AGRONOMY SCIENCE
wcześniej – formerly
Annales UMCS sectio E Agricultura

VOL. LXXX (1) 2025

https://doi.org/10.24326/as.2025.5463

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Predicting soil compaction from soil electrical conductivity based on scanning methods. A review

Wykorzystanie metod skanowania gleby do predykcji jej zwięzłości na podstawie przewodności elektrycznej. Praca przeglądowa

Abstract. Soil compaction is a crucial agricultural issue impacting plant growth, water infiltration, and soil health. Because of its sensitivity to soil variables such as texture, moisture content, and salinity, soil electrical conductivity (ECa) has emerged as a promising indirect predictor of soil compaction. This review summarizes selected studies on the relationship between soil compaction and apparent electrical conductivity and examines various prediction approaches. It also considers the potential applications and limitations of using ECa to estimate soil compaction, including methods based on machine learning. Future advancements in technology, modeling, and data integration will be key to fully realizing the potential of ECa in soil compaction management.

Keywords: soil, electrical parameters, estimation, soil compaction

INTRODUCTION

Soil electrical conductivity (ECa) is a measure of the soil's ability to conduct an electric current. ECa plays an important part in understanding soil characteristics, including salinity, moisture content, and nutrient availability. ECa is a quick, reliable, easy-to-take

Citation: Tembeck Mbah J., Pentoś K., 2025. Predicting soil compaction from soil electrical conductivity based on scanning methods. A review. Agron. Sci. 80(1), 85–101. https://doi.org/10.24326/as.2025.5463

soil measurement that often relates to crop yield [Corwin and Lesch 2005, Sudduth et al. 2005]. Geophysical techniques such as electrode-based electrical resistivity tomography (ERT), and electromagnetic induction (EMI) have emerged as promising non-invasive tools for assessing soil properties. ECa maps are better known for representing an agricultural field based on nutrient needs [Vrindts et al. 2005, Barbosa and Overstreet 2022]. Accurate soil ECa prediction and mapping are critical for precision agriculture, soil health monitoring, and environmental management. Electromagnetic induction (EMI) is one of the most useful tools for obtaining spatial parameters influencing crop productivity. Its depth of inquiry, longevity, and link to crop growth parameters make it useful in precision agriculture [Corwin and Lesch 2003, Grisso et al. 2005, Pentoś et al. 2022].

Soil ECa measurements are directly related to soil texture, moisture, and salinity [Corwin and Lesch 2003], while Othaman et al. [2021] and Vrindts et al. [2005] opined that soil ECa is directly related to nutrient concentration and inversely proportional to the soil depth. Soil texture is an important factor in crop yields because it relates to water-holding capacity, cation-exchange capacity, rooting depths, drainage, and other properties that influence crop production [Corwin and Lesch 2005, Lund 2008]. Soil ECa is widely used as an indirect indicator of a soil profile's physical and chemical properties [Vrindts et al. 2005]. It is also used to map spatial variations of edaphic properties: soil salinity, soil particle content, soil water content, and organic matter, as well as anthropogenic properties of soils; leaching, irrigation, drainage patterns, and compaction [Corwin and Lesch 2005].

ECa is influenced by a combination of physicochemical properties including soluble salts, clay content and mineralogy, soil moisture content, bulk density, organic matter, cation exchange capacity, soil pore size and distribution, and soil temperature [McNeill 1992, Corwin and Lesch 2005, Sudduth et al. 2005, Othaman et al. 2021]. Soil ECa can be measured by physical direct contact (contact sensor) of a minimum of four electrodes with soil or by electromagnetic induction (noncontact sensor) that uses a transmitter coil to induce a magnetic field into the soil with a receiver coil to measure the response [Sudduth et al. 2005, Hemmat and Adamchuk 2008]. EMI is one of the most used techniques for obtaining spatial parameters influencing crop productivity [Corwin and Lesch 2003]. Lund [2008] stated that soil ECa expressed in millisiemens (mS) is the inverse of soil resistance reported in ohms (W). Conductivity and resistivity are two sides of the same coin; if the soil has high conductivity, it will have low resistance.

The need to improve agricultural yields has led to the development and widespread use of heavy machinery, exacerbating several agrarian problems such as soil compaction. Soil compaction refers to the reduction in soil volume caused by external influences that reduce soil production and environmental quality [Duiker 2005, Hemmat and Adamchuk 2008, McKenzie 2010]. It occurs when a force compresses the earth, pushing air and water out, and causing it to become dense and lose its inherent resistance to equipment movement [Hoorman et al. 2009]. Soil compaction can be classified into topsoil and subsoil, and both reduce yields [Duiker 2005, Hoorman et al. 2009, Tekin and Yalçin 2019]. Compression from machinery or stock trampling, agricultural/land-use intensification, and foot and vehicle traffic are the main causes of soil compaction [Duiker 2005, Tekin and Yalçin 2019, Hu et al. 2021].

According to Hemmat et al. [2008], soil compaction is a key issue in agriculture and land management, resulting in variable growth in agricultural areas, impeded water infiltration, and overall soil health, inadequate root systems, and low yields affect trees, reduced soil fertility, and increase soil erosion [Nawaz et al. 2013]. Soil compaction also reduces soil porosity, increases soil density and root penetration resistance, decreases vertical microporosity, increases nitrogen dioxide emissions, decreases infiltration, and slows plant germination [Duiker 2005, McKenzie 2010, Nawaz et al. 2013, Peralta et al. 2021, Yue et al. 2021. According to Nawaz et al. [2013], the key factors influencing soil compaction are soil organic matter content, moisture content, and soil texture. Friedman [2005] and Tekin and Yalçin [2019] stated that soil strength is the primary determinant of soil compaction, influenced by soil variables (bulk density, moisture, and soil texture). The impact of soil compaction is determined by the amount of root zone compacted, the continuity of the compacted zone, and crop vulnerability [Nawaz et al. 2013, Tekin and Yalçin 2019].

Soil compaction has been investigated using direct methods such as penetration resistance tests or bulk density measurements, which are both time-consuming and labor-intensive. For the reason that soil compaction impacts many of the same elements as ECa, such as water content and soil structure, ECa has the potential to be used as a soil compaction indicator [Pentoś et al. 2022].

Because of its efficiency and cost-effectiveness, there has recently been an increased interest in using soil electrical conductivity as a proxy to anticipate soil compaction. This paper reviews the relationship between soil compaction and soil electrical conductivity, various scanning methods, and assesses their usefulness and limitations.

MECHANISM LINKING SOIL ELECTRICAL CONDUCTIVITY AND SOIL COMPACTION

Soil structure relating to compaction, particularly the collapse of macropores, leads to a more conducive environment for electrical currents. This is especially visible in clay-rich soils, where compaction can greatly boost ECa values.

Compacted soils have a higher bulk density and lower porosity. ECa measures correlate strongly with bulk density because compaction modifies the soil matrix, affecting conductivity.

Compacted soils have reduced pore space, resulting in poorer moisture retention and electrical conductivity. Higher compaction reduces pore space, affecting how quickly water and ions travel through the soil, which can be determined with ECa tests.

METHODS OF ESTIMATING SOIL ELECTRICAL CONDUCTIVITY (ECA)

Several methodologies, such as sensor-based mapping, machine learning algorithms, and integrating data with soil properties, have been advanced for predicting soil compaction from electrical conductivity data. Sensor-based electromagnetic induction (EMI) mappings employing EM38, DUALEM, and galvanic contact resistivity (GCR) employing Veris are widely employed in mapping electrical conductivity over large areas. A data logging station is mounted to record data for all scanners with scanner-specific softwares (tab. 1).

EM38 is an EMI conductivity meter and movable field instrument used in approximating soil electrical parameters (electrical conductivity and magnetic susceptibility) in the rooting zone (1.5 m in depth). Its rapidity and accuracy make it ideal for large-scale soil conductivity measurements. EM38 measures electrical parameters vertically (EM38V) at a depth of about 1.5 m and horizontally (EM38H) at 1 m. It is assisted by a GPS receiver, which tracks the locations of all soil electrical parameter measurement sites in the field. EM38 must be positioned on a non-metallic cart to prevent sensor signal interference. It measures the voltage difference between a source and a sensor electrode. EMI does not make direct contact with the soil, instead, it uses a transmitter coil to generate a magnetic field in the soil and has a receiver coil that measures the reaction. The electrode configuration is called the Wenner array configuration; four electrodes are equidistantly spaced in a straight line at the soil surface, with the two outer electrodes acting as transmission electrodes and the two inner electrodes serving as receivers. The electrical current's penetration depth and measurement volume are directly related to the distance between the transmission and receiving electrodes. The larger the spacing, the deeper and larger the electrical measurements. The advantages of EM-38 include being non-invasive, allowing for quick data collection over large areas, and providing high sensitivity to detect subtle soil variations. It is versatile and works in different soil types and conditions. However, it has limitations, such as measuring only shallow soil layers (up to 1.5 meters), requiring proper calibration for accurate results, and being prone to interference from other objects, which can affect the accuracy of readings [McNeill 1980, Corwin and Lesch 2003, Lund 2008, Siqueira et al. 2014, Su and Adamchuk 2023].

Table 1. Specification of instruments used; adapted from Su and Adamchuk [2023]

Specification	VERIS	EM-38	DUALEM-21S	Topsoil Mapper
Method	GCR/DC	EMI	EMI	EMI
Dimension (m)	1.43 × 1.50 × 0.69	1.06 × 0.13 × 0.3	2.41 × 0.09 × 0.09	1.67 × 0.34 × 0.265
Mass (kg)	136	3	5	24
Power supply	12 V DC external	9 V DC internal	12 V DC external	12 V DC external
Number of depths	2	2	4	4
Operating frequency	20 Hz	14.6 kHz	9 kHz	9 kHz
Data output rate	1 Hz	14 Hz	5 Hz	5 Hz

DUALEM consists of a 2.41 m long tube with one transmitter coil and four receiving coils. Two of these four receiving coils form a horizontal coplanar (HCP) array at 1 m (DUALEMHCP-1) and 2 m (DUALEMHCP-2) distances, while the other two form a perpendicular coplanar (PRP) array at 1.1 m (DUALEMPRP-1.1) and 2.1 m (DUALEMPRP-2.1) distances. DUALEM is a frequency-domain multi-receiver EMI sensor with a single frequency of 9 kHz. It has two pairs of horizontal coplanar and perpendicular (PRP) receiver coil arrays that measure electrical parameters in distinct soil volumes at the same time. The transmitter is at one end and is shared by all reception coils at distances of 1.1 m and 2.1 m for PRP coil configurations and 1 m and 2 m for HCP configurations. The depth of exploration is expressed in terms of coil spacing and array orientation. It is equipped with a GPS receiver that tracks the locations of all soil electrical parameter measurement sites in the field. High-resolution, depth-specific readings, a non-invasive approach to soil research, and the ability to gather data quickly over wide areas are some of its benefits. Also, it is quite adaptable and works well in a variety of soil types and situations. The DUALEM scanner does have certain drawbacks, though, such as its sensitivity to soil heterogeneity, which may compromise measurement accuracy. Additionally, it needs to be properly calibrated to guarantee accurate findings, and environmental elements like moisture and temperature may have an impact, reducing its usefulness in some circumstances [McNeill 1980, Su and Adamchuk 2023].

Veris soil scanner is a three-sensor system platform that can measure acidity (pH), organic matter percentage, electrical conductivity, and altitudes in a single operation. In this electrode-based approach, sensors are pushed across the fields, establishing direct soil contact, and measurements are recorded concurrently utilizing six rolling colters as electrodes, producing two simultaneous ECa values. Its collectors collect soil electrical conductivity readings from two depths every second. One pair of disc electrodes injects current into the soil, while the change in voltage is monitored across the other two pairs of disc electrodes, resulting in simultaneous ECa values for the top three feet of soil. The Veris usually consists of 3 pairs of rolling colters, and it is generally used for shallow (0–30 cm) soil ECa measurements [Adhikari et al. 2009]. A Global Positioning System (GPS) receiver fitted on the Veris unit tracks the location of each ECa measurement site in the field. The Veris scanner offers several advantages, including accurate and reliable measurement of soil ECa, which helps identify variations in soil texture. It enables precise soil mapping, supports variable-rate applications, and reduces the need for extensive soil sampling, saving time and costs. However, the device has limitations, such as reduced effectiveness in dry, sandy soils with low conductivity. It requires consistent soil contact for accurate data, making it less effective on rocky or uneven terrains. Additionally, the Veris scanner is expensive, and proper training is needed for data interpretation and application [Grisso et al. 2005, Adhikari et al. 2009, Su and Adamchuk 2023].

The Topsoil Mapper (Topsoil Mapper SoilXplorer AgXtend; Geoprospectors GmbH, Traiskirchen, Austria) is an advanced soil scanning device designed to provide non-contact, on-the-go soil analysis for agriculture, including texture, compaction, moisture content, and organic matter content. It utilizes electromagnetic induction technology to measure the soil ECa, offering non-invasive and precise analysis without physical sampling. The device is mounted on a tractor, allowing for continuous measurement during field operations. It is integrated with AgXtend technology, enabling real-time tillage depth adjustments based on site-specific soil conditions. This scanner utilizes a multi-coil electromagnetic induction (EMI) array configuration. It consists of four induction coils that serve as both transmitters and receivers. These coils are arranged to measure soil conductivity at different depths, ranging from 0 to 55 cm (from shallow to deeper soil layers). The effective measurement depth reaches 1.5 meters, and it can operate in either basic mode or pro mode. The device examines the soil structure at three different depths and provides information such as soil type, relative soil moisture, and soil compaction. The Topsoil Mapper also delivers insights into heterogeneity at individual depths, identifying zones such as sand and clay, as well as relative humidity and compaction. It can function in all conditions and is capable of providing ECa values at various depths. A Global Positioning System (GPS) receiver fitted tracks and records the location of each ECa measurement site in the field. Fast, non-invasive soil data collection and high-resolution mapping of soil property variations are two of its benefits. When recognizing regions with different soil fertility and moisture content, it works very well. Some drawbacks of the Topsoil Mapper include its limited depth penetration, which usually only measures thin soil layers. Additionally, soil heterogeneity may impact the precision of its data, necessitating meticulous calibration and perhaps being impacted by external elements such as soil moisture and temperature [Trinks et al. 2016, De Feudis et al. 2025]. The characteristics of the selected methods for estimating soil electrical conductivity are presented in table 2.

Table 2. Instruments and recorded measurement; adapted from Su and Adamchuk [2023]

Measurement	Instrument	Array configuration	Distance (m)	Effective sensing depth (m)
Veris- EC	Veris	wenner	0.25	0.30
EM-38 $_{HCP-1}$	EM-38	horizontal colplanar	1.00	1.55
EM-38 $_{VCP-1}$	EM-38	vertical coplanar	1.00	1.0
DUALEM $_{HCP-1}$	DUALEM	horizontal coplanar	1.00	1.55
DUALEM$_{PRP-1.1}$	DUALEM	perpendicular coplanar	1.10	0.54
DUALEM$_{HCP-2}$	DUALEM	horizontal coplanar	2.00	3.18
DUALEM$_{PRP-2.1}$	DUALEM	perpendicular coplanar	2.10	1.03
EMI	Topsoil mapper	multi-coil array	1.68	1.5

Soiloptix sensor technology is a non-contact, pre-calibrated sensor that measures natural geological properties emitted from soil decay. It offers a wide range of individual soil mapping layers that give an in-depth look at soil aspects such as physical properties, macronutrients, micronutrients, and soil health. Soiloptix eliminates limitations typical of other scanners (contact and noncontact scanners). It faces no interference from crop residues, field vegetation, soil moisture, frozen ground, or light snow (5-inch thick) cover [Adamchuk 2015]. Gamma-ray detectors are typically composed of closely packed crystal blocks and collide with electrons as they pass through the crystals. These collisions create charged particles that can be detected [Peterson 2003]. Using Soiloptix sensors to scan soil involves four stages: soil mapping/scanning, extraction of soil samples, data processing, and retrieving results. About 25 layers of soil variables can be shown on maps. A GPS receiver tracks the location of each ECa measurement site in the field. One of its benefits is that it offers accurate, real-time data on soil variability, enabling highly accurate, detailed mapping across wide areas. It is perfect for precision agriculture since it is quick, non-invasive, and adaptable. Its limited depth of measurement, which usually only works for superficial soil layers, is one of its drawbacks. Furthermore, soil heterogeneity may impact its performance, and accurate calibration is necessary to guarantee accuracy, especially under a variety of environmental circumstances. The technological differences between the selected instruments are contained in table 3.

Table 3. Technology differences; adapted from Adamchuk [2015]

Specification	Grid Sampling	EC – Zone Sampling	SoilOptix
Measuring	soil nutrients	electrical conductivity	gamma radiation
Frequency	every crop cycle	– year 1 – ec survey – zone sample after (yearly or every crop cycle)	– survey year one – good for 10 years – soil sample every year or every crop cycle
Collection process	industry standard – 1 sample per 2.5 acres	– 40’–80’ swath widths – soil samples after zones have been determined	– 40’ swaths (narrower on special cases) – soil sample done immediately after the survey of the field is complete – sample locations derived from in-field radiation variability
Data resolution	statistics fill in data between points	– 1 sample per zone – 3–7 zones per field	– 1 sample per 8 acres surveyed – 335 data points per acre

Advancements in machine learning have enabled the development of predictive algorithms that use ECa data to anticipate soil compaction levels. This technique combines ECa measurements with other soil and environmental characteristics, resulting in reliable forecasts across a wide range of soil types and conditions. Technologies such as remote sensing and scanning approaches are used to quantify and analyze soil compaction on a geographical and temporal scale. Moreover, Infrared (IR) models accurately analyze soil particle-size distribution by relying on variables such as soil preparation, technology (sedimentation, laser), settling durations, and pertinent soil properties. Machine learning can relate a wide range of independent variables that may affect near-infrared spectroscopy to evaluate the particle-size distribution [Parent et al. 2021].

SELECTED METHODS FOR PREDICTING SOIL COMPACTION

Over the years, numerous sensor systems used in predicting soil features linked to soil compaction have been devised and refined [Hemmat and Adamchuk 2008, McKenzie 2010]. There are many sensor systems used to estimate soil compaction.

The technique of using bulk density to predict soil compaction involves measuring a soil core’s diameter and length to determine its volume. To obtain the dry weight, the soil core is oven-dried. Soil bulk density is defined as the dry weight of soil divided by its volume expressed in grams per cubic centimeter (g cm^{-3}). Soil bulk density has an indirect relationship with pore space and varies with freezing and thawing, wetting, and drying cycles. In addition to offering a straightforward and accurate measurement of soil porosity, a critical component in comprehending soil compaction, using bulk density to assess soil compaction has other benefits. It assists in evaluating the soil’s capacity to hold water and air, which affects plant development. Bulk density also provides quantitative data that is easy to quantify. The possibility of sampling disruption, which could compromise accuracy, is one of its disadvantages. Also, because it disregards soil structure and variability at different depths, bulk density might not give a comprehensive picture of soil compaction [Bache et al. 2008, Hemmat and Adamchuk 2008, McKenzie 2010].

Another method of measuring soil compaction is using a penetrometer, which gives faster field results in a short time. Expressed in kilopascals (kPa), it is used to measure soil compaction by assessing the resistance of soil to penetration. It is useful in finding hard layers that obstruct root penetration and water flow through the soil. Penetrometers estimate soil strength and soil resistance to root penetration. Factors affecting penetration resistance measured by penetrometers include cone angle, cone diameter (surface area), and soil penetration rate. A penetrometer is equipped with a load cell and a depth cell. Measurements are conducted using a cone with a base area of 0.0001 m^2 and an angle of 60 degrees. With the use of data analytics and technological advancements, penetrometers have been developed and improved. These devices assess soil resistance when a probe penetrates the ground, with sensors gathering force and depth data. Modern penetrometers use digital interfaces for instantaneous analysis, GPS for accurate location tracking, and electronic sensors for real-time data collection. Data from these sensors are analyzed using advanced algorithms, providing insights into soil strength, density, and compaction. Penetrometers provide quick, cost-effective assessments of soil compaction, offering real-time data for decision-making. However, their accuracy can be affected by operator technique, soil moisture, and heterogeneity. They struggle in rocky or very dry soils and primarily measure surface compaction, potentially overlooking deeper soil conditions [Hemmat and Adamchuk 2008, Pentoś et al. 2022].

Soil probe is another tool used to detect soil compaction, and it is subject to content and soil density. A drier soil will probe harder than wet soil. Soil probes can be used effectively to monitor differences in the soil moisture profile. Soil probes are simple, cost-effective tools for sampling and assessing soil properties like moisture and texture. They provide quick, direct access to soil profiles. However, they can be difficult to use in hard, compacted, or rocky soils, may disturb samples, and provide limited data. Soil probe devices have replaced simpler manual probes as the primary means of forecasting soil characteristics associated with compaction. At first, soil samples were extracted using basic metal rods, but with the introduction of GPS and electronic sensors, it became possible to gather accurate, real-time data on soil density and texture. To provide more precise evaluations of compaction, soil probes incorporate pressure sensors that measure resistance as they penetrate the soil. This method is much more refined because of data analytics and wireless connection, which make it possible to process, visualize, and integrate data into precision agriculture for better soil management [Vaz 2008, Hemmat and Adamchuk 2008, Jeschke and Lutt 2018].

Soil strength is the ability of soil to resist stresses causing compaction, and it is directly related to compaction [van den Akker et al. 2023]. Soil strength sensors are applicable in mapping soil compaction in a general or localized, specific soil layer. This is done by measuring the vertical force of a reference tool. A draft/vertical force is the force required to pull a tillage tool through the soil. Soil strength sensors are also used to sense soil strength profiles throughout an agricultural field and involve time-based soil sensors. Factors that affect soil strength are water content, structure, and bulk density. Soil strength sensors measure the resistance of soil to penetration, providing valuable data on compaction levels. These sensors, often integrated with penetrometers, load cells, or strain gauges, have been refined through advancements in real-time data collection, GPS integration, and machine learning algorithms. They help predict soil features like density, porosity, and moisture content, improving precision agriculture practices. Its advantages include offering real-time, high-resolution data, enabling targeted soil management, and reducing fuel use. Its disadvantages are that variability in soil conditions affects accuracy, and sensor calibration is required. Additionally, high costs and complex data interpretation can limit accessibility for small-scale farmers [Hemmat and Adamchuk 2008, Abbaspour-Gilandeh and Khalilian 2011].

Modeling complicated interactions in agriculture, including soil parameters, artificial intelligence, and machine learning techniques, is widely used. Dynamic field probes that monitor the mechanical properties of agricultural soils have a special function in this context and allow for the evaluation of soil compactness, defined as cone penetrometer resistance in both horizontal and vertical planes, spanning numerous layers. For more precise in-situ measurements, dynamic field probe methods predict compaction-related soil characteristics. These probes used manual impact techniques, recording the quantity of hammer blows needed to penetrate the soil. The system has undergone an upgrade to include electronic sensors and GPS technology. Its advantages include providing rapid, in-situ measurements of soil compaction, effective for large-scale assessments. Also, it is easy to use, portable, and offers real-time data. However, their accuracy is influenced by soil moisture, heterogeneity, and operator technique. It also struggles to penetrate hard or rocky soils and focuses on surface compaction. Also, interpreting data can be complex, requiring proper calibration and experience [Naderi-Boldaji et al. 2013, Niedbała 2019, Pentoś et al. 2020, Piekutowska et al. 2021, Pentoś et al. 2022, Hara et al. 2023].

Remote sensing is another tool used to determine soil properties. According to Abdulraheem et al.[(2023] and Ben-Dor et al. [2009], remote sensing is a valuable instrument for obtaining precise and relevant soil data by detecting its characteristics through acoustic and electromagnetic techniques. It provides global coverage, allowing monitoring and analysis of soil parameters on a larger scale across various landscapes and locations. It offers a non-intrusive method to test soil without affecting the ecosystem. With the development of satellite and aerial imaging technology, remote sensing systems for forecasting soil characteristics associated with compaction have changed. In the beginning, remote sensing evaluated surface conditions indirectly associated with compaction using visible or infrared imaging. The incorporation of multispectral and hyperspectral sensors has improved these systems over time, making it possible to identify minute changes in moisture content and soil texture. Machine learning algorithms and data analytics have further improved the precision of interpretation, enabling more accurate forecasts. Advantages of using remote sensing to predict soil compaction include its ability to cover large areas quickly and non-invasively, providing detailed, high-resolution data across diverse terrains, and cost-efficient tools for studying soil compaction. It also allows for continuous monitoring and detecting subtle changes in soil properties and minimizes the need for frequent field visits. Its disadvantages include reliance on environmental conditions, such as weather or vegetation cover, which can affect the accuracy of data. Also, it does not directly measure soil compaction but infers it from surface features, which can sometimes lead to less precise results [Ben-Dor et al. 2009, Ghazali et al. 2020, Ebrahimzadeh et al. 2023].

Increased compaction has been linked to fluctuations in ECa, especially in fine-textured soils where compaction alters the soil's moisture-holding capacity. In sandy soils, where the texture allows for greater drainage, changes in ECa caused by compaction may be less severe. Kumar et al. [2021] employed ECa sensors to predict soil compaction in clay loam soils and discovered a strong relationship between ECa values and soil bulk density. When paired with moisture data, ECa data predicted compaction levels with great accuracy. The researchers also stated that soil ECa is essential for understanding soil qualities, which have a direct impact on agricultural production, allowing for better soil management approaches, such as site-specific irrigation and fertilization schemes. Sudduth et al. [2005] emphasized that apparent soil electrical conductivity is a useful tool for indirectly forecasting many soil physical and chemical properties. ECa sensors are efficient and cost-effective, gathering not just ECa data but also providing information on soil types, management plans, and weather conditions. According to their findings, soil electrical conductivity is most closely connected to clay content and cation exchange capacity, both of which are important markers of soil fertility and structure. Moisture, silt, sand, and organic content all have a lower connection with ECa than clay and cation exchange capacity. These findings demonstrate the utility of ECa in precision agriculture for soil characterization and management.

Pentoś et al. [2022] stated that developing management zones in modern agriculture is critical for yield maximization, cost minimization, and reducing environmental impact. Furthermore, researchers concluded that data from dynamic soil electrical conductivity and magnetic susceptibility probe measurements have potential alternative uses in estimating mechanical parameters, such as soil compaction in different soil layers. This is essential for conserving and protecting agricultural soils from both natural and anthropogenic erosion, including over-compaction. Moreover, according to Abbaspour-Gilandeh and Khalilian [2011], there is a substantial link between soil electrical conductivity and soil compaction. The use of ECa data for the identification of zones of high and low drag force (the force required to draw a tillage tool through the soil) is useful for the overall reduction in energy consumption during tillage. Even though draft force changes with soil texture, using soil ECa data to identify zones with high or low draft force in precision agricultural management is advantageous. Galambosová et al. [2020], in their study on using electrical conductivity to assess trafficked areas in silty clay soil, stated that an increase in machinery size and random traffic in fields leads to soil compaction, which harms soil structure and diminishes soil function. The researchers concluded that using electrical conductivity data to forecast trafficked areas in agricultural fields can effectively identify compacted areas in silty clay soil; however, data from nearby areas should also be considered. Nogués et al. [2006] discovered that ECa measurements in sandy soils might more accurately identify compacted areas in agricultural fields than traditional soil sample methods. The study found that ECa mapping could save up to 60% of the time and money compared to manual compaction testing.

Pathirana et al. [2024] while using random forest (RF), simple linear regression (SLR), and multiple linear regression (MLR) from ECa and dielectric constant (Kr) data to predict soil bulk density, found that geophysical methods- ground-penetrating radar (GPR) and electromagnetic induction to be very useful in assessing soil properties and variables in agriculture. This is because of their ability to overcome the limitations of traditional methods. Also, according to Ding et al. [2020], in their study of using EMI observation data and machine learning algorithms to predict soil ECa and analyze its variations in the spatial distribution in oasis agroecosystems and desert-oasis ecotones, stated that electrical conductivity data provide a reliable and cost-effective tool for obtaining high-resolution soil maps that can be used for better land evaluation and soil improvement at larger scales. As electrical conductivity depth increased, soil-related variables diminished in influence, while climate-related variables grew more significant. According to the study, climate-related variables have the most substantial impact on ECa fluctuations, followed by vegetation-related variables and then soil-related variables. Heil et al. [2017] state that rapid and accurate assessments of within-field variation are crucial for identifying field-wide heterogeneity, which can lead to improved agricultural land management. The interpretation and use of apparent soil electrical conductivity readings are highly site- and soil-dependent; therefore, understanding the soil characteristics that affect ECa measurements is essential. The researchers also noted that ECa applications are necessary to achieve sustainable agriculture, maximize economic returns, and protect the environment, particularly soil health. In their study, Grisso et al. [2005] found that accurate soil property maps are essential for making effective precision farming decisions. Soil property segregation and classification are challenged by insufficient sampling density and the high costs of traditional soil sampling and analysis. Additionally, soil ECa maps can be utilized to establish management zones and reveal clear patterns in soil parameters. Su and Adamchuk [2023], while measuring apparent soil electrical conductivity using galvanic contact resistivity (Veris) and electromagnetic induction (EM38 and DUALEM) techniques, stated that Veris and DUALEM electrical conductivity measurements are more stable over short periods and resistant to temporal drift and operational noise over time and are frequently conducted to reveal spatial soil heterogeneity.

ADVANTAGES OF USING ECA DATA FOR SOIL COMPACTION PREDICTION

Using ECa data for predicting soil compaction offers significant advantages in precision agriculture. ECa data provides a non-invasive, real-time assessment of soil properties that are closely linked to compaction levels. By identifying compacted areas accurately, farmers can adjust tillage practices, optimize machinery use, and reduce energy consumption, leading to increased productivity and cost savings. ECa-based mapping minimizes the need for extensive physical sampling, saving time and resources while ensuring more precise, site-specific soil management. ECa data enhances decision-making, supports sustainable farming, and improves soil health.

Data from dynamic soil ECa measurements have the potential to estimate mechanical soil parameters, such as soil compaction. This is crucial for conserving agricultural soils from natural and human-induced erosion and over-compaction [Pentoś et al. 2022]. Soil ECa sensors provide real-time data, enabling quick assessments of compaction and facilitating precise tillage or repair treatments in affected areas [Sudduth et al. 2005, Su and Adamchuk 2023, Sanches et al. 2025]. EMIs, a type of non-contact ECa sensor, can rapidly map large fields, offering a significant advantage over traditional point-based soil compaction testing [Heil et al. 2017]. Once calibrated, these sensors provide a cost-effective method for monitoring soil compaction and creating spatial variability maps, which aid in planning variable-depth tillage to optimize energy consumption and operational costs [Deng et al. 2020, Pentoś et al. 2022].

Continual monitoring using ECa sensors helps farmers implement preventive measures, such as adjusting tillage operations or applying targeted aeration, to mitigate compaction-related yield losses [Maharjan et al. 2018]. The ability to predict soil compaction levels based on soil electrical conductivity is particularly useful when scaling from small plots to entire fields [Korsaeth 2005, Brogi et al. 2020]. Technologies like Veris and DUALEM electrical conductivity sensors have proven stable over short periods, showing resistance to temporal drift and operational noise, ensuring reliable long-term data collection [Su and Adamchuk 2023].

CHALLENGES IN USING ECA DATA FOR COMPACTION PREDICTION

For agricultural soil mapping, conventional near-surface geophysical prospection systems have either relied on electromagnetic induction measurements using EMI devices or on earth resistance measurements using electrode disks that require soil contact, both of which have shortcomings. The relationship between ECa and soil compaction is highly dependent on soil type. Accurate predictions require detailed knowledge of the soil's physical properties, including texture, bulk density, porosity, moisture content, and organic matter. Soil texture, which includes the proportions of sand, silt, and clay, influences water retention and compaction levels, thereby affecting accuracy. Both bulk density and porosity determine the movement of air and water, impacting predictions about soil structure. Moisture content alters both conductivity and strength, which affects sensor readings. Additionally, organic matter enhances soil aggregation, influencing estimates of compaction and aeration [Dexter 2004, Silva et al. 2018].

Because soil moisture significantly affects ECa, predictions of soil compaction based on ECa readings can be skewed by natural moisture variations. This makes it necessary to correct or account for moisture content in real-time measurements to ensure accuracy [Su and Adamchuk 2023]. For ECa data to serve as a reliable predictor of soil compaction, it must be calibrated against direct compaction measurements, such as bulk density and penetration resistance. However, calibration models may differ depending on soil type, field conditions, and farming practices [Su and Adamchuk 2023]. ECa's sensitivity to soil texture also reduces its reliability in heterogeneous soils, such as those with mixed sand and clay layers, necessitating separate calibrations for different soil compositions [Siqueira et al. 2014, Su and Adamchuk 2023, Sanches et al. 2025].

Soil ECa measurements are not always trustworthy, particularly when high amounts of manure or fertilizers have been applied. In such cases, excessive salts from these additives can distort ECa readings, making them reflect changes in soil amendments rather than actual soil conductivity. This can lead to misleading compaction maps if not properly accounted for [Corwin and Lesch 2005, Grisso et al. 2005, Sanches et al. 2025]. The interpretation and utility of ECa readings are highly dependent on location and soil characteristics, requiring a clear understanding of the specific soil properties influencing the measurements to ensure their effective use in agricultural management [Su and Adamchuk 2023].

FUTURE DIRECTIONS AND CONCLUSIONS

Machine learning algorithms can enhance the accuracy of soil compaction predictions based on ECa data by incorporating additional variables, such as soil texture and moisture content. Advanced techniques that assess multiple factors simultaneously can produce more precise, localized compaction estimates, potentially reducing the need for direct soil sampling. Integrating ECa sensors with other soil health indicators, such as moisture and texture sensors and penetrometers, can further improve prediction accuracy, providing a more comprehensive understanding of compaction and related issues. Moreover, combining ECa measurements with remote sensing technology enables large-scale monitoring of soil compaction across agricultural fields. Automating ECa sensor calibration using drone or satellite data could reduce the need for extensive fieldwork, making ECa-based compaction prediction more scalable. Advances in real-time sensor technology also facilitate dynamic soil compaction monitoring, offering farmers and land managers valuable data to optimize field management practices.

Overall, soil ECa is a promising tool for predicting soil compaction, particularly when combined with other monitoring technologies and properly calibrated. It provides a scalable, efficient, and cost-effective alternative for managing soil compaction in agricultural fields in real-time. Predicting soil compaction with ECa data can be a faster and less expensive approach compared to traditional methods, yet it has limitations. Factors like soil type variability, moisture dependence, and the need for thorough calibration can reduce ECa's reliability as a standalone predictor. Continued research and advancements in precision agriculture are essential to improve ECa's accuracy and practical use. Addressing challenges like soil type variability, moisture fluctuations, and calibration issues is crucial for wider adoption. Ongoing research is needed to strengthen the link between soil ECa and compaction, enabling more effective and sustainable soil management in agriculture.

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The source of research funding: UPWr Doctoral School.

Received: 11.12.2024
Accepted: 7.04.2025
Published: 19.05.2025