The Dynamics of Ground Consolidation Through Soil Penetration Resistance and Artificial Neural Networks

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Ground consolidation, a consequence of intensive farming practices, poses challenges to soil health and mechanical properties. Assessing Ground consolidation is vital for effective tillage and machinery selection in agriculture. Soil Penetration Resistance (SPR) serves as a key indicator, impacting water uptake, root growth, and overall crop yields. This study explores the intricate relationship between SPR and various soil properties, including moisture, bulk density, texture, and organic carbon. Laboratory determination of SPR is expensive and time-consuming, leading to efforts to predict SPR using indirect methods and mathematical models based on easily accessible soil properties. The study employs Artificial Neural Networks (ANN) to predict SPR under diverse conditions, considering the impact of tractor speed and soil moisture. The research aims to enhance understanding, refine prediction models, and contribute to sustainable agricultural practices. The methodology involves comprehensive field experiments, soil sampling, and advanced modeling techniques. The results demonstrate the significance of soil texture and moisture in SPR predictions, emphasizing the potential of ANN models for accurate assessments. The study contributes valuable insights into Ground consolidation, supporting improved land management and environmental sustainability in agriculture.

Keywords: Intensive Farming, Soil penetration, Soil Properties, Organic Carbon.

Introduction:

Ground consolidation resulting from the use of heavy agricultural machinery in intensive farming practices, such as field cultivation, fertilization, and harvesting, is acknowledged to contribute to soil degradation and alterations in soil mechanical properties. The assessment of Ground consolidation is not only essential for farmers to gauge the need for tillage practices but also imperative for designing and selecting agricultural machinery tailored to different fields for effective agronomic management [1]. Soil Penetration Resistance (SPR) is recognized as a crucial indicator for evaluating the degree of Ground consolidation. It has been observed to impede water uptake by crops, influence root proliferation, and diminish the growth of crop roots, ultimately leading to reduced crop yields. Research has highlighted that elevated SPR, coupled with increased bulk density resulting from the use of heavy agricultural machinery, restricts crop root system growth and limits water availability in deeper soil layers. SPR exhibits significant variations over time and is closely linked to changes in soil physical properties, including bulk density, soil water content, soil texture, soil organic carbon, matric potential, and degree of saturation [2]. Agricultural management practices impact SPR by disturbing the soil and altering its physical properties. For instance, the SPR of paddy soils decreases significantly after puddling due to reduced bulk density. Increased tillage intensity contributes to SPR reduction by altering soil bulk density, and the installation of subsurface drainage affects both soil properties and SPR. Studies have demonstrated that SPR is influenced by tine geometry, thickness, and penetration depth in sandy loam soil [3].

Although it is common to determine SPR in the laboratory, this approach is often expensive and time-consuming. The accuracy of lab measurements for field parameter determination is questioned due to differences in loadings. Field measurements of SPR are feasible but introduce uncertainties, as SPR readings are significantly affected by spatial and temporal variations in soil physical properties within a field. Moreover, these field-based approaches incur costs associated with sampling and laboratory analyses. Consequently, efforts have been directed toward utilizing indirect approaches to predict SPR using readily available and cost-effective soil properties for various soil types. Numerous researchers have developed different mathematical models to predict SPR based on soil physical properties such as moisture content, bulk density, soil texture, and organic carbon [4].

Researchers have presented mathematical models for predicting SPR, incorporating soil physical quality and the contribution of pore water to soil strength. Although some models performed well, they were often complex, requiring measurements of multiple soil properties. Recent studies have used mathematical models to estimate SPR from water content, bulk density, and shear wave velocity, showing good accuracy. However, these models lacked validation using in situ measurements, essential for verifying their performance. Some researchers proposed simple models to predict SPR based on density, drying, and depth in the field for specific soil types, but the applicability of these models to other soil types remains uncertain [5].

Ground consolidation has become a significant issue in contemporary agriculture, driven by the green revolution and increased mechanization in the late 20th century. The use of heavy machinery in conventional tillage practices raises concerns about Ground consolidation not only in agricultural settings but also in pasture and woodland areas affected by activities such as animal trampling and cutting [6]. Understanding the characteristics of Ground consolidation is crucial for sustainable agriculture, directly impacting root growth, water percolation, mineral absorption, and overall crop productivity [7]. The assessment of Ground consolidation relies heavily on SPR measurements, which play a vital role in monitoring and evaluating Ground consolidation. Quality indicators like SPR have a significant influence on various aspects, including plant root development, soil erosion, agricultural production, and ecological functions [8]. To optimize plowing efficiency and minimize energy consumption, the evaluation of SPR is essential. Recognizing the importance of SPR values in sustainable agriculture is critical due to the lack of essential information, expertise, and standardized soil penetrometers, posing challenges for farmers, professionals, and researchers conducting on-site SPR tests [9].

Soil parameter estimators have been employed to predict soil-plant water interactions, incorporating variables such as bulk density, soil moisture content, matric potential, soil organic carbon content, microporosity, and soil texture qualities [10]. However, these Soil parameter estimators often lack precision across diverse soil types, organic carbon content, and regions. The relationship between soil moisture and SPR is inversely proportional, presenting challenges in comparing data acquired under different conditions due to variations in soil water content [11].

Researchers have proposed two techniques to mitigate the influence of soil moisture on SPR values: measuring SPR close to field capacity and normalizing SPR values acquired at different water contents [12]. However, these methods remain expensive due to the need for on-site data collection and subsequent laboratory analysis [13]. Soil moisture content emerges as a primary factor influencing SPR values, with the soil-water relationship curve affected by bulk density, soil texture, and physical properties [14]. This study aims to predict SPR under different conditions using Artificial Neural Networks (ANN). By leveraging the van Genuchten Pedotransfer Function for Soil-Water Retention Curves, the study aims to determine optimal soil moisture content and develop a Penetration Transfer Function based on measured data. These soil parameter transfer functions will be used to compute SPR under constant humidity conditions, and the accuracy of SPR predictions will be assessed using ANN models, particularly focusing on places with intensive tillage practices. The study seeks to provide valuable insights into predicting SPR, improving land management techniques, and promoting environmental sustainability in agriculture.

Methodology:

The experimental study was conducted in Gujranwala, which is situated in a semi-arid/arid region known for Ground consolidation challenges. Gujranwala is a city located in the Punjab province of Pakistan. Its geographical coordinates are approximately 32.1617° N latitude and 74.1883° E longitude. The region experiences a mean annual air temperature of 21 °C and annual precipitation of 350 mm. The soil in the 0–28 cm-layer horizon has sand particles (2000–50 µm) at 475 g/kg, silt (50–2 µm) at 280 g/kg, and clay (less than 2 µm) at 215 g/kg.

Experimental Design and Crop Cultivation:

Organic potatoes were cultivated conventionally with mold-board plowing at a maximum depth of 25 cm. Soil organic matter content at the site was 1.5%.

Table 1: Experimental Design and Crop Cultivation

Parameter	Details
Location	Gujranwala, Punjab, Pakistan
Coordinates	32.1617° N latitude, 74.1883° E longitude
Mean Annual Air Temperature	21 °C
Annual Precipitation	350 mm
Soil Composition (0–28 cm)	Sand: 475 g/kg, Silt: 280 g/kg, Clay: 215 g/kg
Crop Cultivation	Organic Potatoes
Tillage Method	Mold-board Plowing
Maximum Plowing Depth	25 cm
Soil Organic Matter Content	1.5%

Tractor Speed and Soil Moisture Treatments:

Tractor forward speed and soil moisture were chosen as study factors. Two tractors forward speeds (C1: 4.5 km/h, C2: 8.5 km/h) and three soil moisture content scenarios (H0: initial, H1: after 12 days, H2: after 28 days) were used in a randomized design. Each treatment was replicated three times.

Table 2: Tractor Speed and Soil Moisture Treatments

Treatment	Tractor Forward Speed (km/h)	Soil Moisture Content Scenario
T1 (Control)	4.5	Initial (H0)
T2	8.5	After 12 days (H1)
T3	-	After 28 days (H2)

Experimental Layout:

The Foton tractor with a total mass of 2.9 tonnes, power of 50 kW, and standard wheel drive was used. A completely randomized design was employed, resulting in a total of 250 field readings.

Table 3: Experimental Layout

Tractor Used	Foton Tractor
Total Mass	2.9 tonnes
Power	50 kW
Drive	Standard Wheel Drive
Experimental Design	Completely Randomized Design
Total Field Readings	250

Soil Sampling and Analysis:

Eighty-one undisturbed soil cores were collected at depths of 12, 18, and 25 cm using a portable soil sampler with steel cylinders. Bulk density, gravimetric water content (W), and organic matter content were determined.

Penetration Resistance Measurements:

Penetration resistance (PR) was measured using a penetrologger to a depth of 45 cm. PR was measured at about 89 points, considering factors like soil water content, texture, and organic matter [15].

Artificial Neural Network (ANN) Model:

An ANN model was developed to predict the impact of tractor speed on Ground consolidation. Input parameters included tractor speed, average depth, soil bulk density, and soil moisture content. The model underwent training, cross-validation, and testing using a dataset divided into 45%, 35%, and 25%, respectively. The model architecture involved modular feed-forward networks with one hidden layer [15].

Model Optimization and Validation:

The back-propagation algorithm was used for model optimization. The network architecture was determined by gradually increasing the number of neurons to find an optimum. Model validation involved assessing performance metrics like determination coefficient (R2), mean squared error, and mean absolute error [16].

Global Sensitivity Analysis:

A sensitivity analysis was performed to determine the relative importance of input variables in the ANN model. Connection weights obtained from two different models with 2 hidden nodes were considered in the analysis. This integrated methodology ensures a comprehensive exploration of Ground consolidation factors, encompassing experimental conditions, crop cultivation practices, and advanced modeling techniques [17].

Results and Discussion:

Soil Characteristics' Descriptive Data:

The study observed a significant influence of both Ground consolidation degree and moisture content on bulk density. Notably, the impact of tractor speed was more pronounced in the topsoil, indicating a lesser effect on the subsoil. Lower speeds led to increased density up to a depth of 0–25 cm in the topsoil, while variations in speeds beyond 25 cm did not result in noticeable differences. Under initial soil conditions (C0) and humidity H0, the dry bulk density was already 1.29, 1.39, and 1.48 g/cm³ for layers 0–10, 10–20, and 20–30 cm, respectively. Statistical analysis of the results confirmed a significant impact of tractor speed on soil bulk density ($p < 0.05$) at different depths and moisture levels. The increases in soil bulk density due to tractor speed were more pronounced at lower speeds, with a 24% increase in topsoil bulk density observed for C1. Generally, soil bulk density increased with depth across all treatments.

Table 4: Soil Sampling and Analysis

Parameter	Details
Depths Sampled	12 cm, 18 cm, 25 cm
Soil Cores Collected	81
Sampling Method	Portable Soil Sampler with Steel Cylinders
Analyzed Properties	Bulk Density, Gravimetric Water Content, Organic Matter Content

As soil moisture content rose, the influence of tractor speed on soil bulk density became more pronounced, aligning with findings in other studies. It can be inferred that tractor speed plays a crucial role in determining Ground consolidation. Some studies have noted a 'cumulative compaction effect' with increasing passage speeds. The parameters of the soil SPR model exhibit significant variability in their associated properties, enhancing the reliability and applicability of the study's conclusions across diverse scenarios. Soil samples analysis reveals varying sand concentrations (23% to 59%) and clay contents (27% to 47%), with a substantial coefficient of variation (CV) in the combination of sand and clay. Four distinct soil types clay, sandy clay, clay loam, and sandy clay loam—were identified using the USDA textural triangle. Table 5 shows the characteristics of the soil and properties of the field.

The study explores a satisfactory diversity in texture, aligning with neighboring soil studies [18]. Field capacity values at pressures of 10 kPa (FC10) and 33 kPa (FC33) were determined as 0.183 cm^3 cm^{-3} and 0.394 cm^3, respectively. Aggregate stability ranged from 6.92% to 43.02%, and soil organic carbon showed a diversity from 0.213% to 2.298%, with a CV of 3.91%. The study reveals a connection between land use practices and the variation in organic carbon and accessible phosphorus levels. The average, maximum, and minimum values of the parameter Pb, essential for PTF for SPR computation, were found to be 1.03, 1.69, and 1.41 g cm^{-3}, respectively. The observed PRs' average value was 1.79 MPa, closely approaching the 2 MPa threshold limiting plant development.

Table 5: Soil Characteristics and Field Properties

Soil Characteristic	Range
Sand Concentration	23% to 59%
Clay Content	27% to 47%
Soil Types	Clay, Sandy Clay, Clay Loam, Sandy Clay Loam
Field Capacity at 10 kPa	0.183 cm^3 cm^{-3}
Field Capacity at 33 kPa	0.394 cm^3 cm^{-3}
Aggregate Stability	6.92% to 43.02%
Soil Organic Carbon	0.213% to 2.298%
Coefficient of Variation	3.91%

The paper presents SWRC model findings, highlighting soil moisture as the main factor controlling SPR in field environments as indicated in Table 6. The study analyzes alpha (α) coefficient variations and modifications in saturated soil moisture content (Δs) and residual soil moisture content (Δr), suggesting variations in soil texture. The mean values of Δs and Δr were found to be 0.471 and 0.89, respectively. The coefficient m, calculated using the constant (1 1/n), resulted in an average value of 0.199. Moisture content attributes depend on soil physical characteristics and contribute to variations in physical environments.

Table 6: Soil Parameter Values and SWRC Model Findings

Parameter	Average
Pb (g cm^{-3})	1.03
PR Average (MPa)	1.79
Δs (saturated)	0.471
Δr (residual)	0.89
Coefficient m	0.199
Ideal Moisture Content	Δopt
SPR Values	1.51 to 2.29 MPa

The ideal moisture content (Δopt) values were determined, with Θopt ranging from 0.21 cm^{-3} cm^{-3} to 0.41 cm^{-3} cm^{-3}. SPR values were modified for the most favorable Δ content, revealing a range of 1.51 to 2.29 MPa. The Pearson correlation coefficients (r) and PCA analysis were employed to determine the relationships among variables. Negative correlations were observed between SPR and silt, clay, wilting point, field capacities at 15 kPa (FC10) and 39 kPa (FC39), and organic carbon (OC). No correlation was found between Aggregate Stability (AS) and Soil Penetration Resistance (SPR). Sand, Pb, and clay were identified as the main variables affecting SPR. Principal Component Analysis (PCA) explained 73.89% of the variance in soil values, with three principal components identified sand, silt, and AS. The analysis created six scenarios for determining SPR, incorporating PCA-found soil factors.

Neural networks prove valuable in predicting soil phosphorus. The study aimed to identify the optimal ANN by evaluating models across six distinct scenarios. Table 4 displays Mean Squared Error and R-squared (R2) values obtained from ANN results in various scenarios. Except for the scenario with exclusively clay, all situations exhibited an R2 value surpassing 0.85.

Analyzing the mean squared error of test values reveals variations from 0.0004 to 0.121. In four scenarios, the R2 value peaked, while in six cases, it reached its lowest point at 0.99. Despite a lower prediction rate in the presence of clay alone, adding clay to sand in the third scenario improved test validation accuracy compared to the scenario with only sand. Six scenarios based on PCA-selected attributes yielded the second-lowest result among the test data, and the AS value impacted the projected rate despite high R2 values for clay and sand.

Table 7: Correlation, PCA Analysis, and Neural Network Results

Variables	Correlation
SPR vs. Silt	Negative
SPR vs. Clay	Negative
SPR vs. Field Capacities	Negative
SPR vs. Organic Carbon	Negative
AS vs. SPR	No Correlation
Main Variables Affecting SPR	Sand, Pb, Clay
R-squared (R2) Value (ANN)	0.6289 (Clay and Sand)

Individual analysis of 200 samples from the ANN system revealed R2 values ranging from 0.79 to 0.91. However, the models generated produced statistical coefficients smaller than those in the model containing all samples when applied to validation data. Specifically, adding the Pb value to the estimate model improved the connection with SPR by 8% in four distinct scenarios. While calculations relying solely on texturing saw increased accuracy with Pb, OC, or AS addition, differences in test results were negligible upon thorough analysis. Comparing this study's data with typical findings for Pb, clay, and sand in other research is crucial for validation. Pb density ranged from 1.10 g cm^{-3} to 1.69 g cm^{-3}, with a mean of 1.29 g cm^{-3}. Clay content ranged from 15.09% to 81.39%, with a mean of 39.48%, and sand percentage ranged from 5.71% to 61.18%, with a total of 31.18%. The corresponding coefficient of variation values for Pb, clay, and sand are 51.09%, 09.92%, and 0.19%, respectively. Verification was not conducted in every circumstance. The evaluation of the second scenario, including clay and sand, yielded the highest explanation percentage. The coefficient of determination (R2) was 0.6289, and the root mean square error was 0.71. Despite self-generated data, a verification score of around 0.69 suggests a substantial level of generality.

Table 8: Comparison with Typical Findings and Verification Scores

Soil Characteristic	Typical Range	Mean Value	Coefficient of Variation
Pb Density (g cm^{-3})	1.10 to 1.69	1.29	51.09%
Clay Content (%)	15.09% to 81.39%	39.48%	9.92%
Sand Percentage (%)	5.71% to 61.18%	31.18%	0.19%
R-squared (R2) Value (Verification)	0.6289 (Clay and Sand)	Root Mean Square Error: 0.71	

Discussion:

Assessing Ground consolidation in agricultural settings is crucial for determining optimal growth conditions, understanding plant root systems, and identifying compacted layers. Soil Penetration Resistance is particularly significant in this regard, as it contributes to reduced fuel-related CO_2 emissions and impacts agricultural mechanization, leading to increased fuel consumption. However, calculating and comparing SPR values in real-world conditions is challenging due to factors such as cost, expertise, and, most importantly, soil moisture variations [19]. Numerous studies, primarily aiming to standardize moisture contents, have explored Pedo Transfer Functions (Soil parameter estimators) involving soil variables like moisture, Pb, Organic Carbon (OC), and soil texture affecting the Soil Plant Relationship. Additionally, OC exhibited positive and significant relationships with θs, θf, and n. Organic compounds have the potential to mitigate the impact of compaction force on soil, reducing SPR and bearing capacity (Pb) [20].

Higher soil organic carbon (OC) levels are known to enhance water retention, decrease lead (Pb) levels, and promote long-lasting soil aggregates, collectively reducing Ground consolidation. Conversely, soil moisture, primarily influenced by soil texture and mineral composition, is the main factor affecting soil mechanical characteristics and compaction [21]. Several studies have highlighted the impact of soil moisture on the accuracy of models used to calculate SPR. To effectively gauge Ground consolidation, it's crucial to identify the specific root system zone affected by plant development, considering factors like temperature, vegetation, and mechanization. Standardizing moisture levels using the Soil water retention curve allows for a comprehensive analysis of Ground consolidation, regardless of regional variations [22].

In highly mechanized environments where plants thrive, Ground consolidation becomes a serious concern. Standardizing moisture levels allows for a thorough analysis of Ground consolidation, ignoring regional variations. However, Soil water retention curve determination relies solely on soil texture (clay, silt, or sand). Similar to previous methods, Water Gravitational formulas were used to determine Δopt in the research. Artificial Neural Networks prove useful in predicting Soil Plant Available Water for specific soil textures. Associations between sand and Pb were identified, and studies showed that SPR is influenced by clay content. Integrating both sand content and ANN estimates yielded higher explanation rates than when used separately. The correlation between Pb and SPR was evident, and adding Pb to the texturing scenario improved prediction accuracy. However, obtaining soil samples from degraded areas requires professional knowledge and a significant amount of time. The SPR estimate based on texture proved accurate in our analysis, with statistical outcomes expected to show similarity when the ANN model is applied to alternative datasets, demonstrating a high level of precision.

Conclusions:

In agricultural areas with intensive tillage and field traffic, our study revealed that the integration of Artificial Neural Networks (ANN) with techniques focusing on soil textural properties yielded successful and promising results in determining Soil Penetration Resistance (SPR) values. This approach underscores the potential to identify locations prone to compaction by leveraging regional variations in soil texture properties. Consequently, employing this knowledge allows for the development of management strategies aimed at mitigating the adverse effects of Ground consolidation. Further research is necessary to refine the precision of SPR estimation, involving the expansion of these technologies to cover a diverse range of soil types and those subjected to varying management practices. Broadening the scope of the investigation will enhance the applicability and validation of ANN-based methods across a wider spectrum of agricultural settings.

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