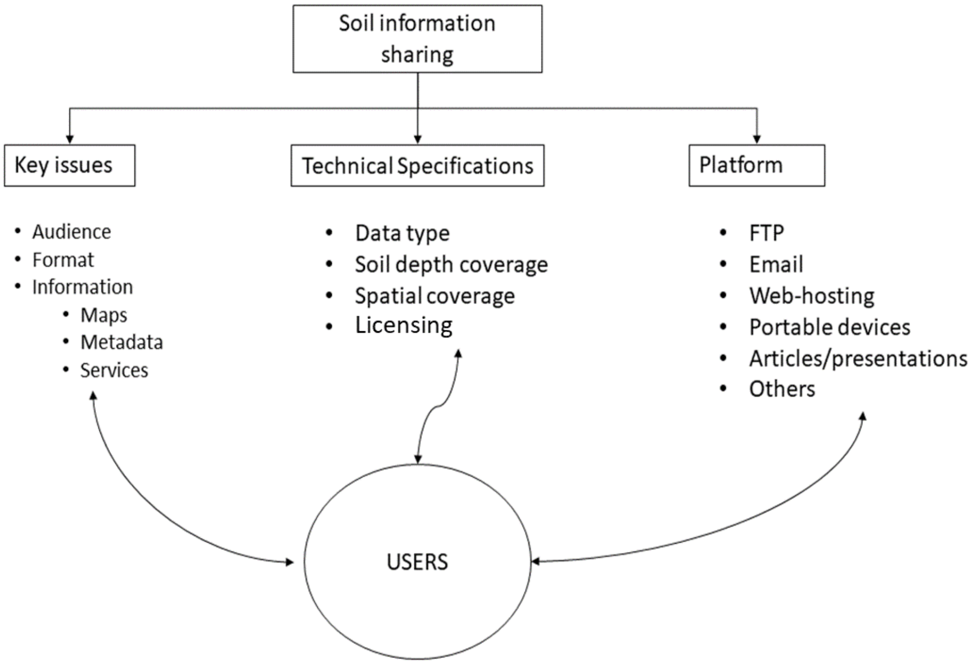


Figure 6.4: Areas for consideration when planning information sharing

The types of target audience influence the type of information format, characteristics, and information content to be shared. For example, researcher and modellers at the regional level may require coarse resolution GIS files while extension officers at farmer-fields may require paper/digital images at high resolution. The design for information sharing to target these two examples are significantly different. The type of audience also influence the type of media to employ as the vehicle for information sharing (Figure 6.4). These are some of the key issues for consideration when designing information sharing system. The GSP-FAO has proposed geoTiff raster files at 1 km spatial resolution for maps of soil indicators (EC, pH, and ESP) and maps of salt-affected soils for information sharing between countries and users at the regional and global levels (Table 6.1). However, each country may use own recommendations for planning systems for sharing information of salt-affected soils.

Technical specification is concerned with the characteristics of the map products and information content to be shared. The characteristics define the features of the information products that users will look for when searching for the information. They include map data (EC, pH, ESP, salt-affected soils, etc.), the vertical and horizontal resolution of the maps, data age, information access/use rights, and file formats for access. Technical specifications are particularly important in guiding information development since the features that they define should be included during map development. Table 6.1 is an example of specifications of the three products proposed by the GSP-FAO for updating national and global information of salt-affected soils. These specifications are also contained in the country guidelines for developing national information of salt-affected soils (FAO, 2020).

Table 6.1: Summary checklist for developing and sharing country-level maps of salt-affected soils

Category	Depth	Product 1	Product 2	Product 3	Platform
Soil property (1 km pixel size)	0 – 30 cm	EC, pH, ESP GeoTiff maps (WGS 84 Geographic)	Accuracy statistics (RMSE, ME, r^2, NSE)	Metafile	FTP
	0 – 30 cm	EC, pH, ESP Uncertainty GeoTiff maps	Statistics (Prediction width)	Metafile	FTP
	30-100 cm	EC, pH, ESP GeoTiff maps (WGS 84 Geographic)	Accuracy statistics (RMSE, ME, r^2, NSE)	Metafile	FTP
	30-100 cm	EC, pH, ESP Uncertainty GeoTiff maps	Statistics (Prediction width)	Metafile	FTP
Classified salt-affected Soils (1 km pixel size)	0 – 30 cm 0 – 30 cm	Severity GeoTiff maps (WGS 84 Geographic) Uncertainty GeoTiff maps (WGS 84 Geographic	Accuracy statistics (Kappa) Statistics (Prediction width)	Metafile Metafile	FTP FTP
	30-100 cm	Severity GeoTiff maps (WGS 84 Geographic)	Accuracy statistics (Kappa)	Metafile	FTP
	30-100 cm	Uncertainty GeoTiff maps (WGS 84 Geographic	Statistics (Prediction width)	Metafile	FTP

Copyright issues are important when it comes to information sharing. Many countries hold primary information such as measured soil profile data on EC, pH, ESP, etc. under copyright but may be willing to share secondary information under general public license (GPL). The secondary information includes maps developed from primary data, technical reports, and scientific publications. Other countries have strict copyright on all soil information. There are also other countries with GPL on all soil information. Publicly shared information needs to be under GPL.

Platform for information dissemination is the ultimate consideration for information sharing. Its choice is influenced by many factors including target audience, advances in technology and software development, information security, and magnitude of available data. Alternatives for platform for information sharing are physical and digital libraries (portals), online sever (geoserver), social/news media, dedicated website (soil information system), accessible online storage (google driver), etc. Since many countries are now developing national soil information systems (http://www.fao.org/global-soil-partnership/pillars-action/4-information-data/glosis/inventory-countrysis/en/), they can use the soil information service platforms as suitable alternatives for sharing their soil information on salt-affected soils. GSP-FAO has dedicated file transfer protocol (FTP) for sharing national information and a *geoserver* for globally contributed information on salt-affected soils.

6.3 Reference

Buckley A. 2012. Make maps people want to look at: Five primary design principles for cartography. Winter 2012. https://www.esri.com/news/arcuser/0112/files/design-principles.pdf

FAO. 2020. Country guidelines and specifications for mapping salt-affected soils. Rome

7 Resource mobilization

7.1 Resource mobilization strategy

7.1.1 Needs assessment

Building and updating information on salt-affected soils require resources. Associated activities such as data generation and/or collection, data analysis, developing information sharing protocol, and information update and monitoring are some of the core components that are resource intensive. Proper planning for resources mobilization is necessary for successful development and maintenance of information on salt-affected soils.

As already outlined in Section 1, salt-affected soils are very important in the global resource management and utilization. They occupy more than 1 billion hectares globally and are predominant in arid and semi-arid climate zones. This significant areal proportion can positively contribute to the global economy if economically utilized in a sustainable way (Wicke et al., 2011). Salt-affected soils are also home to many forms of biodiversity (Wu et al., 2015). Their proportion of the global land area can be resourceful for implementing carbon sequestration activities. They also support global food production through biosaline agriculture activities (Abdelly et al., 2008; Dajic-Stevanovic et al., 2008; Nikalje et al., 2018; https://www.biosaline.org/). These positive aspects reinforce the need for proper information on the status and extent of salt-affected soils. Besides the positive aspects of salt-affected soils, they are not truly desirable in agriculture areas. They have overall negative impacts in crop productivity. A lot of efforts are in progress globally to manage, reduce or prevent, and reclaim salt-affected soils in agriculture areas.

Resource mobilization for developing and periodically updating soil information of salt problems is important for sustainable management of salt-affected soils. According to (FAO, 2012) an initial step towards planning resources mobilization is the needs assessment. Needs assessment considers the core areas where resources mobilization is critical. It is also a process for justifying investment in developing information on salt problems in the soil (Figure 7.1). The following resource-intensive areas can be used as guidelines for planning resources mobilization needs assessment:

- Soil survey and laboratory analysis for estimation of soil indicators of salt problems
- Acquisition of equipment and high-resolution spatial predictors of salt-affected soils

- Technical capacity development for building spatial information products
- Developing infrastructure for spatial information sharing (system)
- Establishment and implementation of periodic monitoring systems

Assessment of resource mobilization needs should establish the significance for developing or updating soil information on salt-affected soils. Alignment with government development priorities, regional and global initiatives, and stakeholder synergies are some of the areas that should be targeted during evaluation of resource mobilization needs assessment. They help to identify opportunities for buy-in by these important stakeholders.

Resource mobilization needs assessment can be done through surveys such as interview, discussions, and literature review (FAO, 2012). Its output feeds into the development of strategy for resource mobilization (Figure 7.1).

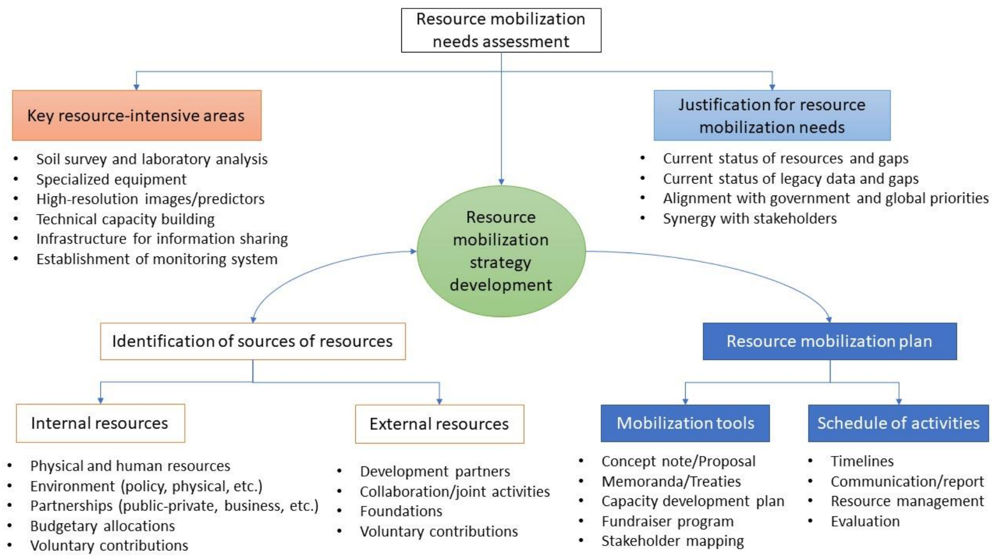


Figure 7.1: Resource mobilization strategy for building and updating soil information on salt-affected soils

7.1.2 Identification of sources

Identification of sources of resources is a priority focus in resource mobilization. It entails assessing the characteristics of different types and number of sources. It also incorporates mapping out the timing and duration of resource availability for the identified sources. This is especially important where multiple sources are targeted. A proper identification of sources of resources improves efficiency when selecting the appropriate resource mobilization vehicle(s) (tools).

Internal and external sources are the two major categories of sources for resource (FAO, 2012). Internal sources include available human and capital resources such as technical capacity, equipment, institutional (environment) framework, income generating activities, partnerships (public-private or communal-private partnerships), internal government budgetary allocations, and voluntary contributions from local foundations or individuals. Available soil database and network between technical experts on salt-affected soils and network between institution holding soil data are also important resources. Internal sources are critical during soil survey and when implementing sustainable long-term monitoring of salt problems in the soil. The institutional environment also affects data sharing, income generating activities to support monitoring framework, and potential engagement with/acquisition of resources from external sources of resources. External sources include international/regional development partners, potential collaboration (even research) activities with regional or international bodies/institutions on specific areas, among others. Some international/regional organization have rich technical cooperation programs (TCPs), which can provide substantial support in many of the key areas in soil and environmental information development.

7.1.3 Resource mobilization plan

Resource mobilization plan is the practical roadmap for mobilizing resources to implement the development and periodic update of spatial information on salt-affected soils. It entails the development of plans for communication, implementation of resource mobilization activities, and progress monitoring and evaluation. The resource mobilization plan outlines the vehicle (tools) to use for resource mobilizing and the timeline for their implementation. Examples of tools often used for sourcing funds are concept notes and proposals while memoranda are often used for mobilizing in-kind contributions, equipment, and network of expertise (FAO, 2012; Kipchumba et al., 2013). A suitable mobilization plan should have multiple strategies using different tools (vehicles) to target many sources of resources. This is particularly appropriate for salt-affected soils where field survey, laboratory analysis, and online hosting of soil information service are heavy one-time initial investment. This kind of investment is mostly tackled with multiple sources of resources.

Different organization have different requirements and format for the tools for resource mobilization (also known as vehicle for resource mobilization). It is important that these requirements are clearly adhered to when preparing communication strategy. Since these tools presents the mobilization idea and needs to the donor, it’s important that they are given adequate attention during their preparation. Important areas of focus when preparing the tools are:

a) target resource-intensive area for the development/update of information on salt-affected soils
b) Indicative/actual cost for implementing the identified target area in (a) above
c) justification for resource mobilization
d) schedule of activities

Table 7.1 gives a summary of the five steps for developing and implementing resource mobilization plan. The sequential steps begin with the identification of target area(s) requiring resource mobilizations and corresponding potential sources of resources. Subsequent steps are guided by the first step; implying that the first step determines the success/failure of the mobilization plan (FAO, 2012).

Table 7.1: Steps for planning resource mobilization for updated information on salt-affected soils

Step 1	**Step 2**	**Step 3**	**Step 4**	**Step 5**
Identification of sources of resource	**Tools identification**	**Tools development**	**Negotiation**	**Monitoring and evaluation**
Map out potential sources and their interests	Match potential tools and donor requirement	Start source-partner meetings	Reach out agreement and conditions	Periodically monitor and evaluate progress
Verify source and their conditions	Identify appropriate tools	Develop the tools for resource mobilization	Develop and formalize binding agreement	Feedback report
Identify areas they can support		Initiate communication with the identified source	Secure the resource	
Identify funding gaps				

7.2 Technical capacity development program for spatial information development

7.2.1 Program overview

Capacity building program in digital mapping of salt-affected soils is designed to help countries or GSP partners to gain technical knowledge and skills for developing maps of salt-affected soils and be able to periodically monitor salt problems in their countries. In the spirit of country-driven approaches and global soil information system, the need for harmonized national capacities and products cannot be over-emphasized. It is envisaged that national capacity building and harmonized information on salt-affected soils will give uniform message for raising national, regional, and global awareness on the need for sustainable management and economic use of these soils.

There are many methods and approaches in the literature as well as indicators for assessing salt-affected soils. This capacity development program focuses on supporting harmonization of protocols, uniform reporting, and technical empowerment of national officers to provide reliable information on national status of salt-affected soils. It uses digital soil mapping concepts, statistical computing, and GIS tools to produce spatial information of soil salinity.

This program targets national focal persons tasked with mapping salt-affected soils in their countries. The program is also suited to practitioners who are keen on information generation and management of salt-affected soils. People interested in digital soil mapping and monitoring of salt problems may find the program suitable for enhancing their spatial modelling skills.

7.2.2 Duration and requirements

This program is designed to take two weeks of data collection and 64 contact hours between participants and instructors for spatial information development. Participants are required to have own datasets during the training.

Successful implementation of the program requires the following:

1) Expertise
    a. Basic soil science and understanding of salt-affected soils
    b. GIS and computing knowledge
    c. Adequate understanding of soil salt problems in the country of focus
    d. Basic understanding of indicators of soil salts and laboratory methods of analysis

2) Computer and software
    a. Computer with minimum of core i3 processor, 8GB RAM, and enough storage capacity
    b. Installed latest versions of QGIS, ILWIS, R, and RStudio software
    c. The following installed plugins and packages:
        i. QGIS – Semi Automatic Classification, Profile Tool
        ii. R – Rstudio, raster,caret,rgdal,sp,soiltexture,soilassessment,randomforest, gstat, arm, automap, e1071,GSIF,Hmisc,corrplot,factoextra,spup,purr,ncf,aqp,car,plyr, kernlab
    d. Spreadsheet program (such as Excel and Access)
3) Resources
    a. Internet connectivity
    b. Technical manual on mapping salt-affected soils
    c. Country data for mapping soil salinity (Table 4.1)

7.2.3 Objectives and outcomes

Program goal: The overall goal of this program is to enhance technical capacities of countries to produce consistent, reliable, and comparable spatial information on salt-affected soils.

Program outcomes: At the end of the program, participants are expected to:

1. Produce updated database for mapping salt-affected soils in their countries
2. Establish baseline for monitoring salt-affected soils in theory countries
3. Produce national maps of status of salt-affected soils in their countries
4. Contribute to global mapping of salt-affected soils

Learning objectives: The program is designed to:

1. Enable participant to assemble and organize relevant data for mapping salt-affected soils
2. Expose participants to cutting-edge digital soil mapping methodologies
3. Enhance technical capacities of participants in developing spatial information of salt-affected soils
4. Enable participants quantify accuracy and uncertainties of maps of salt-affected soils
5. Improve participants' skills and awareness in documentation and soil information sharing

7.2.4 Schedule

Table 7.3: generic training outline

#	Topic	Sub-topics	Duration	Output
Part 1: Input data preparation and software installation				
Resources		**1.** Country guidelines and technical specification for mapping salt-affected soils **2.** Lecture 1 notes: Requirements and data preparation		
1	Identification of sources and collection of required data	Identification of soil/GIS data sources	1 week	Assembled national soil and GIS data for mapping salt-affected soils
		Collection of data		
		Verification of data		
		Documentation of collected data		
2	Input data preparation	Preparation of soil data	1 week	Organized input data
		Preparation of GIS data		
Resources		1. Lecture 2 notes: Software installation and data organization		
3	Software installation and data organization	Software acquisition	1 week	
		Software installation and beginners guide		
		Input data organization		

#	Topic	Sub-topics	Duratio n	Output
Part 2: Case-study modelling of salt-affected soils				
Resources		Lecture 3 notes: Spatial modelling of soil indicators (properties) Lecture 4 notes: Spatial modelling of salt-affected soils Case-study data		
1	Basics of salt-affected soils	Salt-affected soils and salinity problem	1 hr	
		Distribution of salt-affected soils		
		Importance of assessing salt-affected soils		
		Classification methods		
		Activity: Short Quiz		Score
2	Input data requirements	Indicators of salinity		
		Soil properties	1 hr	

	for mapping salt-affected soils	remote sensing indicators		
		Other covariates		
		Data types and data sources		
		Activity: Short Quiz	30 min	Score
4	Input data preparation	Spreadsheet data organization	2 hrs	Updated Database & Documentation
		GIS spatial layers organization	3 hrs	
		Reporting and documentation	1.5 hrs	
		Activity: Organize mapping database	30 min	
5	Introduction to software	Spreadsheet operations	4 hrs	
		QGIS: GIS operations and terrain analysis		
		ILWIS: GIS database development		
		R and RStudio: Statistical DSM modelling		
		Activity: Short Quiz		Score
6	DSM of indicators of salt-affected soils	Input data harmonization	3 hrs	Salinity indicator maps
		DSM modelling	20 hrs	
		Accuracy assessment		Accuracy report
		Reporting and documentation		Documentation
7	Modelling salt-affected soils	Salinity classification	6 hrs	Salinity map
		Uncertainty assessment		Uncertainty Maps
		Reporting and documentation		Documentation
8	Information sharing	Data sharing policy	4 hrs	submission to Global Salinity Map
		Contents of information sharing		
		Contribution to global soil salinity mapping		
Part 3: Developing national database of salt-affected soil				
Resources		Country level data for developing spatial information on salt-affected soils		
9	Indicators mapping	Developing spatial information of soil indicators of salt problems	1 day	Shared maps of indicators and types of salt-affected soil
10	Salt-affected soils mapping	Developing spatial information of salt -affected soils	1 day	

7.2.5 Mode of delivery

The program is designed for physical/online lectures, hands-on demonstrations, and reflection quizzes.

1) **Lectures**

Items 1 and 2 are parts of introductory lecture designed to expose the participants to the basics of salt-affected soils, classification, and input data requirements for mapping. PowerPoint presentations, class-discussions, and consultation with resource materials should be adequate for knowledge transfer. The quizzes give feedback on the understanding of the lectures

2) Demonstrations with worked examples

Part 2 of the program is focused on exposure of the participants to the mapping tools. Demonstrations using case-study dataset is emphasized to help the participants understand the procedural steps for mapping salt-affected soils and familiarity with the mapping tools.

3) Hands-on practical exercise with own data

Part 3 of the program is dedicated to working with own datasets. The participants will apply the skills in Part 1 on their own datasets. They may work independently on their country dataset.

7.2.6 Deliverables

The following deliverables are anticipated at the end of the training program:

i. Updated and harmonized national database of salt-affected soils
ii. Spatial national information (map with documentation) on salt-affected soils
iii. National maps of salt indicators (EC_{SE}, pH, ESP) for 0-30 and 30-100 cm soil depths submitted to the GSP as contribution to global mapping of salt-affected soils
iv. National maps of uncertainties for mapping salt-affected soils

7.3 References

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Glossary

Absorption: Uptake of matter or energy by a substance Acid soil: Soil with a pH value less than 7.0.

Acidification: Process whereby soil becomes acid (pH < 7) because acid parent material is present or in regions with high rainfall, where soil leaching occurs. Acidification can be accelerated by human activities (use of fertilizers, deposition of industrial and vehicular pollutants).

Adsorption: Process by which atoms, molecules or ions are retained on the surfaces of solids by chemical or physical bonding.

Alkali (sodic) soil: A soil having so high a degree of alkalinity (pH 8.5 or higher) or so high a percentage of exchangeable sodium (15 percent or more of the total exchangeable bases), or both, that plant growth is restricted

Anion: Particle with a negative charge. Her anion exchange capacity is sum of exchangeable anions that a soil can adsorb. Usually expressed as centimoles, or millimoles, of charge per kilogram of soil (or of other adsorbing material such as clay).

Base saturation: The degree to which material having cation-exchange properties is saturated with exchangeable bases (sum of Ca, Mg, Na, and K), expressed as a percentage of the total cation-exchange capacity.

Calcareous soil: A soil containing enough calcium carbonate (commonly combined with magnesium carbonate) to effervesce visibly when treated with cold, dilute hydrochloric acid.

Calcification: Process whereby the soil is kept sufficiently supplied with calcium to saturate the soil cation exchange sites.

Cation exchange capacity: The total amount of exchangeable cations that can be held by the soil, expressed in terms of mill equivalents per 100 grams of soil at neutrality (pH 7.0) or at some other stated pH value. The term, as applied to soils, is synonymous with base-exchange capacity but is more precise in meaning.

Decalcification: Removal of calcium carbonate or calcium ions from the soil by leaching.

Electrical conductivity (EC): Conduction of electricity through water or a solution of soil commonly used to estimate the soluble salt content in solution, e.g. soil solution

Hydromorphic soils: Formed under conditions of poor drainage in marshes, swamps, seepage areas or flats.

Ion: Electrically charged atom or group of atoms.

Irrigation: Application of water to soils to assist in production of crops. Methods of irrigation are:

- Basin: Water is applied rapidly to nearly level plains surrounded by levees or dikes.
- Border: Water is applied at the upper end of a strip in which the lateral flow of water is controlled by small earth ridges called border dikes, or borders.
- Controlled flooding: Water is released at intervals from closely spaced field ditches and distributed uniformly over the field.
- Corrugation: Water is applied to small, closely spaced furrows or ditches in fields of close-growing crops or in orchards so that it flows in only one direction.
- Drip (or trickle): Water is applied slowly and under low pressure to the surface of the soil or into the soil through such applicators as emitters, porous tubing, or perforated pipe.
- Furrow: Water is applied in small ditches made by cultivation implements. Furrows are used for tree and row crops.
- Sprinkler: Water is sprayed over the soil surface through pipes or nozzles from a pressure system.

- Subirrigation: Water is applied in open ditches or tile lines until the water table is raised enough to wet the soil.
- Wild flooding: Water, released at high points, is allowed to flow onto an area without controlled distribution.

Natric horizon: A special kind of argillic horizon that contains enough exchangeable sodium to have an adverse effect on the physical condition of the subsoil. Neutral soil A soil having a pH value of 6.6 to 7.3. (See Reaction, soil.)

pH value: A numerical designation of acidity and alkalinity in soil. (See Reaction, soil).

Profile soil: A vertical section of the soil extending through all its horizons and into the parent material.

Reaction soil: A measure of acidity or alkalinity of a soil, expressed as pH values. A soil that tests to pH 7.0 is described as precisely neutral in reaction because it is neither acid nor alkaline. The degrees of acidity or alkalinity, expressed as pH values, are:

- Ultra acid: Less than 3.5.
- Extremely acid: 3.5 to 4.4.
- Very strongly acid: 4.5 to 5.0.
- Strongly acid: 5.1 to 5.5.
- Moderately acid: 5.6 to 6.0.
- Slightly acid: 6.1 to 6.5.
- Neutral: 6.6 to 7.3
- Slightly alkaline: 7.4 to 7.8.
- Moderately alkaline: 7.9 to 8.4.
- Strongly alkaline: 8.5 to 9.0.
- Very strongly alkaline: 9.1 and high.

Saline soil: A non-sodic soil (see sodic soil) containing sufficient soluble salt to adversely affect the growth of most crop plants. The lower limit of electrical conductivity in the saturation extract of such soils is conventionally set at 4 dS m-1(at 25°C), though sensitive plants are affected at about half this salinity and highly tolerant ones at about twice this salinity. Salt-affected soils with a high exchangeable sodium percentage (ESP) greater than 15%, pH usually less than 8.5; in general, these soils are not suitable for agriculture.

It's a soil that containing soluble salts in an amount that impairs growth of plants. A saline soil does not contain excess exchangeable sodium.

Salt-affected soil: Soil that has been adversely affected by the presence of soluble salts, with or without high amounts of exchangeable sodium. See also saline soil, saline-sodic soil, and sodic soil.

Sodic soil: Soil with excess of sodium, pH is higher than 7, usually in the range 8-10, exchangeable sodium percentage, ESP> 15 and very poor soil structure. These soils need special management and are not used for agriculture; non-sodic soils are without excess of sodium.

Sodic (alkali) soil: A soil having so high a degree of alkalinity (pH 8.5 or higher) or so high a percentage of exchangeable sodium (15 percent or more of the total exchangeable bases), or both, that plant growth is restricted.

Sodicity: The degree to which a soil is affected by exchangeable sodium. Sodicity is expressed as a sodium adsorption ratio (SAR) of a saturation extract, or the ratio of Na^+ to Ca^{++} + Mg^{++}. The degrees of sodicity and their respective ratios are:

- Slight: Less than 13:1.
- Moderate: 13–30:1.
- Strong: More than 30:1.

Sodium adsorption ratio (SAR): A measure of the amount of sodium (Na) relative to calcium (Ca) and magnesium (Mg) in the water extract from saturated soil paste. It is the ratio of the Na concentration divided by the square root of one-half of the Ca + Mg concentration.

Soil: A natural, three-dimensional body at the earth's surface. It is capable of supporting plants and has properties resulting from the integrated effect of climate and living matter acting on earthy parent material, as conditioned by relief and by the passage of time.

Soil monitoring: Repeated observation and measurement of selected soil properties and functions, mainly for studying changes in soil conditions.

Soil morphology: Form and arrangement of pedological features. Subsoil technically, the B horizon; roughly, the part of the solum below plow depth. Surface soil, the A, E, AB, and EB horizons, is considered collectively. It includes all subdivisions of these horizons.

Appendices

Appendix A: Example image download from USGS

This section outlines the procedure for downloading remote sensing images such as Landsat OLI, Sentinel, and MODIS images and elevation (DEM) from the site https://earthexplorer.usgs.gov/. It is important to note that the steps outlined here are different for data download from other online repositories and that the illustration given here is purely for demonstration purposes.

1. Step 1: Launch the website by either pasting the link in a web browser or simultaneously press *Ctrl* (on the keyboard) and click to the link.
2. Step 2: Navigate to the area of interest (e.g. country boundary) by pressing and holding left-click of the mouse and moving the “hand pan” to the area (country) of interest. It may be necessary to zoom in or out (by using + or – navigation signs at the top-right part of the screen) for locating the area/country of interest. The download site has four buttons around the top-left corner: *Search Criteria*, *Data sets*, *Additional Criteria*, and *Results*. *Search Criteria* allows input spatial parameters for data search. This is done either by manually digitizing the corners of a polygon bounding the study area or uploading the file (shapefile or kml/kmz) (Figure A1).

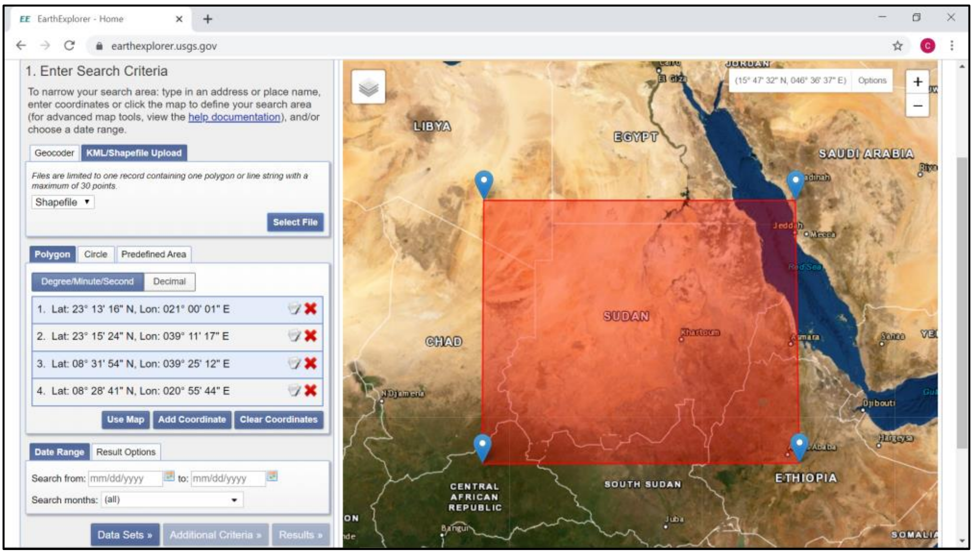


Figure A1: Earth-Explorer interface for data download

3. Step 3 (**Dataset** selection): Activate the *Data Sets* button to launch the window for viewing available datasets. This window lists available images by category such as Digital Elevation, Aerial Imagery, Sentinel, etc. (Figure A2). Each category has expandable (+) sign at the beginning of the list, which reveal available dataset in the group when expanded. Choosing the white square boxes next to the data selects data of interest. Furthermore, a click to the symbol opens a new window with metadata details about the selected dataset. Expansive areas may use elevation data (GMTED2010) and images (MOD9A1 V6) while Landsat OLI/Sentinel and SRTM DEM (30/90 m) may be ideal for less-expansive smaller areas. It is important to select each data category at a time for easy tracking and data download.

4. Step 4 (selection **Results view)**: Choosing the results button opens a new window in the interactive map-view. Here, the data is chronologically listed. Choosing the footprint icon () displays the image in the interactive map-view. Thereafter, a window for confirming the selection pups-up and the data download begins. It's important to ensure adequate internet connectivity at this point. GMTED2010 contains elevation data in three options: 1km (30 arc-second), 500 m (15 arc-second) and 250 m (7.5 arc-second). The appropriate option should be selected for download (Figure 4.8).

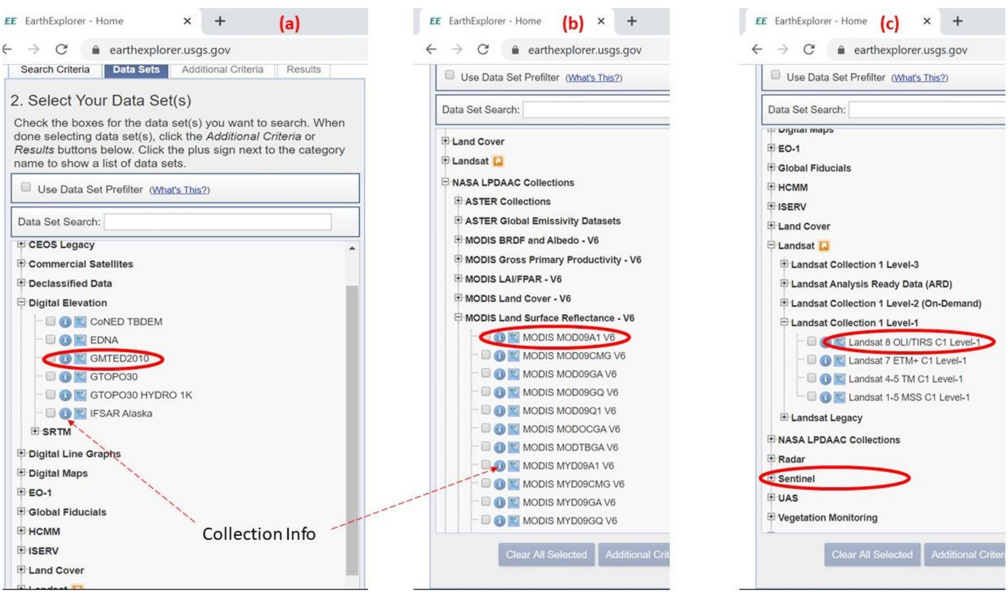


Figure A2: Choosing the dataset: a-elevation, b- MODIS and c-Landsat and Sentinel

(1) Downloading land cover and climate data

Online repertory for land cover data are available at (USGS) https://earthexplorer.usgs.gov/, GLC200 at (JRC)https://forobs.jrc.ec.europa.eu/products/glc2000/products.php), GLCS database at (FAO) http://www.fao.org/geonetwork/srv/en/main.home?uuid=ba4526fd-cdbf-4028-a1bd-5a559c4bff38, Global LC maps at (ESA) https://www.esa-landcover-cci.org/?q=node/158. These datasets are available for direct download for the whole world. Further data sub-setting may be necessary. Landcover data at USGS can be downloaded using the steps outlined in Figure A1 and A2.

Climate data is downloadable at http://www.worldclim.org/ in GeoTiff files at 1km spatial resolution for the whole world.

Appendix B: Frequently asked questions when implementing R

A. Errors with file types

1. **Replacement has 0**: I have got the following error when running line …

```
Error in `[[<-.data.frame`(`*tmp*`, name, value = numeric(0))
:
  replacement has 0 rows, data has 536766
```

This error occurs when processing multiple layers/variables to produce an output. It occurs when one of the input layers/variables is missing. Start by checking if all input layers/variables for that line are available by checking the global environment or running summary such as summary(predictors) or summary(soil1). Repeat the previous lines to ensure all previously created variables/layers were created.

2. **Object not found**: I have an error in line 161 saying:

```
Error in is.data.frame(x) : object 'predicters' not found
```

This type of error occurs when a file or data was not created. Either the line for its creation was skipped or the line also had error and did not successfully create of the file. It’s better to trace the line where file/layer or data was first created and implement the line again.

3. **Warning message**: There is an error message in line 128

```
Warning message:
In sqrt((nir * red - blue * green)/(nir * green + blue * green)) :
NaNs produced
```

This is not an error but a warning message. Checking the output may confirm if there is any peculiarity in the created layer/data

4. **Null summary**: The summary result is NULL when I run line …summary(predictors$ECtse)

```
Length  Class   Mode
0    NULL    NULL
```

This occurs when the layer/variable was either not created or the layer name is incorrectly spelt. Checking if the layer is available in the global environment or its correct spelling can help resolve the error

5. **Undefined columns selected**: Error in line 292: undefined columns selected

```
Error in `[.data.frame`(predictors@data, , c("SI1", "SI2", "SI3", "SI
4",  :
undefined columns selected
```

This type of error arises if one or more the variable/layer names specified for selection is missing in the dataframe or R object. Running *str* function with the dataframe or R object (*str*(object)) will give a list of the variables contained in the dataframe/object. Confirm if the missing variables/layers are listed with the correct spelling of their names.

6. **NA detected**: Error in line 296 NA in the data

```
Error in regmodelSuit(soil, TSS, lon, lat, EC) :
Remove NA in columns:  clay, ph, TSS, TTS, ECTSS, ESP, ECTTS, X
```

This function does not accept NA in the data and must be removed before executing it.

7. **Box-Cox transformation**: Error in line 273 when running Box-Cox transformation

```
Error in bc1(out[, j], lambda[j]) :
First argument must be strictly positive.
```

This type of error occurs when the target variable has zero or negative entries. These entries need to be removed before implementing the transformation. If there are zeros, a very small value (like 0.0001) may be added to the target variable to eliminate discontinuities around zero and a return of the error message.

8. **Histogram**: There is an error message when I run histogram function

```
Error in hist.default(soil1$TSS.1, main = "Frequency distribution (be
fore transformation)",  :
'x' must be numeric
```

9. **Graphical display**: Error in plot

```
Error in plot.new() : figure margins too large
In addition: Warning messages:
```

This error occurs when the plot window is too small. Manually enlarging the plot window by dragging its boundaries upwards and leftwards eliminates the error.

10. **Many plus signs in console**: There are many plus (+) signs in the console

This phenomenon occurs when one of the lines was executed without a closing bracket or quotation marks. Typing two or more closing brackets (or quotation marks) in the console will stop the error (of course with a warning message).

11. **Cursor orientation**: The cursor is horizontal and not vertical

This happens when *Insert* button on the keyboard was inadvertently struck. Striking the *Insert* key again restores the cursor orientation

12. **Depth harmonization**: Error in site function

```
[1] "pedons (616) rows of site data (619)"
Error: invalid site data, non-unique values present in horizon data?
```

This type of error occurs when the library (aqp) has not been updated or when there are mismatches in the reported profile. The mismatch often occurs when there are differences in (1) *lower* and *upper* entries in sample depths/horizons. It is important to ensure that for all profiles, the *upper* depth entry for any row (sampled depth/horizon) should be equal to the *lower* entry of the preceding row (sampled depth/horizon) (refer to Figure 4.5), (2) *Pit* number or Latitude/Longitude entry for the same pit differs for any given sampled depth/horizon (Figure 4.5), (3) incorrect columns were selected when developing the profile database. Correcting these anomalies will solve the error.

13. **Depth harmonization**: Error when running *prof1* line

```
Error in data.frame(id, lon, lat) :
arguments imply differing number of rows: 407, 0
```

This error arises when one of the parameters for depth harmonization was not properly specified. Check the global environment is each of the parameters (lon, lat, id, horizon, etc.) have been created, not NULL, and are of numeric file types (except for horizon and id which may be factor).

14. **Unexpected symbol**: Error of unexpected symbol

```
Error: unexpected symbol in "loncurv=readGDAL("loncurve.mpr")band"
```

This error occurs when a character is misplaced or missing in the script line. The character should be solved accordingly.

15. **Variable type**: Not meaningful for factors

Sometimes some operations are not permitted for factor type of data and will return errors for factor or integer type of variables. This happens when (during spreadsheet data organization) the entries are converted to integer/factor because of no decimal places (or NA in the data). It is important to cross-check the decimal places in the spreadsheet software before importing the data into R

B. Errors with libraries

1. **Missing functions**: I have got an error indicating "cannot find function…"

This type of error arises when the libraries where not loaded or not installed. Type a question mark followed by the missing function in R console and enter. A window will pop-up showing definition of the function. The name of the library containing that function is indicated at the top-left corner of the window. If the library is already installed, re-load it by typing *library* (missing library) in the console. If the library is not installed, install it and load it after installation. Some functions may be masked by other libraries. They can be accessed by appending the associated libraries before them using double colon (e.g. *dplyr::count(predictors$saltaffected)*). NB: It is important to run all the libraries as a first thing every time RStudio is restarted.

2. **Cannot install package**: Install packages does not work

This happens if 1) there is no internet connectivity, 2) there is write-protection to the folders (my documents or C/Programs/R), 3) the cran mirror is not responding, 4) the package is not available for installation. Check for internet connectivity and try to install the package again. Check for administrative rights and try installation again.

Change the cran mirror by typing *chooseCRANmirror()* in the console. A list will be displayed with selection option availed at the end of the list. Check for the numbers in the list and choose the number corresponding to the nearest working mirror. Insert it and enter. Then try installing the package again. Some packages which are not published in R CRAN may be available at GitHub. They can be installed using the specifications provided in the GitHub links.

C. Errors with working directors

1. No file in directory: Cannot find file

```
Error in file(file, "rt") : cannot open the connection
In addition: Warning message:
In file(file, "rt") :
cannot open file 'soildataU2.csv': No such file or directory
```

This error occurs when 1) the working directory is not correctly specified, 2) the file name is not properly spelt, 3) the import script has syntax errors. Check for the correct path to the working directory, check for spaces or pathname for the directory, check for correct spelling for the filename. Check the script for correct parameters and spelling of the parameter names (e.g. soil=read.csv("soildata.csv", heade=T).. the *header* parameter is missing *r* at the end and will return import error).

E. Errors with computing capacity

1. I have got an error indicating " cannot allocate vector of size…"

This error occurs when the computer memory is low. Sometimes adjusting the memory improves the performance (such as memory.limit(size=NA) or increasing the size by replacing NA with a higher value corresponding to or close to the computer RAM). The best option is to use a better computer with a higher memory

2. My computer is taking too long or is frozen

This happens when the software is executing simulations with higher threshold or for large datasets. It is better to be patient and wait for the process to progress to completion.

3. The computer keeps crushing and restarting

This happens when the computer has low RAM or when certain functions are returning infinite calculations.

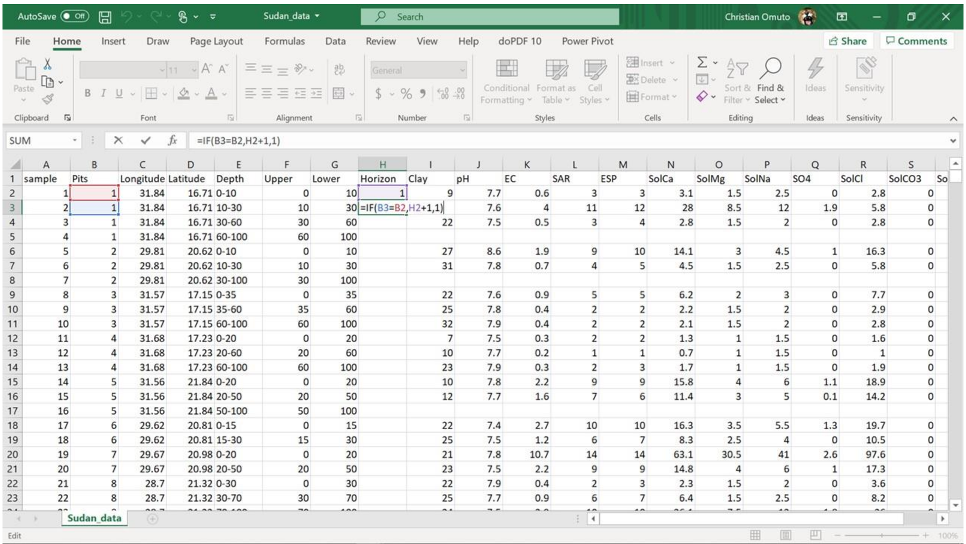
Appendix C: Checking for correct data organization in Excel

1. Inserting sequential numbers for horizon/sampling depth

Horizon/depth codes are sequential numbers from 1 at the top sampled horizon/depth and increasing consecutively (i.e. increasing by 1) to the last sampled horizon/depth (Figure 4.5).

- Step 1: Rank the *Pit, Longitude, Latitude, and Pit* columns in that order. This will order the Depth column accordingly.
- Step 2: Create three new columns after the *Depth* column (because of three elements in the *Depth* items – first depth, minus (-)/underscore (_) symbol for range, and last depth, 0-15). Creating new columns is achieved by selecting the column after the *Depth* column, right-click the mouse, and choose *insert*.
- Step 3: Copy and paste the *Depth* column into the nearby newly created column
- Step 4: Select the pasted column in step 3. Go to Data panel among the top row of buttons, click it and select text-to-columns option. A new window comes with *Delimited* option selected. Click next, choose *other* and type the symbol for the range as used in the data (either – or _). Click next till completion (finish).
- Step 5: Rename the columns as *Upper* and *Lower* for the first part and the second part respectively
- Step 6: Name the next column as *Horizon* and enter 1 in the 1st cell (directly below the column name). Then calculate consecutive series for all entries in the same *Pit*. Enter the formula

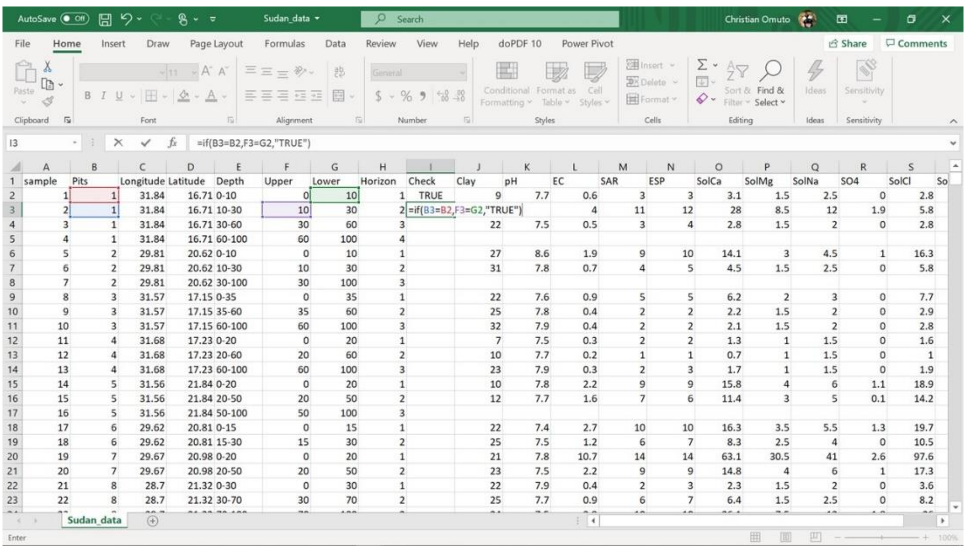
=if(B3=B2,H2+1,1) in the 2nd cell in *Horizon* column. Copy the results to all cells in the entire column. This formula means that if the *Pit* code in the previous row is the same as the current row, then add 1 to the value of *Horizon* in the previous row or else return *1*. 1 is added so that each *Horizon* begins from 1.



	sample	Pits	Longitude	Latitude	Depth	Upper	Lower	Horizon	Clay	pH	EC	SAR	ESP	SolCa	SolMg	SolNa	SO4	SolCl	SolCO3
2	1	1	31.84	16.71	0-10	0	10	1	9	7.7	0.6	3	3	3.1	1.5	2.5	0	2.8	0
3	2	1	31.84	16.71	10-30	10	30	=IF(B3=B2,H2+1,1)		7.6	4	11	12	28	8.5	12	1.9	5.8	0
4	3	1	31.84	16.71	30-60	30	60		22	7.5	0.5	3	4	2.8	1.5	2	0	2.8	0
5	4	1	31.84	16.71	60-100	60	100												
6	5	2	29.81	20.62	0-10	0	10		27	8.6	1.9	9	10	14.1	3	4.5	1	16.3	0
7	6	2	29.81	20.62	10-30	10	30		31	7.8	0.7	4	5	4.5	1.5	2.5	0	5.8	0
8	7	2	29.81	20.62	30-100	30	100												
9	8	3	31.57	17.15	0-35	0	35		22	7.6	0.9	5	5	6.2	2	3	0	7.7	0
10	9	3	31.57	17.15	35-60	35	60		25	7.8	0.4	2	2	2.2	1.5	2	0	2.9	0
11	10	3	31.57	17.15	60-100	60	100		32	7.9	0.4	2	2	2.1	1.5	2	0	2.8	0
12	11	4	31.68	17.23	0-20	0	20		7	7.5	0.3	2	2	1.3	1	1.5	0	1.6	0
13	12	4	31.68	17.23	20-60	20	60		10	7.7	0.2	1	1	0.7	1	1.5	0	1	0
14	13	4	31.68	17.23	60-100	60	100		23	7.9	0.3	2	3	1.7	1	1.5	0	1.9	0
15	14	5	31.56	21.84	0-20	0	20		10	7.8	2.2	9	9	15.8	4	6	1.1	18.9	0
16	15	5	31.56	21.84	20-50	20	50		12	7.7	1.6	7	6	11.4	3	5	0.1	14.2	0
17	16	5	31.56	21.84	50-100	50	100												
18	17	6	29.62	20.81	0-15	0	15		22	7.4	2.7	10	10	16.3	3.5	5.5	1.3	19.7	0
19	18	6	29.62	20.81	15-30	15	30		25	7.5	1.2	6	7	8.3	2.5	4	0	10.5	0
20	19	7	29.67	20.98	0-20	0	20		21	7.8	10.7	14	14	63.1	30.5	41	2.6	97.6	0
21	20	7	29.67	20.98	20-50	20	50		23	7.5	2.2	9	9	14.8	4	6	1	17.3	0
22	21	8	28.7	21.32	0-30	0	30		22	7.9	0.4	2	3	2.3	1.5	2	0	3.6	0
23	22	8	28.7	21.32	30-70	30	70		25	7.7	0.9	6	7	6.4	1.5	2.5	0	8.2	0

2. Checking for correct/consistent entries in *lower* and *upper* depth entries

- Step 1: Insert a new column after *Horizon* and call it *Check*. This column will check (and return TRUE) if the *Upper* in the current row is the same as *Lower* in the previous row.
- Step 2: Type TRUE in the 1st cell immediately below *Check.* Enter the formula =if(B3=B2, F3=G2, “TRUE”) in the second cell. Copy the formula in all cells.



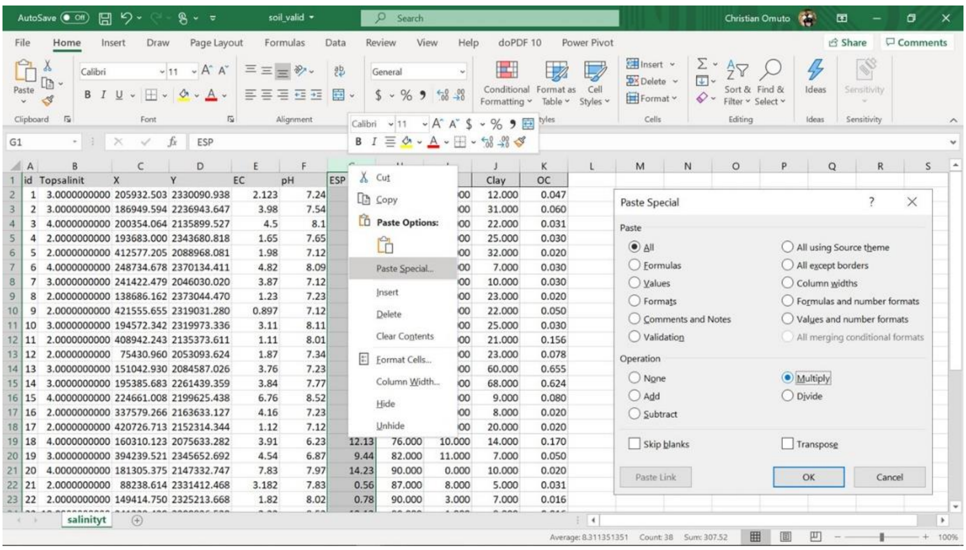
	sample	Pits	Longitude	Latitude	Depth	Upper	Lower	Horizon	Check	Clay	pH	EC	SAR	ESP	SolCa	SolMg	SolNa	SO4	SolCl
2	1	1	31.84	16.71	0-10	0	10	1	TRUE	9	7.7	0.6	3	3	3.1	1.5	2.5	0	2.8
3	2	1	31.84	16.71	10-30	10	30	2	=if(B3=B2,F3=G2,"TRUE")			4	11	12	28	8.5	12	1.9	5.8
4	3	1	31.84	16.71	30-60	30	60	3		22	7.5	0.5	3	4	2.8	1.5	2	0	2.8
5	4	1	31.84	16.71	60-100	60	100	4											
6	5	2	29.81	20.62	0-10	0	10	1		27	8.6	1.9	9	10	14.1	3	4.5	1	16.3
7	6	2	29.81	20.62	10-30	10	30	2		31	7.8	0.7	4	5	4.5	1.5	2.5	0	5.8
8	7	2	29.81	20.62	30-100	30	100	3											
9	8	3	31.57	17.15	0-35	0	35	1		22	7.6	0.9	5	5	6.2	2	3	0	7.7
10	9	3	31.57	17.15	35-60	35	60	2		25	7.8	0.4	2	2	2.2	1.5	2	0	2.9
11	10	3	31.57	17.15	60-100	60	100	3		32	7.9	0.4	2	2	2.1	1.5	2	0	2.8
12	11	4	31.68	17.23	0-20	0	20	1		7	7.5	0.3	2	2	1.3	1	1.5	0	1.6
13	12	4	31.68	17.23	20-60	20	60	2		10	7.7	0.2	1	1	0.7	1	1.5	0	1
14	13	4	31.68	17.23	60-100	60	100	3		23	7.9	0.3	2	3	1.7	1	1.5	0	1.9
15	14	5	31.56	21.84	0-20	0	20	1		10	7.8	2.2	9	9	15.8	4	6	1.1	18.9
16	15	5	31.56	21.84	20-50	20	50	2		12	7.7	1.6	7	6	11.4	3	5	0.1	14.2
17	16	5	31.56	21.84	50-100	50	100	3											
18	17	6	29.62	20.81	0-15	0	15	1		22	7.4	2.7	10	10	16.3	3.5	5.5	1.3	19.7
19	18	6	29.62	20.81	15-30	15	30	2		25	7.5	1.2	6	7	8.3	2.5	4	0	10.5
20	19	7	29.67	20.98	0-20	0	20	1		21	7.8	10.7	14	14	63.1	30.5	41	2.6	97.6
21	20	7	29.67	20.98	20-50	20	50	2		23	7.5	2.2	9	9	14.8	4	6	1	17.3
22	21	8	28.7	21.32	0-30	0	30	1		22	7.9	0.4	2	3	2.3	1.5	2	0	3.6
23	22	8	28.7	21.32	30-70	30	70	2		25	7.7	0.9	6	7	6.4	1.5	2.5	0	8.2

- Step 3: Filter the newly created *Horizon* and select and highlight entries with *FALSE* and investigate or correct them accordingly.

3. Removing error in format

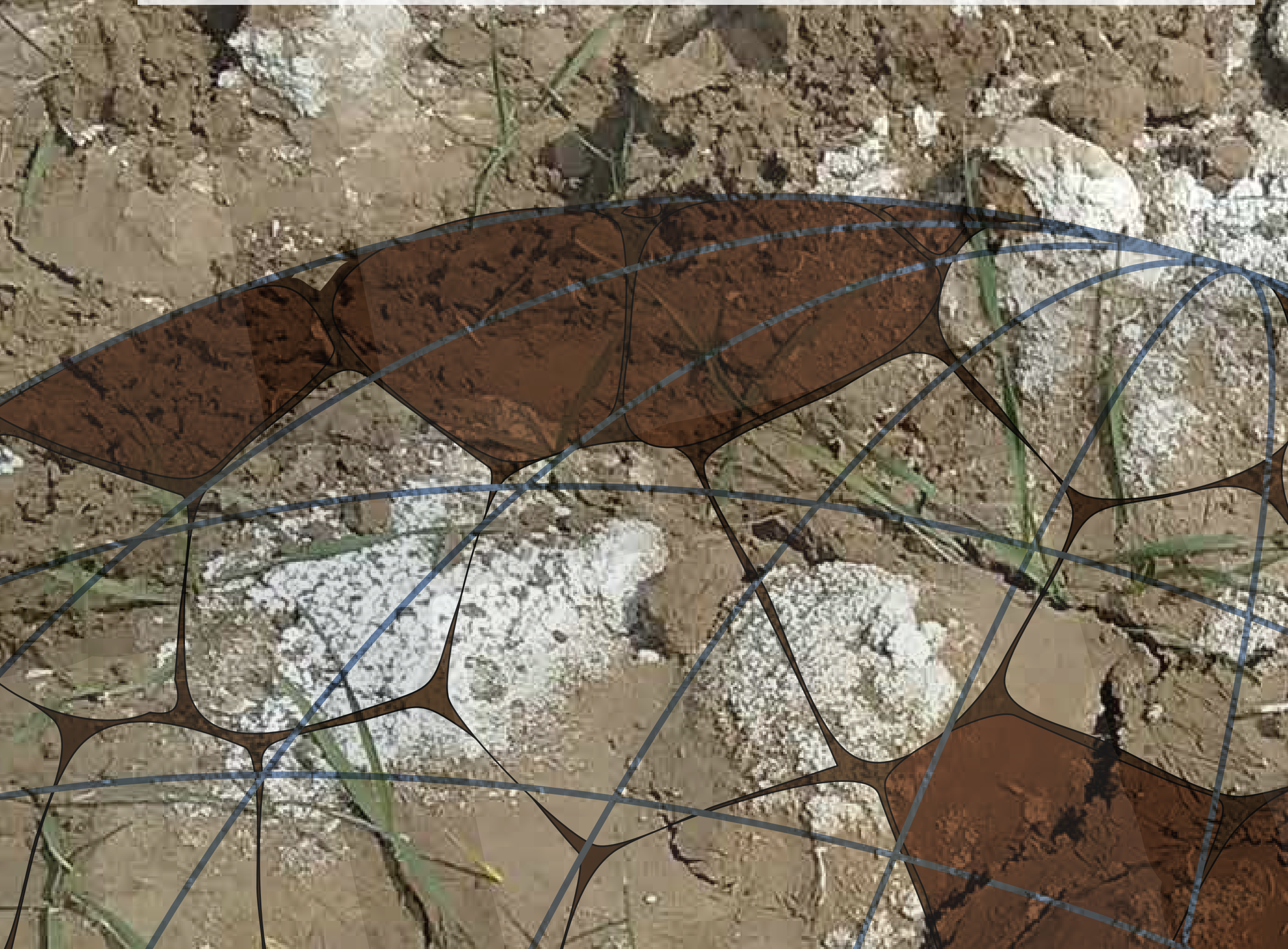
Sometimes some columns could show formatting errors with a green tag at the top left corner of the cells. This may be due to autocorrection of a formula or suspected differences in number sequencing or just general formatting errors. They can be removed by converting the cells (or the columns) into numbers.

- Step 1: Type 1 in any empty cell in a new sheet. Then copy the cell and return to the original sheet
- Step 2: Select the column to format beginning from the numerical entries which showed formatting
- Step 3: Right -click and choose *Paste special*, then select *Multiply* and click *Ok*. The error will be cleared



GLOBAL SOIL PARTNERSHIP

The Global Soil Partnership (GSP) is a globally recognized mechanism established in 2012. Our mission is to position soils in the Global Agenda through collective action. Our key objectives are to promote Sustainable Soil Management (SSM) and improve soil governance to guarantee healthy and productive soils, and support the provision of essential ecosystem services towards food security and improved nutrition, climate change adaptation and mitigation, and sustainable development.



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