



# Internet of things (IoT) assisted soil salinity mapping at irrigation schema level

Rab Nawaz Bashir<sup>1</sup> · Imran Sarwar Bajwa<sup>2</sup> · Muhammad Zahid Abbas<sup>1</sup> · Amjad Rehman<sup>3</sup> · Tanzila Saba<sup>3</sup> · Saeed Ali Bahaj<sup>4</sup> · Hoshang Kolivand<sup>5,6</sup>

Received: 13 August 2021 / Accepted: 7 March 2022 / Published online: 10 April 2022  
© The Author(s) 2022

## Abstract

Soil salinity accumulates a high concentration of salts in soils that interfere with normal plant growth. Early detection and quantification of soil salinity are essential to effectively deal with soil salinity in agriculture. Soil salinity quantification and mapping at the irrigation scheme level are vital to evaluating saline soil's reclamation activity. Existing solutions of salinity mapping are costly, time-consuming, and inadequate for applications at the irrigation scheme level. Internet of Things (IoT) assisted salinity mapping at the irrigation scheme level is proposed to quantify and map the soil salinity in agriculture. The proposed IoT-assisted salinity mapping characterizes the soil salinity in terms of Electric Conductivity, pH, and Total Dissolved Salts. The proposed IoT-assisted salinity mapping effectively observes impacts of reclamation activities in saline soil by frequent observation of soil salinity cost-effectively. The accuracy of proposed IoT-assisted salinity mapping is evaluated against the standard method of salinity measurements. The proposed IoT-assisted salinity mapping is cost-effective, and portable, which is very useful for site-specific treatments and soil zones management in saline soils.

**Keywords** IoT · Soil salinity · Salinity mapping · Electric conductivity (EC) · pH · Total dissolved salts (TDS) · Water management · Water resources · Economic resources

## Introduction

Soil degradation is a severe concern for sustainable developments in agriculture. Soil salinity is a land degradation phenomenon due to a high concentration of salts in the soils (Muller and Niekerk 2016; Kumar et al. 2015). Soil salinity

has adverse implications in agriculture with severe impacts on socioeconomic developments (Wang et al. 2018). Poor agriculture production and loss of precious land resources are the major impacts on socioeconomic developments. Furthermore, soil salinity is a serious hazard for the Food and Agriculture Organization (FAO) objective to feed the ever-increasing human populations that are expected to reach up to ten billion by 2050 (Singh 2018; Yu et al. 2018).

Soil salinity may be due to the parent material of soil or due to poor agricultural practices, known as primary and secondary soil salinity, respectively (Zaman et al. 2018). Intensive agricultural activities have diversified the issues of secondary soil salinity especially in arid and semi-arid regions (Abou Samra and Ali 2018). High temperatures and low rainfall in arid and semi-arid regions favor the process of soil salinization due to the high evaporation rate in these conditions.

Soil salinity turns the fertile soil into unfertile soil. Thus, soil salinity makes soil unfit for agriculture purposes (Muller and Niekerk 2016; Bashir et al. May 2020). Soil salinity also has adverse impacts on farms and infrastructures, resulting in barren lands (Muller and Niekerk 2016). According to one

✉ Amjad Rehman  
arkhan@psu.edu.sa

<sup>1</sup> Department of Computer Science, COMSATS University Islamabad, Vehari Campus, Vehari, Pakistan

<sup>2</sup> Department of Computer Science and IT, Islamia University Bahawalpur, Bahawalpur, Pakistan

<sup>3</sup> Artificial Intelligence & Data Analytics Lab (AIDA) CCIS, Prince Sultan University, Riyadh 11586, Saudi Arabia

<sup>4</sup> MIS Department, College of Business Administration, Prince Sattam Bin Abdulaziz University, Alkharj 11942, Saudi Arabia

<sup>5</sup> School of Computer Science and Mathematics, Liverpool John Moores University, Liverpool, UK

<sup>6</sup> School of Computing and Digital Technologies, Staffordshire University, Staffordshire, UK

estimate, one billion hectares worldwide is salt-affected with soil salinity, which is about seven percent (7%) of the total earth's continental surface area (Zewdu et al. 2017). More than one hundred and twenty-four countries are suffering from the issue of soil salinity (Zewdu et al. 2017). The distribution of the soil salinity in different regions of the world is given in Table 1.

The high concentration of salts in saline soil has a severe impact on plant growth and crop production. Soil salinity harms crop and plant growth with a reduction in agriculture productivity (Clenio et al. 2015). The uptake of the high concentration of salts from the saline soil has several negative effects on plant growth. Followings are some of the negative impacts of high concentrations of salts in the soil.

1. A high concentration of salts in saline soil interferes with normal plant physiology, which causes the poor growth of plants.
2. A high concentration of salts also negatively impacts hormonal activities and cell membrane functions of crop plants (Zaman et al. 2018).
3. A high concentration of salts causes oxidative stress in plants.
4. The plant's ability to uptake nutrients from the saline soil is severely affected.

There is an immense need for a solution for mapping and quantifying soil salinity at the irrigation scheme level to effectively deal with the issue of soil salinity. Early detection of salinity hazards is essential to support reclamation activities accordingly (Yu et al. 2018; Liu and Nelson 2008). Mapping and quantifying soil salinity are also essential to observe the impacts of reclamation activities against soil salinity. Therefore, there is a need for a solution that enables the farmers to determine the salinity level in the field in an accurate, frequent, and cost-effectively manner. In addition, soil scientists require a soil characteristics database at the regional, continental, and international levels to ascertain the issues related to soil. Such a database could be very helpful in dealing with issues related to soil across the world (Nocita et al. 2015). Different approaches to salinity mapping have emerged in recent years each with its advantages.

**Table 1** Region-wise salinity distribution (Tellaiche et al. 2011)

| Regions   | Salinity distribution (%) |
|-----------|---------------------------|
| Australia | 38.4                      |
| Asia      | 33.9                      |
| America   | 15.8                      |
| Africa    | 8.6                       |
| Europe    | 3.3                       |

The emerging techniques of salinity mapping are explored in the literature review sections.

Soil salinity is the measure of the concentration of salts in soils. Different parameters and models appraise the concentration of salts in soil. The Electric Conductivity (EC), Total Dissolved Salts (TDS), and pH are very common parameters for appraising the soil salinity. These parameters appraise soil salinity in terms of the concentration of total salts present in the soil.

IoT has shown tremendous success in many areas of life, including agriculture (Rehman et al. 2022). The IoT has the potential to deal with different challenges in agriculture (Kolivand et al. 2019). Emerging IoT-assisted environment monitoring solutions are very popular and successfully improve productivity in agriculture (Saba et al. 2017; Khan et al. 2021). IoT-assisted Precision Agriculture (PA) and smart farming applications have shown tremendous successes in environmental monitoring, irrigation water management, remote equipment control, animal monitoring, and many more (Rehman et al. 2022; Khan et al. 2021).

IoT is an exciting discipline that can provide context-aware services that are useful for dealing with agriculture issues. Up to the end of 2020, about seventy-five million IoT devices will be deployed in agriculture (Rehman et al. 2022). IoT also improves the process in agriculture to support energy efficiency, which leads to sustainable development in agriculture (Akram et al. 2020; Shaikh et al. 2017). IoT has shown tremendous success in monitoring and controlling the crop field environment in agriculture (Ismail et al. 2020). The ameliorative strategy for saline soil requires accurate temporal and spatial salinity mapping. IoT has the potential to map the soil salinity accurately and cost-effectively to deal with soil salinity effectively.

## Organization of the study

The study discusses the issue of soil salinity, its impacts, and distribution across the world in the "introduction" section. In the "literature review," section the emerging soil salinity mapping techniques are reviewed. The advantages and disadvantages of different techniques of salinity mapping are also discussed to identify the prospects of the proposed solution and to identify the research gap for the study. In the "Material and method" section, the architecture of the proposed solution, the model of soil salinity, and the implementation of the proposed solution are described. In the "evaluation" section the accuracy of the proposed solution is evaluated against the standard method. At last, the analysis and discussion with limitations of the study are given.

## Contribution of the study

In agriculture, early detection of salinity hazards and support of reclamation activities in saline soils is critical. Therefore, there is a need for a cost-effective solution for soil salinity quantification and mapping and supports the frequent observation of soil salinity at the irrigation scheme level in agriculture. IoT can play a significant role in addressing salinity mapping issues at the irrigation schema level in agriculture (Fern et al. 2017). The main contributions of the study are listed here.

1. Proposed a portable IoT architecture of salinity mapping at the irrigation scheme in a cost-effective way.
2. Assessment of proposed solution in terms of its accuracy to observe the soil salinity parameters.

The proposed solution is designed to address the problems and issues associated with the existing methods of salinity mapping at the irrigation scheme level in agriculture. The proposed IoT-assisted salinity mapping at the irrigation scheme level is designed to detect salinity hazards in agriculture fields. The proposed solution is unique in its portability and applicability of salinity mapping at the irrigation scheme level cost-effectively. The proposed solution is portable to use in empty as well as crop fields. The proposed solution is also beneficial for validating reclamation activities and supports other methods like RS for validation purposes.

## Literature review

Many techniques of mapping soil salinity and reclamation activities have emerged in recent years. The most important are chemical analysis of soil samples, Electro-Magnetic Induction (EMI) surveys, and Remote Sensing (RS)-based hyperspectral data analysis techniques. Each of these approaches has its advantages and issues.

The laboratory-assisted chemical approach is a valid and accurate method of salinity mapping. Salinity is observed using the chemical analysis of the soil in laboratories. The most common approach in chemical analysis is the evaporation of the gravitational approach in which soil solution is evaporated and remaining solute particles are weighed. Chemical analysis of soil samples is the most rigorous and accurate technique of salt measurements in saline soil (Don Bennett 2021). This technique provides the exact composition of different salts solutes and their concentration in the soils. This information is useful to deal with the issue of soil salinity effectively. However, chemical analysis of soil sampling is a costly and time-consuming process. For each sample, chemicals must be used that increase the cost. On average, it takes fifteen minutes and 2.31 US\$ per sample

for a 400-hectare survey using chemical-based soil analysis. Continuous and frequent mapping of the soil salinity is essential to observe the impact of reclamation activities on soil salinity. Chemical analysis-based salinity mapping is not suitable for continuous and frequent soil salinity mapping due to the cost and time.

Many new technologies also emerge to deal with the issue by recording different ways of salinity mapping like RS and EMI. EMI is based on the principle of Induction to determine the EC of the soil. EMI is used extensively in agriculture to map soil variability in terms of nutrients and fertility (Doolittle and Brevik 2014). EMI is also used as a salinity mapping with reasonable accuracy (Doolittle and Brevik 2014). EM-3 and EM-4 are popular EMI devices for mapping soil salinity (Doolittle and Brevik 2014). EMI-based salinity survey is a fast and quick approach to salinity mapping for large or small geographical areas. However, EMI approach requires the expert to map soil salinity. The initial cost of this equipment is high. The EMI devices are also susceptible to interference from other devices.

RS-based salinity mapping by hyperspectral data analysis is a cost-effective method of salinity identification and mapping over a large geographical area (Pouladi et al. 2019). Due to soil salinity, the white crystalline soil surface is the basis of the reflectance property of the soil to identify the salinity hazard (Gorji et al. 2017). This technique is called the direct method of salinity mapping using RS-based hyperspectral data. Different types of indices are developed to identify the salinity from RS hyperspectral data. The crop and vegetative growth on the soil surface make the direct method of RS salinity mapping challenging to implement. Plants in saline soil show retarded growth and yellowish color. The reflectance property of plants affected by the salinity is also used as an indirect approach of RS to salinity identification from hyperspectral data. Hyperspectral data from RS has emerged as a cost-effective way of quantifying soil salinity in large geographical areas (Kumar et al. 2015). Many indices and techniques in different parts of the world emerge from mapping the salinity by RS-based hyperspectral data (Gorji et al. 2017).

Ajay Singh proposed RS and Geographical Information System (GIS) assisted salinity mapping at the regional scale in the irrigated areas (Singh 2018). Clenio et al. (2015) proposed salinity mapping using hyperspectral data from OLI/Landsat-8. Kumar et al. (2015) developed different indexes of salinity quantification with hyperspectral data and correlated these indices with EC observation to find the accuracy of soil salinity quantification. Finally, Doolittle and Brevik (2014) proposed EMI-assisted salinity mapping.

Jiang and Shu (2019) proposed salinity detection in inner layers of the soils from 1 to 50 cm using the hyperspectral remote sensing data. Nastaran Pouladi et al. (Pouladi et al. 2019) recommended vegetation indices for observing soil

salinity by indirect methods from hyperspectral RS data. Peng et al. (2017) proposed Cubist and Partial Least Square Regression (PLSR) models from the EC of the soil salinity. Qian et al. (2019) developed a linear model of salinity estimation from RS hyperspectral data. Wang et al. (2019) evaluated the performance of different machine learning models to estimate soil salinity from hyperspectral RS data. Shiri et al. (2017) developed heuristics models to determine the soil Cation Exchange Capacity (CEC). Blasch et al. (2015) proposed soil pattern analysis based on hyperspectral data. Finally, Ivushkin et al. (2018) proposed an Unmanned Aerial Vehicle (UAV) assisted salinity mapping.

WSN and IoT have an essential role in soil monitoring for context-aware applications in agriculture. This real-time soil monitoring provides opportunities to support sustainable developments. Many solutions have been proposed in recent years regarding soil temperature, moisture, and pH monitoring. Ananthi et al. 2017 recommended monitoring of soil and irrigation water. The proposed solution senses the soil temperature and pH to determine irrigation water accordingly Raut et al (2018). proposed monitoring soil temperature, humidity, and nutrients for efficient irrigation water management. Pandithurai et al. 2017 recommended WSN based soil temperature, humidity, and pH monitoring to recommend irrigation water according to these soil characteristics. Nocita et al. (2015) proposed cost-effective soil spectroscopy-based soil monitoring and soil analysis to reduce the cost associated with soil analysis. Nagaraju and Chawla (2020) proposed soil temperature, humidity, and pH monitoring for precise irrigation water recommendations. Filippi et al. (2018) proposed soil monitoring to assess the soil's pH to identify the soil's acidification. Harshani et al. 2018 proposed IoT-assisted soil pH level, moisture, temperature, and humidity monitoring .

Łostowski et al. (2020) proposed IoT bases low powered module for observing the soil parameters. The proposed solution is based on Low Power Wide Area Network (LPWAN) to communicate and share data with the server. Safiyah et al. (2021) proposed EC and PH monitoring in hydroponics systems to determine the nutrient contents. Krishna et al. (2020) recommended an industrial multiparameter sensor node to overcome the problems of developing IoT-based automation systems in water monitoring applications. Duy et al. (2015) proposed an IoT system for Irrigation water quality monitoring in aquaculture. The proposed solution continuously monitors the temperature, pH, and Dissolved Oxygen (DO) of aquaculture ponds. Yasin et al. (2021) review the role of IoT in the conservation of freshwater usage in agriculture and home usage. Othaman et al. (2020) proposed an IoT system to observe the EC in crop fields to determine the nutrients in the paddy rice field. The study elaborates the EC relationship to the temperature in the crop field. Rajesh Kumar Yadav et al. proposed

irrigation water quality monitoring and the Irrigation Water Quality Index (WQI) model based on salinity and sodic. The proposed IWQI is based on the tracking of  $\text{Na}^+$ ,  $\text{Cl}^-$ , EC,  $\text{HCO}_3^-$ , and SAR (Sodium Absorption Ratio). The proposed Index helps assess water quality to reduce the cost and time associated with laboratory-based testing of water (Gupta et al., 2018).

Nigussie et al. 2020) proposed a resource-efficient IoT system to monitor the soil, microenvironment conditions, and water parameters to recommend irrigation water according to the prevailing condition. Roux et al. (2019) proposed Unmanned Aerial Vehicle (UAV) assisted IoT architecture for environment monitoring. Julien Roux et al. proposed a low-powered sensor module for observing the soil moisture and salinity. The proposed sensor is based on capacitive reading on a cylindrical performance to optimize the contact surface for minimal time to read. The low-powered sensor is easy to insert in soil, low energy consumption architecture. The proposed sensor can easily communicate with Sigfox or LoRa network. Stühmer et al. (2013) proposed a framework of modern technologies like IoT for the desalination of the water. The study explores the possibilities of the application of IoT to efficiently handle the desalination of water. Yıldız and Karakuş (2020) recommend the water monitoring for the Sodium Absorption Ratio (SAR), Kelly Index (KI), Permeability Index (PI) Sodium Percentage (Na%), and Irrigation Water Quality Index to assess the quality of surface water. The study also evaluates four different surface water quality assessment models from the observed parameters of water collected from thirty-two stations. The result concluded that Artificial Neural networks (ANN) best assess irrigation water quality from the selected parameters.

### Problems of existing approaches

After the comprehensive literature review, it was found out that the laboratory-based chemicals analysis approach is accurate but costly and time-consuming (Abou Samra and Ali 2018). This approach is not suitable for frequent monitoring of soil salinity. Electro-EMI is applicable at farmer's level applications but is very costly to be affordable by the individual farmers of low-income countries in arid and semi-arid regions. EMI devices are costly and require expert knowledge to operate and maintain. Most of the available EMI devices interfere with agronomic activities. The RS approach of using the reflectance property of the saline soil also becomes popular. This approach is suitable for large geographical area monitoring. RS techniques are suitable for salinity mapping over a large geographical area. The direct method of salinity mapping by RS is valid when salts have appeared at the soil's surface. However, the direct approach of RS suffers from issues like the presence of salt-tolerant plants in saline soils and salinity in lower layers of soils.

The indirect approach of RS also faces issues due to the presence of halophytes and the crop rotation policy of the farmers. Therefore, both these approaches of RS are not suitable for the early detection of salinity hazards. Moreover, salinity is usually a lower ground phenomenon that is hard to identify from RS techniques early. Therefore, RS approaches are only applicable when salinity has appeared at the surface or in the upper layers of the soil.

The indirect method of salinity mapping by RS is based on the detection of retarded growth and change in the color of the plants. The presence of salt-loving plants and crop rotation policy are also major issues associated with the accuracy of the indirect method of salinity mapping by RS. RS techniques are difficult to apply at the irrigation scheme level. Moreover, the resources and time required for the existing approaches make them unsuitable for frequent salinity mapping at the irrigation scheme level. Soil salinity is a lower ground phenomenon that is hard to identify from hyperspectral data of RS. Therefore, early detection of salinity hazard development by the RS approach is not feasible.

## Material and method

The IoT-assisted salinity quantification and mapping at the irrigation scheme level are proposed. The architecture of the proposed solution, the equipment used for the implementation purpose, and implementations detail is given in this section. The primary objective of the proposed solution is to map soil salinity at the irrigation scheme level frequently, accurately, and cost-effectively.

The proposed solution is beneficial to observe the impacts of different reclamation activities by frequent observation of the soil salinity at the farmer level at a low cost. Therefore, the study aims to propose an architecture of mapping soil salinity at the farmers' level in agriculture. The study also implements and evaluates the proposed architecture to identify the accuracy of the proposed solution in mapping the soil salinity.

## Proposed architecture

Architecture for IoT-assisted salinity mapping is proposed to map soil salinity from remote areas using the proposed sensor nodes. The architecture is based on the EC sensor node, pH sensor node, TDS sensor node, Solid-State Drive (SSD) card, and gateway node shown in Fig. 1. The soil EC, pH, TDS, and temperature sensors are attached to a gateway node microcontroller board. The data from this sensor node are transferred to the server using the gateway node. The data at the server are processed and presented to the end-user in the required formats. The data from the sensor node are saved on the SSD card as backup and transferred to the

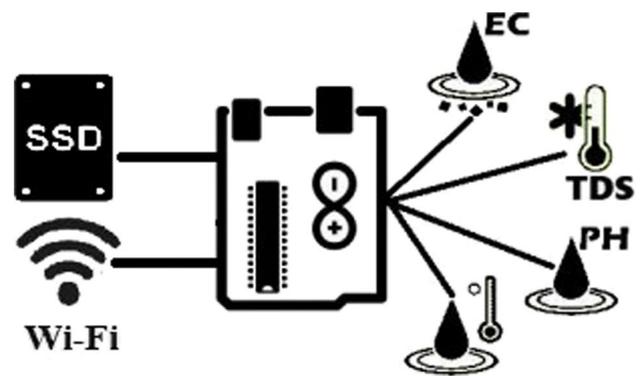


Fig. 1 The architecture of sensor nodes

server on the availability of the Internet. This architecture makes the proposed solution interoperable and functional in remote areas where Internet connectivity is not available.

The proposed architecture enables the mapping of soil salinity in a portable manner. The proposed solution is light-weight and can be moved easily from one field to another. The proposed architecture is portable to move quickly from one field to another. The raw data from the sensor node has been transferred to the server. From the server, users can access the information.

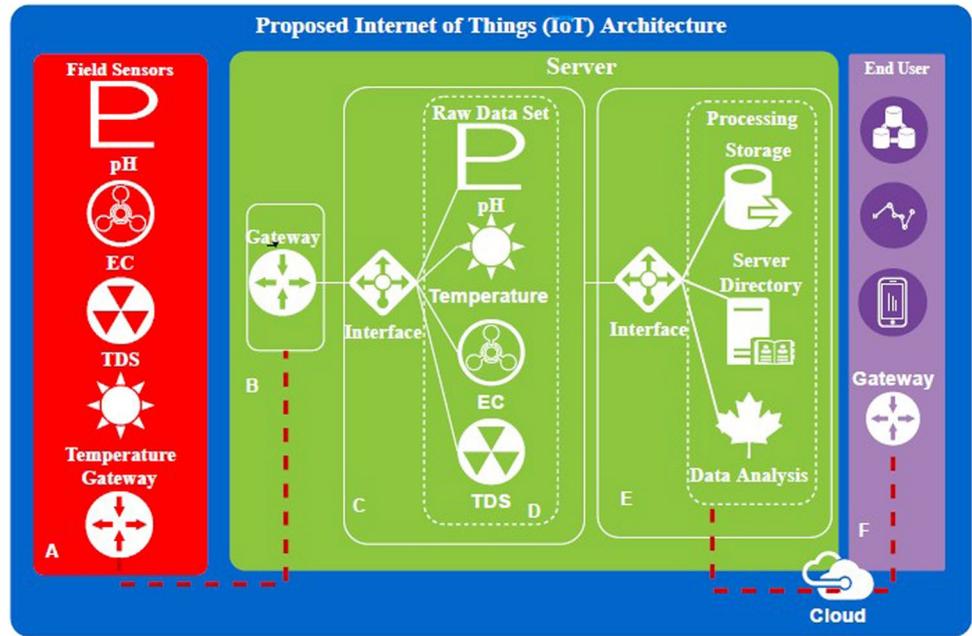
Solid State Drive (SSD) storage plays a significant role in improving the portability, interoperability, and accessibility of the proposed solution by making it functional in remote areas where the Internet is not available. In case of lack of Internet connectivity, the data are temporarily stored on the SSD storage. On the availability of Internet connectivity, the data from the SSD storage are transferred to the server. This architecture allows the proposed solution to be functional in remote areas where Internet connectivity is not available. The implication of SSD improves the accessibility, portability, and interoperability of the proposed architecture.

Components of the proposed architecture for salinity mapping at the irrigation scheme are shown in Fig. 2. The proposed architecture is designed to map salinity at the irrigation scheme level, in an accurate, portable, and cost-effective manner. The three layers of the architecture are shown in Fig. 2, with a field sensor layer, data processing layer, and end-user support layer.

## Soil salinity model

The study maps the soil salinity based on the EC, pH, and TDS in soil solution. The model map salinity based on the concentration of all salts in soil rather than the concentration of each salt in the soil. The soil particles and moisture are neutral in nature. Therefore, the ability of the soil to conduct electricity is only due to the presence of salt particles in the soil. The more salts particles in the soil,

**Fig. 2** Components of IoT Architecture



the more would be the EC and TDS of the soil. EC is the measure of the total concentration of the total salt particles in the soils. The EC model of soil salinity is applicable in nature due to the availability of related sensing technologies. The EC model of soil salinity is recognized by the United States Salinity Laboratories (USSL) (Zaman et al. 2018).

The basic unit of EC is the Siemens and Deci-Siemens per meter ( $\text{dSm}^{-1}$ ). EC is affected by temperature (Fern et al. 2017). Soil EC increases at 1.9% with a rise of one degree of soil temperature. Therefore, the observation of the EC is also made with the temperature to standardize the EC at 25 °C. EC observed at different temperatures is converted to interpolated EC by temperature coefficient (ft). The interpolated EC at 25 °C is determined by Eqs. 1, 2, and 3.

$$EC_{25} = F_t + EC_t \tag{1}$$

where,

$$F_t = 1 - 0.20(T) + 0.38T^2 - 0.0055T^3 \tag{2}$$

where,

$$T = [\text{Temperature} - 25]/100 \tag{3}$$

According to the USSL, the soil classification based on the EC range is shown in Table 2.

The pH is the measure of acidity and alkalinity of the soil. pH is used to characterize the acidity and alkalinity of the soil. pH is the measure of hydrogen ion concentration in the soil. Due to the high concentration of hydrogen ions, the pH scale is a logarithmic scale of hydrogen ions. For one unit of pH increase the acidity decrease by a factor of 10.

**Table 2** EC-based Soil classification (undefined FAO and FAO-Food and Agriculture Organization of the United Nations 2018)

| EC ( $\text{dSm}^{-1}$ ) | Salinity Class       | Impacts on crop               |
|--------------------------|----------------------|-------------------------------|
| 0–2                      | None                 | Plants are not affected       |
| 2–4                      | Slightly Saline      | Sensitive crops affected      |
| 4–8                      | Moderately saline    | Mostly crops affected         |
| 8–16                     | Strongly saline      | Resistant crop survive        |
| > 16                     | Very strongly saline | The high resistive crops grow |

pH is a revers scale with high pH means low concentration of hydrogen ions. The acidity increases due to the presence of hydrogen ion concentration; therefore, the low pH means more acidity (T. S. of Queensland 2016). The pH scale ranges from 1 to 14, shown in Fig. 3. The pH level 1 means the highest level of acidity and 14 means the highest alkalinity with the lowest level of hydrogen ion concentration. Mostly the pH of the soils ranges from 3.5 to 10. The soil classification based on pH values is given in Table 3.

The TDS is the sum of organic and inorganic substances present in a solution passing through the filters. TDS of a solution is the measure of the presence of different anions and cations in the solution. The TDS is measured in milli gram per liter (mg/l). The higher the TDS value, the more would be the chance of soil salinity. TDS value of more than 2000 mg/l in irrigation water is not suitable for the crop (Vargas et al. 2018). TDS-based soil characterization is given in Table 4, with impacts on crop plants.

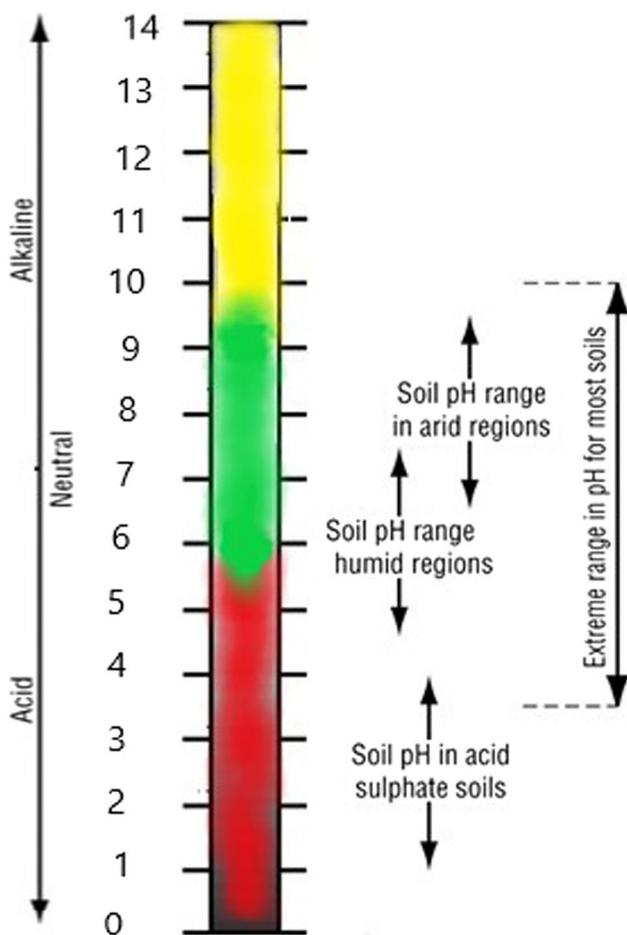


Fig. 3 pH range in soil (T. S. of Queensland 2016)

Table 3 pH based soil classification (T. S. of Queensland 2016)

| Soil Classification | pH level |
|---------------------|----------|
| Strongly Acidic     | < 5.5    |
| Acidic              | 5.5–6.5  |
| Neutral             | 6.5–7.5  |
| Alkaline            | 8.6%     |
| Europe              | 3.3%     |

Table 4 TDS-based soil classification

| TDS (mg l <sup>-1</sup> ) | Salinity Class              | Impacts on crop          |
|---------------------------|-----------------------------|--------------------------|
| < 450                     | None                        | Plants are not affected  |
| 450–2000                  | Slightly to Moderate Saline | Sensitive crops affected |
| > 2000                    | Severe saline               | Mostly crops affected    |

**Characteristics of proposed solution**

The following are the significant characteristics of the proposed solution.

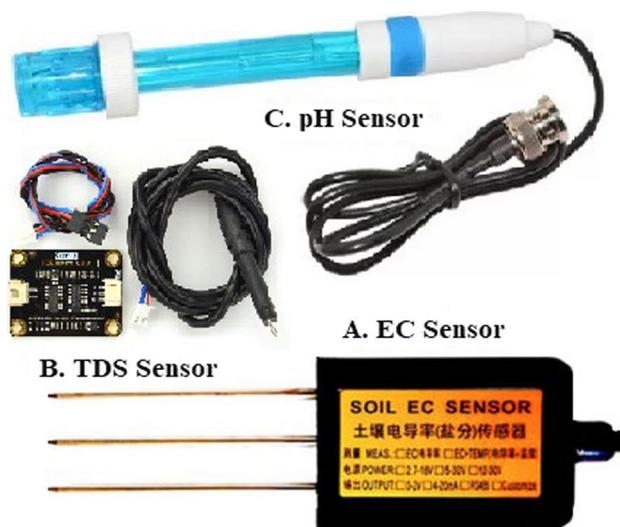


Fig. 4 Salinity mapping Sensors

1. The proposed solution is cheap compared to the EMI and RS-based solutions in terms of initial cost and operating cost.
2. The proposed solution is applicable to map soil salinity at the irrigation scheme level in agriculture.
3. The proposed solution is portable in nature that can be quickly moved across the field, without any cost of the transfer.
4. The data about the soil salinity is stored at one location that can be accessed by farmers, research organizations, and regulatory authorities. The IoT helps to keep sampled data at a single database that would be useful for the soil scientist and other organizations to use data from a single place.
5. The proposed solution can be used frequently in a cost-effective manner.
6. The proposed solution can be effectively used for early detection and quantification of salinity and to observe the impacts of reclamation activity applied against the soil salinity.

**Implementation details**

The equipment used to implement the proposed solution is the soil EC sensor, pH sensor, and TDS sensor shown in Fig. 4. These are cheap, commercially available sensors. These sensors are configured with a NodeMCU as a gateway node to transfer data from the sample point to the server shown in Fig. 5.

The sensed data are displayed and transferred to the server for further processing, storage, and analysis purpose. The data from the sensor are received at the server that is available for decision-making for different stakeholders. The



**Fig. 5** Sensor node porotype with sampling in the field



**Fig. 6** The experiment area with salts appeared on the surface

sensor node with sampling in the field is shown in Fig. 4. Each sensor node also displays the sensed data on a portable display, attached to each sensor node.

## Evaluations

The proposed solution aims to map the soil salinity at the irrigation scheme level accurately and cost-effectively. The accuracy of the proposed solution in soil salinity mapping is compared against the laboratory-based chemical analysis method. The laboratory-based chemical analysis is the standard method for soil salinity quantification. For experiment purposes, an area of one acre with 207 feet in length and width is selected, which is severely affected by soil salinity, shown in Fig. 6. In the experiment area, sixty-four samples

are observed by both proposed and standard methods to evaluate the difference in observations by both methods. At these sixty-four sampling points, the proposed IoT-assisted salinity mapping and standard laboratory-based chemical analysis observe the soil EC, pH, and TDS.

The sixty-four sampling points are equally spaced in the selected experiment area. One sample is taken for the area of  $8 \times 8$  feet in length and width. A single sensor would read the values from each sample point location by moving the prototype from one sample point to other. The sampling area depends on the objectives of sampling, the time available, and the level of salinity in the field. The comparison by the proposed IoT-assisted salinity mapping against the standard method is made to determine the accuracy of the proposed solution to map soil salinity for selected parameters of EC, pH, and TDS for soil salinity.

## Accuracy comparison

Salinity is mapped by three important salinity parameters that are EC, pH, and TDS. The selected salinity characteristics EC, pH, and TDS define the soil salinity sufficiently. The observations of these parameters by the proposed IoT-assisted salinity mapping and standard methods are compared in the next section.

### Accuracy of electric conductivity (EC)

The proposed IoT-assisted salinity mapping shows the EC observations in the experiment area at sixty-four sampling points in part “A,” and by the standard method in part “B” of Fig. 7. It is observed that EC values in the experiment area are higher on one side of the selected area as compared to the other directions by both types of observations. The EC observations by the proposed IoT-assisted salinity mapping and standard method show similar values at most of the sixty-four sample points in the experiment area, shown in Fig. 7. The Bland–Altman difference plot is used to find the difference in salinity mapping and quantification by two methods.

To analyze the difference in observation by two methods, the Bland–Altman difference plot is drawn in Fig. 8. The difference in observation of two methods is plotted against the mean of two observations in Fig. 8.

It is observed that the mean difference between the EC observation by the proposed IoT-assisted salinity mapping and the standard method is  $-0.05$  for each sampling point. Thus, the bias between the two methods for EC observations is  $-0.05$  for each sample point. This means that the proposed IoT-assisted salinity mapping, on average, measures  $0.05$  less EC than the standard method of soil salinity for each sample point observation. Thus, the bias between the proposed IoT-assisted salinity mapping and the standard

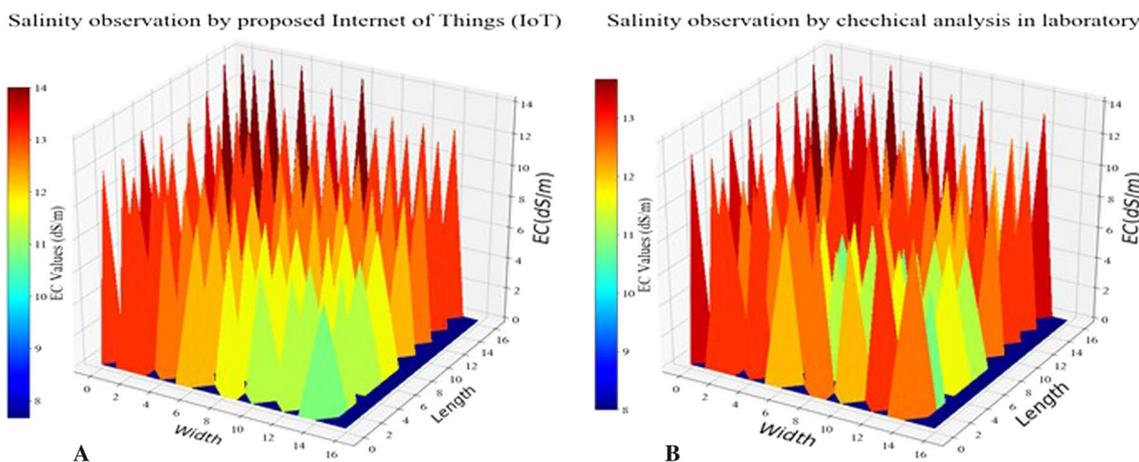


Fig. 7 EC observations

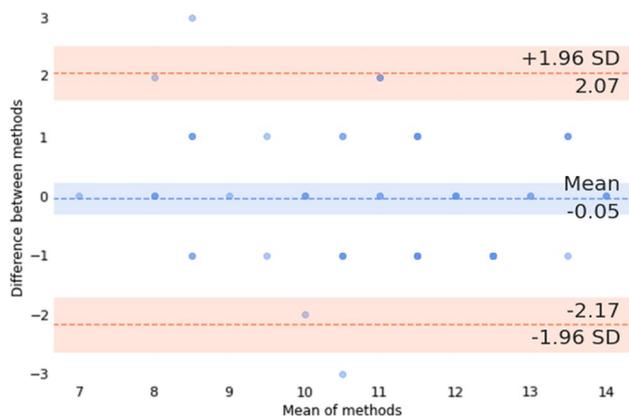


Fig. 8 Bland Altman difference plot for EC observations

method is very low. The bias can be used to calibrate the proposed IoT-assisted salinity mapping by Eq. 4, where  $EC_m$  is observed EC, and  $EC_c$  is the calibrated EC.

$$EC_c = EC_m + 0.05 \tag{4}$$

**Accuracy of pH observations**

The pH observations by the proposed IoT-assisted salinity mapping are shown in part “A” and by the standard method of chemical analysis in part “B” of Fig. 9. Both methods show similar pH observations at most of the sampling points. Both methods observed the pH in the range of 6–9 at each of sixty-four sample points in the selected experiment area.

The Bland–Altman plot in Fig. 9, shows the mean difference in pH observation for sixty-four sample point observations by both the proposed and standard methods. The mean difference for the pH observation by the proposed IoT-assisted

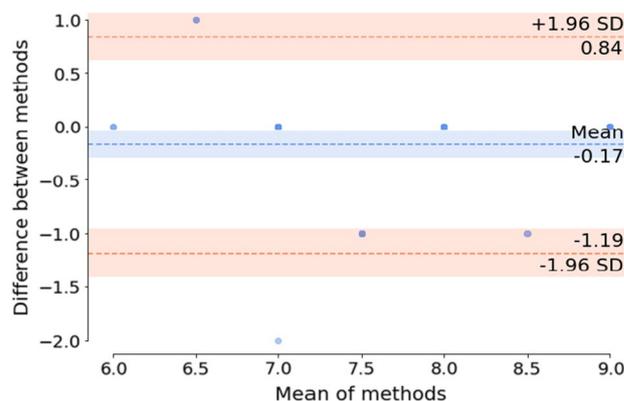


Fig. 9 Bland Altman difference plot for pH observations

salinity mapping and standard method is  $-0.17$ . Thus, the bias between the two methods for pH observation of soil pH. is  $-0.17$ . The bias  $-0.17$  in pH observation, means that the proposed IoT-assisted salinity mapping, on average, measures 0.17 less pH than the laboratory method of soil salinity for each sample point observation. Thus, the bias between the proposed IoT-assisted salinity mapping and the standard method is low for pH observations. The bias can be used to calibrate the proposed IoT-assisted salinity mapping by Eq. 5, where  $pH_m$  is the observed pH, and  $pH_c$  is the calibrated Ph (Fig. 10).

$$pH_c = pH_m + 0.17 \tag{5}$$

**Accuracy of TDS observations**

The TDS observations by the proposed IoT-assisted salinity mapping are shown in part “A” and by the standard

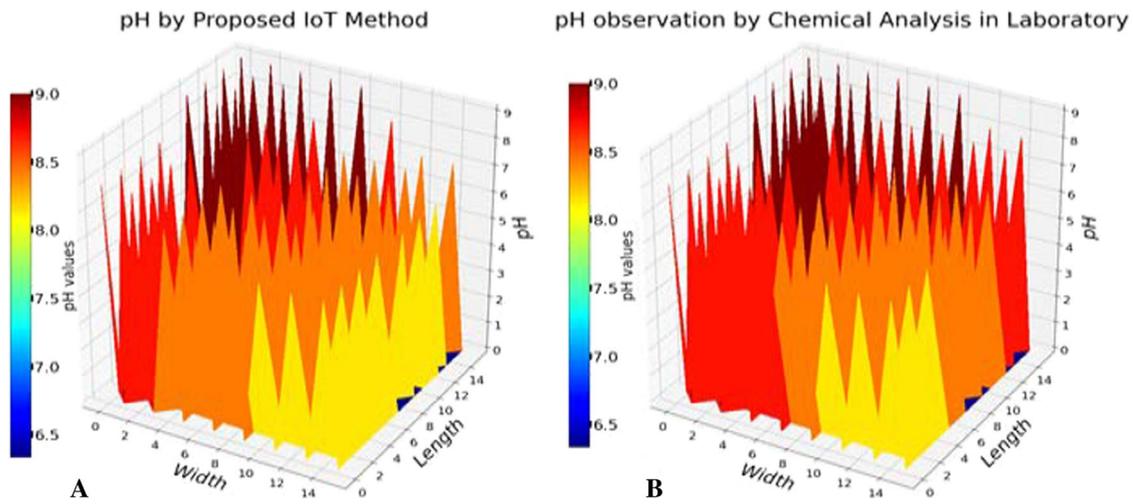


Fig. 10 pH observations

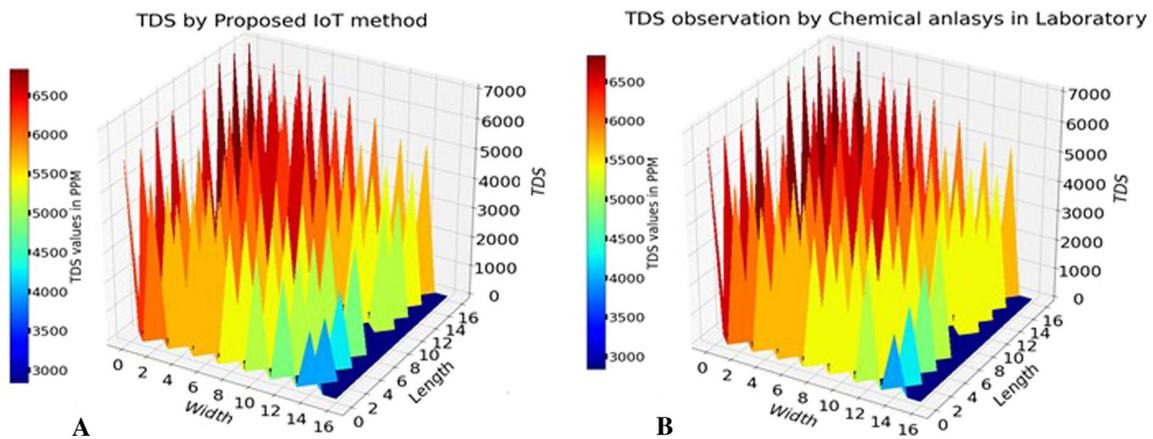


Fig. 11 TDS observations

method of chemical analysis in part “B” of Fig. 11. Both methods show similar TDS observations at most of the sample points. The Bland–Altman plot in Fig. 12 shows the mean difference in TDS observation by both the proposed and standard methods. From Fig. 12, it is observed that the mean difference for TDS observation by the proposed IoT-assisted salinity mapping and standard method of soil salinity is  $-164.06$ . The bias of  $-164.6$  in TDS observation means that the proposed IoT-assisted salinity mapping, on average, measures  $0.164.06$  less than the laboratory method for each of the sixty-four observations. Thus, the bias between the proposed IoT-assisted salinity mapping and the standard method is low. The bias is used to calibrate the proposed IoT-assisted salinity mapping by Eq. 6, where  $TDS_m$  is observed TDS, and  $TDS_c$  is the calibrated TDS.

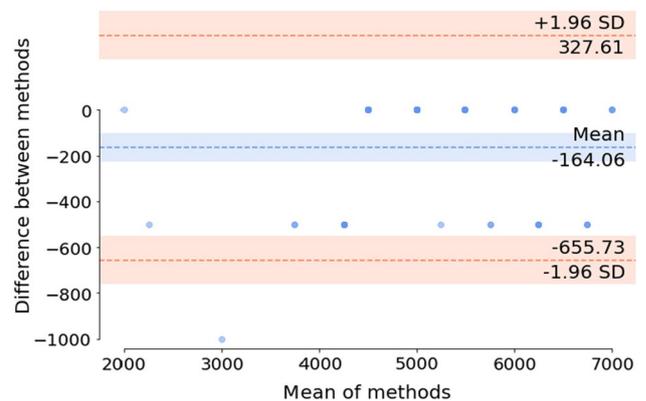


Fig. 12 Bland Altman difference plot for TDS observations

$$TDS_c = TDS_m + 164.06 \quad (6)$$

### Cost comparison

The cost of the proposed solution is compared against the existing methods of salinity mapping in terms of installation cost, operational cost, and per unit sampling costs. The cost of methods is subjective in nature and changes from one part of the world to other.

The installation cost is a one-time cost that covers the cost of equipment and related software and accessories. Commercially available sensors develop the proposed solution. The installation cost of the proposed solution is 1000 US\$, which is low against the other methods. The installation cost of the proposed solution is much lower compared to the chemical analysis, EMI devices, and RS-based solutions that cost very high.

The operational cost is the cost incurred during the sampling process like the cost of labor and material used in the sampling process. The operational cost of the proposed solution is 0.2 US\$ that is very low as compared to other solutions. On the other hand, the operational cost of RS solutions for salinity mapping is very high compared to the proposed solution.

The cost of sampling per unit area is also compared. As per the objective of the study to map salinity at the irrigation scheme level, one Hectare (Ha) is taken as the unit of sampling. The per-unit cost of sampling by proposed solution is lower than chemical analysis and EMI-based solutions. On the other hand, the per-unit sampling cost of the proposed solution is higher than the RS-based solutions. Still, the RS-based solutions are not feasible to be applied at local irrigation scheme levels due to the inherent nature of the RS-based solutions at large geographical areas.

The cost of the different salinity mapping solutions is summarized in Table 5. It is observed that the installation cost of the chemical analysis, EMI devices, and RS is much higher than the proposed solution. The operation cost of these methods for a single sample is also very high as compared to the proposed solution. In the case of per unit sampling cost, the RS-based methods are cheap than the other methods. Although RS-based methods are cost-effective in the case of per unit sampling cost, these solutions are not feasible to be applied at irrigation scheme levels. RS-based solutions aim to map salinity at a large geographical area in a cost-effective manner. Hence the proposed solution is cost-effective against the existing solutions especially in the case of application at the irrigation scheme level.

**Table 5** Cost comparison of different solutions

| Method            | Installation cost (US\$/device) | Operational cost (US \$/sample) | Per hectare cost (US\$) |
|-------------------|---------------------------------|---------------------------------|-------------------------|
| Chemical analysis | 1500                            | 2.31                            | 26.54                   |
| EMI devices       | 10,970                          | 9.32                            | 1.52                    |
| Remote sensing    | 20,000                          | 1000.0                          | 0.2                     |
| Proposed solution | 1000                            | 0.2                             | 1.00                    |

### Portability of proposed solution

The weight of the proposed prototype is only 1.2 kg, which is very easy to move from one sample point to another and across the field. The prototype's low weight and easy movement across the field make the proposed solution portable in nature. EMI devices and sampling is costly in term of required labor to move devices and samples from field to laboratory.

### Analysis and discussion

In this section, a detailed analysis is carried out for the difference and similarities between the proposed IoT-assisted salinity mapping and the standard method for salinity quantification.

The EC observation by proposed and standard method are compared in Fig. 13. The total number of differences between the observation at sixty-four sample points by both methods is given in Table 6. It is observed that at twenty-two sample points there is no difference in EC observations by two methods. The absolute difference is only one in EC observation at thirty-seven sample points by the proposed IoT-assisted salinity mapping and by standard method. The maximum absolute difference in EC observation by two methods is 3 dSm<sup>-1</sup>. This maximum absolute difference of 3 dSm<sup>-1</sup> is observed at only two sample points. The EC value is appraised less by the proposed IoT-assisted salinity mapping against the standard method at sixteen sample points. At twenty-six sampling points, the EC is highly appraised by the proposed IoT-assisted salinity mapping as compared to the standard method. The mean difference for EC observation between the two methods for each sample point is -0.05.

The pH observation by the proposed IoT assisted and standard salinity mapping method are compared in Fig. 13. The value of pH observation by proposed IoT assisted salinity mapping at sixty-four sample points is shown in part "A" and by the standard method in part "B" of Fig. 14. The difference in pH observations by proposed and

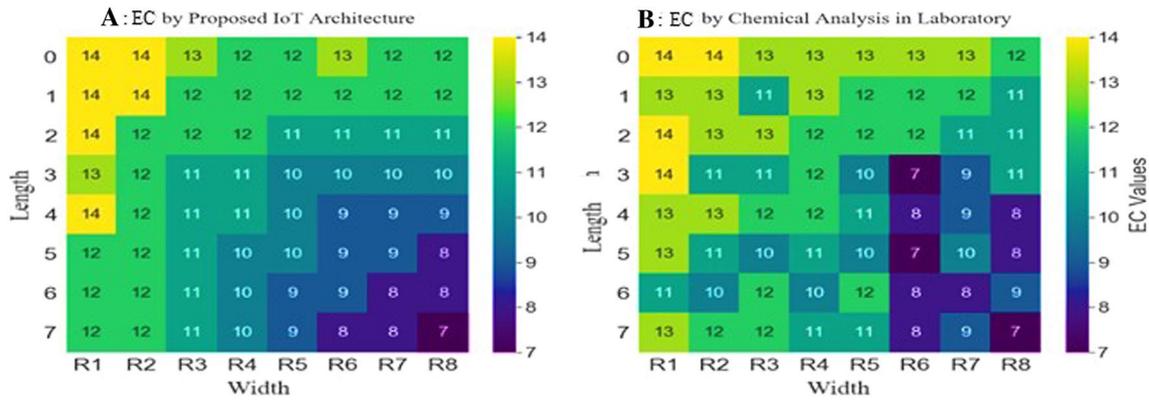


Fig. 13 EC observations by two methods

Table 6 Analysis of EC observations

| The difference in EC observations | Number of sample points |
|-----------------------------------|-------------------------|
| 0                                 | 22                      |
| 1                                 | 24                      |
| 2                                 | 1                       |
| 3                                 | 1                       |
| -1                                | 13                      |
| -2                                | 2                       |
| -3                                | 1                       |

standard methods at sixty-four sample points is summarized in Table 7. It is observed that at forty-eight sample points there is no difference in pH observations by proposed IoT assisted salinity mapping and by standard method. At fifteen

sample points, the absolute difference in pH observation is only one between the two methods. The maximum difference in pH observations by two methods is only two, observed at a single sample point. At twelve sample points, the pH is appraised high by the proposed IoT-assisted salinity mapping compared to the standard method. At three sample points, the pH is appraised less by the proposed IoT-assisted salinity mapping. The mean difference in pH observations by the two methods is -0.17.

The values of TDS observation by proposed IoT assisted salinity mapping at sixty-four sample point is shown in part “A” and by the standard method in part “B” of Fig. 15. TDS is observed in the units of mg/liter. The observed TDS values are rounded to the nearest five hundred to simplify the analysis. The difference in TDS observation by proposed and standard methods at sixty-four sample points is summarized in Table 8. It is observed that at

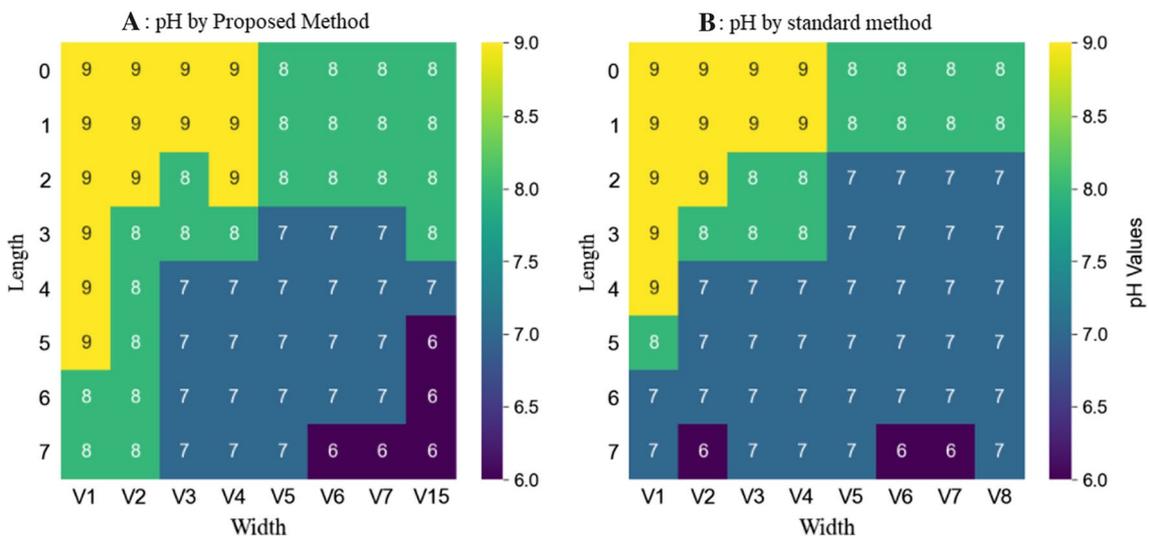


Fig. 14 pH observations by two methods

**Table 7** Analysis of pH observations

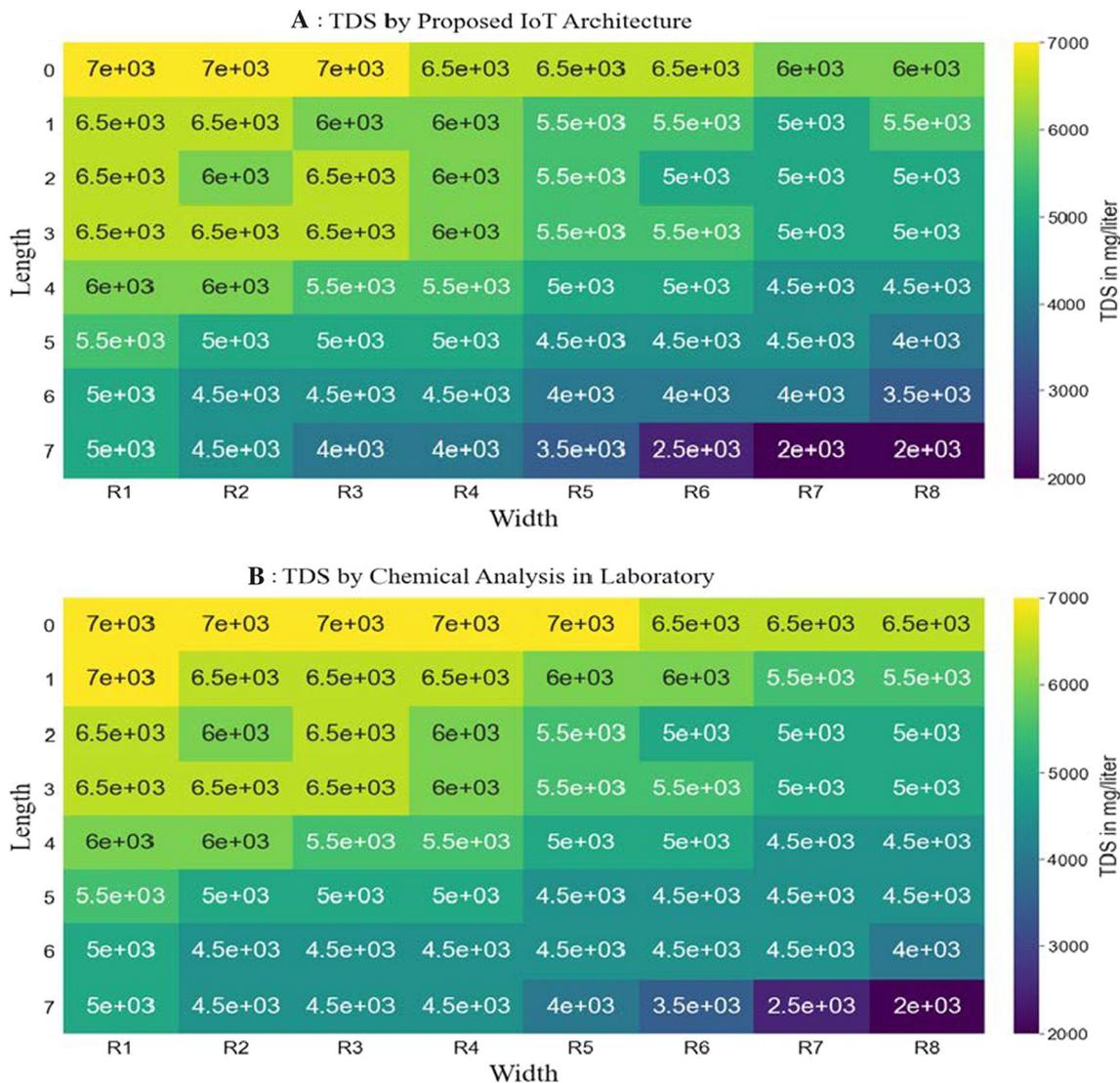
| The difference in pH observations | Number of sample points |
|-----------------------------------|-------------------------|
| 0                                 | 48                      |
| 1                                 | 12                      |
| -1                                | 3                       |
| 2                                 | 1                       |

forty-four sample points there is no difference in TDS values by proposed IoT assisted salinity mapping and by standard method. At only twenty (20) sample points there is no difference in TDS observation by two methods. The maximum difference in TDS observation by two methods is one thousand ppm, observed at a single sample point.

The TDS is appraised higher by the proposed IoT-assisted salinity mapping than the standard method at two sample points. The mean difference in TDS observation by two methods is - 164.06.

**Limitation of the study**

Present sensing technology limits for the use of EC, pH, and TDS model of salinity mapping. This model relies on the total concentrations of salts in soils rather than the determination of the individual concentration of each salt. In the future with the development of sensing capabilities to sense the individual concentration of each salt, the IoT-assisted salinity would be more interesting and valuable.



**Fig. 15** TDS values by two methods

**Table 8** Analysis of TDS observations

| The difference in TDS observations | Number of sample points |
|------------------------------------|-------------------------|
| 0                                  | 44                      |
| – 500                              | 19                      |
| – 1000                             | 1                       |

## Conclusion

IoT-assisted salinity mapping at the irrigation scheme level in the agriculture field is proposed to detect salinity developments in agriculture fields. The proposed solution characterizes the soil salinity in terms of EC, pH, and TDS quantification. The proposed architecture can map soil salinity in a portable, cost-effective, and frequent manner. The data about soil salinity are transferred, stored, and processed at a server that is easily accessible for different stakeholders. The proposed solution is accurate in quantification and mapping of soil salinity by three important salinity parameters of EC, pH, and TDS, when compared against the standard chemical analysis approach. Furthermore, the proposed solution can be used frequently to observe the impacts of any reclamation activity applied against the soil salinity and saline soil zone management.

**Acknowledgements** This research is technically supported by Artificial Intelligence & Data Analytics Laboratory (AIDA) CCIS Prince Sultan University, Riyadh, Saudi Arabia

**Funding** The author(s) received no specific funding for this work.

## Declarations

**Conflict of interest** Authors declare no conflict & all contributed equally scientifically.

**Humans and animals rights** No experiments are performed on animals/humans.

**Ethical conduct** This work as a whole or in part is not submitted in any other venue and is free from similarity.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

## References

- Abou Samra RM, Ali RR (2018) The development of an overlay model to predict soil salinity risks by using remote sensing and GIS techniques: a case study in soils around Idku Lake Egypt. *Environ Monit Assess*. <https://doi.org/10.1007/s10661-018-7079-3>
- Akram T, Sharif M, Saba T (2020) Fruits diseases classification: exploiting a hierarchical framework for deep features fusion and selection. *Multimed Tools and Appl* 79(35):25763–25783
- Ananthi N, Divya J, Divya M, Janani V (2018) IoT based smart soil monitoring system for agricultural production'. In: *Proceedings–2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development, TIAR 2017*, vol 2018, pp 209–214, doi: <https://doi.org/10.1109/TIAR.2017.8273717>
- Bashir RN, Bajwa IS, Shahid MMA (2020) Internet of things and machine-learning-based leaching requirements estimation for saline soils. *IEEE Internet Things J* 7(5):4464–4472. <https://doi.org/10.1109/JIOT.2019.2954738>
- Blasch G, Spengler D, Hohmann C, Neumann C, Itzerott S, Kaufmann H (2015) Multitemporal soil pattern analysis with multi-spectral remote sensing data at the field-scale. *Comput Electron Agric* 113:1–13. <https://doi.org/10.1016/j.compag.2015.01.012>
- Clenio L, Moreira J, Teixeira S, Galvão LS (2015) Potential of multi-spectral and hyperspectral data to detect saline-exposed soils in Brazil. *Giscience Remote Sens* 52(4):416–436. <https://doi.org/10.1080/15481603.2015.1040227>
- Don Bennett JS (2021) 'Measuring soil salinity | agriculture and food'. <https://www.agric.wa.gov.au/soil-salinity/measuring-soil-salinity> (Accessed Apr. 24, 2021).
- Doolittle JA, Brevik EC (2014) The use of electromagnetic induction techniques in soils studies. *Geoderma* 223–225(1):33–45. <https://doi.org/10.1016/j.geoderma.2014.01.027>
- Duy NTK, Tu ND, Son TH, Khanh LHD (2015) Automated monitoring and control system for shrimp farms based on embedded system and wireless sensor network. In: *2015 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT) 2015*, doi: <https://doi.org/10.1109/ICECCT.2015.7226111>
- Fern BM, Rahim MSM, Saba T, Almazyad AS, Rehman A (2017) Stratified classification of plant species based on venation state. *Biomed Res* 28(13):5660–5663
- Filippi P, Cattle SR, Bishop TFA, Odeh IOA, Pringle MJ (2018) Digital soil monitoring of top- and sub-soil pH with bivariate linear mixed models. *Geoderma* 322:149–162. <https://doi.org/10.1016/J.GEODERMA.2018.02.033>
- Gorji T, Sertel E, Tanik A (2017) Monitoring soil salinity via remote sensing technology under data scarce conditions: a case study from Turkey. *Ecol Indic* 74:384–391. <https://doi.org/10.1016/j.ecolind.2016.11.043>
- Gupta SK, Goyal MR, Singh A (eds) (2018) *Engineering practices for management of soil salinity: agricultural, physiological, and adaptive approaches*. CRC Press
- Harshani PR, Umamaheswari T, Tharani R, Rajalakshmi S, Dharani J (2018) Effective crop productivity and nutrient level monitoring in agriculture soil using iot', doi: <https://doi.org/10.1109/ICSNS.2018.8573674>
- Ismail W, Khan M A, Shah SA, Javed MY, Rehman A, Saba T (2020) An adaptive image processing model of plant disease diagnosis and quantification based on color and texture histogram. In: *2020 2nd International Conference on Computer and Information Sciences (ICCIS)*. IEEE, pp 1–6
- Ivushkin K et al (2019) Geoderma UAV based soil salinity assessment of cropland. *Geoderma* 338(2018):502–512. <https://doi.org/10.1016/j.geoderma.2018.09.046>

- Jiang H, Shu H (2019) Optical remote-sensing data based research on detecting soil salinity at different depth in an arid-area oasis, Xinjiang, China. *Earth Sci Informatics* 12(1):43–56. <https://doi.org/10.1007/s12145-018-0358-2>
- Khan MA, Akram T, Sharif M, Alhaisoni M, Saba T, Nawaz N (2021) A probabilistic segmentation and entropy-rank correlation-based feature selection approach for the recognition of fruit diseases. *EURASIP J Image Video Process* 2021(1):1–28
- Krishna S., Sarath TV, Kumaraswamy MS, Nair V (2020) IoT based Water Parameter Monitoring System. In: 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp 1299–1303. doi: <https://doi.org/10.1109/ICCES48766.2020.9138001>.
- Kolivand H, Fern BM, Saba T, Rahim MSM, Rehman A (2019) A new leaf venation detection technique for plant species classification. *Arab J Sci Eng* 44(4):3315–3327
- Kumar S, Gautam G, Saha SK (2015) Hyperspectral remote sensing data derived spectral indices in characterizing salt-affected soils: a case study of indo-gangetic plains of India. *Environ Earth Sci* 73(7):3299–3308. <https://doi.org/10.1007/s12665-014-3613-y>
- Liu X, Nelson M (2008) The value of information in precision farming
- Lostowski A et al. (2020) Wireless IoT communication module with low power consumption for a soil moisture and salinity sensor. In: 2020 Baltic URSI Symposium (URSI), pp 33–37, doi: <https://doi.org/10.23919/URSI48707.2020.9253753>
- Muller SJ, van Niekerk A (2016) An evaluation of supervised classifiers for indirectly detecting salt-affected areas at irrigation scheme level. *Int J Appl Earth Obs Geoinf* 49:138–150. <https://doi.org/10.1016/j.jag.2016.02.005>
- Nagaraju M, Chawla P (2020) Systematic review of deep learning techniques in plant disease detection', In: International journal of system assurance engineering and management ,vol 11, pp 547–560, <https://doi.org/10.1007/S13198-020-00972-1>.
- Nigussie E, Olwal T, Musumba G, Tegegne T, Lemma A, Mekuria F (2020) IoT-based irrigation management for smallholder farmers in rural Sub-Saharan Africa. *Procedia Comput Sci* 177:86–93. <https://doi.org/10.1016/J.PROCS.2020.10.015>
- Nocita Met al. (2015) Soil spectroscopy: an alternative to wet chemistry for soil monitoring. In: *Advances in Agronomy*, vol 132, pp 139–159. doi: <https://doi.org/10.1016/bs.agron.2015.02.002>
- Othaman NNC, Isa MNM, Ismail RC, Ahmad MI, Hui CK (2020) Factors that affect soil electrical conductivity (EC) based system for smart farming application. *AIP Conf Proc* 2203(1):020055. <https://doi.org/10.1063/1.5142147>
- Pandithurai O, Aishwarya S, Aparna B, Kavitha K (2017) Agro-tech: A digital model for monitoring soil and crops using internet of things (IOT). In: *ICONSTEM 2017 - Proceedings: 3rd IEEE International Conference on Science Technology, Engineering and Management*, vol 2018-Janua, pp 342–346, doi: <https://doi.org/10.1109/ICONSTEM.2017.8261306>
- Peng J et al (2017) Estimating soil salinity from remote sensing and terrain data in southern Xinjiang Province China. *Geoderma*. <https://doi.org/10.1016/j.geoderma.2018.08.006>
- Pouladi N, Jafarzadeh AA, Shahbazi F, Ghorbani MA (2019) Design and implementation of a hybrid MLP-FFA model for soil salinity prediction. *Environ Earth Sci* 78(5):1–10. <https://doi.org/10.1007/s12665-019-8159-6>
- Qian T, Tsunekawa A, Peng F, Masunaga T, Wang T, Li R (2019) Derivation of salt content in salinized soil from hyperspectral reflectance data: a case study at Minqin Oasis, Northwest China. *J Arid Land* 11(1):111–122. <https://doi.org/10.1007/s40333-019-0091-9>
- Raut R, Varma H, Mulla C, Pawar VR (2018) Soil monitoring, fertigation, and irrigation system using IOT for agricultural application. In: *Lecture Notes in Networks and Systems*, vol. 19, Springer, pp 67–73
- Rehman A, Saba T, Kashif M, Fati SM, Bahaj SA, Choudhary H (2022) A revisit of internet of things technologies for monitoring and control strategies in smart agriculture. *Agronomy* 12(1):127
- Roux J et al (2019) A new Bi-frequency soil smart sensing moisture and salinity for connected sustainable agriculture. *J Sens Technol* 9(3):35–43. <https://doi.org/10.4236/JST.2019.93004>
- Saba T, Rehman A, AlGhamdi JS (2017) Weather forecasting based on hybrid neural model. *Appl Water Sci* 7(7):3869–3874
- Safiyah L, Adiimah RSN, Hanan F, Suzanna, Irwan K (2021) Implementation of EC and PH value monitoring for NFT-based hydroponic system applying internet of things (IoT). In: *Proceedings of the 1st International Conference on Electronics, Biomedical Engineering, and Health Informatics*, vol 746 LNEE, pp 309–319, doi: [https://doi.org/10.1007/978-981-33-6926-9\\_26](https://doi.org/10.1007/978-981-33-6926-9_26).
- Shaikh FK, Zeadally S, Member S, Exposito E (2017) Enabling technologies for green internet of things. *IEEE Syst J* 11(2):983–994. <https://doi.org/10.1109/JSYST.2015.2415194>
- Shiri J et al (2017) Modeling soil cation exchange capacity using soil parameters: assessing the heuristic models. *Comput Electron Agric* 135:242–251. <https://doi.org/10.1016/j.compag.2017.02.016>
- Singh A (2018) Managing the salinization and drainage problems of irrigated areas through remote sensing and GIS techniques. *Ecol Indic* 89(February):584–589. <https://doi.org/10.1016/j.ecolind.2018.02.041>
- Stühmer R, Verginadis Y, Alshabani I, Morsellino T, Aversa A (2013) PLAY: semantics-based event marketplace. *IFIP Adv Inf Commun Technol* 408:699–707. [https://doi.org/10.1007/978-3-642-40543-3\\_73](https://doi.org/10.1007/978-3-642-40543-3_73)
- T. S. of Queensland (2016) Soil pH | Environment, land and water | Queensland Government', The State of Queensland, 2016. <https://www.qld.gov.au/environment/land/management/soil/soil-properties/ph-levels> (Accessed Nov. 13, 2021).
- Tellaeché A, Pajares G, Burgos-Artizxu XP, Ribeiro A (2011) A computer vision approach for weeds identification through support vector machines. *Appl Soft Comput J* 11(1):908–915. <https://doi.org/10.1016/j.asoc.2010.01.011>
- Undefined FAO and FAO-Food and Agriculture Organization of the United Nations (2018) Handbook for saline soil management. Food and Agriculture Organization of the United Nations and Lomonosov Moscow State University
- Vargas R, Pankova EI, Balyuk SA, Krasilnikov PV, Khasankhanova G M (2018) Handbook for saline soil management. Food and Agriculture Organization of the United Nations and Lomonosov Moscow State University
- Wang X, Zhang F, Ding J, Kung H, Latif A, Johnson VC (2018) Science of the total environment estimation of soil salt content (SSC) in the Ebinur lake wetland national nature reserve ( ELWNNR ), Northwest China, based on a Bootstrap-BP neural network model and optimal spectral indices. *Sci Total Environ* 615:918–930. <https://doi.org/10.1016/j.scitotenv.2017.10.025>
- Wang F, Yang S, Yang W, Yang X, Jianli D (2019) Comparison of machine learning algorithms for soil salinity predictions in three dryland oases located in Xinjiang Uyghur autonomous region (XJUAR) of China. *Eur J Remote Sens* 52(1):256–276. <https://doi.org/10.1080/22797254.2019.1596756>
- Yasin HM et al (2021) IoT and ICT based smart water management, monitoring and controlling system: a review. *Asian J Res Comput Sci* 8(2):42–56. <https://doi.org/10.9734/AJRCOS/2021/V8I230198>
- Yıldız S, Karakuş CB (2020) Estimation of irrigation water quality index with development of an optimum model: a case study. *Environ Dev Sustain* 22(5):4771–4786. <https://doi.org/10.1007/S10668-019-00405-5>
- Yu H, Liu M, Du B, Wang Z, Hu L, Zhang B (2018) Mapping soil salinity/sodicity by using Landsat OLI imagery and PLSR algorithm

- over semiarid West Jilin province, China. *Sensors* (switzerland) 18(4):1–17. <https://doi.org/10.3390/s18041048>
- Zaman M, Shahid SA, Heng L (2018) *Guideline for salinity assessment, mitigation and adaptation using nuclear and related techniques*, 1st edn. Springer Nature Switzerland AG, Cham, Switzerland
- Zewdu S, Suryabhagavan KV, Balakrishnan M (2017) Geo-spatial approach for soil salinity mapping in sego irrigation farm, South Ethiopia. *J Saudi Soc Agric Sci* 16(1):16–24. <https://doi.org/10.1016/j.jssas.2014.12.003>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.