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Research on methods for soil quality assessment in arable soils in the Tokachi region, Hokkaido, Japan

Doctoral Course, Regional Environmental Studies Unit, Environmental Frontier Course,
Graduate School of Agriculture, Hokkaido University

Yoshimura, Motohiro

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1. Foreword

1.1. Agriculture in Hokkaido: Status of Agricultural Data Utilization

Hokkaido accounts for approximately 1,130,000 hectares of arable land, constituting about 29% of Japan's total arable land area. It hosts 32,300 agricultural enterprises, representing 3.5% of the national total (Statistics Department, Minister's Secretariat, Ministry of Agriculture, Forestry and Fisheries 2023c, 2023d). These figures highlight a distinctive characteristic of Hokkaido's agricultural sector: large-scale operations managed by a relatively small number of enterprises compared to the national average. Furthermore, the aging demographic profile of the agricultural workforce is increasingly pronounced, reflecting a broader national trend (Statistics Department, Minister's Secretariat, Ministry of Agriculture, Forestry and Fisheries 2023a). This demographic shift underscores the urgent need for strategies aimed at consolidating farmland ownership and promoting the transfer of farmland to younger or new farmers, which are critical for ensuring the long-term sustainability of the agricultural sector. In this context, there is a potential for farmland of uncertain historical usage to be acquired, raising challenges related to land management. Additionally, rising input costs, including fertilizers and other materials, emphasize the importance of optimizing farmland management to reduce both labor intensity and financial expenditures. To address these challenges, leveraging agricultural data—particularly data on field characteristics and cultivation management—could facilitate the adoption of labor-saving technologies and advanced cultivation management practices. This data-driven approach could play a vital role in enhancing the efficiency, productivity, and sustainability of agriculture in Hokkaido.

In the Tokachi Agricultural Cooperative Federation (*Tokachi nougyou kyoudou Kumiai rengoukai*, 十勝農業協同組合連合会) operates the Tokachi Total Assistance System for Farmers (TAF system) in Hokkaido's Tokachi region. This system enables farmers to access and input detailed information for each field, supporting informed decision-making in field management. In soil management, the TAF system utilizes accumulated soil pH data to calculate the necessary quantity and cost of materials for soil improvement. By inputting the target soil pH and the chosen amendment material, the system provides precise recommendations. Additionally, if records of organic matter applications are maintained, the system can estimate the required amounts of fertilizers—specifically nitrogen, phosphorus, potassium, and magnesium—and their approximate costs for subsequent crops, based on established fertilizer standards for each crop.

This data-driven approach enhances the efficiency and sustainability of agricultural practices in the Tokachi region.

Conversely, achieving optimal soil conditions to support crop productivity necessitates consideration of not only pH levels and fertilizer application but also the appropriate balance of other essential components and soil physical properties. To facilitate the sustainable production of high-quality agricultural products, the Hokkaido Agriculture Department (*Hokkaido Nouseibu*, 北海道農

政部) published the Hokkaido Fertilizer Guide in 2020. This guide provides comprehensive recommendations for fertilizer and soil management with the objectives of ensuring a stable fertilizer supply, reducing production costs, and minimizing environmental impact. Based on findings from prior research conducted in Hokkaido, the guide introduces "soil diagnostic reference values," which serve as benchmarks for optimal soil physicochemical properties to promote favorable crop growth and yield. However, while these reference values are established for various soil properties, the guide does not assign weighting to prioritize which properties are most critical for crop productivity. As a result, when producers analyze soil physicochemical data for their fields, they can compare their soil properties against these reference values to identify relative deviations. However, the absence of a prioritization framework prevents them from determining the most critical areas for improvement or identifying which fields require intervention most urgently. This limitation underscores the need for an integrated approach to soil management that incorporates prioritization mechanisms to enhance decision-making and resource allocation.

1.2. What is soil quality?

The quantification of soil quality has been a focal area of research, particularly in the United States, with the aim of elucidating the relationship between soil quality and crop productivity. This relationship involves a complex interplay of soil physicochemical parameters, encompassing physical properties and nutrient content. Soil quality is broadly defined as the capacity of soil to perform its functions sustainably while preventing degradation, within the context of specific land use (Doran & Parkin 1994, Karlen et al. 1997). In Japan, the concept of soil quality is interpreted through varying terminologies, such as *dojou no shitsu* ("quality of soil," 土壌の質) (Yanai et al. 2012, Kaneko 2018) and *dojou shitsu* ("soil quality," 土壌質). Analogous to terms like "water quality" and "air quality," which assess the impacts of water and air on health, ecosystems, and infrastructure, the term *dojou shitsu* appears more suitable. This term emphasizes soil as an integral component of the natural environment, enabling a comprehensive evaluation of its role in productivity, environmental sustainability, and broader ecological impacts. The assessment of soil quality is inherently dependent on the management objectives, such as maximizing productivity, promoting waste recirculation, or conserving nature (Andrews et al. 2004). However, the concept remains complex, rendering direct field or laboratory measurements challenging (Stocking 2003). A significant limitation in this field is the lack of a universally standardized method for soil quality estimation (Bouma, 2002, de Paul Obade & Lal 2016). To address these challenges, the Soil Quality Index (SQI) was developed. The SQI framework identifies critical soil physicochemical properties relevant to specific management goals. Each property is assigned a score based on its relative quality, and these scores are weighted and integrated to calculate a single SQI value. A higher SQI value indicates superior soil quality, offering a quantitative means to evaluate soil functionality and guide management practices. However, no studies to date have evaluated the relationship between SQI and yield in fields managed by different producers, which provides limited SQI knowledge for improve soil management practice for each producers. This study defines the main objective function for soil quality as crop productivity because this study discussed the relationship between SQI and crop yield to develop decision-making method for farmers' soil management.

1.3. Objectives of the study

The present study was conducted in the Tokachi region of Hokkaido, Japan. This region had well developed system to which farmers accumulate the field data but the data was not being utilized sufficiently. One of the reasons is the lack of the integrated approach to soil management that incorporates prioritization mechanisms to enhance decision-making. The development of SQI could be one solution to this issue.

SQI framework had been developed in Europe and America and SQI study is limited in Japan. This means that it is unclear whether this framework can be applied in Japan. The present study evaluated the possibility and the prospect of SQI for farmers' field in Japan.

The primary objective of this study is to analyze soil physicochemical properties and yield data from field sites in the Tokachi region, with the aim of developing a method to calculate a Soil Quality Index (SQI) for the assessment of crop productivity. Additionally, the study seeks to identify the critical elements of soil quality assessment and evaluate the conditions under which the SQI is most strongly associated with crop yield.

The specific objectives of the study are threefold:

1. To consolidate and organize existing knowledge: By integrating and analyzing current data, the study aims to provide a foundation for a quantitative understanding of soil quality and its relationship to crop productivity.
2. To identify data gaps and recommend future data collection: The study will highlight additional soil and crop data that should be systematically collected in the field to enhance soil quality assessment.
3. To provide quantitative evidence for soil management decision-making: By linking SQI values to crop yields, the study aims to offer actionable insights that can inform and optimize soil management strategies.

This research is expected to contribute to the development of evidence-based approaches for sustainable agricultural practices in the Tokachi region and beyond.

This thesis consists of 10 parts; a foreword, a history of research, study sites and methods, three research parts, a general discussion, a conclusion, a summary, and references. The research parts are as below:

1. Evaluation of crop productivity by soil quality indices in wheat field surface layers: This part

discussed relationship between SQI and wheat yield analyzing soil in 0-30 cm depth.

2. SQI considering the thickness of the surface soil in potato and wheat fields: This part discussed the importance of SQI considering surface soil thickness.
3. Estimation of the relationship of soil physicochemical properties and soil quality indices to long-term soil carbon storage capacity: This part discussed the estimation of soil carbon storage capacity indicator and its relationship with SQI or scores of physicochemical properties.

2. History of research

2.1. The genesis of soil quality in soil assessment

The assessment of soil quality has evolved as a critical component of understanding soil conditions and their role in agricultural productivity. Bünemann et al. (2018) provide an extensive review of contemporary advancements in soil assessment methodologies, encompassing concepts, research methods, and data interpretation. They also identify key challenges persisting in current research on soil quality, particularly in agricultural contexts. The evaluation of soil quality, particularly its suitability for crop growth, has likely been practiced since before the advent of written records. Historical accounts, such as ancient Chinese texts like Yugong and Zhouli (Harrison et al. 2010), and Roman works, including those of Columella (70 BC describe early methods for diagnosing soil properties based on their influence on agricultural productivity. These assessments laid the foundation for the modern concept of **soil fertility**, which has been a cornerstone of agricultural science. Originating from German *Bodenfruchtbarkeit* literature, soil fertility traditionally focuses on the soil's capacity to sustain crop yields (Patzel et al. 2000). The Food and Agriculture Organization (FAO) defines soil fertility as "the ability of soils to sustain plant growth through the supply of chemically, physically, and biologically favorable features and essential plant elements as plant growth and habitat" (FAO Soil Fertility) (https://www.fao.org/global-soil-partnership/areas-of-work/soil-fertility/en/). Mäder et al. (2002) expand on this definition, emphasizing that a fertile soil must not only provide essential nutrients for crop growth but also support a diverse and active biological community, exhibit stable soil structure, and maintain effective decomposition processes. Despite these comprehensive definitions, the concept of soil fertility is often limited to the chemical and, to a lesser extent, physical aspects of nutrient and water supply for crops (Shibahara 2010). This narrow focus highlights a need for a broader approach that integrates biological, physical, and chemical factors to holistically assess soil quality in diverse agricultural systems.

The concept of land quality was introduced as a holistic framework to address the physical and biological properties of soils within the broader context of land evaluation. A comprehensive early description of land quality was provided by the FAO in 1976. This concept encompasses a wide array of attributes, integrating physical and biological characteristics such as soil, water, climate, topography, and vegetation. Land quality is used to assess the suitability of land for various applications, including agriculture, forestry, and conservation (Carter et al. 1997, Dumanski & Pieri 2000). Soil surveys play a pivotal role in the assessment of land quality, providing critical data for evaluation. However, these surveys often depend on field observations that are limited in scope, with sparse measurements and infrequent sampling (Huber et al. 2001). Despite these limitations, land quality assessments are vital for identifying areas with high soil fertility in low-population-density regions and diagnosing limiting factors for agricultural productivity in high-population-density areas. In the latter context, the goal is often to mitigate productivity constraints, such as low organic matter content, through targeted soil amendments (Van Diepen et al. 1991). Beyond agricultural productivity, land quality assessments are employed to explore broader land use possibilities (van Latesteijn 1995). This includes proposing objective recommendations for sustainable land management and soil capability. Soil capability refers to the soil's contribution to ecosystem services and the conditions necessary for it to perform its ecological and productive functions effectively (Bouma et al. 2017). By integrating these diverse factors, land quality evaluation provides a robust framework for sustainable land use planning and management.

The concept of soil quality first appeared in the scientific literature in Mausel's (1971) definition, which described it as "the ability of soils to produce maize, soybean, and wheat under high levels of management conditions." This initial definition focused narrowly on agricultural productivity, aligning soil quality closely with land valuation and emphasizing its utility for crop production. In response to the need for a broader perspective, Larson and Pierce (1991) argued that soil quality should be distinguished from agricultural productivity. They highlighted the limitations of equating soil quality solely with crop yield, advocating for a more comprehensive approach that considers soil's multifunctionality. Doran and Parkin (1994) further expanded the concept, defining soil productivity as "the ability of soils to maintain their function while limiting soil degradation within land use boundaries." They introduced a broader definition of soil quality as "the capacity of soil to function within ecosystem boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health." This definition emphasized soil's role in supporting ecosystem services beyond agricultural outputs, incorporating environmental quality and the health of plant and animal systems. Building on these developments, Larson and Pierce (1991) integrated the concept of the natural environment's quality and its capacity to support biological health into their definition of soil quality. This shift marked a critical evolution in soil science, transitioning from a productivity-centric view to a more holistic understanding that recognizes soil as a foundational component of ecosystems and its pivotal role in sustainability.

The debate surrounding **soil health** emerged in the 1990s as a response to criticisms of the concept of soil quality, which was perceived as overly focused on agricultural productivity. Soil health was introduced as a broader concept, encompassing "ecological attributes of the soil that have implications beyond soil quality and the ability to produce specific crops." These ecological attributes include factors related to soil biota, such as biodiversity, food web structure, and the activity of soil organisms (Pankhurst et al. 1997). Pankhurst et al. (1997) posited that while soil quality and soil health are not entirely distinct and are often used interchangeably, they differ in focus. **Soil quality** is primarily concerned with the soil's capacity to meet human-defined demands, such as crop production, whereas **soil health** emphasizes the soil's ability to sustain plant growth and maintain its overall functionality over time. This perspective, which highlights the dynamic and ongoing capacity of soil to support ecosystem functions, has gained significant acceptance in the scientific community. Over time, the interpretation of soil quality has shifted to align more closely with that of soil health, leading to the emergence of the concept of **dynamic soil quality**, which is effectively synonymous with soil health (Moebius-Clune 2016). This shift underscores a distinction between the two concepts: **soil quality** is often associated with inherent soil properties, while **soil health** emphasizes dynamic, changeable attributes influenced by management and environmental conditions. The United States Department of Agriculture's Natural Resources Conservation Service (NRCS) defines **soil health** as "soil quality" and describes it as "the ability of soils to continue to function as living ecosystems that support plants, animals, and humans" (NRCS Soil Health) (http://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/health/). This dual usage of terms reflects the ongoing convergence of the two concepts. A review by Bünemann et al. (2018) further supports this convergence, equating soil health and soil quality, suggesting that the distinction between them is now more a matter of preference than principle. This evolution highlights a growing recognition of the importance of integrating both inherent and dynamic soil attributes into a unified framework for assessing soil sustainability and functionality.

2.2. Methodology and framework for assessing crop productivity of soils in Japan

The **Fundamental Soil Survey for Soil Fertility Conservation** (*Chiryoku hozen kihon chosa*, 地力保全基本調査), conducted between 1959 and 1979, was a landmark initiative aimed at assessing the physical and chemical properties of agricultural soils across Japan. This comprehensive survey underscored the critical role of both physical and chemical soil properties in determining agricultural productivity. In recent decades, the scope of soil evaluation has expanded to include its role as an environmental resource, with increasing attention to its biological properties as essential for conservation. In response to these evolving perspectives, the **Soil Fertility Promotion Act** (*Chiryoku zoushin hou*, 地力増進法) was enacted in 1984. The act emphasized improving soil chemical, physical, and biological properties. It established a foundational framework for soil fertility enhancement, including quantitative objectives for improving soil physicochemical properties based on soil parent materials (Society for the Study of Soil Fertility Problems, 1985；地力問題研究会 1985). These principles provided a structured approach to soil management, integrating diverse soil attributes into conservation strategies.

To ensure appropriate soil and fertilizer management, many prefectures have since adopted fertilizer application standards tailored to specific soil physicochemical properties. In Hokkaido, the **Hokkaido Agricultural Administration Department** developed the **Hokkaido Fertilizer Guide** (*Hokkaido sehi guide*, 北海道施肥ガイド) in 2020. This guide aims to promote sustainable practices by focusing on three primary objectives:

1. Ensuring a stable supply of high-quality agricultural products,
2. Reducing production costs, and
3. Minimizing environmental impact.

The guide incorporates findings from extensive research conducted in Hokkaido to establish **soil diagnostic reference values**, which define optimal soil physical and chemical criteria for crop growth and yield. However, despite these advancements, the guide does not assign specific weightings to individual soil properties to reflect their relative importance for productivity in different fields. This lack of prioritization highlights a critical gap in the practical application of the reference values and underscores the need for further refinement in soil fertility assessment methodologies.

The **Soil Productivity Potential Classification** (*Dojou seisanryoku kanousei bunkyu*, 土壌生産力可能性分級) is a widely utilized framework for evaluating land productivity in Japan. This method assesses various soil properties based on predefined criteria, with results expressed both symbolically and numerically. Thirteen categories, including factors such as topsoil thickness, permeability, and nutrient abundance, are evaluated. Each category is classified on a scale ranging from **Grade I** (excellent) to **Grade IV** (poor). To streamline this complex evaluation process, the **simplified classification formula** (*Kanryaku bunkyu shiki*, 簡略分級式) is often employed. This approach highlights the most inferior category within a soil area, providing a straightforward summary of limitations (National Council of Soil Conservation Research Projects, 1991; *Dojo hozen chosajigyou zenkoku kyougikai*, 土壌保全調査事業全国協議会). In the **Fundamental Soil Survey for Soil Fertility Conservation**, simplified classification formulas are provided for each soil area, the smallest classification unit in the survey. While this approach offers practical insights into the limitations of specific soil areas, it does not assign weights to the relative importance of individual categories. This lack of prioritization can limit the utility of the classification for targeted soil management. Additionally, the diversity of measured items and the extensive effort required to collect and analyze the necessary data present significant challenges. These limitations highlight the need for more efficient methods that integrate the relative importance of soil properties and streamline data collection while maintaining the robustness of soil productivity evaluations.

Following the completion of the **Fundamental Soil Survey for Soil Fertility Conservation**, the framework was extended through the **Basic Soil Environment Survey** (*Dojou kankyou kiso chosa*, 土壌環境基礎調査), which continued until 1998. This survey aimed to monitor temporal changes in soil physicochemical properties. Observations were conducted at approximately 20,000 fixed points across Japan, representing the country's major soil types. Data collection occurred on a five-year cycle, providing valuable insights into long-term soil dynamics (Hidaka 2007, Kusaba & Ishioka 2008). Subsequent soil monitoring efforts have been implemented on a smaller scale through specialized projects, including:

1. **Demonstration and Dissemination Project for Soil-Based Greenhouse Gas Measurement**

and Control Technology (*Dojou yurai onshitsukouka gas keisoku yokusei gijutsu jissho fukyu jigyou*, 土壌由来温室効果ガス計測・抑制技術実証普及事業): Conducted from 2008 to 2012, this project monitored approximately 3,000 sites to develop greenhouse gas measurement and mitigation techniques.

2. **Basic Survey on Soil Greenhouse Gas Emissions from Agricultural Land** (*Nouchi dojou onshitsukouka gas haisyutsuryou santei kiso chousa jigyou*, 農地土壌温室効果ガス排出量算定基礎調査事業): Conducted from 2013 to 2015, this survey similarly covered 3,000 sites to assess greenhouse gas emissions.
3. **Basic Survey on Soil Carbon Storage in Agricultural Land** (*Nouchi dojou tanso choryutou kiso chousa jigyou*, 農地土壌炭素貯留等基礎調査事業): Initiated in 2016 and ongoing, this project monitors approximately 3,000 sites to study carbon storage in agricultural soils (Takata & Mishima, 2017).

The results from these fixed-point surveys contribute to understanding soil properties in the context of climate change and agricultural sustainability. Many of the findings are available through the **Japan Soil Inventory**, published by the **National Agriculture and Food Research Organization (NARO)**. This resource provides accessible data for researchers and policymakers to support soil conservation and management efforts (Japan Soil Inventory) (https://soil-inventory.rad.naro.go.jp/).

2.3. Methods and frameworks for assessing soil quality abroad

Two major soil quality assessment methodologies have been developed in the United States, particularly focused on plot-level evaluations:

1. **Soil Management Assessment Framework (SMAF)**
   Developed by the Soil Quality (Andrews & Carroll 2001, Andrews et al. 2004; Karlen et al. 2001, Wienhold et al. 2004, 2009), the SMAF is notable for its **flexible indicator selection**. Indicators are chosen from a pool of 81 candidates based on predefined rules aligned with specific ecosystem services or management objectives. While this flexibility allows users to customize assessments, it can result in a lack of comparability between sites. Users have the discretion to disregard or modify proposed indicator combinations. Measured values for the selected indicators are interpreted through scoring curves, where higher scores represent superior soil conditions. The overall **Soil Quality Index (SQI)** is obtained by summing these scores.
2. **Cornell Soil Health Test (CSHT)**
   The CSHT (Idowu et al. 2008, Moebius-Clune 2016) adopts a more standardized approach, using a generalized set of measurement items and scoring curves. In addition to providing individual scores for each soil health parameter and the overall SQI, the CSHT offers management recommendations tailored to the assessment results.

In Europe, diverse soil quality assessment and monitoring methodologies have been developed:

- **France**:

  The **French Soil Quality Observatory** has been conducting surveys at 11 fixed sites since 1986 (Martin et al. 1998). More recent initiatives use a 16×16 km grid to collect data for the **Soil Information System** (Antoni et al. 2007, Jolivet et al. 2006).
- **United Kingdom**:

  Initial efforts focused on soil quality in forestry and semi-natural ecosystems (Loveland & Thompson 2002). Refinements led to the proposal of specific measurement indicators (Merrington et al. 2006). The **Countryside Survey**, active since 1978, monitors soil properties such as pH, organic carbon, and soil biodiversity (Black et al., 2003).
- **European Union**:

  A common European soil monitoring framework has been proposed to standardize soil quality assessments across member states (Huber et al. 2001). Under the EU FP6 project **ENVASSO** (Environmental Assessment of Soil for Monitoring), priority indicators were identified for each soil-related threat. These indicators were further refined under the EU FP7 project **RECARE** (Preventing and Remediating Degradation of Soils in Europe through Land Care) (Huber et al. 2008).

These methodologies highlight regional differences in soil quality assessment, with the U.S. favoring flexible, management-focused frameworks and Europe emphasizing long-term monitoring and standardization. Collectively, these approaches contribute valuable tools for understanding and improving soil health across diverse agricultural and environmental contexts.

2.4. Calculation method for Soil Quality Index

The concept of soil quality is inherently abstract; however, efforts to quantify it have led to the development of the Soil Quality Index (SQI). Calculating the SQI from soil physical and chemical data typically involves three key steps: (1) selection of parameters, (2) scoring of parameters, and (3) weighting and integration of scores. The flexible approach outlined in the Soil Management Assessment Framework (SMAF) is frequently employed for this purpose. To simplify analysis, minimize collinearity effects, and reduce measurement costs, the number of parameters used is reduced. This streamlined dataset is referred to as the Minimum Data Set (MDS). Initially, MDS selection relied on expert judgment (Doran & Parkin 1994), however, modern practices often select parameters that capture the majority of variability within the dataset (Andrews & Carroll 2001, Kosmas et al. 2014, Schipper & Sparling 2000, Shukla et al. 2006). When employing multivariate analysis methods, such as Principal Component Analysis (PCA), parameters essential to soil function may be excluded from the MDS if their variation is minimal within the dataset. To ensure the validity of the MDS, the relationship between selected parameters and objective soil function (e.g., crop productivity) should be examined prior to use. Each parameter in the MDS is assigned a dimensionless score ranging from 0.0 (poor quality) to 1.0 (excellent quality). This scoring is achieved using one of three principal scoring functions, chosen to align with the parameter's relationship to soil quality:

1. "More is Better" Function: Higher parameter values correspond to higher scores (e.g., nutrient content).
2. "Less is Better" Function: Lower parameter values correspond to higher scores (e.g., salinity levels).
3. "Optimal" Function: Scores are highest within an optimal range and decrease as values fall outside this range (e.g., pH).

The selection of scoring functions is guided by expert judgment and supported by diagnostic reference values. Thresholds for these functions vary depending on the dataset and the accumulation of previous findings in the study region (Andrews et al. 2002a). When diagnostic reference values are available, scoring functions can use these thresholds directly (Nakajima et al. 2015, Tang et al. 2019). In cases where reference values are absent, scoring functions are derived from the frequency distribution of regional data, often assigning high scores to the top 25%, bottom 25%, or 40–60% of measurement values (Idowu et al. 2008, Mukherjee & Lal 2014). When applying scoring functions developed from regional datasets to other regions, it is critical to assess their applicability to ensure consistent results. Parameter scores are weighted and aggregated to calculate the final SQI. Weighting reflects the relative influence of each parameter on soil quality and is derived from the proportion of variability each parameter contributes to the dataset. Initially, weights were determined through expert judgment (Doran & Parkin 1994). However, with the adoption of multivariate analysis techniques, weights are now typically assigned based on the degree of variability exhibited by each parameter, prioritizing those with greater variability as they are more representative of field conditions (Andrews & Carroll 2001, Kosmas et al. 2014, Shukla et al. 2006). The final SQI is computed by multiplying each parameter score by its corresponding weight, summing the weighted scores, and multiplying the result by 100. This yields an SQI value ranging from 0 to 100, where a score of 100 represents optimal soil quality for the evaluated field. This comprehensive approach ensures that the SQI reflects both the inherent variability of soil properties and their relative importance in influencing soil quality.

2.5. Status of the use of soil quality indicators

A range of treatment scenarios, including variations in crop type, the presence or absence of cover crops, the type and quantity of applied materials, and tillage practices, have been established at experimental stations and producer fields in the United States to investigate the relationship between the Soil Quality Index (SQI) and crop yield. These studies consistently demonstrate a significant positive correlation between SQI and yield across all examined scenarios (Andrews et al. 2002a, de Paul Obade & Lal 2016, Mukherjee & Lal 2014, Nakajima et al. 2015). In Japan, Tang et al. (2019)

utilized data from the Basic Soil Environment Survey (1979–1998) to assess the effects of different fertilizer types on SQIs in paddy soils. However, no studies to date have evaluated the relationship between SQI and yield in fields managed by different producers, where no specialized treatment plots for a single crop were established. This gap in research indicates that while SQI effectively quantifies the impact of soil treatments on specific crop yields, particularly in controlled experimental settings. Furthermore, no decision-support tools have been developed to guide soil management practices based on SQI scores, highlighting a critical area for further research and application. Proposals for method to utilize soil data would motivate farmers to accumulate soil data. This would hopefully lead to a virtuous cycle of further developing data utilization tools.

3. Study sites and methods

3.1. Study sites

The present study was conducted in the Tokachi region of Hokkaido, Japan, one of the country's largest agricultural areas, encompassing approximately 255,000 hectares of arable land. The majority of this land is utilized for the cultivation of field crops, including autumn-sown wheat, sugar beet, and beans (Hokkaido Tokachi Regional Development Bureau 2022; 北海道十勝総合振興局). The primary soil parent materials in this region consist of fluvial deposits and volcanic ash, with soils derived from different parent materials often found in close proximity (Kikuchi 1981). This unique soil distribution makes the Tokachi region particularly suitable for comparative analyses of crop productivity across diverse soil types. The region experiences an annual rainfall of approximately 1,000 mm, 60% of which is concentrated between June and September. This results in excessive soil moisture, a significant limiting factor for crop growth (Kikuchi 1981, Niwa et al. 2014). Additionally, inadequate drainage has been identified as a major contributor to the reduced yields of crops such as wheat, sugar beet, and potato (Niwa et al. 2003, 2014). Despite these challenges, the specific effects of drainage and other soil physicochemical properties on crop productivity have not been thoroughly quantified. This study aims to address this knowledge gap by evaluating the importance of soil physicochemical properties both collectively and individually in influencing crop productivity. A key objective is to develop methods for calculating a Soil Quality Index (SQI) that incorporates these properties, providing a robust framework for understanding and improving soil management practices in the Tokachi region.

The study was conducted between 2017 and 2023 across multiple agricultural fields in the Tokachi region of Hokkaido, Japan (Fig. 3-1). In general, distinct plots were selected each year; however, some overlap in plot selection was observed during the study period. The primary soil parent materials in the Tokachi region consist of fluvial deposits and volcanic ash, with certain soils characterized by volcanic ash in the surface layer and fluvial deposits in the subsurface layers (Niwa et al. 2014). The study plots were classified according to the first draft of the Comprehensive Soil Classification (Obara et al. 2011), predominantly falling into the allophanic Andosol group, the Brown Lowland soil major group, and the terrestrial immature soil group. The classification of soil types was further refined using the methodology of Niwa et al. (2008). Soil types for the study fields were identified based on the arable soil map of Hokkaido, derived from the Basic Survey of Land Conservation, and classified according to the composition of their parent materials:

- Andosols: Parent material was unconsolidated igneous rock.
- Brown Lowland soils: Parent material consisted of unconsolidated hydrous rock.
- Brown Lowland soils with alluvial deposits: Parent material consisted of unconsolidated igneous rock overlying unconsolidated hydrous rock.
- Peat soils: Parent material was predominantly peat.

The soils were also classified using the World Reference Base for Soil Resources (WRB) as follows:

- Umbic Andosols: Corresponding to Andosols.
- Haplic Fluvisols: Corresponding to Brown Lowland soils and Brown Lowland soils with alluvial deposits.
- Andic Histosols: Corresponding to Peat soils.

According to Niwa et al. (2008), Andosols with a total carbon content exceeding 100 g kg^{-1} are typically classified as wet Andosols. However, in this study, all fields were treated as Andosols without differentiation based on total carbon content, as only four fields met the criteria for wet Andosols. This approach ensured a consistent classification framework for the analyzed plots.

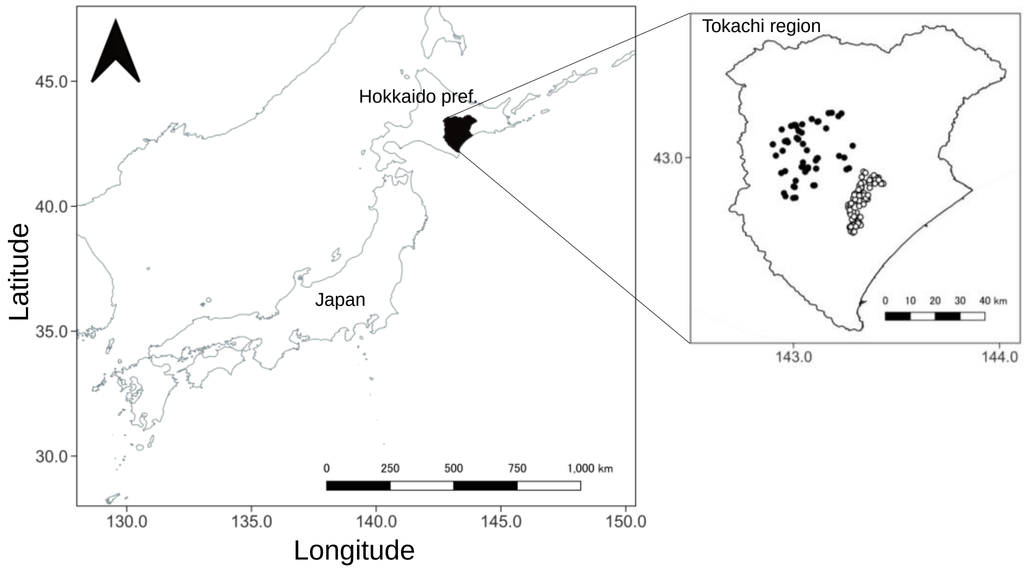

Figure 3-1. Research site

Black plots (●) indicate the location of wheat fields in chapter 4 and white plots (○) do potato and wheat fields in chapter 5 and 6

3.2. Soil survey and sampling

The study focused on fields planted with two crops in the Tokachi region of Hokkaido:

1. **Wheat (*Triticum aestivum* L.)**: Cultivated from 2017 to 2023.
2. **Potato (*Solanum tuberosum* L.)**: Cultivated from 2021 to 2023.

Soil Survey Schedule

- **Wheat Fields**:
    - From 2017 to 2019, soil surveys were conducted approximately **one month prior to the wheat harvest**.
    - From 2020 to 2023, soil surveys were conducted approximately **one month after the**

wheat harvest.

- **Potato Fields**:
  - Soil surveys were conducted **one year after the potato harvest**, from 2020 to 2023.

An undisturbed soil sample was collected using a 100 cm^3 soil collection tube, while disturbed soil was obtained using a trowel. The disturbed soil samples were air-dried and sieved through a 2 mm mesh prior to chemometric analysis. All analyzed items were necessary to compare with the soil diagnosis references in Hokkaido (Table 3-1). The following analyses were performed on the soil samples:

1. **Chemical Properties**:
   - **pH (H_2O)**: Measured using the glass electrode method.
   - **Available Phosphate Content**: Determined using the Troug method.
   - **Phosphate Absorption Coefficient**: Evaluated by the SPAD simplified method.
   - **Cation Exchange Capacity (CEC) and Exchangeable Base Content** (Ca, Mg, K): Analyzed using the Schollenberger method.
   - **Hot-Water Extractable Nitrogen**: Quantified by the autoclave method.
   - **Hot-Water Dissolved Boron**: Measured using the azomethine H method.
   - **Easily Reducible Manganese**: Extracted with 1 N ammonium acetate solution containing hydroquinone.
   - **Acid-Soluble Zinc and Copper**: Determined using 0.1 N hydrochloric acid extraction.
2. **Physical and Mineralogical Properties**:
   - **Soil Texture**: Assessed using the pipette method. Suspensions were prepared by removing organic matter with 30% hydrogen peroxide and dispersing particles with a sodium hexametaphosphate solution.
   - **Total Carbon Content**: Measured by dry combustion using either a **Vario MAX CNS** (Elementar Ltd., Hesse, Germany) or a **SUMIGRAPH NC-TRINITY** (Sumika Analysis Centre Co., Osaka, Japan).
3. **Physical Properties** (Undisturbed Samples):
   - **Macropore Ratio**: Quantified as pore space corresponding to a matric potential of -3.1 kPa (pF 1.5) or higher, using the sa**nd column method** (DIK-3521, Daiki-Rika Kogyo, Saitama, Japan) and a **centrifuge** (CR21G, Hitachi Koki Co., Tokyo, Japan).
   - **Available Moisture**: Measured as pore space corresponding to a matric potential range of -98.1 to -3.1 kPa (pF 1.5–3.0), indicating water retention properties.

- **Solid content and Bulk Density**: Determined using a **three-phase ratio analyzer** (DIK-1130, Daiki-Rika Kogyo, Saitama, Japan).
- **Soil Penetration Resistance**: Measured at a depth of 0–60 cm below the surface using a **digital penetration soil hardness tester** (DIK-5520, Daiki-Rika Kogyo Co., Saitama, Japan).

These analytical protocols were performed in accordance with guidelines established by the **Hokkaido Research Organization, Agricultural Research Department (2012)** and the **Soil Environmental Analysis Method Editorial Committee (1997)**. This comprehensive suite of measurements provides detailed insights into soil physicochemical and physical properties, enabling robust soil quality assessments.

3.3. How the Soil Quality Index was calculated

The selection and weighting of parameters, representing soil physicochemical properties, used for the calculation of the Soil Quality Index (SQI) were conducted following the methodologies outlined by Klimkowicz-Pawlas et al. (2019) and Mukherjee and Lal (2014). Principal Component Analysis (PCA) was utilized to derive the weights assigned to each parameter.

3.3.1. Selection of parameters

The parameters included in the analysis were those for which reference values are specified in the Hokkaido Fertilizer Guide (Table 3-1). This ensured alignment with regionally relevant soil management practices and guidelines. The guideline aimed favorable crop growth and minimum environmental impact, therefore, parameter candidates all aligned with soil quality assessment in this study which evaluated function of crop productivity.

Table 3-1. Soil diagnosis reference in Hokkaido Japan

Soil property	Criteria	Unit	Scoring function	Remarks
pH (H_2O)	5.5–6.5		optimum	
Available phosphate	100–300	mg P_2O_5 kg^{-1}	more is better	Determined by Troug method. This study defined the function as `more is better' function with 100 mg P_2O_5 kg^{-1} lower threshold because of considering the effect on the productivity.
Exchangeable Ca content	1000–1700 (coarse textured soil)	mg CaO kg^{-1}	optimum	applied when cation exchangealbe capacity (CEC) ($cmol_c$ kg^{-1}) is 7–12
	1700–3500 (medium textured soil)		optimum	applied when CEC ($cmol_c$ kg^{-1}) is 12–25
	3500–4900 (fine textured soil)		optimum	applied when CEC ($cmol_c$ kg^{-1}) is 25–35 This study also applied that function when CEC ($cmol_c$ kg^{-1}) is 35 or more.
Exchangeable Mg content	250–450	mg MgO kg^{-1}	optimum	
Exchangeable K content	150–300	mg K_2O kg^{-1}	optimum	
Mg / K	≧ 2		more is better	equivalent ratio
Ca / Mg	≦ 6		less is better	equivalent ratio
Lime saturation percentage	40–60	%	optimum	
Base saturation percentage	60–80	%	optimum	
Hot-water dissolved B content	0.5–1.0	mg kg^{-1}	optimum	
Easily reducible Mn content	50–500	mg kg^{-1}	optimum	
Acid-soluble Zn content	2–40	mg kg^{-1}	optimum	
Acid-soluble Cu content	upper threshold: 8.0 lower threshold: refer the remarks	mg kg^{-1}	optimum	lower threshold (mg kg^{-1}) total C content (g kg^{-1}) < 86.2: 0.7 total C content (g kg^{-1}) 86.2-172.4: 0.5 total C content (g kg^{-1}) > 172.4: 0.3
Solid content	25–30 (volcanic ash soil)	× 10^{-2} m^3 m^{-3}	optimum	applied when phosphate absorption coefficient (mg P_2O_5 kg^{-1}) is 15,000 or more
	≦ 40 (lowland and upland soil)		less is better	applied when phosphate absorption coefficient (mg P_2O_5 kg^{-1}) is less than 15,000
Bulk density	70–90 (volcanic ash soil)	× 10^{-2} Mg m^{-3}	optimum	applied when phosphate absorption coefficient (mg P_2O_5 kg^{-1}) is 15,000 or more
	90–110 (lowland and upland soil)		optimum	applied when phosphate absorption coefficient (mg P_2O_5 kg^{-1}) is less than 15,000
Macropore ratio	15–25	× 10^{-2} m^3 m^{-3}	optimum	Macropore ratio is defined as the air ratio of –3.1 kPa (pF1.5) .
Available moisture	≧ 10	× 10^{-2} m^3 m^{-3}	more is better	Available moisture is defined as the difference of water contents between –98.1 kPa and –3.1 kPa (pF 1.5–3.0) .
Effective soil depth	≧ 50	cm	more is better	Effective soil depth is defined as the depth until gravel, pan or compacted layer with 10 cm or more. The compacted layer depth was defined as the depth with high penetration resistance (≧ 1.5 MPa) of cone penetrometer.

The data is based on Hokkaido Fertilizer Guide (Hokkaido Agriculture Department, 2020).

3.3.2. Minimum Data Set construction and weighting by Principal Component Analysis

The Minimum Data Set (MDS) was developed by applying Principal Component Analysis (PCA) to the measured parameter values, thereby reducing the dimensionality of the dataset by condensing a large number of parameters into a smaller set of principal components (PCs) while preserving the variance structure of the original data. PCs were selected for inclusion in the MDS based on the Kaiser criterion, which retains components with eigenvalues greater than 1.0. Parameters contributing to the MDS were chosen from each selected PC by identifying those with the highest absolute eigenvector values, provided these values fell within 10% of the maximum eigenvector value for that PC (Wander & Bollero 1999). To avoid redundancy within the dataset, parameters with relatively low eigenvector magnitudes were excluded if they exhibited statistically significant correlations with other parameters within the same PC. Additionally, PCs displaying significant correlations with other PCs were excluded if their eigenvalues were comparatively small. Statistical significance of correlations was determined using Holm's adjustment for multiple comparisons, with a threshold p-value of <0.05, accounting for the extensive number of parameters analyzed. The weighting of each PC was calculated as the proportion of variance explained by the PC, normalized by the total variance explained by all selected PCs. If multiple parameters were selected within the same PC, the corresponding PC weight was distributed equally among those parameters. This approach ensured that the MDS was both statistically robust and minimally redundant, while retaining its capacity to represent key variability within the dataset.

3.3.3. Scoring

The measured values of each parameter were transformed into dimensionless scores ranging from 0.0 (representing poor quality) to 1.0 (representing excellent quality). The transformation process employed one of three scoring function types, designed to assign lower scores to values deviating further from the reference threshold. The scoring functions were categorized into three distinct types: (1) a "more is better" function, (2) a "less is better" function, and (3) an "optimal" function. The function types and corresponding thresholds for each parameter were derived from the soil diagnostic reference values specified in the Hokkaido Fertilizer Guide 2020 (Hokkaido Agriculture Department, 2020) (Table 3-1). The "more is better" function is mathematically represented by Equation (1).

$$Score = \begin{cases} \dfrac{X}{L} & X < L \\ 1 & L \le X \end{cases} \qquad (Eq. 1)$$

Let X represent the measured soil physicochemical property and L denote the lower threshold of this property. The "less is better" scoring function can be mathematically expressed as shown in Equation (2).

$$Score = \begin{cases} 1 & X < U \\ \frac{U}{X} & U \leq X \end{cases} \quad (Eq.2)$$

Let U represent the upper threshold of the soil physicochemical property. The "optimum" type scoring function is mathematically defined as shown in Equation (3).

$$Score = \begin{cases} \frac{X}{L} & X < L \\ 1 & L \leq X < U \\ \frac{U}{X} & U \leq X \end{cases} \quad (Eq.3)$$

For instance, for hot-water dissolved boron content, with a diagnostic reference range of 0.5–1.0 mg kg^{-1}, the following scoring functions were applied: a "more is better" type function for values below 0.5 mg kg^{-1}, a "less is better" type function for values above 1.0 mg kg^{-1}, and a score of 1.0 for values within the range of 0.5–1.0 mg kg^{-1}.

For available phosphate content, previous research (Takahashi et al. 1980) indicates that excessive injury to plant growth typically occurs at levels of 3,000–5,000 mg kg^{-1}. However, any sites in the present study did not have such high phosphate levels. As a result, only the lower threshold of 100 mg kg^{-1}, associated with crop productivity, was considered. The scoring function for available phosphate content was thus designated as a "more is better" type function with a lower limit of 100 mg kg^{-1}.

The diagnostic reference values for some parameters differed depending on the soil characteristics (Table 3-1). Soil structure development as classified by cation exchangeable capacity determines the threshold value for exchangeable calcium content. Parent material determines the threshold value for solid content and bulk density. Soil samples with a phosphate absorption coefficient exceeding 15,000 mg P_2O_5 kg^{-1} were classified as Andosols indicating volcanic ash soil, and the respective reference values were applied accordingly. Lower threshold of acid-soluble copper content is determined by total carbon content.

3.3.4. Calculation of Soil Quality Index

The SQI was calculated by converting the selected measurements from the MDS into scores, which were subsequently combined using a weighted summation, as described in Equation (4). The resulting SQI value was then multiplied by 100, producing a final index score within a range of 0 to 100.

$$\mathrm{SQI} = \sum_{i=1}^{n} \{(\mathrm{Weight}_i) \times (\mathrm{Score}_i)\} \times 100 \quad \text{(Eq. 4)}$$

Let Weight represent the weighting value of the measurements calculated by PCA as Section 3.3.2.

3.4. Statistical analysis

Statistical analyses were performed using R version 4.0.2 (R Core Team 2021). Analysis of Variance (ANOVA) and multiple comparison tests based on the Tukey-Kramer method were utilized to evaluate the effects of harvest year, soil type, and soil sampling depth on yield, soil physicochemical properties, and cultivation management practices.

- Ratios such as Mg/K, Ca/Mg, lime saturation percentage, and base saturation percentage were log-transformed, as these measurements were assumed to follow a Cauchy distribution.
- Scores for soil physicochemical properties and the SQI were analyzed using non-parametric methods, as normality could not be assumed due to the data transformation inherent in the scoring function.

Statistical Tests

1. Non-Parametric Analysis:

   - Kruskal-Wallis Test: Used for one-way ANOVA or as part of a mixed two-way ANOVA after aligned rank transformation to analyze non-normally distributed variables.
   - In cases of significant differences, multiple comparison tests with Holm's method for p-value correction were conducted.

2. Correlations:

   - Pearson product-moment correlation coefficients were calculated to assess relationships between pairs of measured variables.

3. Penetration Hardness and Standardized Penetration Depth:

   - Given that soil penetration hardness and year-standardized penetration depth by soil type could exceed 60 cm, these variables were analyzed using Kruskal-Wallis tests.
   - If significant differences were detected, multiple comparison tests with corrected p-values were applied using Holm's method.

Statistical Thresholds

In all analyses, a 5% significance level ($p < 0.05$) was applied to determine statistical significance. This rigorous methodological framework ensured robust evaluation of the relationships between soil properties, crop yield, and cultivation practices.

4. Evaluation of crop productivity by Soil Quality Index in wheat field surface layers

4.1. Introduction

This chapter explores methods for evaluating crop productivity using wheat fields as a case study. In Japan, the self-sufficiency rate for wheat in 2021 was 17% based on calorific value (Ministry of Agriculture, Forestry and Fisheries, 2023c) and 15% by weight (Statistics Department, Minister's Secretariat, Ministry of Agriculture, Forestry and Fisheries, 2023b). Consequently, Japan relies heavily on imports to meet its wheat supply demands. Supply and demand dynamics for domestically produced wheat illustrate significant variability. From 2012 to 2015, the supply exceeded demand by 40,000 to 154,000 tons, while during the 2016 to 2020 harvests, this excess narrowed to 14,000 to 72,000 tons. Conversely, in the 2021 to 2023 crop years, surplus supply ranged between 51,000 and 111,000 tons (Ministry of Agriculture, Forestry and Fisheries, 2023b). These data highlight the inherent instability of Japan's wheat supply-demand equilibrium. Given these fluctuations, the ability to achieve stable domestic wheat production and improve the accuracy of demand forecasts has become increasingly critical. This chapter will discuss the application of Soil Quality Indices (SQIs) as a tool to assess crop productivity, aiming to contribute to a more consistent and predictable wheat supply.

Comparative analyses of wheat yield across various soil types in Japan have demonstrated notable relationships with soil physicochemical attributes. For instance, Brown Lowland soils, characterized by relatively high phosphorus and nitrogen fertility, tended to produce higher yields compared to Andosols, which had low phosphorus fertility, and red soils, which were associated with low nitrogen fertility (Sato et al. 1988). Similarly, studies from other regions indicated that wheat yields were higher in clayey soils with greater water retention capacity (Erekul & Köhn 2006, Masoni et al. 2007). However, these international examples were conducted in regions with higher temperatures and lower precipitation levels compared to Japan. While the climate of the Tokachi region shares some similarities with these overseas locations, the environmental differences limit the direct applicability of their findings to Tokachi. As such, the relationship between wheat yield and soil physicochemical properties requires a tailored examination in this region. In a domestic context, Inamura et al. (2007) employed Principal Component Analysis (PCA) to investigate factors influencing yield variation within a single wheat field. However, their analysis did not address the variability across fields with significantly different soil physicochemical properties. Additionally, the soil factors they considered were limited to four parameters: water content, permeability, soil hardness, and available nitrogen. Other studies have attempted to identify the influence of soil factors on crop yield through statistical modeling and sensing data analyses (Kitada 1989, Kohyama 1996, Shiga 1997). Despite these efforts, there remains a lack of research that directly compares the yield of individual fields with their comprehensive soil physicochemical properties. Furthermore, there is limited exploration of methods for calculating integrated evaluation indices of crop productivity derived specifically from producer-managed fields, as is the focus of this study. This gap underscores the importance of developing robust methodologies to link soil characteristics to yield outcomes, enabling more precise and actionable soil management strategies. In this chapter, data on wheat yield and soil physicochemical properties from wheat-producing fields in the Tokachi region of Hokkaido, collected over a three-year period, are compiled and analyzed. The primary objective is to evaluate crop productivity by quantifying soil quality using the SQI. Additionally, an effort is made to elucidate variations in wheat yield by integrating the SQI with meteorological data and cultivation management practices. This approach aims to provide a comprehensive understanding of the factors influencing wheat productivity in the region.

4.2. Materials and methods

4.2.1. Research location

A series of surveys was conducted in the Tokachi region from 2017 to 2019 as part of this study. The wheat cultivar investigated was *Yumechikara*, which is typically sown in autumn. Surveys were carried out in 27 fields in 2017, 22 fields in 2018, and 12 fields in 2019, resulting in a total of 61 surveyed fields. The soil types were classified based on the criteria outlined in Section 3.1. Notably, soils with a phosphorus absorption coefficient below 15,000 mg P_2O_5 kg^{-1} were classified as Brown Lowland soils, even when exhibiting characteristics of Andosols with alluvial deposits. The surveyed fields were located within the municipalities of Shikaoi, Shihoro, Otofuke, Memuro, and Shimizu (Fig. 3-1). The mean annual temperature and annual cumulative precipitation across these municipalities were 6.0°C and 950 mm, respectively. Meteorological data were derived by averaging climatological standard normal values for each field using mesh agricultural meteorological data provided by the National Agriculture and Food Research Organization (Ohno et al. 2016).

The yield of each plot was measured by sampling a minimum area of 6 m^2 during late July to early August, with specific sampling periods spanning July 21 to August 1 in 2017, July 25 to August 2 in 2018, and July 23 to July 30 in 2019. Grain yield (g m^{-2}) was calculated by weighing grains retained on a 2.2-mm sieve. Grain protein content was determined non-destructively using a near-infrared analyzer (Inframatic 9500, PerkinElmer, Inc., Massachusetts, USA). Both yield and grain protein content were expressed on a moisture-adjusted basis of 135 g kg^{-1}. No lodging was observed in the sampling areas during the study period.

4.2.2. Soil sampling and survey

Soil sampling was conducted annually between mid-June and mid-July, with specific sampling periods from July 10 to July 12 in 2017, June 18 to June 20 in 2018, and June 18 to June 19 in 2019. Representative soil samples were collected at depths of 0–15 cm for disturbed soil and 5–10 cm for undisturbed soil. Both types of samples were analyzed for their physicochemical properties following the procedures detailed in Section 3.2. Penetration resistance of the soil was measured to a depth of 0–60 cm below the surface. However, in many cases, the penetration resistance was sufficiently high that the penetrometer could not reach the 60 cm depth. Consequently, this study focuses on comparing the depth at which the penetrometer was unable to measure further (hereafter referred to as the "penetration depth") rather than the depth of the ploughed layer. In cases where the penetrometer successfully reached 60 cm, the penetration depth was recorded as 60 cm. Soil moisture conditions during measurement varied considerably across the three years, resulting in substantial interannual variability in the ease of penetrometer insertion. To account for this variability, the penetration depth was standardized to a range of 0–1 within each harvest year, and the standardized values were used for subsequent analyses, called "year-standardized penetration depth". Additionally, all fields surveyed in 2019, as well as fields from 2017 and 2018 where the penetration depth was less than 40 cm or where a gravel layer was suspected based on surface observations (a total of 28 fields), were excavated to confirm the depth of gravel emergence.

4.2.3. Other measurement items and statistical analysis methods

Data on sowing dates, seeding rates, harvest dates, and nitrogen fertilization amounts were obtained through interviews with producers. Daily mean values for air temperature, precipitation, and solar radiation were extracted for each field and year using NARO mesh agricultural meteorological data (Ohno et al. 2016). SQIs were calculated following the methodology outlined in Section 3.3. The Minimum Data Set (MDS) used for SQI calculation was based on 18 parameters for which reference values are provided in the Hokkaido Fertilizer Guide (Table 3-1). However, instead of the effective soil layer depth, the year-standardized penetration depth was used as a substitute for each year. Due to absence of an established soil diagnostic reference value of the penetration depth, the upper threshold was set to 1.0 for "more is better" type functions, and the normalized value was used as the score.

To evaluate the significance of the effects of year and soil type on yield, a two-way analysis of variance (ANOVA) was conducted. For factors showing significant differences, multiple comparisons were performed using the Tukey-Kramer method. The effect of soil type on soil physicochemical properties was also examined through multiple comparison tests using the Tukey-Kramer method. Ratios of specific soil properties, including Mg/K, Ca/Mg, lime saturation percentage, and base saturation percentage, were log-transformed prior to analysis to account for their presumed adherence to a Cauchy distribution. For soil physicochemical property scores and SQI scores, which could not be assumed to follow a normal distribution due to artificial transformations introduced by the scoring function, a non-parametric approach was employed. These items were analyzed using a one-way ANOVA based on the Kruskal-Wallis method. When statistically significant differences were detected, multiple comparisons were conducted with p-values adjusted using Holm's method. Additionally, the effects of soil type on penetration depth and year-standardized penetration depth were analyzed using the Kruskal-Wallis test, a non-parametric ANOVA. In cases where significant differences were observed, multiple comparison tests with Holm's method were applied to correct for multiple testing.

The relationship between the SQI and wheat yield was assessed by calculating the Pearson product-moment correlation coefficient to validate the SQI's predictive capacity. To enable a consistent comparison of yield data across years while accounting for annual yield fluctuations, the product yield was normalized to a "Yield Ratio to Regional Average (%)" by dividing the observed yield by the average yield for the Tokachi region in the corresponding harvest year (Hokkaido Agricultural Administration Office 2018–2020) and multiplying the result by 100.

4.3. Results

4.3.1. Weather conditions

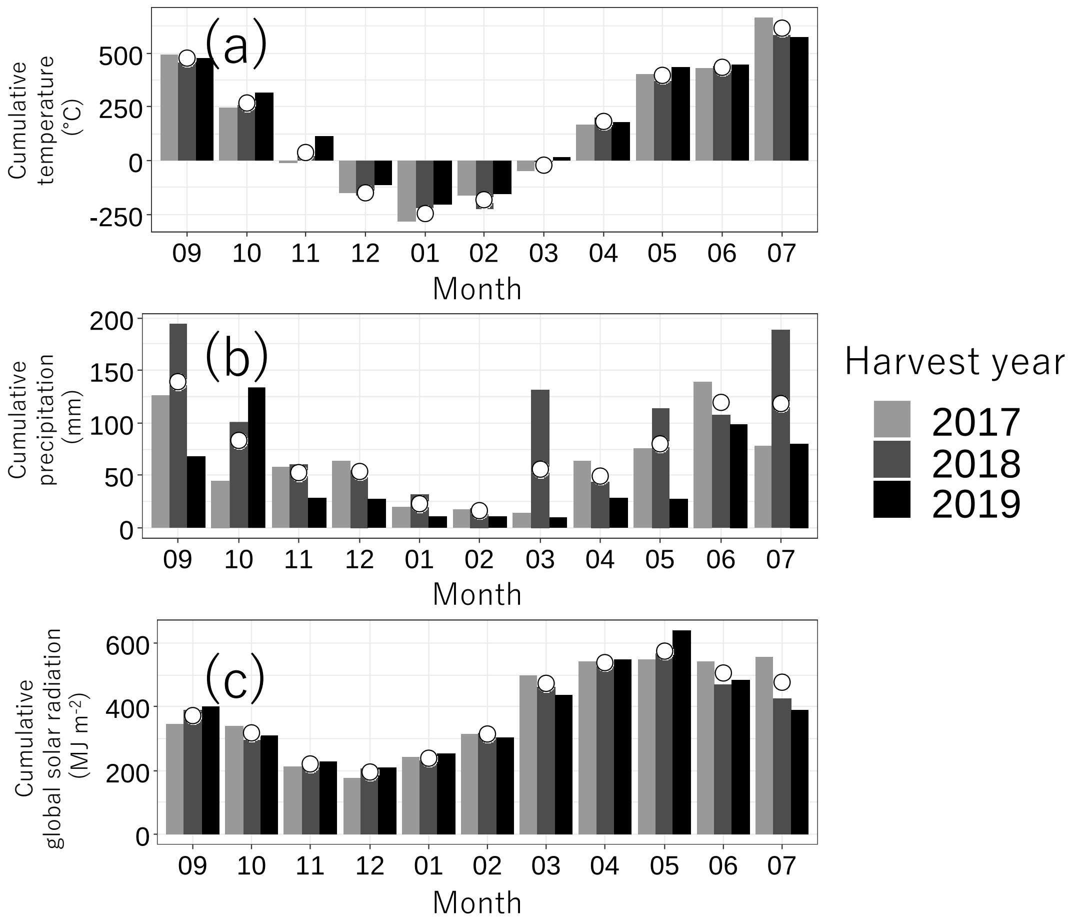

Figure 4-1. Meteorological summary

The values presented represent the monthly means for the target fields in each year for the following variables: (a) cumulative temperature, (b) cumulative precipitation, and (c) cumulative global solar radiation. The white circles (〇) denote the climatological standard normals for the period 2001–2020.

This figure was developed with reference to the National Agriculture and Food Research Organization (NARO) mesh agricultural meteorological data (Ohno et al. 2016).

Figure 4-1 illustrates the monthly accumulated values of temperature, precipitation, and global solar radiation from 2017 to 2019. In 2017, monthly accumulated global solar radiation exceeded the climatological standard normal values from March to July. Additionally, July recorded the highest accumulated temperature among the three years (Fig. 4-1a, c). In contrast, 2018 exhibited below-normal global solar radiation starting in March, while precipitation levels in March, May, and July surpassed those of the other years (Fig. 4-1b, c). The heavy precipitation in March was primarily attributed to significant snowfall that affected much of Japan during 2018. In 2019, precipitation from November to July was below normal, whereas global solar radiation in May was above normal (Fig. 4-1b, c). Lower-than-normal snowfall after November 2018 resulted in reduced snow cover, leaving wheat plants exposed to cold air. This exposure caused browning of leaves, indicative of winter damage, in some fields during March and April.

4.3.2. Field soil type and texture

Table 4-1 provides a summary of the surveyed fields, including soil texture classifications of light clay (LiC), clay (CL), and sandy clay (SCL). Among the Brown Lowland soils, 9 fields were classified as LiC, 1 as CL, and 6 as SCL, with approximately half exhibiting fine-grained textures and the other half sandy textures. For Andosols with alluvial deposits, 11 fields were classified as LiC and 5 as CL, with a notable predominance of fine-grained textures. Among the Andosols, 15 fields were classified as LiC, 13 as CL, and 1 as SCL, again showing a considerable proportion of fine-grained soils. The distribution of soil types by year was as follows: Andosols accounted for 13, 10, and 6 fields in 2017, 2018, and 2019, respectively, making Andosols the most common soil type, representing approximately half of all fields in each harvest year. In 2017, 2018, and 2019, the number of fields classified as Brown Lowland soils was 8, 6, and 4, respectively. Fields of Andosols with alluvial deposits totaled 6, 6, and 2, respectively, indicating slight interannual variation in the proportions of soil types.

Table 4-1. Summary of research sites

ID	Harvest year	Soil type	Town	Soil texture（International Society of Soil Science (ISSS) standards）
1	2019	Brown Lowland soil	Memuro	LiC
2	2019	Andosol	Memuro	CL
3	2019	Andosol	Memuro	CL
4	2019	Andosol	Memuro	CL
5	2019	Brown Lowland soil	Memuro	LiC
6	2019	Brown Lowland soil	Shikaoi	SCL
7	2019	Brown Lowland soil	Shikaoi	SCL
8	2019	Andosol with alluvial deposits	Shikaoi	LiC
9	2019	Andosol	Shikaoi	LiC
10	2019	Andosol	Shikaoi	LiC
11	2019	Andosol	Shikaoi	LiC
12	2019	Andosol with alluvial deposits	Shikaoi	LiC
13	2018	Brown Lowland soil	Shikaoi	SCL
14	2018	Andosol with alluvial deposits	Shikaoi	LiC
15	2018	Andosol	Shikaoi	LiC
16	2018	Brown Lowland soil	Shikaoi	CL
17	2018	Brown Lowland soil	Shikaoi	CL
18	2018	Andosol with alluvial deposits	Shikaoi	CL
19	2018	Andosol	Shikaoi	CL
20	2018	Andosol	Shimizu	LiC
21	2018	Brown Lowland soil	Shimizu	LiC
22	2018	Andosol	Shimizu	LiC
23	2018	Andosol	Otofuke	LiC
24	2018	Andosol with alluvial deposits	Otofuke	LiC
25	2018	Andosol with alluvial deposits	Otofuke	CL
26	2018	Andosol with alluvial deposits	Shihoro	LiC
27	2018	Andosol	Shihoro	CL
28	2018	Andosol	Memuro	CL
29	2018	Andosol	Memuro	LiC
30	2018	Brown Lowland soil	Memuro	LiC
31	2018	Andosol	Memuro	CL
32	2018	Andosol	Memuro	CL
33	2018	Andosol with alluvial deposits	Memuro	CL
34	2018	Brown Lowland soil	Memuro	SCL
35	2017	Andosol	Shihoro	CL
36	2017	Andosol	Shihoro	LiC
37	2017	Andosol with alluvial deposits	Otofuke	CL
38	2017	Brown Lowland soil	Otofuke	LiC
39	2017	Andosol with alluvial deposits	Otofuke	LiC
40	2017	Andosol with alluvial deposits	Otofuke	LiC
41	2017	Brown Lowland soil	Otofuke	SCL
42	2017	Andosol	Shikaoi	CL
43	2017	Andosol	Shikaoi	CL
44	2017	Andosol with alluvial deposits	Shikaoi	LiC
45	2017	Brown Lowland soil	Shikaoi	LiC
46	2017	Andosol	Shikaoi	LiC
47	2017	Andosol	Shikaoi	LiC
48	2017	Andosol with alluvial deposits	Shikaoi	LiC
49	2017	Andosol	Shikaoi	CL
50	2017	Andosol	Shikaoi	LiC
51	2017	Andosol	Shimizu	LiC
52	2017	Brown Lowland soil	Shimizu	LiC
53	2017	Brown Lowland soil	Shimizu	LiC
54	2017	Brown Lowland soil	Shimizu	SCL
55	2017	Brown Lowland soil	Memuro	LiC
56	2017	Brown Lowland soil	Memuro	LiC
57	2017	Andosol	Memuro	LiC
58	2017	Andosol	Memuro	SCL
59	2017	Andosol with alluvial deposits	Memuro	LiC
60	2017	Andosol	Memuro	CL
61	2017	Andosol	Memuro	LiC

Soil types were classified based on the mode of parent material deposition, as proposed by Niwa et al. (2008). Soil texture was determined using the soil particle size classification system established by the International Soil Science Society.

4.3.3. Harvest data

The product yield was significantly lower in 2018 compared to the other two years, reflecting a trend observed in the Tokachi region, where the mean yields were 632, 456, and 596 g m^{-2} for 2017, 2018, and 2019, respectively. Additionally, grain protein content was significantly higher in 2019 (Table 4-2). However, no significant differences in either yield or grain protein content were observed among soil types across all harvest years.

Table 4-2. Wheat product yield and grain protein content

Harvest year	Soil type	Number of the fields	Product yield g m^{-2}				Grain protein content g kg^{-1}			
2017	All	27	567	±	105	a	148	±	13	b
2018		22	445	±	82	b	152	±	11	b
2019		12	618	±	143	a	165	±	19	a
All	Brown Lowland soils	18	565	±	139	a	153	±	19	a
	Andosols with alluvial deposits	14	500	±	107	a	155	±	17	a
	Andosols	29	529	±	124	a	152	±	10	a

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

4.3.4. Comparison of cultivation management methods

This study showed the management data at the result section, not at methods section because the management was not controlled or designed by the author. The mean values of cultivation management methods were compared across harvest years without accounting for soil type (Table 4-3). The date of sowing (expressed as DOY, the number of days from January 1) showed no significant differences among harvest years, with values of 266 days (September 23) in 2017, 266 days (September 23) in 2018, and 261 days (September 18) in 2019. However, the growing period, defined as the number of days between sowing and harvest, was significantly longer in 2019 compared to 2017, with an average difference of approximately five days. The sowing rate was 9.8 g m^{-2} in 2017, 10.0 g m^{-2} in 2018, and significantly lower in 2019 at 8.4 g m^{-2}. Regarding nitrogen fertilizer application, basal fertilizer application was 5.2, 4.5, and 4.0 g N m^{-2} in 2017, 2018, and 2019, respectively, with no significant differences among the years. Supplemental nitrogen application before the emergence of the flag leaf on the main stem was 9.3 g N m^{-2} in 2017, 8.6 g N m^{-2} in 2018, and significantly lower at 4.8 g N m^{-2} in 2019. The amount of nitrogen applied after the emergence of the flag leaf was 3.7, 3.4, and 3.2 g N m^{-2} in 2017, 2018, and 2019, respectively, with no significant differences among years. Total nitrogen application was 18.2 g N m^{-2} in 2017, 16.6 g N m^{-2} in 2018, and significantly lower in 2019 at 12.0 g N m^{-2}. In 2019, some fields received early spring fertilizer applications. No significant interaction between harvest year and soil type was observed for the cultivation management data. However, when comparing soil types across all years, the amount of supplemental nitrogen fertilizer applied before the emergence of the flag leaf was significantly higher in Brown Lowland soils compared to Andosols with alluvial deposits. No significant differences were observed for other variables.

Table 4-3. Field management data

Harvest year	Soil type	Number of fields	Date of sowing (DOY)			Days of growing (days)			Sowing rate (g m^{-2})			Basal N application (g N m^{-2})			Supplemental N before emergence of flag leaf (g N m^{-2})			Supplemental N after emergence of flag leaf (g N m^{-2})			Total N application (g N m^{-2})		
2017	Brown Lowland soils	8	267 ± 6	A		302 ± 5	A		9.6 ± 1.4	A		5.9 ± 4.8	A		11.5 ± 2.1	A		3.9 ± 4.7	A		21.4 ± 4.9	A	
	Andosols with alluvial deposits	6	264 ± 11	A		307 ± 10	A		9.8 ± 1.8	A		6.2 ± 5.4	A		7.3 ± 3.8	B		3.0 ± 6.4	A		16.5 ± 6.5	A	
	Andosols	13	267 ± 3	A		306 ± 3	A		9.8 ± 1.6	A		4.3 ± 1.1	A		8.9 ± 2.6	B		3.9 ± 2.7	A		17.0 ± 4.1	A	
	All	27	266 ± 6		a	305 ± 6		b	9.8 ± 1.5		a	5.2 ± 3.6		a	9.3 ± 3.1		a	3.7 ± 4.2		a	18.2 ± 5.2		a
2018	Brown Lowland soils	6	267 ± 4			306 ± 5			9.9 ± 1.4			4.3 ± 1.3			10.8 ± 3.3			3.0 ± 2.8			18.0 ± 6.2		
	Andosols with alluvial deposits	6	263 ± 10			311 ± 10			10.3 ± 0.6			4.1 ± 2.1			7.4 ± 2.7			4.6 ± 3.2			16.0 ± 5.8		
	Andosols	10	267 ± 3			307 ± 3			9.9 ± 1.1			5.0 ± 2.4			8.1 ± 5.0			3.0 ± 2.5			16.0 ± 6.7		
	All	22	266 ± 6		a	308 ± 6		ab	10.0 ± 1.1		a	4.5 ± 2.0		a	8.6 ± 4.1		a	3.4 ± 2.7		a	16.6 ± 6.1		ab
2019	Brown Lowland soils	4	262 ± 3			309 ± 6			7.3 ± 1.5			4.4 ± 0.5			7.0 ± 2.4			5.3 ± 4.0			16.7 ± 3.8		
	Andosols with alluvial deposits	2	261 ± 0			311 ± 1			10.0 ± 0.0			1.7 ± 2.4			2.6 ± 0.7			2.6 ± 0.7			7.0 ± 0.9		
	Andosols	6	261 ± 4			311 ± 6			8.6 ± 1.0			4.4 ± 3.5			4.1 ± 3.2			2.1 ± 2.3			10.6 ± 1.8		
	All	12	261 ± 3		a	310 ± 5		a	8.4 ± 1.4		b	4.0 ± 2.7		a	4.8 ± 3.0		b	3.2 ± 3.0		a	12.0 ± 4.4		b

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

4.3.5. Comparison of soil physicochemical properties

In terms of soil physicochemical properties, Brown Lowland soils exhibited significantly higher levels of available phosphate, acid-soluble copper content, bulk density, and solid content compared to the other two soil types (Table 4-4). Additionally, Brown Lowland soils displayed significantly elevated reducible manganese content, higher base saturation percentage, and reduced penetration depth and year-standardized penetration depth relative to Andosols. No significant differences among soil types were observed for the other parameters included in the PCA. The minimum, average, and maximum values for parameters excluded from the PCA are as follows: the cation exchange capacity (CEC), which determines the diagnostic reference range for exchangeable calcium content, ranged from 11.0 to 60.6 cmolc kg^{-1}, with an average of 31.3 cmol$_c$ kg^{-1} (Supplementary Table 1). Hot-water extractable nitrogen, an indicator of nitrogen fertility and crop productivity (Hokkaido Agriculture Department 2022), ranged from 0.8 to 15.2 mg kg^{-1}, with an average of 6.7 mg kg^{-1}. Total carbon content, a widely recognized parameter for assessing soil quality (Bünemann et al. 2018), ranged from 1.1 to 13.1 g kg^{-1}, with an average of 5.2 g kg^{-1} (Supplementary Table 1). No significant differences were observed in hot-water extractable nitrogen content among soil types. However, total carbon content was significantly lower in Brown Lowland soils compared to the other soil types. Gravel content, which influences soil physical conditions, ranged from 0.0 to 277.0 g kg^{-1}, with a mean value of 54.8 g kg^{-1} (Supplementary Table 1). Of the 28 fields examined for gravel depth, nine showed gravel deposits within the 0–60 cm depth range, and six of these fields (IDs: 7, 10, 39, 45, 52, 54) exhibited gravel occurrence within the upper 30 cm layer (Supplementary Table 1).

Table 4-4. Soil properties comparison with soil types

Soil type	Number of fields	pH	Available phosphate content ($mg\ P_2O_5\ kg^{-1}$)	Exchangeable Ca content ($mg\ CaO\ kg^{-1}$)	Exchangeable Mg content ($mg\ MgO\ kg^{-1}$)	Exchangeable K content ($mg\ K_2O\ kg^{-1}$)	Mg / K equivalent ratio	Ca / Mg equivalent ratio
Brown Lowland soils	18	5.5 ± 0.4 a	742.65 ± 279.17 a	2902 ± 1395 a	428.4 ± 207.17 a	326.61 ± 178.78 a	3.472 ± 1.462 a	4.972 ± 1.14 a
Andosols with alluvial deposits	14	5.6 ± 0.3 a	324.50 ± 199.39 b	3996 ± 1561 a	510.8 ± 212.56 a	394.64 ± 245.40 a	3.414 ± 1.244 a	5.886 ± 1.50 a
Andosols	29	5.7 ± 0.3 a	224.65 ± 107.55 b	3685 ± 1913 a	449.0 ± 149.61 a	315.28 ± 137.83 a	3.838 ± 2.266 a	5.693 ± 1.71 a

Soil type	Number of fields	Lime saturation percentage (%)	Base saturation percentage (%)	Hot-water dissolved B content ($mg\ kg^{-1}$)	Easily reducible Mn content ($mg\ kg^{-1}$)	Acid-soluble Zn content ($mg\ kg^{-1}$)	Acid-soluble Cu content ($mg\ kg^{-1}$)
Brown Lowland soils	18	44.8 ± 10.0 a	57.3 ± 11.3 a	0.662 ± 0.245 a	86.1 ± 52.0 a	7.00 ± 4.93 a	2.467 ± 2.267 a
Andosols with alluvial deposits	14	38.6 ± 12.1 a	47.6 ± 13.9 ab	0.721 ± 0.198 a	70.3 ± 46.4 ab	5.07 ± 3.57 a	0.725 ± 0.240 b
Andosols	29	38.3 ± 15.9 a	47.2 ± 17.3 b	0.846 ± 0.726 a	56.2 ± 21.2 b	4.69 ± 3.20 a	0.845 ± 0.486 b

Soil type	Number of fields	Solid content ($\times 10^{-2}\ m^3\ m^{-3}$)	Bulk density ($Mg\ m^{-3}$)	Macropore ratio ($\times 10^{-2}\ m^3\ m^{-3}$)	Available moisture ($\times 10^{-2}\ m^3\ m^{-3}$)	Penetration depth （0～60 cm） (cm)	Year-standardized penetration depth
Brown Lowland soils	18	42.0 ± 6.0 a	1.12 ± 0.17 a	17.1 ± 6.8 a	9.9 ± 3.9 a	39.8 ± 19.5 b	0.50 ± 0.34 b
Andosols with alluvial deposits	14	34.6 ± 3.8 b	0.89 ± 0.10 b	16.8 ± 6.1 a	9.1 ± 2.3 a	50.7 ± 14.6 ab	0.69 ± 0.31 ab
Andosols	29	33.8 ± 2.5 b	0.89 ± 0.07 b	15.3 ± 4.6 a	9.3 ± 2.0 a	55.9 ± 8.6 a	0.81 ± 0.22 a

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

4.3.6. Parameters selected in the Minimum Data Set and their weights

The PCA was conducted on the soil physicochemical properties, and the results are summarized in Table 4-5. Principal components (PCs) were selected for inclusion in the MDS based on the Kaiser criterion, which retains components with eigenvalues greater than 1.0. PC-1 to PC-6 had eigenvalue higher than 1.0 and selected as MDS candidates. Parameters contributing to the MDS were chosen from each selected PC by identifying those with the highest absolute eigenvector values, provided these values fell within 10% of the maximum eigenvector value for that PC (Wander & Bollero 1999). Parameter candidates selected for the MDS from each PC were as follows: exchangeable calcium was selected from PC-1, available phosphate content, solid content, and bulk density were selected from PC-2. Exchangeable potassium was selected from PC-3, and macropore ratio was selected from both PC-4 and PC-5. Hot-water dissolved boron content was selected from PC-6 for the initial MDS. However, due to parameter overlap in PC-4 and PC-5, the final MDS selection was based on PCs 1 through 4 and PC-6. Within PC-2, solid content, which exhibited the largest absolute eigenvector value, was significantly correlated with available phosphate content and bulk density (Supplementary Table 3). Consequently, solid content was chosen for the MDS to represent PC-2. The final MDS included the following parameters: exchangeable calcium content, solid content, exchangeable potassium content, macropore ratio, and hot-water dissolved boron content. These parameters did not significantly correlate each other. Weighting values for each parameter were calculated by dividing the variance proportion of each selected PC by the cumulative proportion of PC-1 to PC-4 and PC-6 (0.743 = 0.811 - 0.068). For example, weighting value for PC-1 was calculated by dividing proportion of variance (0.287) by the cumulative proportion of PC-1 to PC-4 and PC-6 (0.743). The resulting weighting values assigned to each parameter in the MDS were as follows: exchangeable calcium content (0.387), solid content (0.263), exchangeable potassium content (0.153), macropore ratio (0.117), and hot-water dissolved boron content (0.080).

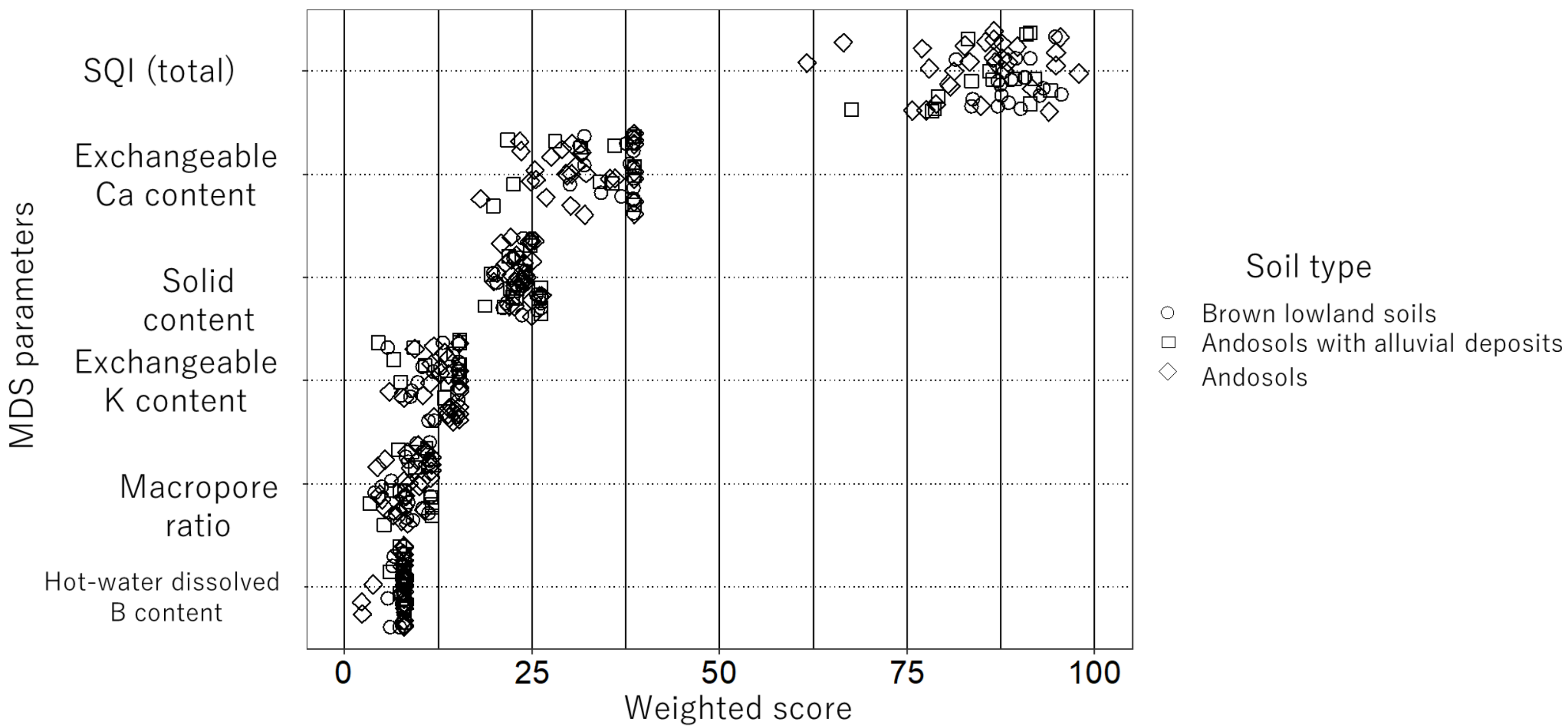

Figure 4-2. Jitter plot showing weighted scores in minimum dataset (MDS)

Table 4-5. Results of principal component analyses (PCA)

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	5.17	3.52	2.05	1.56	1.22	1.07
Proportion of variance	0.287	0.195	0.114	0.087	0.068	0.060
Cumulative proportion	0.287	0.483	0.597	0.683	0.751	0.811
Weighted value	0.387	0.263	0.153	0.117		0.080
Eigenvector						
pH (H_2O)	0.299	0.103	-0.135	0.185	-0.262	0.267
Available phosphate	0.119	**-0.417**	0.135	0.159	0.199	-0.025
<u>Exchangeable Ca content</u>	**<u>0.402</u>**	0.034	-0.035	-0.095	0.023	0.084
Exchangeable Mg content	0.347	-0.044	0.305	-0.139	-0.037	-0.003
<u>Exchangeable K content</u>	0.164	-0.055	**<u>0.492</u>**	0.235	-0.367	0.027
Mg/K	0.159	0.061	-0.325	-0.433	0.354	-0.041
Ca/Mg	0.226	0.140	-0.400	0.089	0.122	0.168
Lime saturation percentage	0.347	-0.225	-0.226	0.075	-0.081	0.175
Base saturation percentage	0.326	-0.278	-0.153	0.095	-0.114	0.153
<u>Hot-water dissolved B content</u>	0.189	0.017	-0.187	-0.108	-0.256	**<u>-0.667</u>**
Easily reducible Mn content	0.141	-0.293	0.250	-0.199	0.311	-0.062
Acid-soluble Zn content	0.289	-0.176	-0.044	0.109	0.010	-0.469
Acid-soluble Cu content	-0.154	-0.352	0.041	-0.073	0.113	-0.208
<u>Solid content</u>	-0.174	**<u>-0.437</u>**	-0.140	-0.144	-0.152	0.159
Bulk density	-0.199	**-0.432**	-0.161	-0.062	-0.130	0.159
<u>Macropore ratio</u>	0.061	0.065	0.055	**<u>0.566</u>**	**0.532**	-0.081
Available moisture	-0.186	-0.019	-0.313	0.310	-0.276	-0.258
Year-standardized penetration depth	0.117	0.186	0.199	-0.370	-0.147	-0.013

PC shows principal component.

Bold values under each component are highly weighted, and underlined bold values are selected in minimum data set.

Weight value is calculated as: variance / total cumulative proportion excluding PC5 (0.743).

4.3.7. Relationship between weighted scores and Soil Quality Index

A comparison of the standard deviations of the weighted scores for the MDS parameters revealed that exchangeable calcium content exhibited the highest variability at 5.81, followed by exchangeable potassium content at 3.00 and the macropore ratio at 2.35. Despite having the second-highest weighting in the MDS, the solid content parameter showed a relatively low standard deviation of 2.00, resulting in a minimal impact on deductions in the SQI. The number of fields meeting the reference values for exchangeable calcium and potassium content—parameters with the highest weighting scores of 38.7 and 15.4, respectively—was 24 and 23 fields, respectively. However, their minimum weighted scores were 18.1 and 4.5, respectively, with exchangeable calcium content exhibiting a larger reduction in score (Fig. 4-2). Hot-water dissolved boron content met the reference value in 46 fields, achieving the maximum weighting score of 8.0. However, in fields ID 15 and 46, the weighted scores were markedly lower at 2.3 and 2.4, respectively, due to measured values significantly exceeding the reference value (Fig. 4-2, Supplementary Table 1). For solid content, only eight fields achieved the reference value, with a maximum weighting score of 26.3. However, the minimum weighted score was 18.7, resulting in a smaller proportion of SQI deductions compared to other parameters (Fig. 4-2, Supplementary Table 1). Similarly, only eight fields achieved a macropore ratio value that met the reference value, with a maximum weighting score of 11.7. A significant number of fields (46) fell below the lower threshold of the reference value for macropore ratio (Fig. 4-2, Supplementary Table 1).

Multiple comparison tests on the weighted scores and SQI (Table 4-6) indicated that the weighted score for exchangeable calcium content was significantly higher in Brown Lowland soils compared to Andosols. However, no significant differences were observed in the weighted scores of the other parameters or in the overall SQI across soil types.

Table 4-6. SQI and weighted scores in minimum dataset (MDS)

Soil type	Number of fields	SQI	Weighted score in MDS: Exchangeable Ca content	Solid content	Exchangeable K content	Macropore ratio	Hot-water dissolved B content
Brown Lowland soils	18	89.2 ± 3.8 a	36.6 ± 3.1 a	24.1 ± 2.1 a	12.2 ± 3.1 a	8.7 ± 2.2 a	7.5 ± 0.7 a
Andosols with alluvial deposits	14	85.2 ± 7.3 a	33.0 ± 7.0 ab	22.9 ± 2.3 a	12.3 ± 3.8 a	9.2 ± 2.8 a	7.8 ± 0.5 a
Andosols	29	84.5 ± 8.2 a	31.5 ± 5.8 b	23.4 ± 1.6 a	13.4 ± 2.4 a	8.7 ± 2.3 a	7.4 ± 1.6 a

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

4.3.8. Relationship between Soil Quality Index and yield

No significant correlation was observed between the SQI and the yield ratio to the regional average when data from all three years were combined (r = 0.223, p = 0.084). However, when analyzed separately by harvest year, a significant positive correlation was identified for 2018 (Fig. 4-3b, r = 0.491, p = 0.020).

Further analysis of the 2018 data, excluding Andosols, revealed a strong and highly significant positive correlation between SQI and yield ratio (Fig. 4-3e, r = 0.762, p = 0.004). In 2017, a weak positive correlation was observed when Andosols were excluded, but this was not statistically significant (Fig. 4-3d, r = 0.518, p = 0.058).

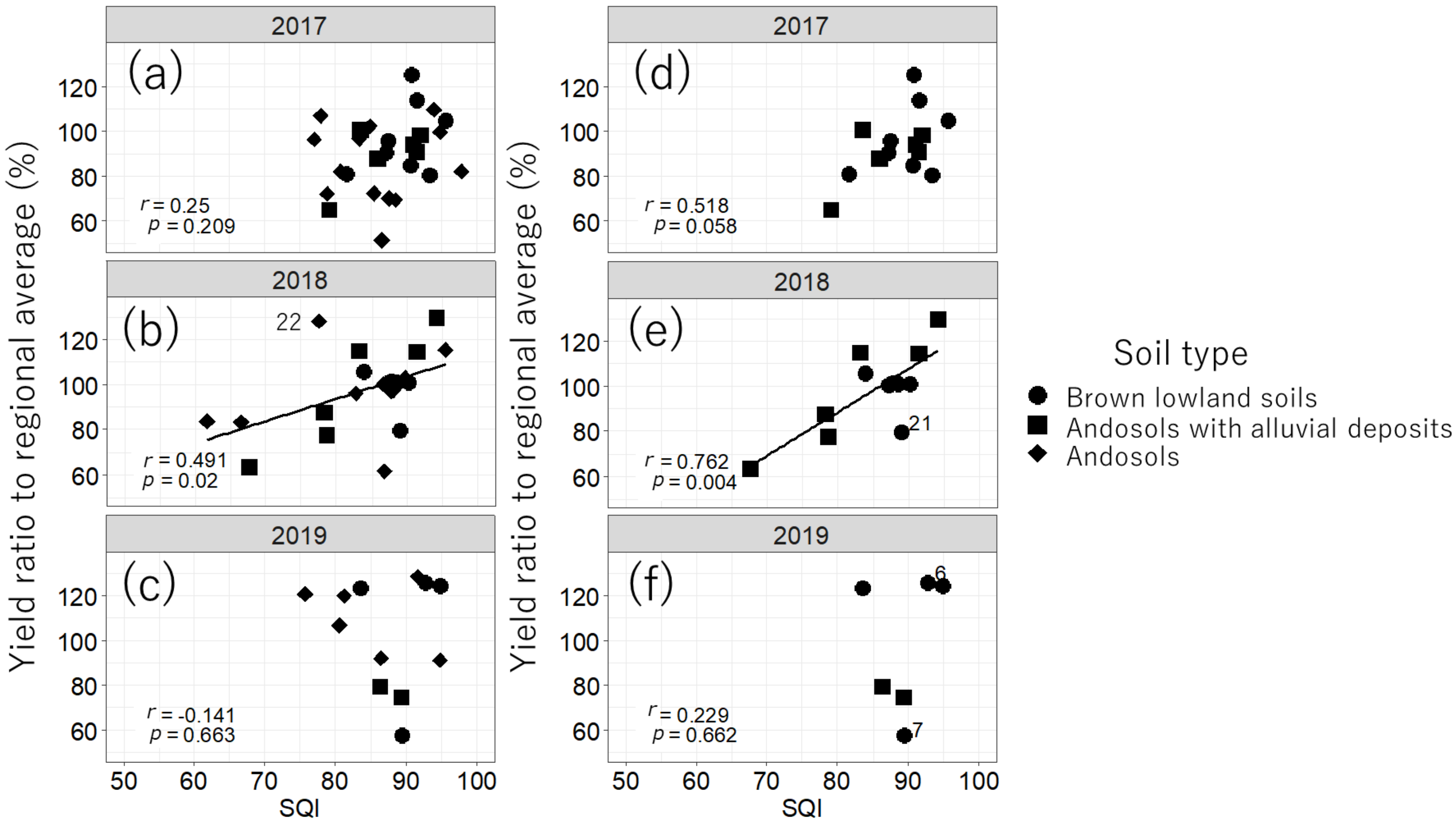

Figure 4-3. Scatter plots showing relationship between yield and SQI

a-c) All soil types, d-f) Excluding Andosols, a, d) 2017, b, e) 2018, c, f) 2019.

Numbers placed by the plot indicate their field IDs.

Solid line shows significant correlation.

4.3.9. Comparison of the same fields in different harvest years

Over the three-year investigation, four cases were identified where the same field was surveyed across different harvest years, corresponding to field IDs 1 and 30, 6 and 13, 16 and 44, and 21 and 52 (Table 4-7). Even within the same field, the SQI varied from year to year. In all cases, the SQI observed in 2018 was lower compared to the preceding years (Table 4-7).

For cases not involving Andosols with alluvial deposits, score deductions were made in 2018 due to exceeding the reference value for the solid content and failing to meet the reference for macropore ratio. Additionally, in cases 1 and 4, the weighted score was significantly reduced because the exchangeable potassium content exceeded the reference value (Table 4-7). In one case involving Andosols with alluvial deposits, the weighted score for exchangeable potassium content was relatively low (below 7.7, equivalent to a score of less than 0.5 without weighting). However, in this instance, the SQI discrepancy was less pronounced, and the yield ratio to the regional average was higher in 2018 (Table 4-7).

The mean coefficient of variation (CV) for SQI across the four cases was 0.037, equivalent to the CV for bulk density (0.036) but lower than those for yield ratio to regional average (0.109), the MDS parameters (exchangeable calcium content, exchangeable potassium content, hot-water dissolved boron content, solid content, and macropore), cation exchange capacity (CEC), and nutrient content per unit volume (calculated as nutrient content multiplied by bulk density) (Table 4-7). Among all parameters, the mean CV for SQI was the smallest, except for the weighted score of exchangeable calcium content, which showed no variation across years (Table 4-7).

The CV for the change in average bulk density over time was 0.036, smaller than that of other parameters (Table 4-7). Consequently, changes in the content per unit volume of exchangeable calcium, exchangeable potassium, and hot-water dissolved boron over time exhibited a similar trend to changes in nutrient content per unit weight of soil.

Table 4-7. Comparison of research cases in the same field in different year

											Coefficient of variance				
			Case 1		Case 2		Case 3		Case 4		Case1	Case2	Case3	Case4	Average
	ID		1	30	6	13	16	44	21	52					
	Harvest year		2019	2018	2019	2018	2018	2017	2018	2017					
	Soil type		Brown Lowland		Brown Lowland		Brown Lowland	Andosols with alluvial deposits	Brown Lowland						
	Yield ratio to regional average	%	120.9	101.3	123.7	101.5	105.8	87.3	79.9	102.4	0.125	0.141	0.139	0.029	0.109
	SQI		95.0	88.5	92.4	87.3	83.9	86.1	88.9	95.6	0.049	0.030	0.040	0.028	0.037
Measurement	Bulk density	Mg m^{-3}	1.06	1.12	1.18	1.31	0.89	0.89	1.16	1.12	0.039	0.076	0.005	0.026	0.036
	Exchangeable Ca	mg kg^{-1}	4491	4858	2188	2399	4198	4137	4812	2359	0.056	0.065	0.010	0.484	0.154
	content	g m^{-3}	4760	5443	2582	3151	3728	3698	5590	2641	0.095	0.141	0.006	0.507	0.187
	CEC	cmol$_c$ kg^{-1}	28.7	32.0	15.2	16.9	35.5	32.4	31.3	21.6	0.077	0.075	0.065	0.259	0.119
	Exchangeable K	mg kg^{-1}	381	511	258	199	788	611	464	359	0.206	0.183	0.179	0.180	0.187
	content	g m^{-3}	404	572	304	261	700	546	539	402	0.244	0.108	0.174	0.206	0.183
	Hot-water dissolved	mg kg^{-1}	0.41	0.48	0.54	0.39	0.94	1.0	0.7	0.68	0.111	0.228	0.022	0.010	0.093
	B content	g m^{-3}	0.43	0.54	0.64	0.51	0.83	0.87	0.80	0.76	0.150	0.154	0.027	0.036	0.092
	Solid content	× 10^{-2} m^3 m^{-3}	39.7	42.1	44.2	49.6	34.7	34.6	44.0	41.1	0.042	0.082	0.003	0.048	0.044
	Macropore ratio	× 10^{-2} m^3 m^{-3}	19.3	14.1	11.8	10.7	14.7	15.3	14.4	27.9	0.221	0.068	0.031	0.450	0.192
Weighted score	Exchangeable Ca content		38.6	38.6	38.6	38.6	38.6	38.6	38.6	38.6	0.000	0.000	0.000	0.000	0.000
	Exchangeable K content		11.6	8.7	14.8	14.8	5.6	7.3	9.6	12.4	0.206	0.000	0.179	0.180	0.141
	Hot-water dissolved B content		6.6	7.8	8.1	6.3	8.1	8.1	8.1	8.1	0.111	0.175	0.000	0.000	0.072
	Solid content		26.0	24.7	23.5	20.9	22.4	22.5	23.6	25.3	0.036	0.082	0.003	0.048	0.042
	Macropore ratio		12.1	8.9	7.4	6.7	9.2	9.6	9.1	11.3	0.221	0.068	0.031	0.151	0.118

4.4. Discussion

4.4.1. Differences in yield and cultivation management according to the weather and soil type in each year.

The yield, grain protein content, and cultivation management methods exhibited variability influenced by weather conditions during the harvest period (Table 4-2). In 2019, precipitation levels in September of the previous year were below the climatological standard normal (Fig. 4-1), which likely enabled sowing to occur earlier than usual. Specifically, sowing could be initiated prior to the optimal sowing period for the Tokachi region, typically between September 22 and 23 (Hokkaido Nosan Association 2022). As a result, it is hypothesized that the overall sowing rate declined in 2019, as many fields did not need to increase the sowing rate to compensate for delayed sowing. This reduction in sowing rate reflects adjustments in management practices influenced by favorable weather conditions for early sowing.

The Hokkaido Fertilizer Guide indicates that the standard nitrogen fertilizer application rate for the Tokachi region is not dependent on soil parent material but is instead adjusted based on growth conditions, such as the number of wheat stems and leaf color (Hokkaido Agriculture Department 2020). In 2019, precipitation levels from November onward were the lowest among the three years studied (Fig. 4-1). This was accompanied by a reduction in the quantity of supplementary nitrogen fertilizer applied until the emergence of the flag leaf stage (Table 4-3). This reduction may be attributed to accelerated growth observed prior to the overwintering period, likely due to the increased number of stems resulting from delayed and reduced snowfall during the preceding year. Additionally, the early sowing observed in some fields in 2019 may have contributed to this outcome. However, supplementary nitrogen fertilizer application up to the flag leaf stage was significantly higher in Brown Lowland soils compared to other soil types. This disparity is hypothesized to result from differences in soil physicochemical properties. Brown Lowland soils exhibited poorer physical properties, such as higher solid content and shallower penetration depth, compared to Andosols (Table 4-3). It is postulated that the initial growth delay caused by poor water retention and aeration in Brown Lowland soils was compensated for by higher fertilizer application rates. Furthermore, some fields received supplementary fertilizer in early spring, likely in response to delayed snowfall, subsequent winter withering, and the presence of brown leaves in certain fields.

In 2018, persistent precipitation was observed starting from the flowering period in early June, accompanied by relatively low temperatures. Although there were days without rainfall, frequent drizzle and prolonged high humidity created conditions conducive to sterility and red rust outbreaks. In the Tokachi region, the occurrence of red mold, caused by *Microdochium nivale*, is strongly associated with low temperatures and high humidity during the flowering period (Soma & Ozawa 2006). These conditions were prevalent in 2018. Additionally, the frequent precipitation likely hindered timely field spraying due to slow field drying and the removal of applied chemicals by rainfall, exacerbating yield losses caused by red rust. Elevated precipitation levels during the wheat maturation phase are known to impede photosynthetic activity and nutrient uptake (Hirano 1971). The substantial rainfall recorded in July 2018 (Fig. 4-1) is also hypothesized to have contributed to growth retardation, further reducing yields.

The higher yields observed in 2017 and 2019 compared to 2018 are speculated to result from the availability of consistent sunlight throughout the growing season (Fig. 4-1). It is generally understood that the quantity of nitrogen accumulated by the flowering stage determines the potential sink size of the grains, while subsequent nitrogen translocation from accumulated and newly absorbed nitrogen contributes to grain filling (Cassman et al. 1992). Despite comparable cultivation management practices between 2017 and 2018, significant yield discrepancies were observed (Tables 4-2, 4-3), suggesting that weather conditions had a more substantial impact on yield variation than management practices. In 2017, nitrogen fertilizer application prior to the emergence of the flag leaf was greater in Brown Lowland soils; however, no significant differences were observed in the total nitrogen application among soil types (Table 4-3). This indicates variability in the timing of fertilizer application between fields, while the total fertilizer amount was standardized according to growth conditions. In 2019, despite indications of winter withering observed in March and April, wheat growth prior to the overwintering period was robust. From April onwards, minimal precipitation, high solar radiation in May, and low temperatures in July (Fig. 4-1) created favorable conditions for growth and ripening. Although the total nitrogen fertilizer applied in 2019 was lower than in 2017, it is postulated that sufficient nitrogen was absorbed before flowering in June, driven by enhanced photosynthetic activity. The subsequent cooler summer conditions likely prolonged the ripening period, facilitating increased grain weight and effective nitrogen translocation to the grains.

Grain weight generally exhibited greater sensitivity to environmental factors than grain nitrogen content, as reported by Triboi & Triboi-Blondel (2002) and Triboi et al. (2006). Additionally, there was typically a negative correlation between yield and grain protein content. However, in 2019, both yield and grain protein content were higher than in 2018, with the latter being the highest across the three-year period. This anomaly is speculated to result from favorable conditions for initial growth in 2019, which facilitated the establishment of a sufficient sink size for grain development. In contrast, unfavorable weather conditions in 2018 likely hindered this process. Despite comparable total nitrogen fertilizer applications in 2019 and 2018, the favorable conditions in 2019 likely enhanced nitrogen uptake during early growth and flowering stages, mitigating challenges associated with nitrogen remobilization to the grains. This combination of factors likely contributed to both higher yields and elevated grain protein content in 2019.

The preceding analysis highlighted that plant growth was influenced by a combination of prevailing weather conditions, soil physicochemical properties, and soil type. Consequently, cultivation management practices were adjusted to respond to these factors. Additionally, yield showed substantial variation across harvest years, indicating that weather conditions played a particularly significant role in influencing yield outcomes compared to other factors affecting plant growth.

4.4.2. Relationship between parameters selected for Minimum Data Set and Soil Quality Index

A potential limitation of multivariate analysis methods in developing the MDS is the possibility that parameters with high variability in the dataset may be selected, even if their relevance to crop productivity is limited. However, in this study, the selected parameters were assumed to be related to crop productivity based on existing knowledge (e.g., Takahashi et al. 1980, Hokkaido Agricultural Administration Department 2020). Therefore, the MDS developed in this study was deemed appropriate for evaluating soil quality. The MDS included physical parameters (solid content, macropore ratio) that reflect the dry and wet conditions experienced by wheat roots, as well as chemical parameters (exchangeable calcium content, exchangeable potassium content, and hot-water dissolved boron content) that indicate the nutrient availability for wheat roots, influenced by the abundance of components and pH levels. Thus, it was hypothesized that all parameters included in the MDS were directly relevant to crop productivity.

An analysis of the weighted scores for each MDS parameter (Fig. 4-2) revealed that the exchangeable calcium content and macropore ratio significantly contributed to the decline in the SQI. Although the score differences between fields for exchangeable calcium content were relatively minor, its high weighting value amplified its impact on SQI. Similarly, the macropore ratio also had a substantial effect on SQI reduction. The exchangeable potassium content and macropore ratio had minor impact on SQI. Conversely, solid content contributed minimally to SQI reduction due to its limited score variation across fields. Hot-water dissolved boron content did not directly correlate with low SQI scores due to less weight value. This suggests that maintaining hot-water dissolved boron content within the reference range can enhance SQI, though it is a lower priority compared to other parameters. These findings underscore the importance of focusing on exchangeable calcium content and macropore ratio for effective soil quality management.

4.4.3. Assessment of wheat yield by Soil Quality Index

In 2018, a significant positive correlation was observed between the SQI and yield. A detailed analysis of the MDS scores revealed that a high proportion of fields showed a decreased macropore ratio score. Specifically, 15 out of 22 fields had weighted scores of 8.7 or less, the median score across all plots over the three years (Supplementary Table 1). Among these, the five fields with SQI below 80 and yield ratios to the regional average below 100 (field IDs 15, 18, 26, 32, and 33) exhibited particularly low macropore ratio scores, falling below the 20th percentile (6.9) of all fields over the three years (Fig. 4-2, Supplementary Table 1). In 2018, precipitation levels were above the climatological standard normal, while global solar radiation was below the normal from May to July. Heavy precipitation in July was accompanied by a reduction in yields (Fig. 4-1, Table 4-2). These conditions likely prevented the typical increase in macropore ratio associated with the wet-dry cycle (Czarnes et al. 2000), leading to reduced macropore ratio scores. Furthermore, it has been reported that elevated soil moisture during the grain-filling period after flowering can reduce plant height and yield (Koyanagi 2008). It is reasonable to infer that fields with low macropore ratios and poor soil quality retained higher soil moisture during the grain-filling stage, contributing to reduced yields. In addition, three of the five fields with SQI scores of 80 or less had exchangeable calcium content scores below the 10th percentile (24.8) across all fields over the three years (Supplementary Table 1). Adverse weather conditions, such as heavy rainfall in 2018, likely exacerbated the sensitivity of these fields to nutrient imbalances, leading to inhibited nutrient absorption and chemical parameter shifts that further affected growth. These findings indicate that fields with low SQI are more vulnerable to yield reductions under adverse weather conditions, such as heavy rainfall. Improving soil quality could reduce annual yield variability by enhancing the resilience of wheat crops to environmental stressors. Additionally, the SQI calculation demonstrated potential for identifying the underlying causes of low yields, although this capability was particularly evident in years with significant weather challenges.

The lack of a correlation between yield and SQI in Andosols across all harvest years is hypothesized to be due to the exclusion of soil thickness as a variable in the SQI calculation. Specifically, if nutrient excess or poor drainage occurs in the surface soil deeper than the sampled 0–15 cm layer (not investigated in this study), the SQI based on this shallow depth could overestimate soil quality. Conversely, if a nutrient deficiency exists in the 0–15 cm layer but sufficient nutrients are present in the deeper surface soil, the SQI might underestimate soil quality. Even though surface soil in 15 cm or deeper may less sufficient nutrients, whole surface soil would have enough amount of nutrients. As noted by Niwa et al. (2011), the World Reference Base (WRB) classification indicates that the effective soil layer in Brown Lowland soils and Andosols with alluvial deposits is typically shallower than in Andosols. This study aligns with that observation, as Andosols were found to have the greatest year-standardized penetration depth, indicating a thicker effective soil layer compared to Brown Lowland soils and Andosols with alluvial deposits (Table 4-4). This limitation suggests that using data solely from the 0–15 cm surface layer may be insufficient for accurately evaluating soil quality or crop productivity in fields with significant variability in surface soil thickness. For example, while a correlation was observed between yield and SQI for Brown Lowland soils and Andosols with alluvial deposits in 2018, field ID 21 demonstrated a lower yield than fields with similar SQI values (Fig. 4-3e). The penetration depth in this field was 59.3 cm, indicating relatively thick topsoil (Table 4-4). This discrepancy may result from an overestimation of soil quality in field ID 21, as the SQI was based on data from only the 0–15 cm layer and did not account for deeper surface soil characteristics. To improve SQI accuracy, even though Brown Lowland soils and Andosols with alluvial deposits, it would be preferable to calculate the SQI using physicochemical data that represent the entire surface soil layer. Conversely, field ID 22, an Andosol in 2018, exhibited a relatively low SQI (77.5) despite a high yield ratio to the regional average (128%) (Fig. 4-3b). The low SQI was largely attributed to low exchangeable calcium content, which resulted in a weighted score of 23.5 and a subsequent reduction in the overall SQI (Fig. 4-2). This suggests that the SQI calculation, based solely on data from the 0–15 cm depth, may have underestimated the soil quality of this field. These examples highlight the potential need for incorporating deeper soil data into SQI calculations to improve the accuracy and applicability of the index in predicting yield outcomes.

The lack of correlation between yield and SQI in 2017 and 2019, which were not characterized by excessive rainfall, for Brown Lowland soils and Andosols with alluvial deposits (surface layer: volcanic ash), suggests that soil physicochemical properties may have had less influence on crop productivity during those years. Favorable weather conditions and cultivation practices likely mitigated potential soil limitations. In 2017 and 2019, high levels of solar radiation after April facilitated sufficient photosynthesis in wheat, while root system development aligned with fertilizer management and plant growth, compensating for unfavorable soil physicochemical properties.

Conversely, in 2018, limited solar radiation after April and prolonged precipitation created conditions unfavorable for root development. Under such adverse conditions, soil physicochemical properties likely played a more pronounced role in determining crop growth and yield. Gravel content, which was not considered in this analysis, may also have contributed to yield variability. A detailed examination of 2019 data revealed significant yield discrepancies in fields ID 6 and ID 7, despite similar SQI values of 92.7 and 89.5, respectively (Fig. 4-3f). The yield ratios to the regional average were 123.7% and 56.8%, respectively, even though both samples were collected from the same field with identical weather conditions and cultivation practices. The difference in yield was likely due to variations in gravel occurrence depths, measured at 58 cm in field ID 6 and 25 cm in field ID 7. These findings suggest that gravel occurrence at shallower depths significantly influenced crop performance under the low rainfall conditions of 2019. This highlights the need to include gravel content within the effective soil layer as a variable in future SQI calculations to improve its predictive accuracy and relevance, particularly under conditions where gravel can affect root development and water availability.

It was notable that the SQI for 2018 was consistently lower than that for 2017 or 2019, even within the same field (Table 4-7). A detailed analysis of the data revealed varying reasons for the reductions in SQI across different cases. In cases 1 and 4, significant reductions were observed in the scores for macropore ratio and exchangeable potassium content in 2018. In contrast, case 2 exhibited a notable decline due to exceeding the reference value for solid content and deficiency in hot-water dissolved boron content. Case 3 demonstrated a substantial score reduction attributable to an excess of exchangeable potassium content. The composition of SQI reductions thus varied depending on the field (Table 4-7). This variation is hypothesized to result from differences in survey points within the same field, highlighting the need for soil quality assessments that account for spatial variability within individual fields. Determining the optimal method for such assessments remains a subject for future research.

Furthermore, given that yield is influenced by weather and cultivation management practices in addition to soil quality, even fields with identical soil quality can exhibit yield fluctuations. Simulation studies reported the inter-annual variability in yield due to weather outweighed soil-texture-related yield variability (Máthé-Gáspár et al. 2003) and fertilizer applications and irrigation reduce variability caused by soil type (Folberth et al. 2016). Targeted fields in this study received enough amount of fertilizer depending on the growth condition and had heaviest precipitation in 2018 of three years. Those condition would emphasize soil effect on crop productivity in 2018. Therefore, a comprehensive evaluation that incorporates weather conditions, cultivation management practices, and soil quality is crucial for accurately interpreting yield variations within a field. However, soil sampling depth may limit the soil quality assessment accuracy and should be considered.

4.4.4. Impact of changes in Soil Quality Index over time

In the study cases involving the same fields, the variation in SQI was smaller than that observed for any of the MDS measures or their weighted scores (Table 4-7), except for the weighted score of exchangeable calcium content. This finding suggests that SQI serves as a relatively robust soil assessment indicator, maintaining consistency across different measurement years. The exchangeable calcium content remained consistently high throughout the study, with no observed differences in weighting scores. This implies that once the reference value for calcium was met, there was no notable loss leading to deficiency in subsequent years. Yield variability within the same fields was greater than the variability in SQI, indicating that meteorological factors exerted a stronger influence on yield than soil-related factors. Among the measured parameters, bulk density exhibited a relatively low coefficient of variation, as did the solid content. Conversely, the macropore ratio demonstrated a high coefficient of variation, suggesting that the overall pore volume remained relatively stable over time, while the distribution of pore size was more susceptible to annual changes. Previous studies have shown minimal annual variation in bulk density for agricultural soils under consistent management practices or in soils transitioning from paddy to non-paddy fields (Koga 2007, Annaka & Shiratani 1987). These findings imply that while high-frequency monitoring of bulk density or overall pore volume may not be necessary, annual monitoring of the macropore ratio could be valuable for capturing changes in soil physical properties related to pore size distribution.

4.4.5. Notes and prospects for soil crop productivity assessment using Soil Quality Index

Previous studies have identified significant positive correlations between yield and the SQI under various scenarios, including different cropping and organic matter management practices (Andrews et al. 2002a, de Paul Obade & Lal 2016), crop rotation systems (Armenise et al. 2013), and tillage intensity (Armenise et al. 2013, de Paul Obade & Lal 2016). These studies presented aggregated results across all treatments, where treatment effects were reflected in both SQI and yield. However, within-treatment correlations were either weak or unexamined. This suggests that when differences in soil physicochemical properties are primarily treatment-specific, the treatment's impact can be effectively captured by both SQI and yield, enabling the assessment of treatment effects through SQI. Conversely, in farmers' fields, where numerous variables such as soil physicochemical properties, climatic conditions, and cultivation management practices simultaneously influence crop performance, direct evaluation of yield using SQI becomes more challenging. This complexity highlights the need for a more nuanced approach to interpreting SQI in the context of real-world field conditions.

The SQI calculated in this chapter demonstrated a significant positive correlation with yield in farmers' fields during years when wheat growth was limited by heavy rainfall, suggesting its potential as a valuable indicator of wheat productivity under weather-constrained conditions (Fig. 4-3a-c). However, the SQI proved unsuitable for assessing crop productivity in fields with thick surface soil, high gravel content, or shallow gravel emergence depths. This limitation arises because SQI calculations were based on soil samples taken from the 0–15 cm surface layer, which avoids gravel and may not fully capture soil properties influencing root development and crop growth. Mukherjee and Lal (2014) found no significant differences in SQI across varying soil depths (0–10 cm, 10–20 cm, 20–40 cm, 40–60 cm) within a single field, emphasizing that management practices and soil type had a greater influence on SQI than soil depth. Nevertheless, depth-related data, such as the effective soil layer, could be invaluable for assessing soil quality in fields with similar management practices and soil types. Incorporating such data may enhance the precision of soil quality assessments and improve the SQI's ability to predict crop productivity in diverse field conditions.

Sato et al. (1988) reported variations in wheat yield between soil types with differing nitrogen fertility. Consequently, this chapter attempted to include hot-water extractable nitrogen content as an additional parameter for SQI calculation by performing PCA. However, hot-water extractable nitrogen content was excluded from the final MDS due to its relatively low eigenvector value (Table 4-8), indicating minimal contribution to the principal components. In this study, hot-water extractable nitrogen content was deemed an unsuitable parameter for summarizing the dataset because it exhibited low variability compared to other parameters. The selection and weighting of MDS parameters were conducted using PCA, which, given the limited sample size, prioritized parameters with higher variability. While this approach was appropriate for the study's scope, it highlights the need for a standardized soil quality assessment method in the future. Such a method would benefit from incorporating MDS parameters that are independent of dataset-specific variability, ensuring more consistent and reliable assessments across diverse field conditions.

Among the items measured in this chapter, several were considered important for crop productivity but lacked established soil diagnostic reference values. These included hot-water extractable nitrogen content, which reflects nitrogen fertility, and total carbon content, which has been widely proposed as a key soil quality indicator (Bünemann et al. 2018). To incorporate these variables into SQI calculations, it would be necessary to establish appropriate thresholds for scoring. One potential approach for defining these thresholds would be to conduct studies in fields that differ solely in total carbon content or hot-water extractable nitrogen content and evaluate their relationship with yield under identical cultivation management practices. Developing such scoring thresholds remains a future task for advancing SQI methodologies. It is noteworthy that total carbon content exhibited significant positive correlations with exchangeable calcium content and cation exchange capacity (CEC; Fig. 4-4, $r = 0.575$, $p < 0.001$ and $r = 0.935$, $p < 0.001$, respectively). Since the threshold for scoring exchangeable calcium content was already determined based on CEC (Table 3-1), incorporating total carbon content into the SQI calculation would necessitate the removal of exchangeable calcium content from the MDS to avoid redundancy. This adjustment would ensure that the MDS remains streamlined while maintaining its effectiveness in evaluating soil quality.

Table 4-8. Results of principal component analyses (PCA)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Eigenvalue	5.54	3.52	2.18	1.58	1.24	1.20	1.00
Proportion of variance	0.291	0.185	0.115	0.083	0.065	0.063	0.053
Cumulative proportion	0.291	0.477	0.592	0.675	0.740	0.803	0.856
Weighted value	0.369	0.234	0.145	0.105		0.080	0.067
Eigenvector							
pH (H_2O)	0.267	0.113	-0.204	0.139	**-0.448**	0.119	-0.011
Available phosphate content	0.134	**-0.417**	0.142	0.154	0.161	0.106	0.022
Exchangeable Ca content	**0.389**	0.043	-0.068	-0.093	0.042	-0.005	0.185
Exchangeable Mg content	**0.350**	-0.040	0.263	-0.168	-0.008	-0.055	0.093
Exchangeable K content	0.181	-0.057	**0.467**	0.169	-0.357	-0.174	0.076
Mg/K	0.143	0.067	-0.327	-0.372	**0.418**	0.088	0.029
Ca/Mg	0.203	0.148	-0.392	0.128	0.108	0.082	0.250
Lime saturation percentage	0.321	-0.214	-0.282	0.058	-0.200	0.113	0.015
Base saturation percentage	0.303	-0.268	-0.214	0.068	-0.246	0.109	-0.037
Hot-water dissolved B content	0.179	0.022	-0.178	-0.064	0.107	**-0.550**	**-0.403**
Easily reducible Mn content	0.142	-0.291	0.193	-0.235	0.177	0.253	-0.139
Acid-soluble Zn content	0.288	-0.171	-0.040	0.127	0.165	-0.212	-0.371
Acid-soluble Cu content	-0.153	-0.354	0.016	-0.092	0.040	0.104	-0.382
Solid content	-0.167	**-0.439**	-0.128	-0.122	-0.083	-0.108	0.226
Bulk density	-0.194	**-0.434**	-0.153	-0.047	-0.112	-0.047	0.152
Macropore ratio	0.060	0.065	0.067	**0.539**	0.248	0.485	-0.287
Available moisture	-0.181	-0.022	-0.237	0.361	-0.069	-0.349	-0.191
Year-standardized penetration depth	0.098	0.190	0.100	-0.437	-0.314	0.128	**-0.416**
Hot-water extractive nitrogen	0.277	-0.029	0.281	0.127	0.317	-0.304	0.232

PC shows principal component adding hot-water extractive nitrogen as a parameter.

Bold values under each component are highly weighted, and underlined bold values are selected in minimum data set.

Weight value is calculated as: variance / total cumulative proportion excluding PC5 (0.790).

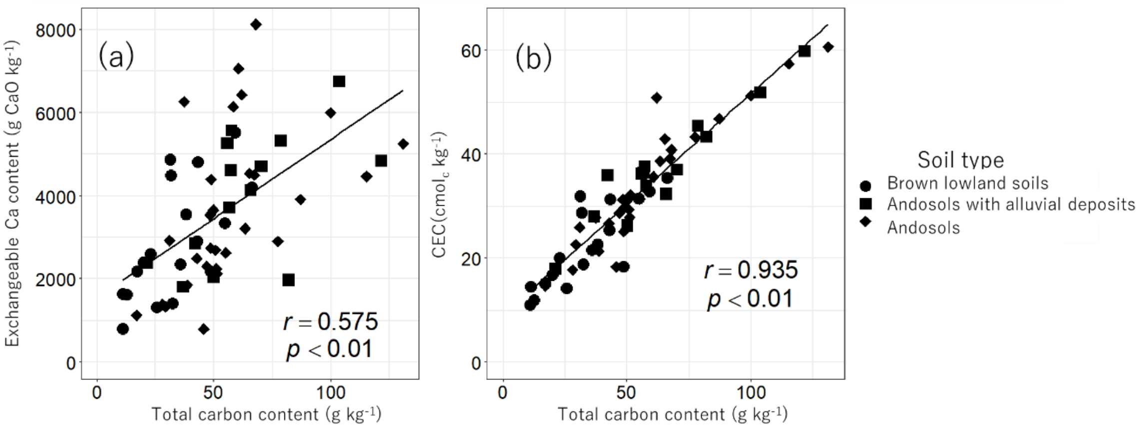

Figure 4-4. Scatter plots showing relationship between Total carbon and soil properties

a) Exchangeable Ca content, b) Cation exchange capacity (CEC).

Solid line shows significant correlation.

4.5. Conclusion

This chapter demonstrated that meteorological conditions and agricultural management practices significantly influenced the correlation between crop yield and the SQI calculated at depths of 0–15 cm. While soil is a critical factor, it is essential to account for other variables, such as weather and cultivation practices, when assessing crop productivity. A comprehensive evaluation of soil effects through SQI provides a framework for understanding the contributions of non-soil factors to yield variability. To achieve a holistic assessment, it is crucial to accumulate data encompassing a wide range of variables, including detailed soil characteristics, meteorological conditions, and cultivation management practices. The integration of such data sets is expected to enable a more comprehensive analysis, fostering the development of effective strategies to enhance soil quality and crop productivity. Future research should focus on building these data resources and employing them to refine SQI methodologies, improve predictive accuracy, and support sustainable agricultural practices.

5. Soil Quality Index considering the thickness of the surface soil in potato and wheat fields

5.1. Introduction

The previous chapter focused exclusively on wheat fields, whereas this chapter extends the assessment of crop productivity to include both potato and wheat fields. In 2021, Japan achieved a self-sufficiency rate of 67% for potatoes on a weight basis and 72% when including sweet potatoes, a rate that has remained relatively stable since 2015 (Statistics Department, Minister's Secretariat, Ministry of Agriculture, Forestry and Fisheries 2023b). By contrast, Japan's total food self-sufficiency ratio in 2021 was only 38% on a calorie supply basis. It has been estimated that a potato-based cropping system would be essential for meeting calorie supply needs solely through domestic production (Ministry of Agriculture, Forestry and Fisheries 2023c). This underscores the importance of ensuring stable potato productivity for Japan's food security.

Traditionally, land assessment has focused on intrinsic soil properties that are relatively static and less influenced by management practices. In contrast, soil quality emphasizes dynamic soil properties that are strongly affected by management and are typically measured in the surface layer (0–25 cm) (Karlen et al. 2003). However, assessing the direct impact of soil quality on factors such as water quality necessitates consideration of soil properties at greater depths. Soil is a critical component of crop productivity, and various methods for calculating the Soil Quality Index (SQI) have been developed to quantitatively assess its contribution, as described in Chapters 2 and 4. Most existing SQI studies have focused on surface soils (<30 cm depth) (Andrews et al. 2002a, 2002b, Armenise et al. 2013, Rahmanipour et al. 2014, Liu et al. 2014). However, a small number of studies have incorporated subsoil properties into SQI assessments, examining the entire soil profile (Vasu et al. 2016, Zhijun et al. 2018, Santos-Francés et al. 2019, Zhou et al. 2022). These studies emphasize the importance of including subsoil layers in soil quality assessments, as soil functions are governed by processes occurring throughout the entire soil profile, called soil control section. Relying solely on surface soil measurements may provide an incomplete picture of soil quality and crop productivity potential. While sampling only surface soil is less labor-intensive, integrating data from both surface and subsoil layers could identify critical factors influencing soil function.

Crop growth and yield depend on root expansion and development, which are in turn influenced by the depth of the effective soil layer. The thickness of this layer directly affects crop productivity by physically limiting root growth and the intake of water and nutrients, and indirectly by determining the total nutrient supply capacity of the soil (Tsunekawa et al. 1997, Nakatsuka & Tamura 2016). Studies have proposed that effective soil layer thickness could serve as a single parameter to express SQI when the relationship between yield and soil properties was analyzed in areas with varying effective soil layer thicknesses (Rhoton & Lindbo 1997). However, SQI calculation methods that account for both effective soil layer thickness and variability in soil physicochemical properties across fields have not yet been developed. While productivity indices have been calculated by scoring individual soil profile layers and summing the scores for a single field (Pierce et al. 1983, Duan et al. 2009), the impact of effective soil layer thickness on these calculations has not been adequately addressed. Incorporating effective soil layer thickness into SQI methodologies may improve their accuracy and relevance for fields with diverse soil conditions and management practices. This approach could help optimize crop productivity assessments and inform sustainable agricultural management strategies.

While the importance of effective soil layer thickness has been widely recognized, the Hokkaido Agriculture Department (2020) defines the effective soil layer as the depth to stones, gravel, pans, or compacted layers with a thickness of 10 cm or more. This definition highlights a challenge in directly equating soil penetrometer penetration depth with effective soil layer thickness. Penetration depth may not accurately reflect the true effective soil layer thickness, which must meet specific criteria, such as exceeding a thickness of 10 cm. In this chapter, the depth to the ploughed pan layer—defined as a penetration resistance of 1,500 kPa or more with continuous penetration over a depth of 10 cm or more—was used as an indicator of surface soil thickness. While this measure represents a layer with lower hardness than the effective soil layer, it can be reliably determined using a soil penetrometer. The ploughed pan layer depth was used to assess whether rooting conditions were favorable or unfavorable. In Chapter 4, the relationship between crop yield and surface soil SQI was analyzed. No significant correlation was observed for soil types with thicker surface soil, whereas a significant correlation was identified for soil types with thinner surface soil. This finding underscores the need to consider surface soil thickness when calculating SQIs applicable to a variety of soil types. The objective of this chapter is to evaluate crop productivity using SQI while accounting for surface soil thickness in potato fields. Furthermore, it aims to identify the key soil information that should be collected in future assessments to improve the accuracy and applicability of SQI in predicting crop productivity under diverse field conditions.

5.2. Materials and methods

5.2.1. Research location

The survey was conducted in Makubetsu Town (42.908627 N, 143.356094 E), located in the Tokachi region of Hokkaido (Fig. 3-1). An overview of the surveyed fields is provided in Table 5-1. A total of 105 fields were included in the study, comprising potato and wheat fields surveyed over multiple years. The number of potato fields surveyed was 23 in 2020, 23 in 2021, and 30 in 2022. The number of wheat fields surveyed was 7 in 2021, 12 in 2022, and 10 in 2023. The climatological standard normal values for the nearest meteorological station, located in Nukanai, indicate a mean annual temperature of 5.4°C and a mean annual precipitation of 1035.3 mm. Notably, the normal precipitation from June to September was 499.4 mm, accounting for nearly half of the annual total.

No severe outbreaks of common scab were observed in the surveyed fields during the study period.

Table 5-1. Summary of research sites

Harvest year	ID	Cultivar	Soil type	Soil texture		Thickness of surface soil (cm)
				0-30 cm	30-60 cm	
2020	1	Sayaka	Peat soil	LiC	HC	47
2020	2	Sayaka	Andosol	LiC	LiC	> 60
2020	3	Sayaka	Andosol	LiC	LiC	35
2020	4	Sayaka	Andosol	LiC	CL	> 60
2020	5	Sayaka	Andosols with alluvial deposits	LiC	LiC	18
2020	6	Sayaka	Andosol	CL	CL	41
2020	7	Sayaka	Andosol	LiC	CL	> 60
2020	8	Sayaka	Brown Lowland soil	LiC	LiC	> 60
2020	9	Sayaka	Andosol	LiC	LiC	50
2020	10	Sayaka	Peat soil	LiC	LiC	> 60
2020	11	Sayaka	Andosol	CL	CL	> 60
2020	12	Sayaka	Andosol	LiC	CL	26
2020	13	Sayaka	Andosol	LiC	CL	29
2020	14	Sayaka	Andosol	LiC	L	30
2020	15	Toyoshiro	Andosol	LiC	LiC	44
2020	16	Toyoshiro	Peat soil	LiC	LiC	> 60
2020	17	Toyoshiro	Andosol	LiC	CL	> 60
2020	18	Toyoshiro	Brown Lowland soil	LiC	LiC	> 60
2020	19	Toyoshiro	Brown Lowland soil	LiC	SCL	42
2020	20	Waseshiro	Andosol	LiC	LiC	> 60
2020	21	Waseshiro	Andosol	LiC	LiC	31
2020	22	Waseshiro	Andosol	CL	CL	> 60
2020	23	Waseshiro	Andosol	CL	SCL	32
2021	24	Sayaka	Peat soil	LiC	SiC	> 60
2021	25	Sayaka	Peat soil	LiC	SiC	> 60
2021	26	Toyoshiro	Andosol	CL	CL	47
2021	27	Toyoshiro	Andosol	L	CL	26
2021	28	Toyoshiro	Andosol	LiC	CL	44
2021	29	Toyoshiro	Peat soil	LiC	HC	> 60
2021	30	Sayaka	Peat soil	CL	CL	> 60
2021	31	Sayaka	Andosol	LiC	LiC	> 60
2021	32	Sayaka	Andosol	L	SiL	51
2021	33	Sayaka	Andosol	LiC	L	> 60
2021	34	Sayaka	Andosol	L	L	> 60
2021	35	Sayaka	Andosol	L	L	> 60
2021	36	Sayaka	Andosol	SL	L	32
2021	37	Sayaka	Andosol	SL	SL	39
2021	38	Sayaka	Andosol	SiL	L	33
2021	39	Sayaka	Andosol	L	L	26
2021	40	Waseshiro	Andosol	L	L	> 60
2021	41	Sayaka	Andosol	L	L	41
2021	42	Waseshiro	Andosol	L	SiL	37
2021	43	Waseshiro	Andosol	L	SL	17
2021	44	Sayaka	Andosol	L	L	> 60
2021	45	Waseshiro	Andosol	SCL	SL	51
2021	46	Sayaka	Andosol	SL	L	30
2022	47	Sayaka	Andosols with alluvial deposits	LiC	LiC	> 90
2022	48	Toyoshiro	Peat soil	LiC	LiC	> 90
2022	49	Toyoshiro	Peat soil	LiC	LiC	> 90
2022	50	Toyoshiro	Brown Lowland soil	LiC	CL	54
2022	51	Toyoshiro	Andosol	LiC	CL	43
2022	52	Toyoshiro	Peat soil	LiC	LiC	> 90
2022	53	Sayaka	Andosol	CL	CL	> 90
2022	54	Sayaka	Andosol	LiC	HC	43
2022	55	Sayaka	Andosol	LiC	SC	> 90
2022	56	Toyoshiro	Brown Lowland soil	LiC	LiC	> 90
2022	57	Sayaka	Andosol	CL	CL	> 90
2022	58	Sayaka	Andosol	CL	SCL	> 90
2022	59	Sayaka	Andosol	LiC	LiC	> 90
2022	60	Sayaka	Andosol	LiC	CL	22
2022	61	Sayaka	Andosol	CL	SCL	18
2022	62	Toyoshiro	Andosol	CL	CL	44
2022	63	Sayaka	Andosol	CL	CL	44
2022	64	Sayaka	Peat soil	LiC	LiC	> 90
2022	65	Sayaka	Andosol	LiC	CL	40
2022	66	Sayaka	Andosol	CL	CL	40
2022	67	Sayaka	Andosol	CL	SL	52
2022	68	Sayaka	Andosol	LiC	CL	60
2022	69	Sayaka	Andosol	CL	SCL	14
2022	70	Waseshiro	Andosol	CL	CL	34
2022	71	Sayaka	Andosol	CL	CL	15
2022	72	Waseshiro	Andosol	CL	CL	46
2022	73	Sayaka	Andosol	CL	CL	15
2022	74	Waseshiro	Andosol	SCL	CL	> 90
2022	75	Sayaka	Peat soil	LiC	LiC	> 90
2022	76	Sayaka	Andosol	CL	CL	40

Harvest year	ID	Cultivar	Soil type	Soil texture		Thickness of surface soil (cm)
				0-30 cm	30-60 cm	
2021	W01	Kitahonami	Brown Lowland soil	SCL	SCL	22
2021	W02	Kitahonami	Brown Lowland soil	LiC	LiC	39
2021	W03	Kitahonami	Brown Lowland soil	LiC	LiC	34
2021	W04	Kitahonami	Brown Lowland soil	LiC	CL	> 60
2021	W05	Kitahonami	Andosols with alluvial deposits	LiC	LiC	36
2021	W06	Kitahonami	Andosol	LiC	LiC	24
2021	W07	Kitahonami	Andosols with alluvial deposits	LiC	LiC	> 60
2022	W08	Kitahonami	Andosol	LiC	LiC	> 60
2022	W09	Kitahonami	Andosol	L	L	> 60
2022	W10	Kitahonami	Andosol	LiC	CL	> 60
2022	W11	Kitahonami	Andosol	SL	L	20
2022	W12	Kitahonami	Andosol	CL	L	34
2022	W13	Kitahonami	Brown Lowland soil	CL	LiC	29
2022	W14	Kitahonami	Brown Lowland soil	L	SL	37
2022	W15	Kitahonami	Andosol	CL	L	> 60
2022	W16	Kitahonami	Andosol	CL	L	17
2022	W17	Kitahonami	Andosol	L	L	14
2022	W18	Kitahonami	Andosol	CL	LiC	12
2022	W19	Kitahonami	Andosol	L	SL	> 60
2023	W20	Kitahonami	Peat soil	LiC	LiC	> 90
2023	W21	Kitahonami	Brown Lowland soil	LiC	LiC	39
2023	W22	Kitahonami	Brown Lowland soil	SiC	SiC	10
2023	W23	Kitahonami	Andosol	LiC	LiC	67
2023	W24	Kitahonami	Andosol	LiC	LiC	> 90
2023	W25	Kitahonami	Andosol	CL	CL	> 90
2023	W26	Kitahonami	Andosol	LiC	LiC	39
2023	W27	Kitahonami	Andosol	CL	SCL	48
2023	W28	Kitahonami	Andosol	CL	CL	44
2023	W29	Kitahonami	Peat soil	LiC	HC	> 90

Soil types were classified by the mode of parent material deposition by Niwa et al. (2008).

Soil texture was determined by soil particle range system of International Soil Science Society.

5.2.2. Soil sampling and survey

Soil sampling was conducted on October 5–8, 2021; October 3–6, 2022; and October 2–6, 2023. For potato fields, soil samples were collected one year after the harvest, whereas for wheat fields, samples were taken in the same year as the harvest. Both disturbed and undisturbed soil samples were collected from two depths: 0–30 cm and 30–60 cm. The physicochemical properties of the soil were analyzed following the procedures outlined in Section 3.2. A digital soil penetrometer was used to measure soil penetration resistance at depths of 0–90 cm in 2023 and 0–60 cm in 2021 and 2022. The depth of the surface soil was defined as the distance from the surface to the point where penetration resistance started to exceed 1,500 kPa for a minimum continuous depth of 10 cm. This threshold was used to assess rooting conditions and surface soil thickness.

5.2.3. How the Soil Quality Index was calculated

The SQI calculation method was conducted as described in Section 3.3. The Minimum Data Set (MDS) used for calculating the SQI was selected from the 17 items utilized in the previous chapter, excluding the effective soil layer, to account for the thickness of the surface soil (Table 4-1). Deeper soil profile can store more water and have a larger zone for roots to grow, enabling them to access larger quantities of water and nutrients (Lal et al. 2011). Therefore, to incorporate surface soil thickness into the SQI, a depth-corrected SQI was defined using Equation (5). This correction ensured that the SQI value was reduced proportionally in cases of thinner surface soil, providing a more accurate assessment of soil quality with respect to rooting conditions and crop productivity.

The depth-corrected SQI was calculated using the following relationship:

$$Depth\ corrected\ SQI = \begin{cases} \dfrac{SQI_{0-30} + SQI_{30-60}}{2} & 60 \leq D \\ \dfrac{SQI_{0-30} + SQI_{30-60}\left(\dfrac{D-30}{30}\right)}{2} & 30 \leq D < 60 \quad (Eq. 5) \\ \dfrac{SQI_{0-30}\left(\dfrac{D}{30}\right)}{2} & D \leq 30 \end{cases}$$

Where SQI_{0-30} and SQI_{30-60} represent the SQI values calculated for the 0–30 cm and 30–60 cm depths, respectively, and D is the thickness of the surface soil. This equation adjusts the SQI to reflect the influence of surface soil thickness, ensuring a comprehensive evaluation of soil quality. When the D is 30-60 cm, SQI is deducted only SQI in 30-60 cm because plant roots easily access 0-30 cm depth but have difficulty to access in a part of 30-60 cm depth.

To address the labor-intensive nature of collecting soil samples from the 30–60 cm depth, particularly in large-scale studies, a simple corrected SQI was defined using Equation (6). This simplified calculation uses soil samples collected only from the 0–30 cm depth, combined with the measured thickness of the surface soil, to estimate soil quality. That was developed to investigate whether reliable soil quality assessments could be achieved without the need for extensive subsoil sampling, thus making large-scale soil quality assessments more practical.

$$Simple\ corrected\ SQI = \begin{cases} SQI_{0-30} & 50 \leq D \\ SQI_{0-30}\left(\frac{D}{50}\right) & D < 50 \end{cases} \quad (Eq. 6)$$

The threshold value for the thickness of the surface soil was referred to here as 50 cm, which was the lower reference limit for the effective soil layer in the soil diagnostic reference.

5.2.4. Other measurement items and statistical analysis methods

The weights of potato and wheat yields per field were obtained through interviews. Statistical analyses were conducted using R version 4.0.2 (R Core Team 2021). To determine whether year, cultivar, and soil type influenced yield, a three-way analysis of variance (ANOVA) was performed. Multiple comparisons for factors showing significant differences were conducted using the Tukey-Kramer method.

To compare soil physicochemical properties across sampling depths and soil types, repeated measures ANOVA was performed, with sampling depth treated as a within-subject factor and soil type as a between-subject factor. Multiple comparisons were conducted using Shaffer's method. Ratios of measured values, specifically Mg/K, Ca/Mg, lime saturation percentage, and base saturation percentage, were log-transformed due to their assumed adherence to a Cauchy distribution.

For soil physicochemical property scores and SQI values that could not be assumed to follow a normal distribution due to the artificial conversion processes used in scoring, a mixed two-way ANOVA was performed after aligned rank transformation. Soil type was treated as a between-subjects factor, and sampling depth as a within-subjects factor (Wobbrock et al. 2011). When interactions were not statistically significant, multiple comparisons were performed with p-values corrected using Holm's method for soil type differences, and Wilcoxon's signed rank test for sampling depth differences. When interactions were statistically significant, the same tests were applied to each level of soil type and sampling depth.

Additionally, differences in surface soil thickness among soil types, which included fields potentially deeper than 60 cm, were analyzed using the Kruskal-Wallis method (a non-parametric test). If significant differences were found, multiple comparisons with p-values corrected using Holm's method were performed.

Finally, the relationship between SQI and yield was assessed by calculating Pearson’s product-moment correlation coefficient.

5.3. Results

5.3.1. Weather conditions

Figure 5-1 provides a meteorological overview of Makubetsu Town. Temperature and precipitation data were obtained from the nearest Nukanai station, while global solar radiation data, unavailable at Nukanai, were sourced from the Obihiro station, the closest station with such data.

Cumulative temperatures from 2020 to 2022 were generally consistent with the climatological standard normal. However, exceptions were observed: below-normal temperatures in July 2020, above-normal temperatures in July 2021–2023, above-normal temperature in August 2020, and above-normal temperatures in August and September 2023 (Fig. 5-1a).

Cumulative precipitation was below normal from May to November 2020, with the lowest levels recorded in May and July (Fig. 5-1b). In 2021, precipitation levels were mostly below normal, except in August, when they nearly doubled the normal amount, reaching 282.5 mm. In 2022, precipitation exceeded the normal range from June to August. Conversely, in 2023, precipitation was below normal from May to August, while September precipitation levels were nearly equivalent to the normal (Fig. 5-1b).

Cumulative global solar radiation from April to November was generally aligned with the normal in 2020 and 2022, but about 10% higher in 2021 and 2023 (Fig. 5-1c). Notable deviations included below-normal radiation in May 2021, above-normal radiation in June and July 2021 and 2023, and a combination of below-normal radiation in May and above-normal radiation in June 2021 (Fig. 5-1c).

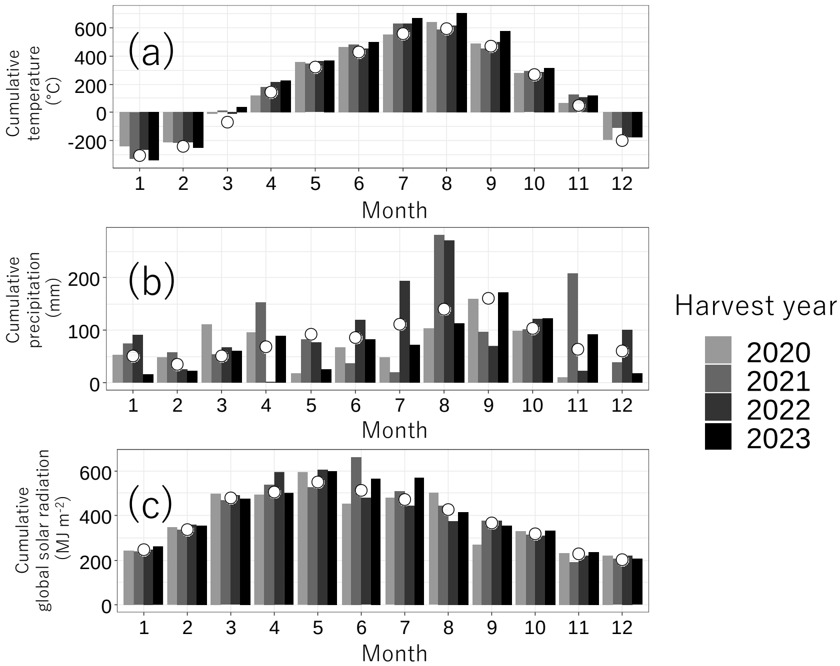

Figure 5-1. Meteorological summary in Makubetsu town

Values are the monthly means in each year: a) Cumulative temperature, b) Cumulative precipitation, c) Cumulative global solar radiation.

White plot (○) shows climatological standard normal between 2001-2020.

Solar radiation data referred meteorological stations at Obihiro and others did at Nukanai.

5.3.2. Field soil type and texture

Table 5-1 provides an overview of the surveyed fields. The target cultivars of potato were Sayaka, Toyoshiro and Waseshiro, all of which were mainly used for processing purposes. Brown Lowland soils were found in three field in 2020 and two fields in 2022 in the potato fields, Andosols with alluvial deposits were found in one field in 2020 and one in 2022, Peat soils were found in three, four and five locations in 2020, 2021 and 2022 respectively and the remaining 57 locations were andosols. In wheat fields, Brown Lowland soil was present at four locations in 2021, two in 2022 and two in 2023, Andosol with alluvial deposits was present at two locations only in 2021, Peat soil was present at two locations in 2023 and the remaining 17 locations were Andosols. The soil texture was classified as light clay (LiC), clay loam (CL), sandy clay loam (SCL), loam (L), heavy clay (HC), sandy loam (SL), silty loam (SiL), silty clay (SiC), and sandy clay (SC). In 0-30 cm soils, 54 field were classified as LiC, 28 as CL, and 14 as L. In 30-60 cm soils, 33 field were classified as LiC, 32 as CL, and 17 as L. In this study, a considerable proportion of soil were classified as Andosols and fine-grained soils.

5.3.3. Harvest data

The three-way ANOVA for potato yield, with cultivar, harvest year, and soil type as factors, revealed a statistically significant effect for cultivar only ($p < 0.001$). No significant interactions were observed (Supplementary Table 5). Among the cultivars, *Waseshiro* produced significantly higher yields compared to the other two varieties (Table 5-2). The two-way ANOVA for wheat yield, with year and soil type as factors, showed a significant effect for year only ($p < 0.001$), with 2023 yields being significantly higher than those of the other two years. No significant interaction was detected (Supplementary Table 5, Table 5-2).

Table 5-2. Potato yield comparison with cultivars or soil types

Cultivar	Harvest year	Number of fields	Yield			Effect of years	Effect of cultivars
				g m^{-2}			
Sayaka	2020	14	3957	±	608	a	a
	2021	15	4173	±	729	a	
	2022	20	3594	±	588	a	
Toyoshiro	2020	5	3193	±	482	a	a
	2021	4	4032	±	674	a	
	2022	7	3922	±	526	a	
Waseshiro	2020	4	2754	±	308	a	b
	2021	4	3104	±	325	a	
	2022	3	3379	±	206	a	
Kitahonami	2021	7	511	±	127	b	
	2022	12	403	±	144	b	
	2023	10	693	±	62	a	

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

5.3.4. Comparison of soil physicochemical properties

For chemical properties, Peat soils exhibited lower values for pH, exchangeable potassium content, easily reducible manganese content, and the Mg/K ratio compared to other soil types. In contrast, they demonstrated higher exchangeable magnesium content and acid-soluble zinc content than Andosols, as well as higher hot-water dissolved boron content compared to both Brown Lowland soils and Andosols. The available phosphate content was found to be lower in Andosols than in the other soil types.

Brown Lowland soils exhibited higher levels of lime saturation percentage and base saturation percentage compared to Andosols and Peat soils. Additionally, the exchangeable calcium content was higher in both Brown Lowland soils and Peat soils, while acid-soluble copper content was highest in Brown Lowland soils compared to all other soil types.

When comparing depths, the pH and Mg/K ratio were higher in the 0–30 cm layer for both Andosols and Peat soils. The available phosphate content was higher in the 0–30 cm layer for all soil types except Andosols with alluvial deposits. Furthermore, the 0–30 cm layer in all soil types exhibited higher values for exchangeable calcium content, exchangeable potassium content, Ca/Mg ratio, lime saturation percentage, base saturation percentage, hot-water dissolved boron content, and acid-soluble zinc content compared to the 30–60 cm layer.

In terms of physical properties, Peat soils exhibited the lowest solid content and bulk density, followed by Andosols. Peat soils also demonstrated the highest available moisture content. At different depths, the solid content and bulk density were lower in the 0–30 cm layer, while the macropore ratio was higher in the 0–30 cm layer across all soil types.

Significant differences in surface soil thickness were observed among the soil types. A multiple comparison test revealed that Peat soils had significantly thicker surface soils compared to Andosols and Brown Lowland soils (Supplementary Table 6).

Table 5-3. Soil properties comparison with soil types or depth

Soil type	Depth (cm)	Number of fields	pH (H_2O)			Available phosphate content (mg P_2O_5 kg^{-1})			Exchangeable Ca content (mg CaO kg^{-1})			Exchangeable Mg content (mg MgO kg^{-1})			Exchangeable K content (mg K_2O kg^{-1})			Mg / K (equivalent ratio)			Ca / Mg (equivalent ratio)	
Brown lowland soils	0-30	13	5.5 ± 0.4		a	424 ± 184	*	a	2233 ± 666	*	a	371 ± 179		ab	258 ± 100	*	a	3.6 ± 2.0		b	4.9 ± 1.8	*
	30-60	13	5.5 ± 0.3			297 ± 227			1889 ± 939			350 ± 197			248 ± 114			3.7 ± 2.6			4.2 ± 1.4	
Andosols with alluvial deposits	0-30	4	5.5 ± 0.1		a	520 ± 356		a	2842 ± 1113	*	b	505 ± 212		ab	388 ± 155	*	a	3.5 ± 2.3		b	4.1 ± 0.4	*
	30-60	4	5.5 ± 0.2			278 ± 240			2383 ± 934			457 ± 178			299 ± 111			4.1 ± 2.3			3.8 ± 0.5	
Andosols	0-30	74	5.7 ± 0.3	*	a	186 ± 103	*	b	2046 ± 838	*	b	339 ± 108		b	310 ± 106	*	a	3.0 ± 2.0	*	b	4.5 ± 1.5	*
	30-60	74	5.7 ± 0.3			112 ± 86			1913 ± 817			335 ± 106			278 ± 106			3.3 ± 2.2			4.2 ± 1.2	
Peat soils	0-30	14	5.1 ± 0.3	*	b	402 ± 142	*	a	3244 ± 808	*	a	446 ± 106		a	162 ± 71	*	b	7.7 ± 3.9	*	a	5.4 ± 1.2	*
	30-60	14	5.0 ± 0.3			229 ± 105			3312 ± 1569			493 ± 223			125 ± 62			11.1 ± 7.5			4.9 ± 0.9	

Soil type	Depth (cm)	Number of fields	Lime saturation percentage (%)			Base saturation percentage (%)			Hot-water dissolved B content (mg kg^{-1})			Easily reducible Mn content (mg kg^{-1})			Acid-soluble Zn content (mg kg^{-1})			Acid-soluble Cu content (mg kg^{-1})		
Brown lowland soils	0-30	13	38.9 ± 10.6	*	a	51.0 ± 16.1	*	a	0.5 ± 0.2	*	b	49.7 ± 22.5		a	3.4 ± 1.7	*	ab	2.3 ± 2.2		a
	30-60	13	36.2 ± 13.2			49.0 ± 18.9			0.5 ± 0.2			52.1 ± 32.1			2.8 ± 1.7			2.4 ± 2.1		
Andosols with alluvial deposits	0-30	4	33.4 ± 8.2	*	ab	44.5 ± 9.4	*	ab	0.7 ± 0.3	*	ab	72.2 ± 28.6		a	3.0 ± 1.9	*	abc	0.6 ± 0.2		b
	30-60	4	33.6 ± 5.6			45.4 ± 6.9			0.6 ± 0.4			53.1 ± 26.5			2.0 ± 1.3			0.8 ± 0.8		
Andosols	0-30	74	30.5 ± 7.3	*	b	40.9 ± 8.4	*	b	0.6 ± 0.2	*	b	50.5 ± 19.7		a	2.2 ± 1.0	*	b	1.3 ± 1.3		b
	30-60	74	29.1 ± 6.9			39.2 ± 8.2			0.5 ± 0.2			51.3 ± 23.3			1.7 ± 0.9			1.0 ± 1.0		
Peat soils	0-30	14	30.4 ± 7.2	*	b	37.2 ± 8.5	*	b	1.0 ± 0.4	*	a	24.5 ± 5.1		b	3.2 ± 1.2	*	a	1.7 ± 1.1		b
	30-60	14	26.4 ± 7.8			32.6 ± 9.4			0.9 ± 0.5			25.2 ± 17.6			2.6 ± 1.2			1.4 ± 0.9		

Soil type	Depth (cm)	Number of fields	Solid content (× 10^{-2} m^3 m^{-3})			Bulk density (Mg m^{-3})			Macropore ratio (× 10^{-2} m^3 m^{-3})			Available moisture (× 10^{-2} m^3 m^{-3})		
Brown lowland soils	0-30	13	37.5 ± 5.4	*	a	1.0 ± 0.1	*	a	23.5 ± 9.9	*		6.4 ± 2.4		b
	30-60	13	44.5 ± 7.1			1.2 ± 0.2			10.5 ± 4.0			6.6 ± 4.1		
Andosols with alluvial deposits	0-30	4	35.3 ± 5.7	*	a	0.9 ± 0.1	*	ab	20.1 ± 8.8	*		5.4 ± 0.8		b
	30-60	4	40.0 ± 5.0			1.1 ± 0.1			9.6 ± 3.9			6.2 ± 5.2		
Andosols	0-30	74	29.9 ± 4.0	*	b	0.8 ± 0.1	*	b	24.0 ± 8.5	*		7.9 ± 2.4		b
	30-60	74	35.1 ± 5.9			0.9 ± 0.2			12.7 ± 7.6			7.0 ± 2.7		
Peat soils	0-30	14	27.8 ± 5.8	*	c	0.7 ± 0.2	*	c	23.0 ± 7.5	*		9.9 ± 2.6		a
	30-60	14	31.1 ± 5.2			0.7 ± 0.2			10.4 ± 4.4			8.6 ± 2.4		

The data are presented as mean ± standard deviation.

The sign of * indicates significant difference between the depths and different letters indicate significant differences between the soil types ($p < 0.05$).

5.3.5. Parameters selected in the Minimum Data Set and their weights

The Principal Component Analysis (PCA) performed for soil physicochemical parameters (Table 5-4). Principal components (PCs) were selected for inclusion in the MDS based on the Kaiser criterion, which retains components with eigenvalues greater than 1.0. The eigenvalues up to the sixth PC were above 1.0. Parameters contributing to the MDS were chosen from each selected PC by identifying those with the highest absolute eigenvector values, provided these values fell within 10% of the maximum eigenvector value for that PC (Wander & Bollero 1999). The selected parameters for initial MDS from each PC were as follows:

- PC-1: Exchangeable calcium content.
- PC-2: Lime saturation percentage and base saturation percentage.
- PC-3: Solid content and macropore ratio.
- PC-4: Ca/Mg.
- PC-5: Ca/Mg and acid-soluble copper.
- PC-6: Available moisture.

However, within PC-2, base saturation percentage exhibited the largest absolute eigenvector value, was significantly correlated with lime saturation percentage (Supplementary Table 3). Consequently, base saturation percentage was chosen for the MDS to represent PC-2. Within PC-3, solid content exhibited the largest absolute eigenvector value, was significantly correlated with macropore ratio (Supplementary Table 3). As a result, solid content was chosen for the MDS to represent PC-3.

Between PC-1, PC-2, and PC-5, exchangeable calcium content was significantly correlated with base saturation percentage, Ca/Mg, therefore base saturation percentage and Ca/Mg were excluded from MDS (Supplementary Table 3). Between PC-3 and PC-6, solid content was significantly correlated with available moisture. As a result, available moisture was excluded from MDS (Supplementary Table 3). Consequently, the selected parameters for final MDS from each PC were as follows:

- PC-1: Exchangeable calcium content.
- PC-3: Solid content.
- PC-5: Acid-soluble copper.

The weighting values for each parameter in the MDS were calculated by dividing the proportion of variance explained by each PC by the cumulative proportion (0.463), excluding PCs 2, 4, and 5. The resulting weighting values were:

- Exchangeable calcium content: 0.543.
- Solid content: 0.294.
- Acid-soluble copper: 0.163.

Table 5-4. Results of principal component analyses (PCA)

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	4.267	3.571	2.315	1.422	1.282	1.083
Proportion of variance	0.251	0.210	0.136	0.084	0.075	0.064
Cumulative proportion	0.251	0.461	0.597	0.681	0.756	0.820
Weighted value	0.543		0.294		0.163	
Eigenvector						
pH (H_2O)	0.229	0.223	0.299	-0.277	0.204	0.080
Available phosphate content	-0.295	0.188	-0.121	0.381	-0.103	-0.140
Exchangeable Ca content	**-0.420**	0.119	-0.040	-0.120	0.265	-0.063
Exchangeable Mg content	-0.327	0.218	-0.076	-0.403	-0.028	-0.249
Exchangeable K content	0.229	0.198	0.200	0.136	-0.079	-0.391
Mg/K	-0.371	-0.044	-0.152	-0.363	-0.033	0.123
Ca/Mg	-0.175	-0.106	0.052	**0.457**	**0.467**	0.286
Lime saturation percentage	-0.128	**0.436**	0.167	-0.033	0.280	0.230
Base saturation percentage	-0.040	**0.475**	0.180	-0.098	0.145	0.151
Hot-water dissolved B content	-0.352	-0.006	-0.025	0.035	-0.266	-0.194
Easily reducible Mn content	0.186	0.291	0.149	-0.088	-0.267	-0.183
Acid-soluble Zn content	-0.278	0.217	-0.006	0.330	-0.235	-0.035
Acid-soluble Cu content	-0.021	0.273	0.127	0.194	**-0.482**	0.387
Solid content	0.173	0.255	**-0.506**	0.065	0.043	0.108
Bulk density	0.245	0.286	-0.409	0.068	0.050	0.101
Macropore ratio	-0.081	-0.025	**0.500**	0.200	0.115	-0.201
Available moisture	-0.076	-0.176	0.225	-0.164	-0.324	**0.546**

PC shows principal component.

Bold values under each component are highly weighted, and underlined bold values are selected in minimum data set.

Weight value is calculated as: variance / total cumulative proportion excluding PC2, 4, and 6 (0.463).

5.3.6. Relationship between weighted scores and Soil Quality Index.

Figure 5-2 presents a jitter plot illustrating the distribution of items selected for MDS and their sum, the SQI. The standard deviation of the SQI was 11.490, while the standard deviations of the weighted scores for individual items were as follows: 9.306 for exchangeable calcium content, 4.502 for acid-soluble copper content, and 2.796 for solid content. The reduction in the score for exchangeable calcium content, which had the largest weighted value and standard deviation, indicated its substantial impact on the reduction in SQI. In contrast, the weighted score for solid content, which had the next largest weighted value, showed a smaller standard deviation than acid-soluble copper content and a relatively minor impact on SQI.

ANOVA was performed to assess the effects of depth and soil type on the weighted scores and SQI of the MDS items (Table 5-5). The results indicated that SQI and the weighted scores for exchangeable calcium were significantly influenced by depth, with higher values observed at 0–30 cm. However, no significant interaction was found between depth and soil type. The weighted score for solid content showed a significant effect from soil type, depth, and their interaction. At 30–60 cm, the weighted score for solid content was significantly affected by soil type, with Peat soils exhibiting higher scores than Andosols.

Additionally, depth had a significant effect on the weighted score for acid-soluble copper content in Brown Lowland soils and Andosols, with higher values observed at 0–30 cm. However, neither the main effect of soil type nor the interaction between depth and soil type was found to be significant.

Table 5-5. SQI and weighted score of MDS

Soil type	Depth	Number of fields	SQI			Exchangeable Ca content score			Solid content score			Acid-soluble Cu content score	
	cm												
Brown Lowland soils	0-30	13	93.6 ± 10.8	*	a	51 ± 8	*	a	28 ± 2	*		14 ± 4	ab
	30-60	13	86.4 ± 8.7			46 ± 10			26 ± 3		AB	14 ± 3	
Andosols with alluvial deposits	0-30	4	88.6 ± 12.1	*	a	48 ± 8	*	a	27 ± 1			13 ± 4	ab
	30-60	4	87.8 ± 12.2			49 ± 7			27 ± 2		AB	12 ± 6	
Andosols	0-30	74	86.3 ± 11.3	*	a	45 ± 9	*	b	28 ± 2	*		13 ± 4	b
	30-60	74	81.4 ± 11.3			45 ± 9			25 ± 3		B	12 ± 5	
Peat soils	0-30	14	92.3 ± 7.5	*	a	48 ± 6	*	a	28 ± 2			16 ± 2	a
	30-60	14	84.1 ± 12.7			42 ± 10			28 ± 2		A	15 ± 4	

The data are presented as mean ± standard deviation.

The sign of * indicates significant difference between the depths, different lowercase letters indicate significant differences between the soil types, and uppercase letters indicate significant differences between the soil types in 30-60 cm depth ($p < 0.05$).

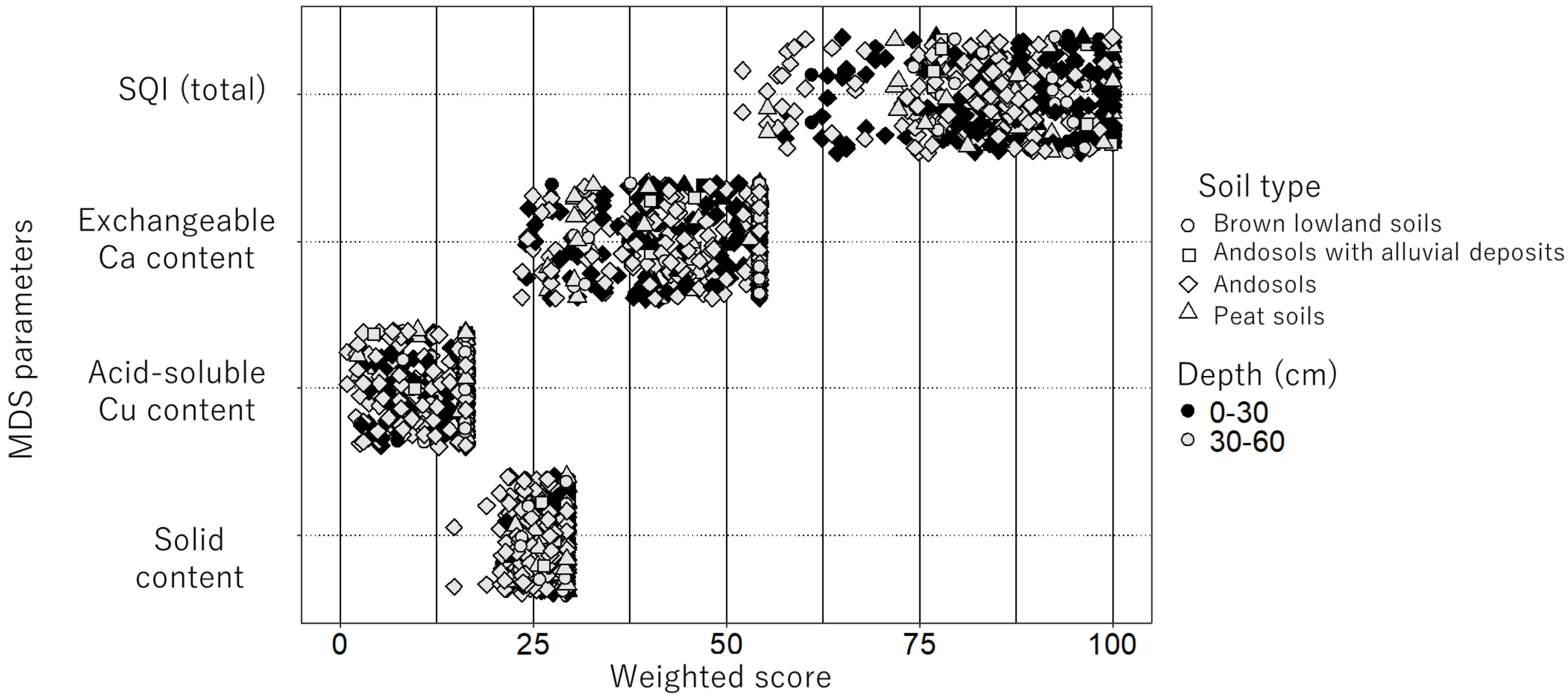

Figure5-2. Jitter plot showing weighted scores in minimum dataset (MDS)

5.3.7. Relationship between Soil Quality Index and yield considering surface soil thickness.

Figure 5-3 presents scatter plots of potato yield and SQI calculated using various methods in 2020. No significant correlation was found between potato yield and the SQI calculated for the 0–30 cm layer or the mean of the 0–30 cm and 30–60 cm layers (Figs. 5-3a and 5-3b). However, significant positive correlations were observed for both the depth corrected SQI and the simple corrected SQI, particularly for all cultivars combined and for the Sayaka cultivar (Figs. 5-3c and 5-3d).

Figures 5-4 and 5-5 display the scatter plots of potato yield and SQI for 2021 and 2022, respectively. In both years, no significant correlation was observed between yield and any SQI calculation method (Figs. 5-4a–d and 5-5a–d).

Figures 5-6, 5-7, and 5-8 illustrate the scatter plots of wheat yield and SQI calculated using various methods for 2021, 2022, and 2023, respectively. No significant correlation was detected between wheat yield and any SQI calculation method across all three years.

These results suggested that the correlation between SQI and crop yield might depend on the calculation method and the specific year or environmental conditions. While depth corrected and simple corrected SQIs showed promise for potatoes in 2020, their effectiveness varied across years and crops.

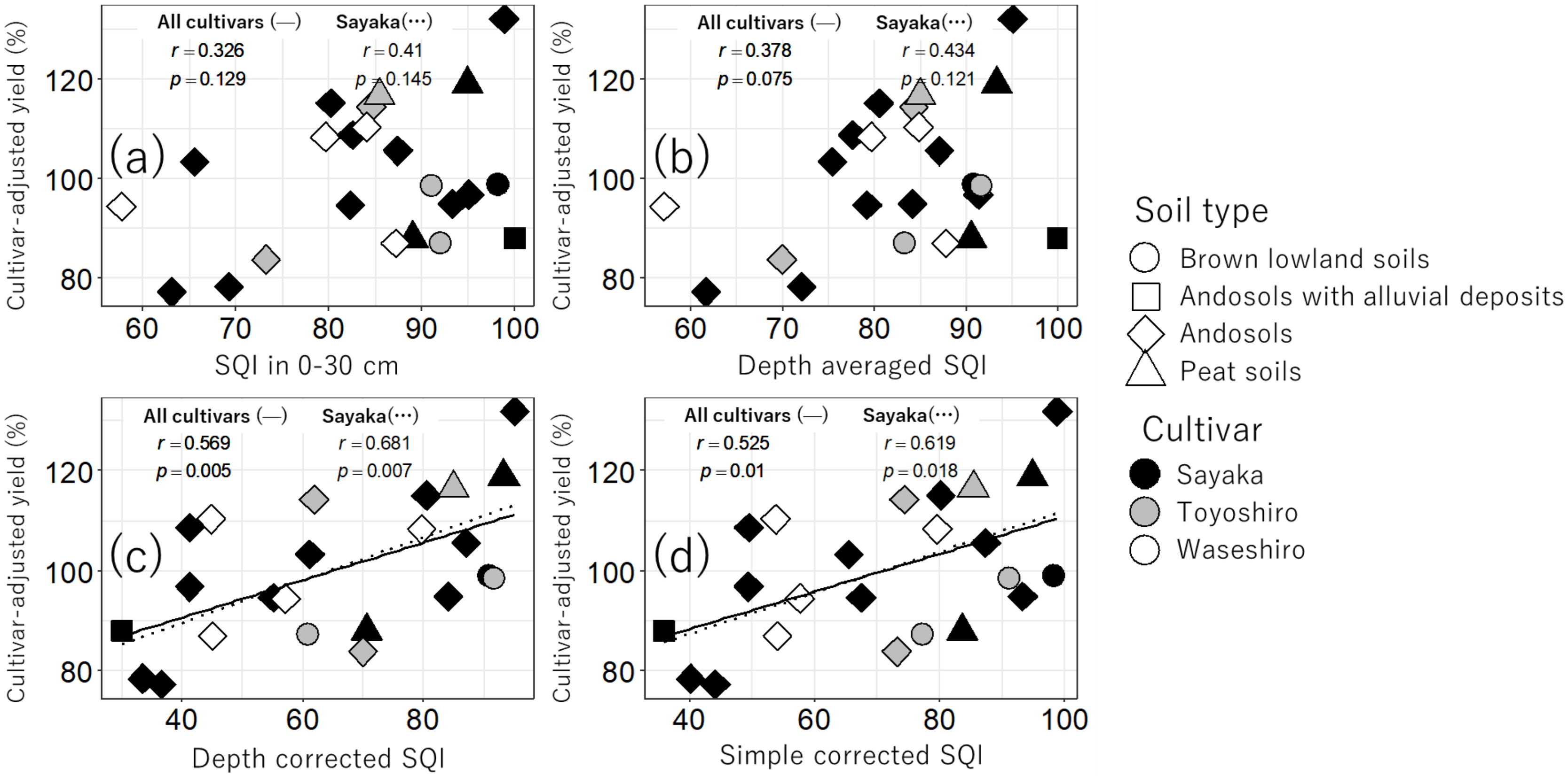

Figure 5-3. Scatter plots showing relationship between potato yield and SQI calculated by different methods in 2020

a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).

The cultivar-adjusted yield was calculated as the percentage of yield relative to the average yield of the cultivar.

Solid and dotted lines show significant correlations in all cultivars and Sayaka, respectively.

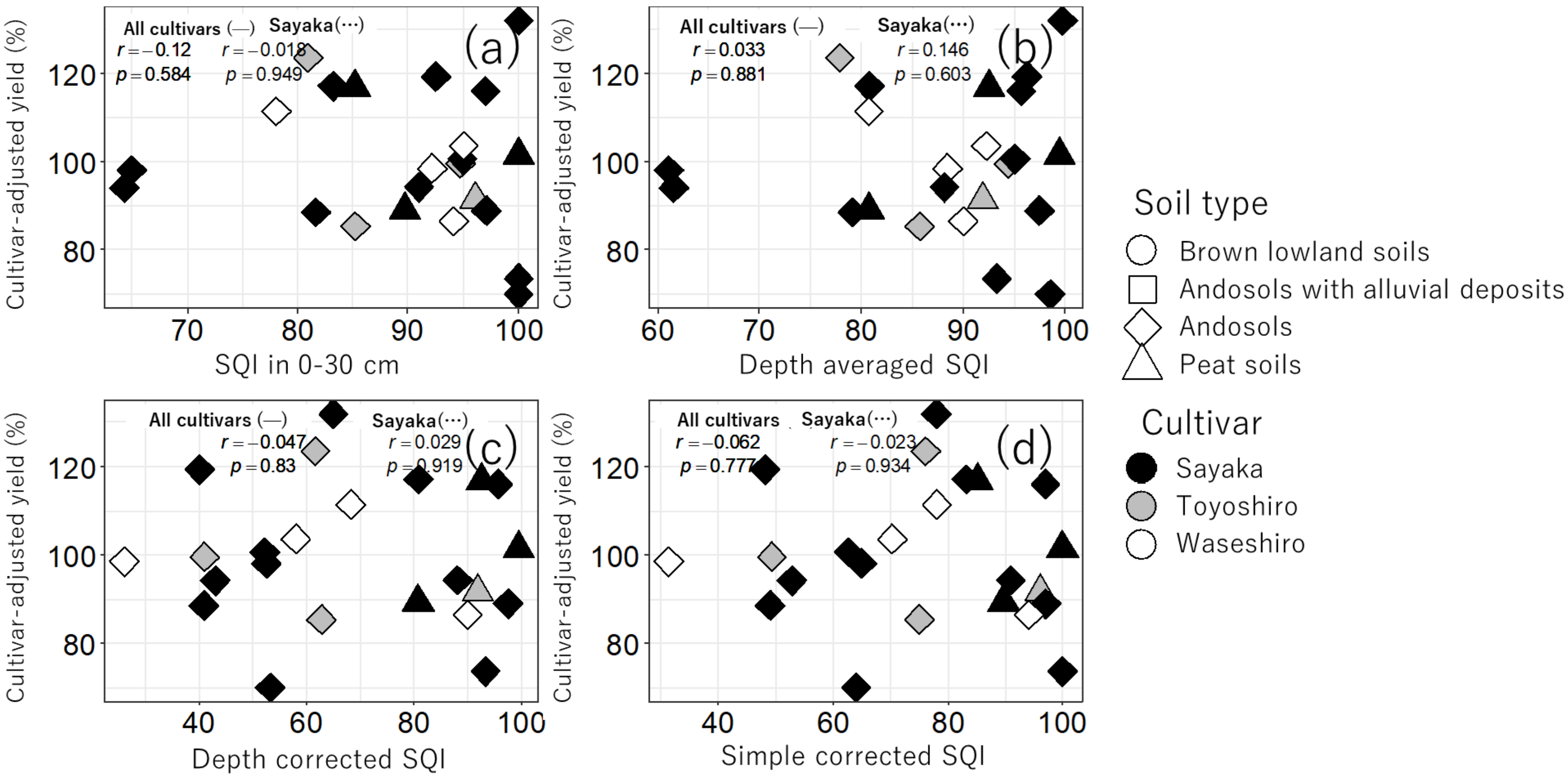

Figure 5-4. Scatter plots showing relationship between potato yield and SQI calculated by different methods in 2021

a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).

The cultivar-adjusted yield was calculated as the percentage of yield relative to the average yield of the cultivar.

Solid and dotted lines show significant correlations in all cultivars and Sayaka, respectively.

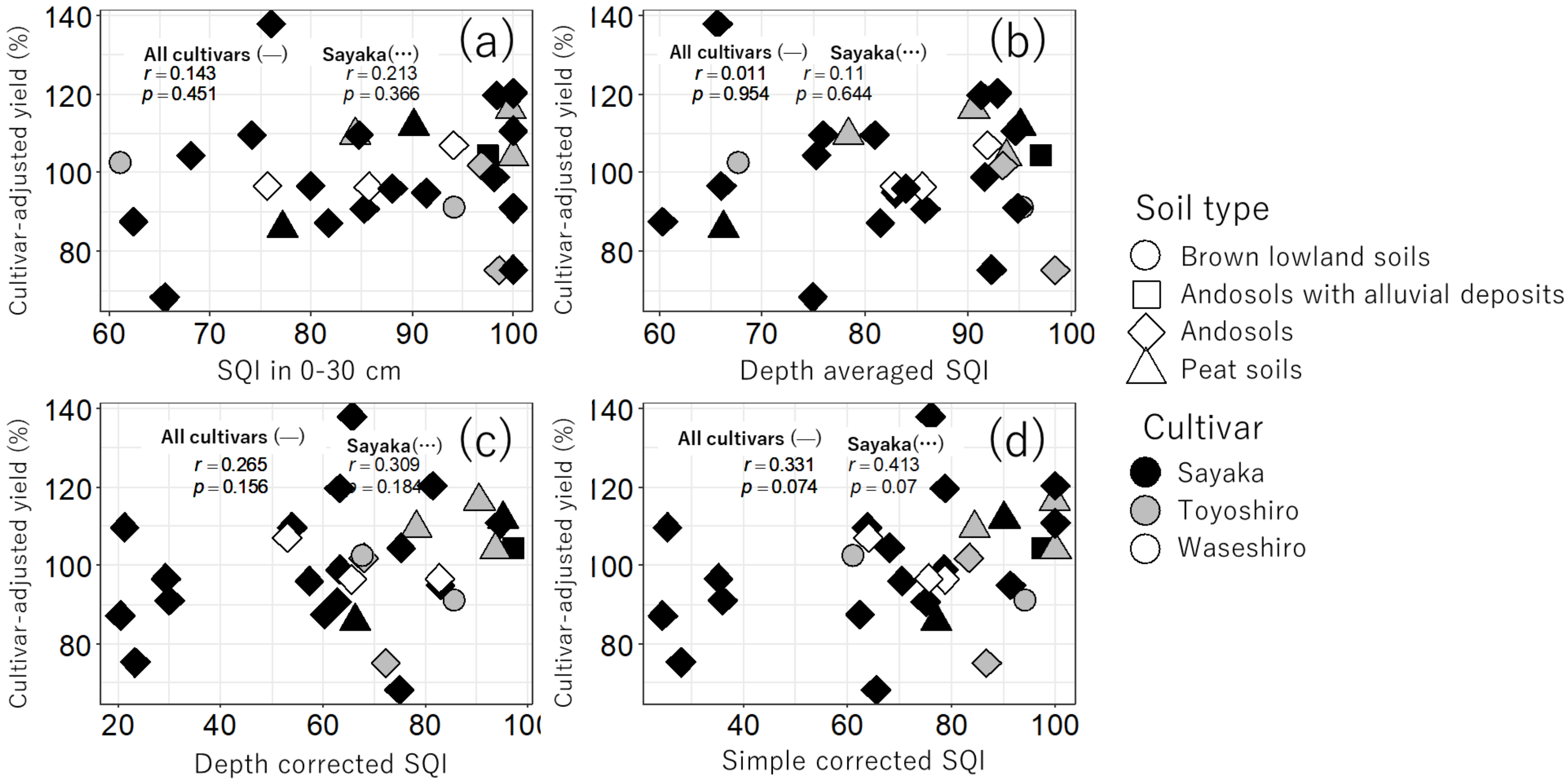

Figure 5-5. Scatter plots showing relationship between potato yield and SQI calculated by different methods in 2022

a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).

The cultivar-adjusted yield was calculated as the percentage of yield relative to the average yield of the cultivar.

Solid and dotted lines show significant correlations in all cultivars and Sayaka, respectively.

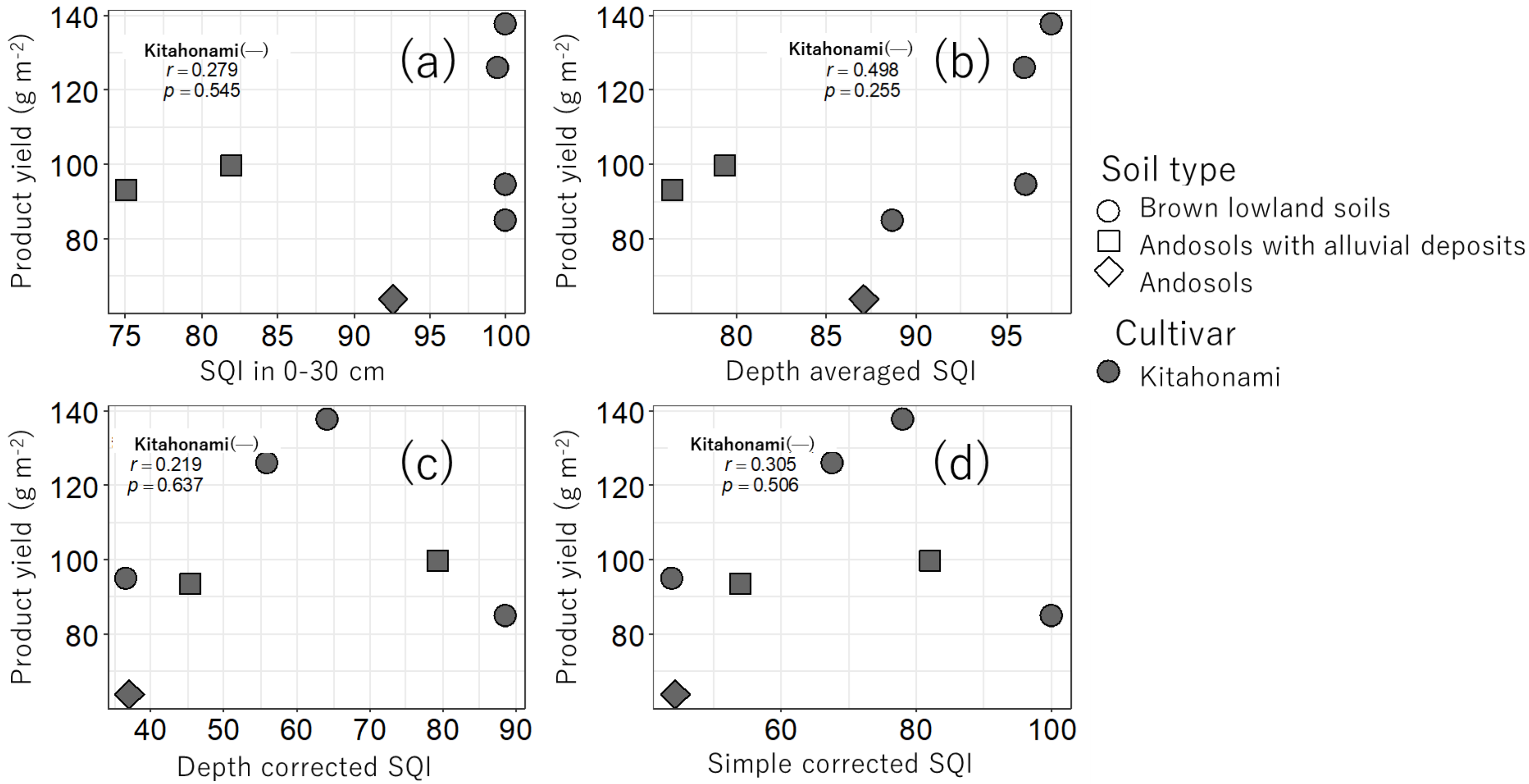

Figure 5-6. Scatter plots showing relationship between wheat yield and SQI calculated by different methods in 2021

a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).

Solid line shows significant correlation.

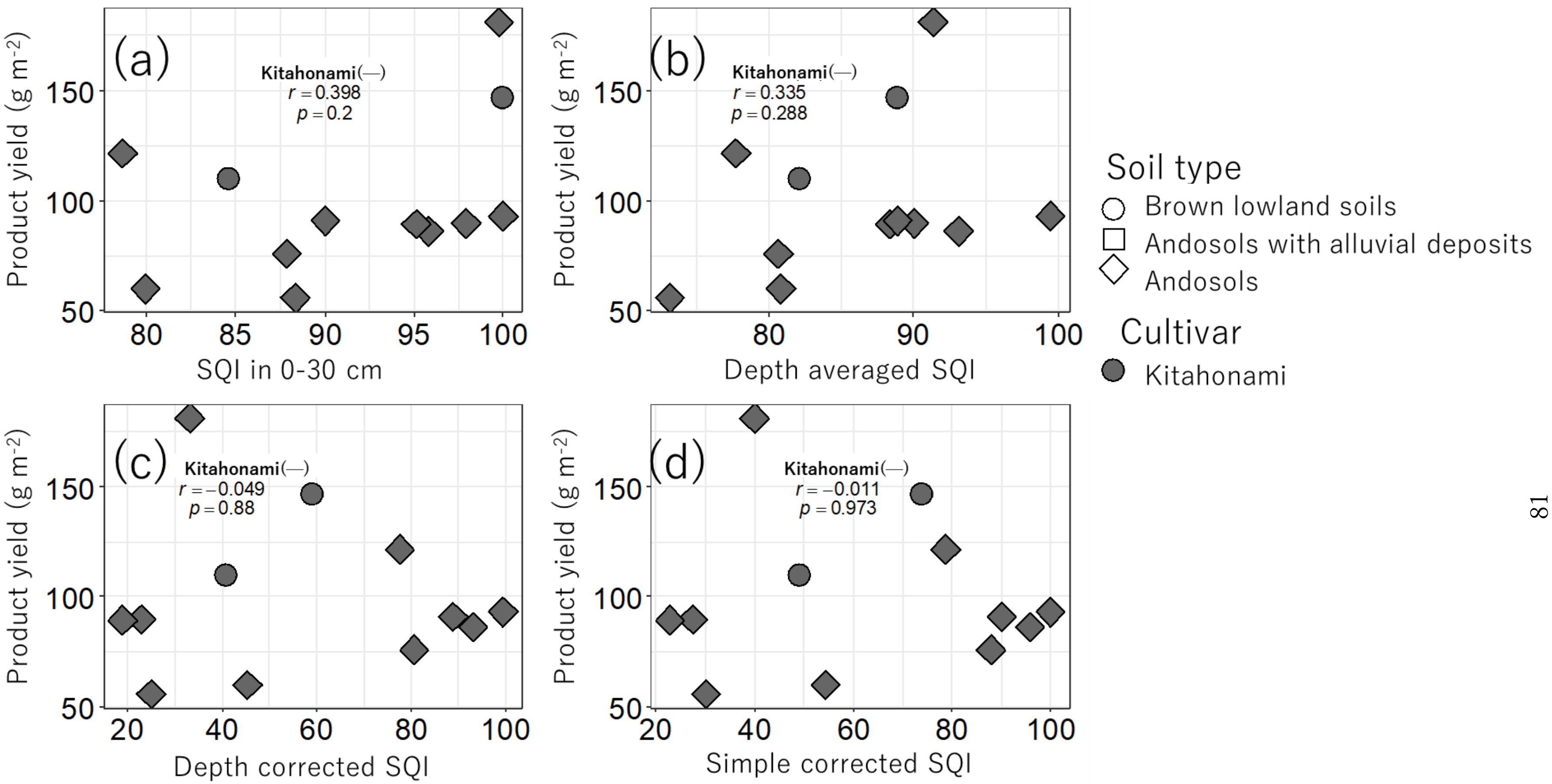

Figure 5-7. Scatter plots showing relationship between wheat yield and SQI calculated by different methods in 2022
a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).
Solid line shows significant correlation.

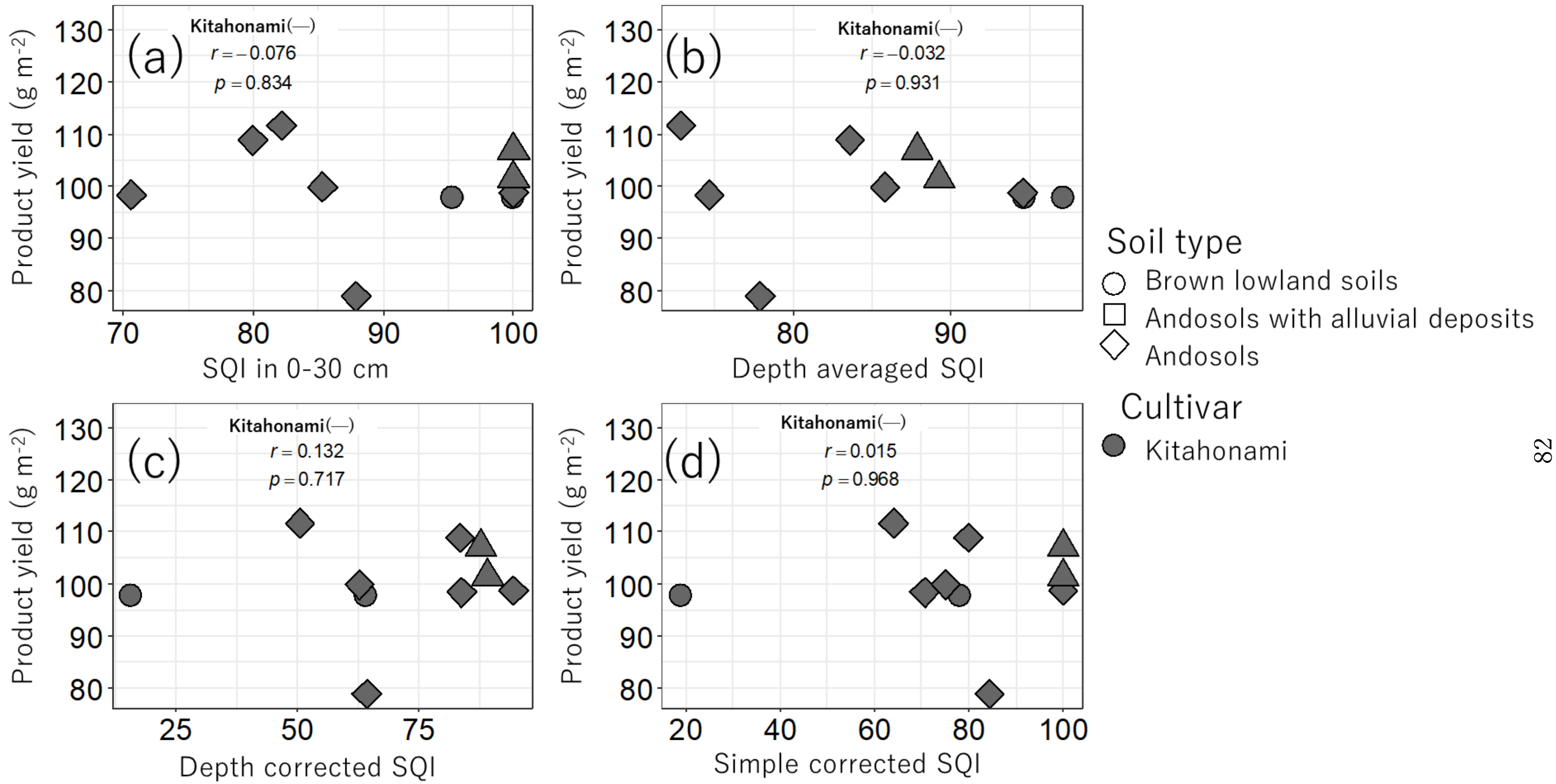

Figure 5-8. Scatter plots showing relationship between wheat yield and SQI calculated by different methods in 2023

a) SQI in 0-30 cm, b) average of SQI in 0-30 cm and 30-60 cm (depth averaged SQI), c) considering SQI in 0-30 cm and 30-60 cm and the surface soil layer depth (depth corrected SQI), and d) considering SQI in 0-30 cm and the surface soil layer depth (simple corrected SQI).

5.3.8. Comparison of the same fields in different harvest years

Two cases were identified in the same field during the three-year study: field IDs 23 and 73 (Case 1) and field IDs 13 and 72 (Case 2) (Table 5-6). The exchangeable calcium content and acid-soluble copper content, selected for the MDS, were calculated on a per-volume basis by incorporating bulk density.

In 2020, Case 1 was cultivated with potatoes and subsequently left fallow after the wheat harvest in 2022. By the time of soil sampling, the surface soil thickness had decreased from 32 cm to 15 cm. The exchangeable calcium content per volume showed no discernible change between the two years when averaged across the 0–30 cm and 30–60 cm depth intervals. The acid-soluble copper content per volume exhibited a reversal between the 0–30 cm and 30–60 cm layers but did not change significantly when averaged over the two depths.

In Case 2, the field was cropped with sugar beet in 2020 and with oat after the wheat harvest in 2022. By the time of soil sampling, the surface soil thickness had increased from 29 cm in 2020 to 46 cm in 2022, while the solid content decreased in both depth intervals. The exchangeable calcium content increased in both depths; however, its per-volume content decreased in the 0–30 cm layer. The acid-soluble copper content per volume increased substantially in both depths, resulting in an overall increase in the SQI.

These cases illustrate changes in soil quality over time influenced by cropping history, management practices, and shifts in physical and chemical properties.

The mean coefficient of variation (CV) for the SQI across both depth intervals of the fields was 0.081, which was comparable to the relative yield CV of 0.076 and lower than the CV of any MDS or CEC measurements, except for the exchangeable calcium content per volume (Table 5-6). Additionally, the mean CV of the SQI was lower than that of the weighted scores for the MDS parameters, except for the acid-soluble copper content.

In Case 2, the variation in the acid-soluble copper content was substantial, whereas the variation in its weighting score was relatively modest. This discrepancy can be explained by the fact that the measured values in 2020 were significantly above the lower threshold but did not exceed the upper threshold. Consequently, the weighting score was constrained to the highest possible score, leading to less variability in the weighted score despite the considerable variation in the measured values.

Table 5-6. Comparison of research cases in the same field in different year

											Coefficient of variance				
			Case 1				Case 2				Case 1		Case 2		Average
	ID		23		73		13		72						
	Harvest year		2020		2022		2020		2022						
	Soil type		Andosols				Andosols								
	Cultivar		Waseshiro		Sayaka		Sayaka		Waseshiro						
	Growing crop at sampling		Chinese yam		Bare field (after wheat)		Sugar beet		Oats (after wheat)						
	Cultivar relative yield	%	110.3		109.6		78.3		96.4		0.005		0.147		0.076
	Thicknes of surface soil	cm	32		15		29		46		0.512		0.321		0.416
	Depth	cm	0-30	30-60	0-30	30-60	0-30	30-60	0-30	30-60	0-30	30-60	0-30	30-60	
	SQI		84.0	85.6	84.7	77.1	69.3	74.9	85.7	85.4	0.006	0.074	0.150	0.092	0.081
Measurement	Bulk density	Mg m^{-3}	0.88	0.96	0.92	1.01	1.09	0.90	0.80	0.78	0.026	0.040	0.217	0.106	0.097
	CEC	$cmol_c$ kg^{-1}	17.6	17.5	16.1	17.5	19.1	20.5	16.6	13.3	0.061	0.003	0.099	0.300	0.116
	Exchangeable Ca content	mg kg^{-1}	1247	1386	1343	1186	1064	1027	1252	1244	0.052	0.110	0.115	0.135	0.103
		g m^{-3}	1102	1329	1231	1203	1155	926	998	965	0.078	0.071	0.103	0.029	0.070
	Solid content	$\times 10^{-2}$ m^3 m^{-3}	31.6	35.3	34.5	38.5	40.9	32.9	28.1	27.9	0.062	0.062	0.264	0.117	0.126
	Acid-soluble Cu content	mg kg^{-1}	4.92	2.29	2.94	4.28	0.59	0.66	2.44	3.25	0.356	0.428	0.863	0.937	0.646
		g m^{-3}	4.35	2.20	2.70	4.34	0.64	0.59	1.94	2.52	0.332	0.464	0.713	0.874	0.596
Weighted score	Exchangeable Ca content		39.8	44.3	42.9	37.9	34.0	32.8	40.0	39.7	0.052	0.110	0.115	0.135	0.103
	Solid content		27.9	25.0	25.6	22.9	21.5	26.8	29.4	29.4	0.062	0.062	0.218	0.066	0.102
	Acid-soluble Cu content		16.3	16.3	16.3	16.3	13.7	15.4	16.3	16.3	0.000	0.000	0.121	0.042	0.041

Cultivar relative yield means the yield ratio to the cultivar average in that year.

5.4. Discussion

5.4.1. Yield differences according to weather, variety and soil type in different years

As of 2023, Sayaka is regarded as an excellent potato cultivar for table use in Hokkaido, whereas Toyoshiro and Waseshiro are primarily cultivated for chipping purposes (Hokkaido Agriculture Department 2023). However, it is important to note that all fields included in this study were dedicated to producing potatoes intended for chipping.

According to the crop report by the Tokachi Agricultural Experiment Station, the yield ratios compared to the normal for the chipping potato cultivars Toyoshiro and Konafubuki were 94% and 91% in 2020, 103% and 109% in 2021, and 107% in 2022, respectively (Tokachi Agricultural Experiment Station 2020, 2021, 2022). In 2020, lower rainfall levels until mid-June resulted in shorter stem lengths compared to the normal, with delayed initial tuber growth identified as a contributing factor to the reduced yield. In 2021, higher-than-average temperatures from June onwards promoted longer stem growth. Despite extremely dry conditions and high temperatures in July causing stems to dry out, subsequent rainfall allowed for the recovery of stems and leaves, which likely contributed to the higher yield compared to the average. In 2022, yields were likely increased relative to the normal due to above-average temperatures from June onward, with the exception of early August. However, the analysis in this chapter did not find a significant effect of harvest year on potato yield (Table 5-2), suggesting various soil type and management by farmers effects on the yield.

An analysis of cultivars revealed that the yields of Sayaka, Toyoshiro, and Waseshiro were superior to that of Danshaku or comparable to Norin-1, which itself had a higher yield than Danshaku (Ministry of Agriculture, Forestry and Fisheries 2023a, Asama et al. 1975). Furthermore, the yield ratios of Sayaka and Waseshiro were 123% and 112%, respectively, compared to Danshaku (Asama et al. 1975, National Agricultural Research Organisation Hokkaido Agricultural Research Centre, Potato Breeding Group [Representative: Motoyuki Mori] 2018). This suggests that Sayaka is a higher-yielding cultivar than Waseshiro. Regarding soil type, all Waseshiro fields were located on Andosol, making it challenging to attribute the yield differences to soil type. These findings indicate that cultivar characteristics may have a stronger influence on potato yield variability than weather conditions or soil type.

The Tokachi Agricultural Experiment Station reported that the normal ratios of wheat yield were 138%, 93%, and 120% in 2021, 2022, and 2023, respectively (Tokachi Agricultural Experiment Station 2021, 2022, 2023). The yield in 2022 fell below expectations, resulting in a crop situation classified as slightly poor. In contrast, in both 2021 and 2023, the duration of sunshine exceeded the average throughout the growing season, leading to high yields. In 2022, crop conditions were normal to slightly good until early July; however, mid-July rainfall caused frequent lodging and poor grain filling.

5.4.2. Validity of the yield assessment according to the parameters selected for the Minimum Data Set.

The MDS was deemed an appropriate analytical tool in this chapter, consistent with its application in the previous chapter. This conclusion was based on the assumption that the selected parameters are relevant to crop productivity, as supported by existing scientific knowledge. Although the MDS selection in this chapter integrated data from both the 0–30 cm and 30–60 cm depths, it was concluded that the MDS could account for differences in depth when assessing soil quality. This was evident as solid content, a parameter significantly affected by depth, was included in the MDS (Table5-3). As in the previous chapter, the MDS in this chapter selected both physical parameters, representing the moisture conditions affecting root development (e.g., solid content), and chemical parameters, representing the nutrient conditions available for root absorption. The latter includes exchangeable calcium content and acid-soluble copper content, whose availability depends on component abundance and pH. In other words, this MDS was designed to reflect parameters that directly influence crop productivity.

Calcium functions not only as an essential element in plant cell walls but also as a component of signaling molecules that mediate plant responses to environmental stresses and hormones. Calcium has been shown to enhance potato yield and quality by strengthening cell walls and increasing heat stress tolerance (Palta 2010). The score for exchangeable calcium content, which had the greatest impact on the reduction in the SQI, was lower than the reference value in all but five samples (Fig. 5-2, Supplementary Table 2). In the Tokachi region, lime application has been discouraged to maintain soil pH at lower levels, which helps prevent common scab. The average soil pH of all samples was 5.58, within the reference range but close to the lower threshold. This suggests that the use of neutral materials could improve SQI by increasing the exchangeable calcium content, thereby enhancing potato yield and its stability.

Although the weighted scores for solid content were adequate in many fields, as indicated by low standard deviations, improving soil quality requires more than just reducing the solid content through tillage. Enhancing soil structure and improving drainage—through practices like reduced tillage intensity and the application of organic matter—would also be necessary.

The score for acid-soluble copper content was consistently below the reference value in all samples. Improving this score might involve copper supplementation or increasing soil total carbon content to lower the threshold of the soil diagnostic reference value. However, while not selected for the MDS, the exchangeable potassium content exceeded the reference value in many fields. Thus, when increasing total carbon content through the application of organic materials, exchangeable potassium content should also be carefully monitored.

Total carbon in soils is an important factor influencing numerous soil properties, including nutrient supply, aggregate stability, and moisture retention (Doran et al. 1998). Many studies have demonstrated improvements in soil quality through treatments that increase total carbon content (Dewi et al. 2022, Jung et al. 2008, Mardegan et al. 2022, Tirol-Padre et al. 2005, Yajuan et al. 2022). Furthermore, total carbon content has been widely identified as a potential indicator for SQI assessments (Bünemann et al. 2018). Although this chapter did not include total carbon as a candidate for the MDS, the diagnostic reference value for exchangeable calcium content was dependent on the value of cation exchange capacity (CEC), which had a strong positive correlation with total carbon ($r = 0.938$, $p < 0.001$). Since exchangeable calcium content was the most heavily weighted factor in the MDS for this chapter, it is reasonable to suggest that total carbon content may have a significant indirect impact on SQI. Moreover, increasing total carbon content could enhance soil quality by improving acid-soluble copper content scores, as discussed earlier.

Previous studies have reported that subsoils generally have lower soil quality compared to surface soils (Gozukara et al. 2022, Zhijun et al. 2018). Similar findings were observed in this chapter, regardless of soil type (Table 5-5). This may be because surface soils are more directly influenced by material applications, which help mitigate deficiencies in exchangeable calcium. Additionally, certain soil types may demonstrate a stronger effect of tillage in improving physical properties. However, when evaluating field soil quality by integrating SQIs from both depths, it can be inferred that subsoil also plays a role. At the same time, conducting soil surveys in multiple fields within limited timeframes remains critical. Therefore, an effort was made to assess the influence of subsoil by measuring the thickness of the surface soil.

5.4.3. Crop productivity assessment by Soil Quality Index considering the thickness of the crop soil layer.

Since the correlation between SQI and crop productivity was stronger in years with unfavorable weather conditions, as observed in the previous chapter, this discussion begins by focusing on the relationship between SQI and potato yield in 2020 and SQI and wheat yield in 2022, when crop conditions were below normal.

In 2020, potato yield exhibited a significant positive correlation with SQI when surface soil depth was considered, irrespective of soil type (Fig. 5-3c, d). Although no correlation was observed between potato yield and the mean SQI of the 0–30 cm and 30–60 cm depths (Fig. 5-3a, b), a significant positive correlation was found when using the simple corrected SQI (Fig. 5-3d). This indicates that surface soil thickness is a more critical factor for assessing crop productivity than the SQI of the 30–60 cm layer. The same result was observed when the analysis focused on the Sayaka dataset, with an improved correlation coefficient, further highlighting the importance of considering surface soil thickness. While the correlation was relatively weak, the result that single soil index expressed yield variation to some degree should be notable because yield could be limited by various reasons such as difference of cultivation practice.

In the Tokachi region, precipitation during the growing season and poor drainage have been identified as factors that reduce yield (Niwa et al. 2008). Increasing the thickness of surface soil has been observed to enhance pore space available for water retention, which is hypothesized to improve crop productivity. However, this chapter did not examine the distribution of plant roots with depth, raising concerns that the observed surface soil thickness may not fully correspond to root development. The SQI proposed in this chapter, which incorporates surface soil thickness, was unable to reliably assess crop productivity in scenarios where yields were high, and plant roots developed well in thin topsoil. Addressing this limitation represents an area for future research.

In contrast, the analysis of wheat yield in 2022 revealed no correlation between SQI and yield, regardless of whether surface soil thickness was included in the assessment. In 2018, when wheat yield was low, the Tokachi Agricultural Experiment Station reported that yields were 78% of the normal level (Tokachi Agricultural Experiment Station 2018). In comparison, yields in 2022 were 93% of the normal level, suggesting that weather conditions in 2022 may not have been sufficiently adverse to reveal a discernible relationship between SQI and yield.

On the other hand, analyzing the relationship between SQI and crop productivity in 2021 and 2022 for potatoes, and in 2021 and 2023 for wheat—when crop conditions were superior to those of a normal year—revealed no significant correlation, regardless of whether surface soil thickness was included as a variable. This finding aligns with the significant correlations observed between yield and SQI during unfavorable weather conditions, as discussed in the previous chapter. It suggests that the impact of weather conditions on crop yield is greater than the effect of soil quality under favorable conditions.

The SQI, which incorporated surface soil thickness, was effective in assessing crop productivity only in years with unfavorable weather conditions, regardless of soil type or cultivar. When focusing on a single cultivar, Sayaka, the correlation between SQI and yield was strengthened. However, this analysis involved a reduced number of fields, limiting the robustness of the relationship. To establish more generalized correlations, it will be essential to accumulate additional field data, particularly from years with adverse weather conditions. The yield in inferior climate condition did not show significant positive correlation with SQI in 0-30 cm but depth corrected SQI as opposed to the yield showed significant positive correlation with SQI in 0-30 cm in Chapter 4. That might be caused by the fact that fields covered in this chapter contain more Andosols, which was considered to have better physical properties and a thick surface layer, than Chapter 4.

5.4.4. Changes in Soil Quality Index and Minimum Data Set scores over time

A comparison of the data from two cases studied in the same field, as presented in Table 5-6, revealed a decrease in SQI in Case 1 and an increase in SQI in Case 2. A significant distinction between the two cases was the presence or absence of plowing following the wheat harvest at the time of sampling in 2022. In Case 1, a decrease in SQI within the 30–60 cm depth was observed, attributed to densification caused by the absence of tillage. However, no significant changes were detected in the exchangeable calcium content or acid-soluble copper content per volume across the entire 0–60 cm depth. In contrast, Case 2 involved plowing in 2022, which resulted in an increase in soil thickness and reductions in both the solid content and bulk density across the 0–30 cm and 30–60 cm depth intervals. The exchangeable calcium content scores increased in 2022, but the exchangeable calcium content per volume decreased in the 0–30 cm depth, remained unchanged in the 30–60 cm depth, and decreased overall across the two depths. These findings suggest that calcium was being absorbed by the sugar beet crop. However, the scoring methodology assessed nutrient concentrations per soil weight, which introduced some inaccuracies in estimating nutrient status. This discrepancy was evident in the decline of exchangeable calcium content per volume and the appearance of deficiencies, despite the higher scores. Additionally, there was a noticeable increase in acid-soluble copper content per volume, indicating the likelihood of copper supplementation.

The CV of the SQI was generally smaller than that of any measured values or weighted scores in the study cases from the same field. This suggests that the SQI is a relatively robust soil evaluation index, even when the year of measurement differs from that presented in Chapter 4. However, unlike in Chapter 4, the mean CV of bulk density was higher than that of the SQI. This discrepancy was likely due to soil sampling in this chapter being conducted after the harvest period, with differences in the presence or absence of plowing between fields and years further contributing to the variation. The CV of measured exchangeable calcium content per volume was lower than that of the SQI, indicating that assessing nutrient content per volume may better explain the soil's nutrient status. This approach accounts for changes in physical properties, such as those resulting from tillage and wet-drying cycles (Czarnes et al. 2000).

A comparison of the two cases demonstrated that changes in SQI and MDS scores over time were influenced by nutrient absorption by sugar beet but were more strongly affected by the presence or absence of tillage and material inputs at the time of soil sampling. This case study showed that the SQI is already robust against temporal changes. However, the diagnostic reference could be improved by converting reference values to content per volume. Currently, as soil diagnostic reference values are expressed in units of content per soil weight, calculating the SQI based on content per volume presents a challenge. The Hokkaido Fertilizer Guide (2020) recommends conducting soil sampling to measure solid content and bulk density prior to tillage. Based on this guidance, it is advisable to avoid soil sampling immediately after tillage when evaluating the SQI. Whether the effort required to improve the robustness of the SQI by converting reference values to content per volume is justified by the resulting enhancements remains a question for future consideration.

5.4.5. Notes and prospects for soil crop productivity assessment using Soil Quality Index

The results in this study and comparison with the crop report by the Tokachi Agricultural Experiment Station as discussed above clarified the SQI effectively assessed crop productivity during years with less favorable weather conditions, highlighting that weather had a stronger impact on crop productivity than soil quality. The analysis also revealed that soil quality influenced crop productivity when weather conditions had a weaker effect on yield increases, particularly when the soil's yield potential was reached.

Additionally, soil quality can be evaluated without sampling at depths of 30–60 cm by considering the thickness of the surface soil. While this approach maintains a significant correlation with crop productivity, the correlation coefficient may decrease slightly. Therefore, the continued collection of data on soil physical properties, surface soil thickness, and soil chemistry remains essential for future field studies. Developing a method to estimate physical properties from disturbed soil using pedotransfer functions (Reidy et al. 2016) would be highly beneficial. This would enable to soil sampling for assess soil quality more effective, eliminating undisturbed soil sampling. It would facilitate the accumulation of data from a larger number of fields.

5.5. Conclusion.

The impact of correcting for surface soil thickness on the calculation of the SQI was examined in potato and wheat fields, where soil quality was evaluated based on the presence or absence of desirable or undesirable physicochemical properties. The findings revealed that, in years with poor crop yields, surface soil thickness was a more significant factor than soil quality at depths of 30–60 cm for predicting crop productivity in potato fields.

As observed in the previous chapter, the correlation between SQI and yield was strong in potato fields during years with poor weather and crop conditions. This suggests that soil quality has the potential to assess the productivity potential of soil, although its influence remains weaker than that of weather conditions. Conversely, the lack of correlation between SQI and yield in wheat fields in this chapter may be attributed to the more favorable crop conditions compared to those in Chapter 4.

To enhance the validity of crop productivity assessments using SQI, it would be advantageous to accumulate additional field data, particularly from years with unfavorable weather conditions. Moreover, soil sampling immediately after plowing should be avoided. This is because soil diagnostic reference values are expressed in terms of soil content per weight, while plowing significantly alters the nutrient content per volume, potentially leading to inaccuracies.

6. Estimation of the relationship of soil physicochemical properties scores and Soil Quality Index to long-term soil carbon storage capacity

6.1. Introduction

The objective of this chapter was to develop the Soil Quality Index (SQI) discussed in Chapters 4 and 5 into a comprehensive soil health assessment. This was achieved by estimating long-term soil carbon storage capacity using equations from existing literature and relating it to soil physicochemical scores and SQI. As noted in Chapter 2, distinguishing between intrinsic and dynamic soil quality and soil health is essential for understanding the relationships between soil properties and their associated characteristics. However, no previous reference has addressed potential differences in the area scale of soils under consideration. The term "soil quality" typically refers to the condition of soil within defined boundaries, such as arable land or forests. In contrast, "soil health" encompasses broader attributes, including ecological considerations, and evaluates whether soil functions are appropriately performed at a landscape or global scale. Thus, soil health represents a higher-scale concept compared to soil quality. Extending the assessment of soil quality to encompass soil health involves examining material cycles on a landscape or global scale to determine the feasibility of sustainable cycles.

Key cyclical substances related to agricultural production include water, carbon (C), and nitrogen. Notably, Earth's soils store approximately 1,700 Pg of carbon, forming a vast reservoir compared to the atmosphere (870 Pg C) and above-ground vegetation (450 Pg C). Even minor changes in soil carbon can significantly impact climate change (Canadell & Koven 2021). Carbon is commonly applied to agricultural fields as organic matter, such as compost, to enhance soil physicochemical properties (soil quality). However, excessive carbon inputs may result in carbon loss to groundwater or the atmosphere, thereby limiting soil's carbon storage function at a landscape scale. Similarly, applying nitrogen-rich compost can lead to nitrogen leaching, wasting valuable resources and creating an environmental burden. Determining and applying field-specific organic matter inputs on a landscape scale could optimize carbon cycling, reduce environmental impact, and enhance soil health. Mineral-associated organic matter (MAOM), organic matter adsorbed onto secondary mineral fractions, is particularly important for long-term soil carbon sequestration. Its carbon (mineral-associated organic carbon, MOC) exhibits turnover rates spanning decades to centuries (Feng et al. 2016). MAOM can be fractionated through size and density methods after soil sonication, isolating dense fractions (below 50 μm, 1.6–1.8 g/cm³, Wagai 2024). In contrast, litter and particulate organic matter (POM) are separated as low-density fractions. The maximum amount of MOC (MOC_{max}) depends on the surface area and properties of secondary minerals. Soils with low MOC saturation (C_{sat}: the ratio of present MOC to MOC_{max}) are hypothesized to store carbon more efficiently, as incoming carbon occupies vacant spaces on the mineral surface (Georgiou et al. 2022). Similarly, fields with higher MOC deficits (C_{def}: the difference between MOC_{max} and MOC) have greater potential for organic matter inputs. However, few studies have examined MOC_{max} in Andosols, which are prevalent in Japanese agricultural lands. Georgiou et al.'s (2022) model, based on global soil data excluding Andosols, estimates MOC_{max} from clay and silt content but exhibits reduced accuracy for Andosols. This limitation underscores the unique properties of Andosols, including carbon adsorption on amorphous or less-crystalline allophane surfaces (independent of grain size, Beare et al. 2014), mesopore network structures in secondary mineral particles (Mayer et al. 2004, McCarthy et al. 2008), and carbon occlusion and aluminum-complex precipitation (Chevallier et al. 2010, Scheel et al. 2007).

The goal of this chapter was to estimate the long-term soil carbon storage capacity of Japanese agricultural lands and assess the compatibility of organic matter inputs aimed at improving soil physicochemical scores and SQI with enhancing long-term soil carbon storage.

6.2. Materials and methods

6.2.1. Soil sample

To compare the long-term soil carbon storage capacity at different soil sampling depths, data from soil samples collected in Makubetsu Town, Tokachi region, Hokkaido, Japan, as described in Chapter 5, were utilized. The soil types were identified based on the results of the Fundamental Soil Survey for Soil Fertility Conservation. However, these classifications did not necessarily correspond to the actual soil types at the sampling fields.

6.2.2. Methods for calculating soil physicochemical properties score and Soil Quality Index.

The same Minimum Data Set (MDS) parameters and their respective weights as those used in Chapter 5 were applied. Specifically, the MDS included exchangeable calcium content, solid content, and acid-soluble copper content, with weights of 0.543, 0.294, and 0.163, respectively. The SQI was calculated as the sum of the weighted scores.

6.2.3. Methods for calculating long-term soil carbon storage capacity.

The estimation of MOC_{max}, MOC, C_{sat}, and C_{def} was conducted with reference to the relational equations and datasets provided by Georgiou et al. (2022). Since the equations were developed for mineral soils, soils with a total carbon content of 120 g kg^{-1} or more were classified as non-mineral soils, belonging to the organic soil group under the Japanese soil classification system (Obara et al. 2011). As a result, fields with such soils at either the 0–30 cm or 30–60 cm depth were excluded from the analysis. The equation relating clay and silt content to MOC_{max} accounted for the activity of clay minerals. Both Flubisols and Andosols (classified as Entisols and Andisols in Soil Taxonomy, Soil Survey Staff 2022), the soils of interest in this study, were considered to have highly active minerals. Georgiou et al. (2022) constructed global soil data set and developed model to estimate MOC_{max} from clay and silt content. The data set also showed relationships between total carbon and MOC depending on soil types. Referring to this global data set, MOC_{max} (g C kg^{-1}) was calculated by multiplying clay and silt content (%) by 86. Additionally, MOC was estimated to constitute 32.35% of total carbon in Andosols and 48.77% in non-Andosols, based on the proportions observed in the Georgiou et al. (2022) dataset. Soils with a phosphate absorption coefficient of 15,000 mg P_2O_5 kg^{-1} or greater were classified as Andosols, while the remaining soils were categorized as non-Andosols. C_{sat} (%) was calculated as the percentage of MOC to MOC_{max}, while C_{def} (g C kg^{-1}) was determined as the difference between MOC_{max} and MOC.

6.2.4. Validation of the maximum amount of MOC estimates using clay silt content.

Before examining the relationship between SQI and soil physicochemical properties for MOC, MOC_{max}, C_{sat}, and C_{def}, the validity of the soil texture data used to estimate MOC_{max} was evaluated. In the estimation of MOC_{max}, clay and silt dispersion was performed using dispersants only, without ultrasonic dispersion. To verify whether ultrasonic dispersion was necessary, one Andosol sample (ID: W09, 0–30 cm depth) and one Brown Lowland soil sample (ID: W21, 0–30 cm depth) were sonicated in 1.6 g cm^{-3} sodium polytungstate. Following sonication, the heavy fraction (>1.6 g cm^{-3}) obtained after centrifugation was isolated, and the percentage of the fraction retained on a 53 μm sieve (generally classified as the sand fraction) was measured. This result was then compared with the soil texture data analyzed in Chapter 3. Ultrasonic dispersion was performed using an ultrasonic generator (SFX 250, Branson Ultrasonics Corp., Brookfield, CT, USA) at an intensity of 800 J mL^{-1}. To align with the USDA soil classification system, the sand fraction (20–2000 μm) defined by the International Soil Science Society was converted to the sand fraction (50–2000 μm) using the conversion formula proposed by Takahashi et al. (2020).

6.2.5. Statistical analysis method

R version 4.0.2 (R Core Team 2021) was used for statistical analysis. Since the distributions of MOC, MOC_{max}, C_{sat}, and C_{def}, calculated by combining clay-silt content and total carbon content, could not be assumed to follow a normal distribution, non-parametric methods were employed. Specifically, a mixed two-way Analysis of Variance (ANOVA) after aligned rank transform was performed, with soil type as a between-subjects factor and sampling depth as a within-subjects factor (Wobbrock et al. 2011). When no significant interaction was observed, multiple comparison tests with corrected p-values using Holm's method were conducted for significant differences in soil type, and Wilcoxon's signed rank test was applied for significant differences in sampling depth. When a significant interaction was found, the same tests were performed separately for each level of soil type and sampling depth. The relationship between MOC, MOC_{max}, C_{sat}, and C_{def} and the weighting score or SQI was evaluated by calculating Pearson's product-moment correlation coefficient. All statistical tests were conducted at a 5% significance level.

6.3. Results

6.3.1. Estimation of long-term soil carbon storage capacity

The ten fields identified as non-mineral soils were designated as follows: ID 1, 10, 16, 24, 29, 48, 49, 52, 64, and W29. All of these fields were classified as Peat soils. The results presented below pertain only to fields excluded from the aforementioned non-mineral soil group.

The mean MOC across all soil types and depths was 13.9 g C kg^{-1}, with the highest values observed in Peat soils and the lowest in Andosols (Table 6-1). Sampling depth had a significant effect, with the greatest MOC observed at the 0–30 cm depth but in the case of Andosols with alluvial deposits and Andosols.

The mean MOC_{max} across all soil types and depths was 43.3 g C kg^{-1}, with the highest values observed in Peat soils and the lowest in Andosols (Table 6-1). Sampling depth had a significant effect, with the greatest MOC_{max} observed at the 0–30 cm depth.

The mean C_{sat} for all soil types and depths was 31.0%, with the highest values in Peat soils and the lowest in Andosols. Sampling depth also had a significant effect on C_{sat}, which was higher in the 0–30 cm layer (Table 6-1).

Regarding C_{def}, sampling depth had a significant effect, with higher values observed at the 0–30 cm depth, but only in the case of Andosols. The differences between soil types for C_{def} were not statistically significant (Table 6-1).

Table 6-1. The comparison of SQI and carbon sequestration conditions with soil types or depth excluding non-mineral soils

Soil type	Depth (cm)	Number of fields	SQI			MOC (g C kg^{-1})			MOC_{max} (g C kg^{-1})			C_{sat} (%)			C_{def} (g C kg^{-1})		
Brown Lowland soils	0-30	13	93.6 ± 10.8	*	a	16.3 ± 9.0		bc	48.4 ± 10.4	*	abc	34.3 ± 18.6	*	ab	32.1 ± 13.3		a
	30-60	13	86.4 ± 8.7			12.7 ± 9.6			45.3 ± 14.9			29.3 ± 19.9			32.5 ± 16.3		
Andosols with alluvial deposits	0-30	4	88.6 ± 12.1	*	a	20.7 ± 7.8	*	ab	55.3 ± 1.9	*	ab	37.0 ± 12.8	*	ab	34.7 ± 6.0		a
	30-60	4	87.8 ± 12.2			18.1 ± 9.4			52.2 ± 6.0			33.7 ± 14.4			34.1 ± 5.5		
Andosols	0-30	74	86.3 ± 11.3	*	a	13.4 ± 7.7	*	c	43.1 ± 8.5	*	c	30.4 ± 14.7	*	b	29.7 ± 7.4	*	a
	30-60	74	81.4 ± 11.3			11.8 ± 7.5			39.8 ± 8.8			28.4 ± 14.3			28.0 ± 6.6		
Peat soils	0-30	4	88.0 ± 9.5	*	a	34.6 ± 16.9		a	55.0 ± 10.8	*	a	60.7 ± 20.6	*	a	20.4 ± 9.3		a
	30-60	4	75.7 ± 18.4			26.9 ± 10.4			54.7 ± 15.3			48.5 ± 8.1			27.8 ± 6.9		
All soil except for non-mineral one	0-30	95	87.5 ± 11.3			15.0 ± 9.4			44.9 ± 9.3			32.5 ± 16.4			29.9 ± 8.6		
	30-60	95	82.1 ± 11.4			12.8 ± 8.5			41.7 ± 10.7			29.6 ± 15.3			28.8 ± 8.6		
	All	190	84.8 ± 11.7			13.9 ± 9.0			43.3 ± 10.1			31.0 ± 15.9			29.3 ± 8.6		

MOC: mineral-associated organic carbon, MOC_{max}: maximum mineral-association organic carbon, C_{sat}: carbon saturation ratio, C_{def}: carbon deficiency

The data are presented as mean ± standard deviation. Different letters indicate significant differences among the cultivars ($p < 0.05$).

The sign of * indicates significant difference between the depths and different letters indicate significant differences between the soil types ($p < 0.05$).

6.3.2. Validation of the maximum amount of MOC estimates using clay silt content

The application of ultrasonic dispersion resulted in a significant reduction in the percentage of sand fractions in the USDA system for the Andosol sample, decreasing from 42.1% (55.6% using the international method) to 27.4%. In contrast, the change in the Brown Lowland soil sample was less pronounced, with sand fractions decreasing from 32.8% (40.7% in the international method) to 29.4%. This suggests that the dispersant (sodium hexametaphosphate) alone was insufficient to fully disperse sand-sized aggregates in the Andosols, potentially leading to an overestimation of sand content.

A comparison of MOC_{max} by soil type revealed that Andosols exhibited significantly lower values than other soil types, accompanied by a higher calculated sand content (Table 6-1). This discrepancy likely reflects insufficient dispersion of aggregates during soil texture analysis, where clay or silt particles may have been erroneously classified as sand.

To address this issue, the results presented in this chapter excluded data from non-mineral soils across all soil types and focused specifically on Brown Lowland soils.

6.3.3. Correlations of soil physicochemical properties scores and Soil Quality Index with long-term soil carbon storage capacity.

Figure 6-1 illustrates the relationship between MOC, MOC_{max}, C_{sat}, C_{def}, and SQI, while Figure 6-2 shows the same relationships divided by sampling depth. When sampling depths were not distinguished, the SQI showed no significant correlation with MOC_{max} or C_{def} (Fig. 6-1b, d) and significant but weak negative correlations with MOC and C_{sat} (Fig. 6-1a, c). When analyzed by sampling depth, MOC and C_{sat} showed significant negative correlations with SQI at the 30–60 cm depth (Fig. 6-2b, f), whereas other correlations were not significant (Fig. 6-2a, c, d, e, g, h).

The relationships between MOC, MOC_{max}, C_{sat}, C_{def}, and the MDS weighting scores are shown in Figures 6-3, 5, and 7, with depth-specific relationships presented in Figures 6-4, 6-6, and 6-8. Weighted scores for exchangeable calcium content showed no correlation with MOC, MOC_{max}, C_{sat}, or C_{def}, irrespective of sampling depth (Fig. 6-3, 6-4).

The weighted score for solid content displayed a significant positive correlation with MOC and C_{sat} and a significant negative correlation with C_{def} when sampling depths were not distinguished, but no correlation with MOC_{max} (Fig. 6-5). When sampling depths were differentiated, correlations with MOC_{max} at both depths and with C_{def} at 30–60 cm became non-significant (Fig. 6-6c, d, h). However, significant positive correlations were observed with MOC and C_{sat} at both depths, and significant negative correlations with C_{def} were found at the 0–30 cm depth (Fig. 6-6a, b, e, f, g).

For acid-soluble copper content, the weighted score showed significant negative correlations with MOC and C_{sat} and a significant positive correlation with C_{def} when sampling depths were not distinguished (Fig. 6-7a, c, d). When sampling depths were differentiated, the correlation with C_{def} at 0–30 cm became non-significant (Fig. 6-8g), while a weak significant negative correlation with

MOC_{max} was identified at 0–30 cm (Fig. 6-8c). Conversely, significant negative correlations with MOC and C_{sat} at both depths and a significant positive correlation with C_{def} at 30–60 cm were observed (Fig. 6-8a, b, d, e, f, h).

For Brown Lowland soils, where sand content measurements were validated, Figure 6-9 presents the relationships between MOC, MOC_{max}, C_{sat}, C_{def}, and SQI, while Figures 6-10, 11, and 12 show the relationships with MDS weighting scores. MOC, MOC_{max}, C_{sat}, and C_{def} showed no significant correlation with SQI or the weighted score for exchangeable calcium content (Fig. 6-9, 6-10). The weighted score for solid content displayed significant positive correlations with MOC and C_{sat}, a significant negative correlation with C_{def}, and no correlation with MOC_{max} (Fig. 6-11). For acid-soluble copper content, the weighted score showed significant negative correlations with MOC and C_{sat}, a significant positive correlation with C_{def}, and no correlation with MOC_{max} (Fig. 6-12).

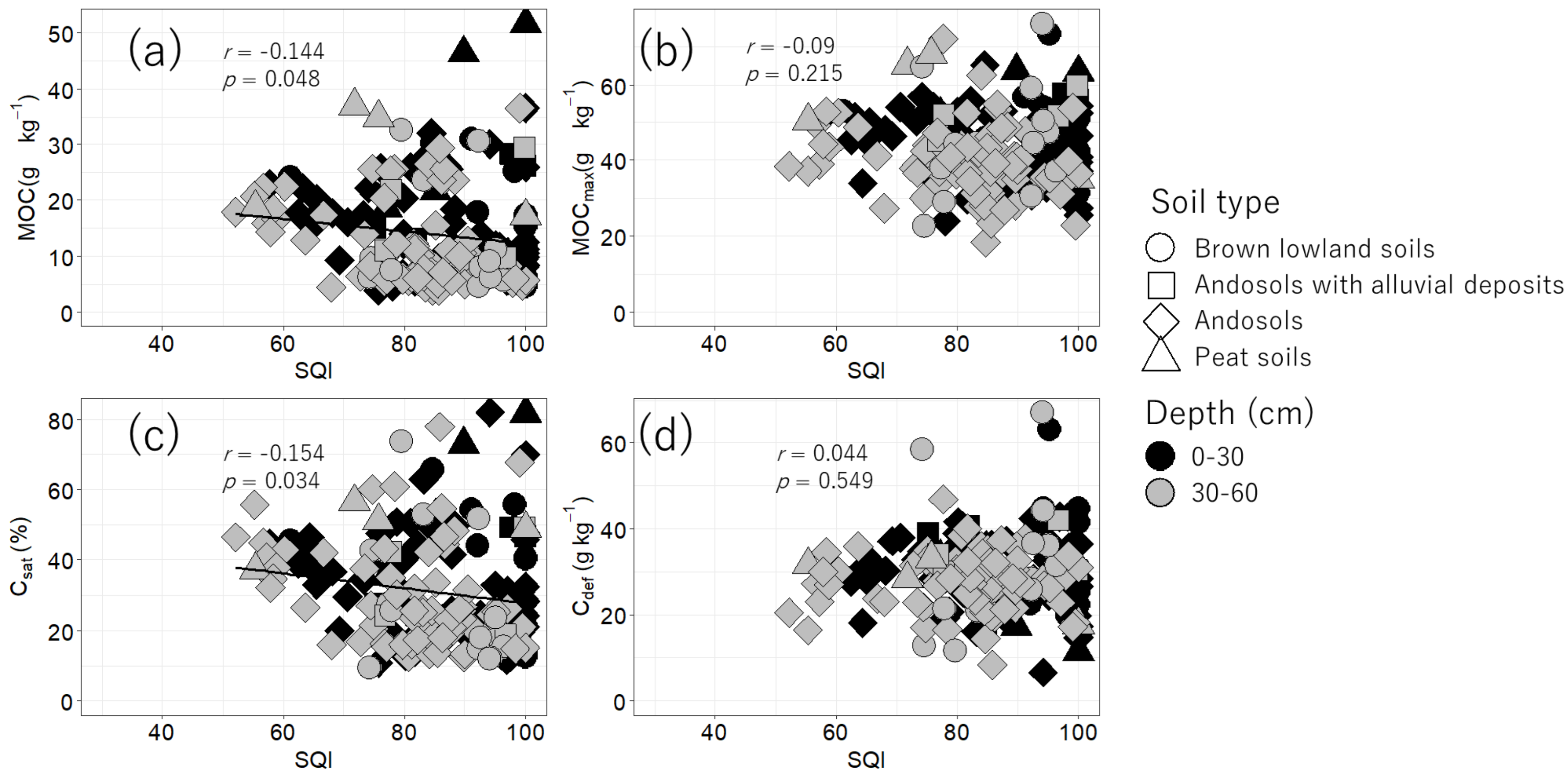

Figure 6-1. Scatter plots showing relationship between carbon sequestration conditions and SQI

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

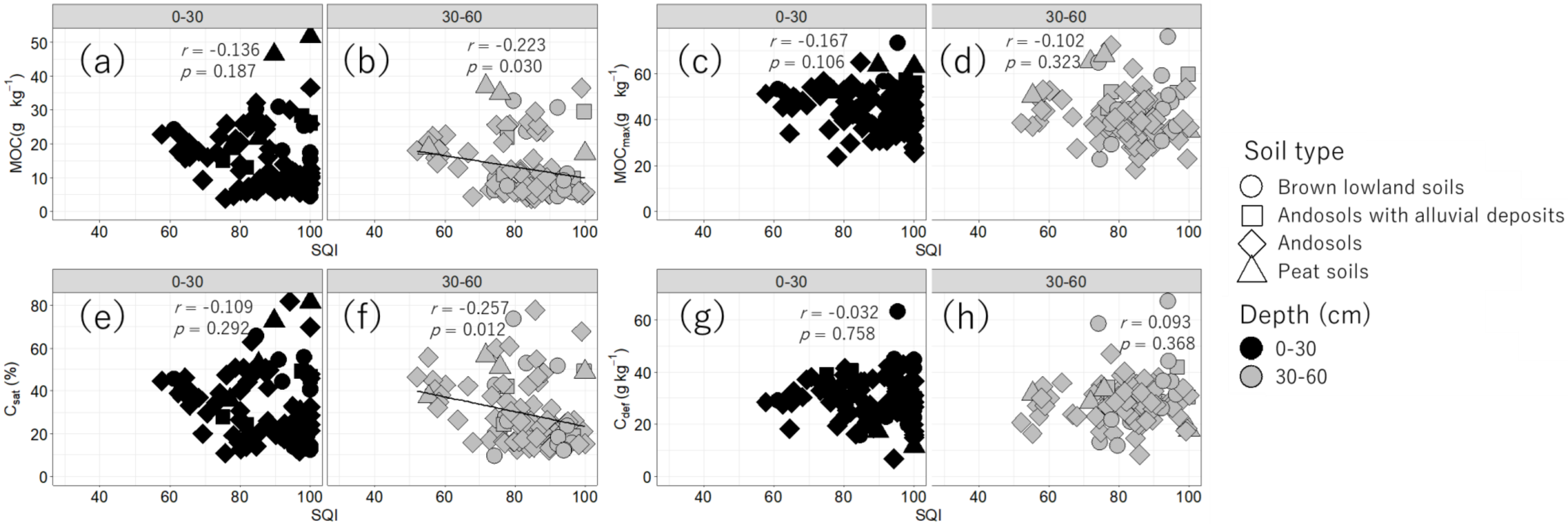

Figure 6-2. Scatter plots showing relationship between carbon sequestration conditions and SQI in each depth

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

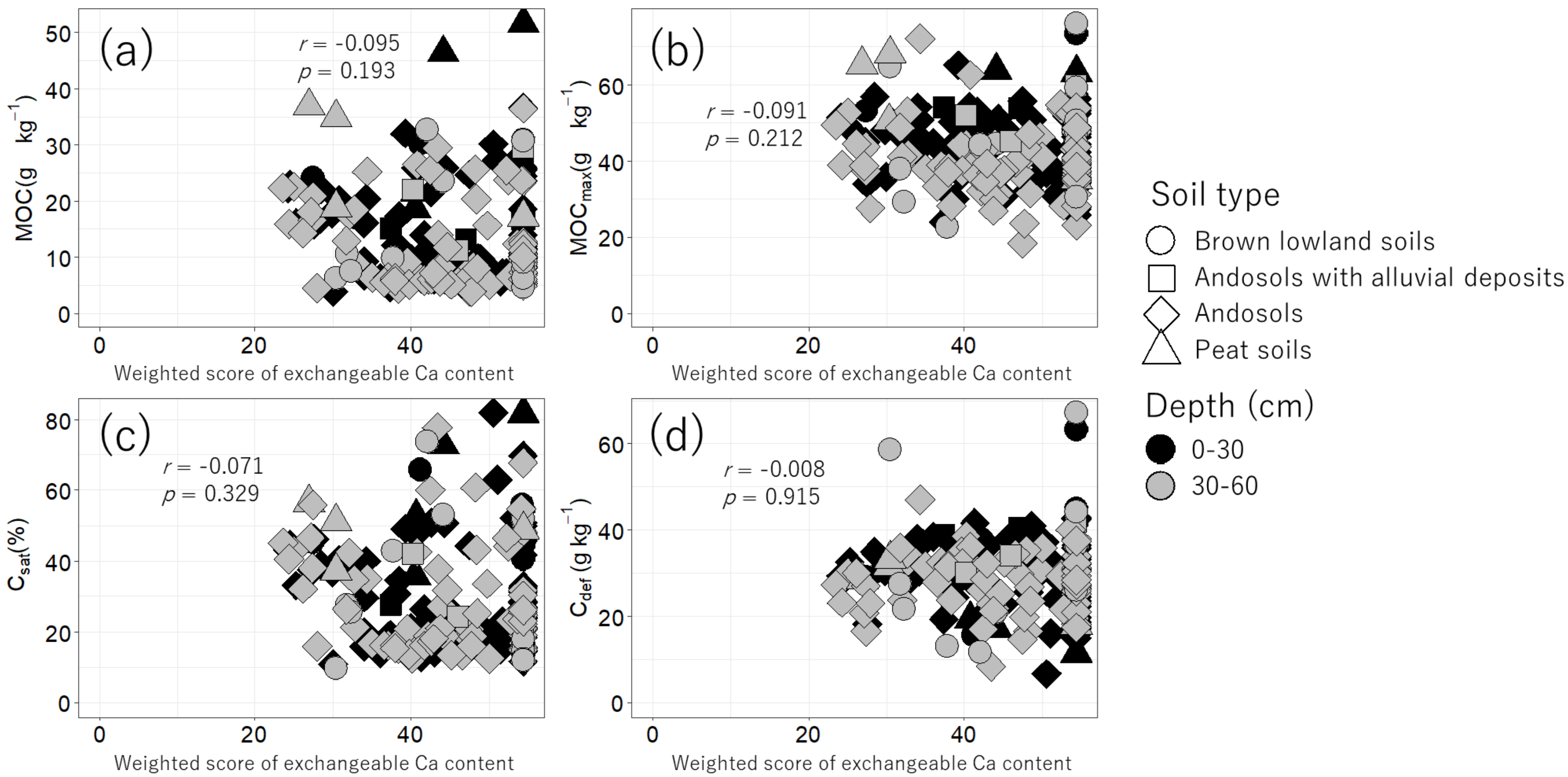

Figure 6-3. Scatter plots showing relationship between carbon sequestration conditions and weighted score of exchangeable Ca content

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

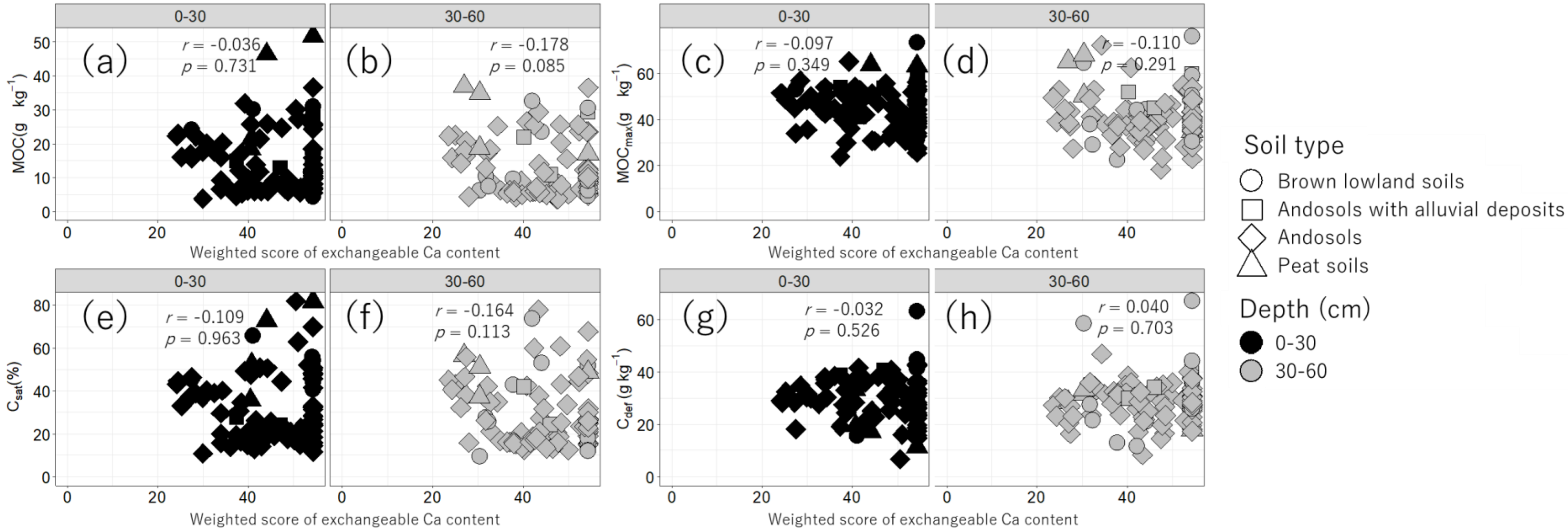

Figure 6-4. Scatter plots showing relationship between carbon sequestration conditions and weighted score of exchangeable Ca content in each depth a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

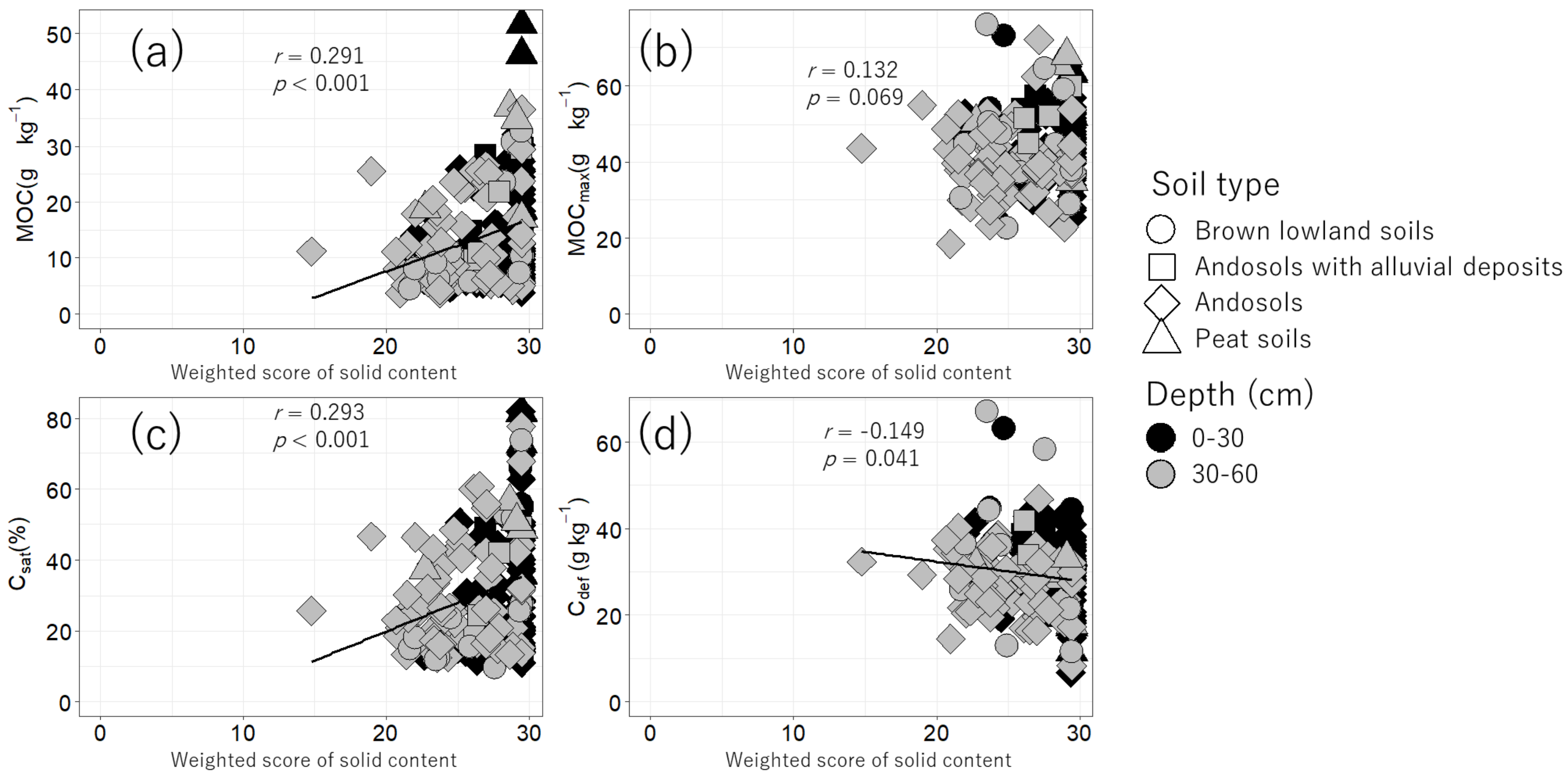

Figure 6-5. Scatter plots showing relationship between carbon sequestration conditions and weighted score of solid content

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

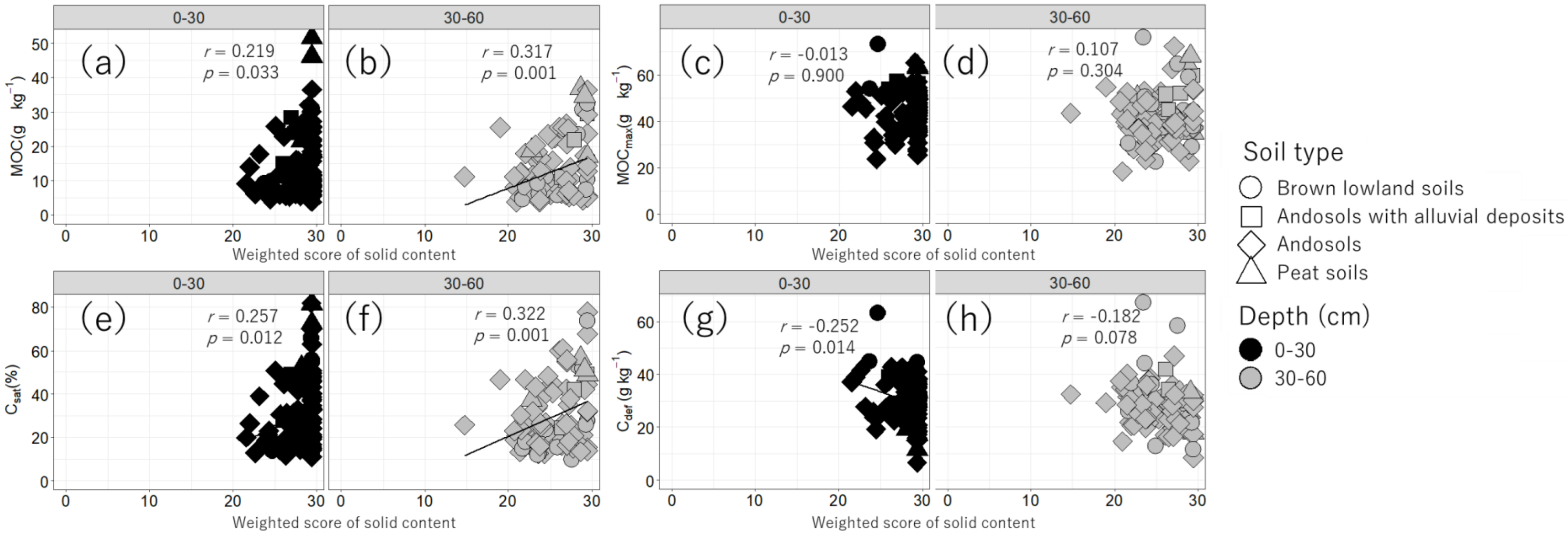

Figure 6-6. Scatter plots showing relationship between carbon sequestration conditions and weighted score of solid content in each depth

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

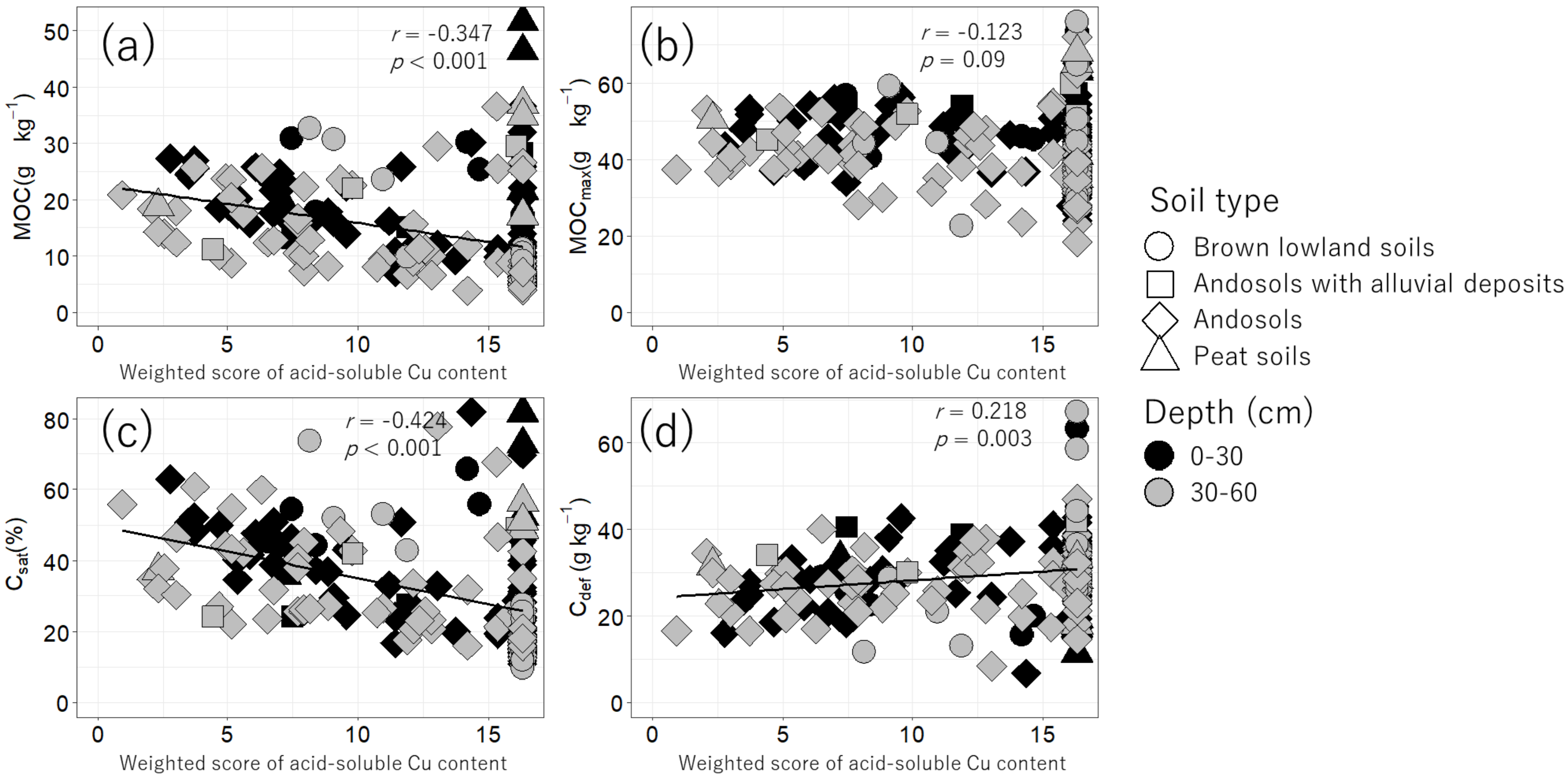

Figure 6-7. Scatter plots showing relationship between carbon sequestration conditions and weighted score of acid-soluble Cu content

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

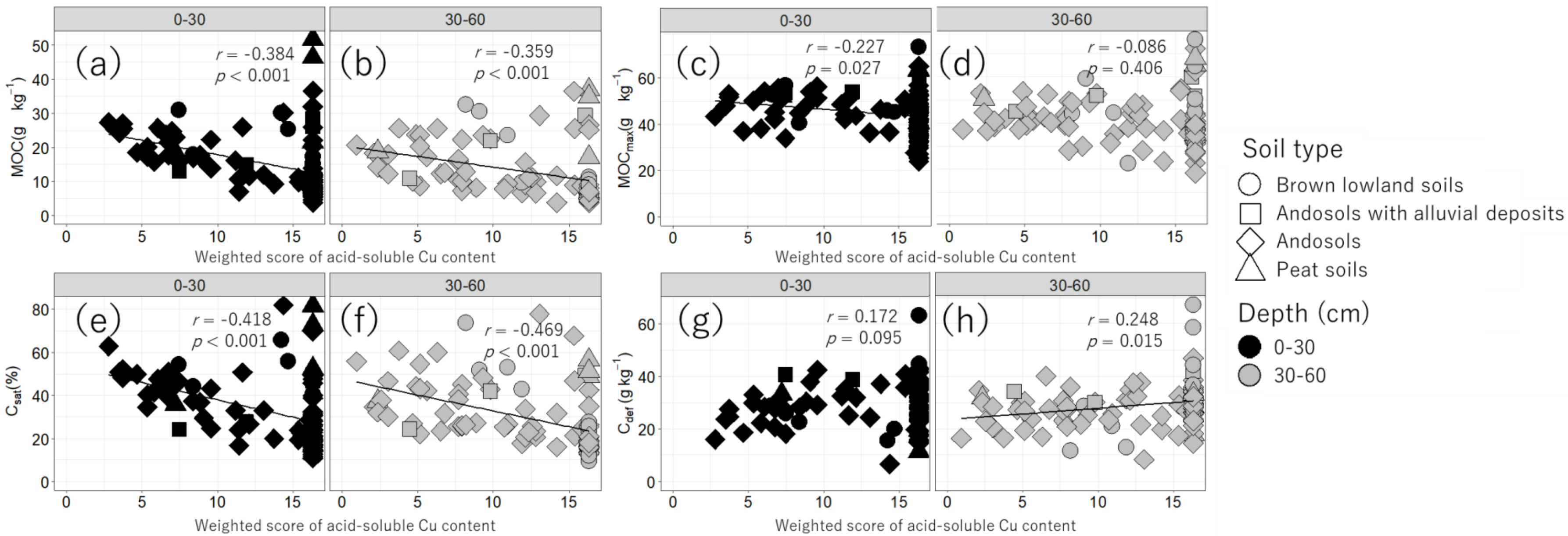

Figure 6-8. Scatter plots showing relationship between carbon sequestration conditions and weighted score of acid-soluble Cu content in each depth

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

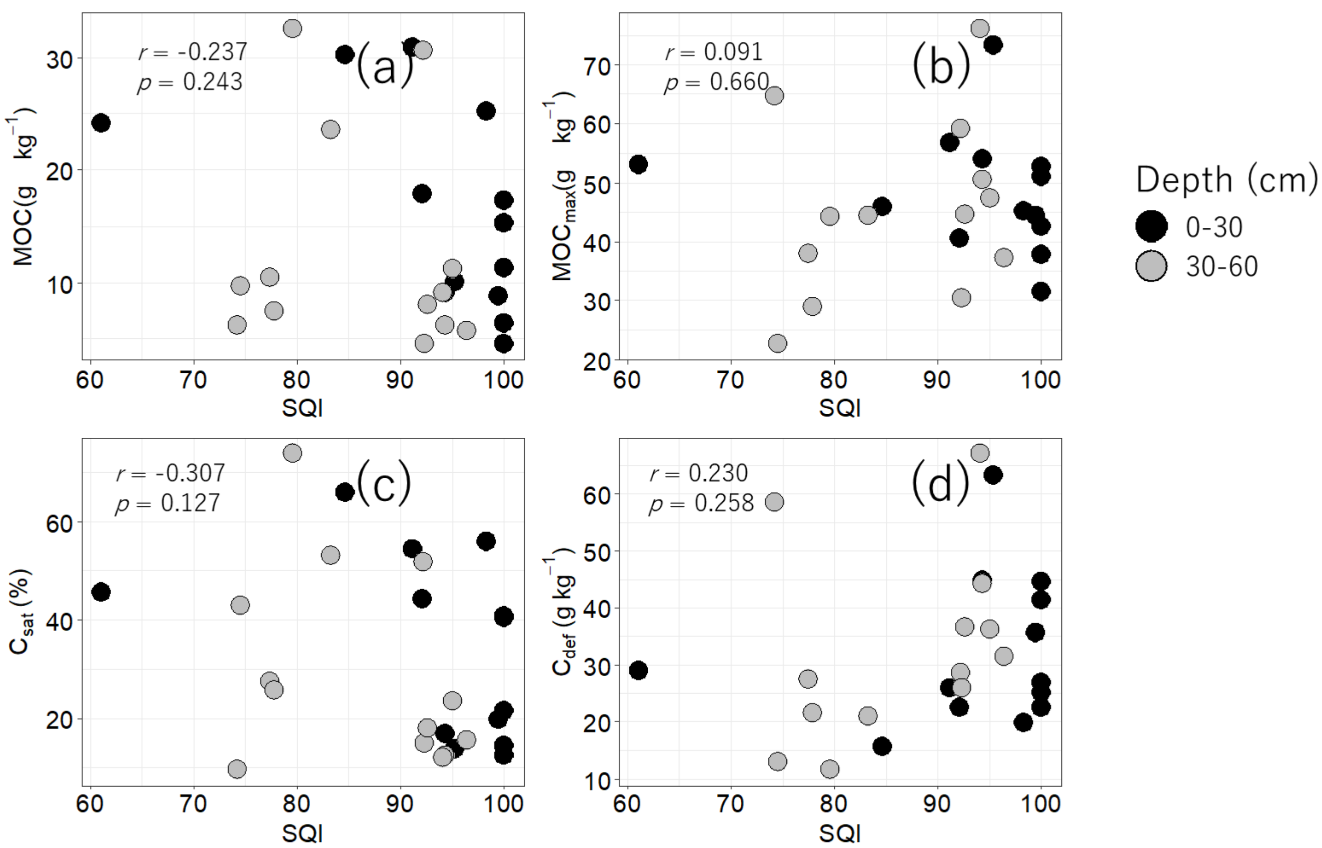

Figure 6-9. Scatter plots showing relationship between carbon sequestration conditions and SQI in lowland soils

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

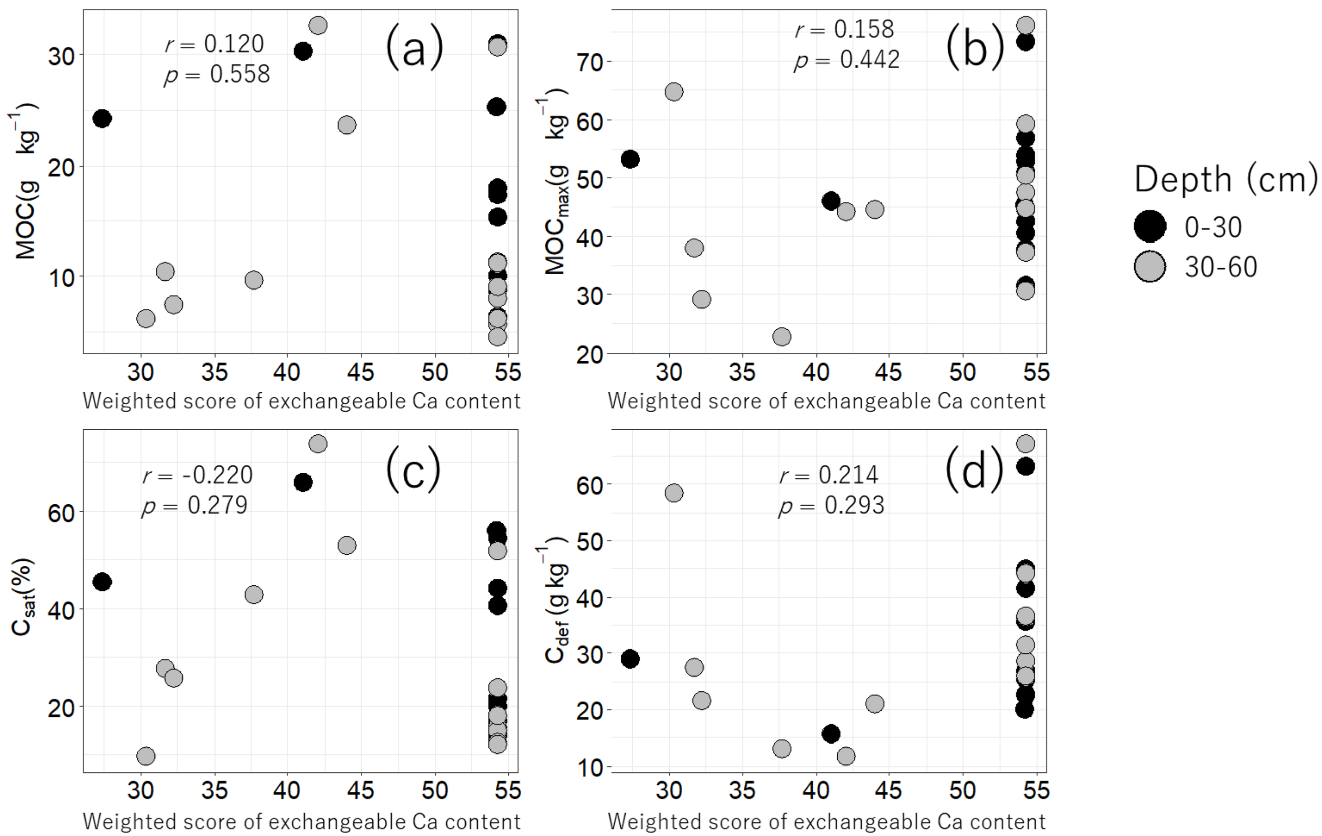

Figure 6-10. Scatter plots showing relationship between carbon sequestration conditions and weighted score of exchangeable Ca content in lowland soils

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

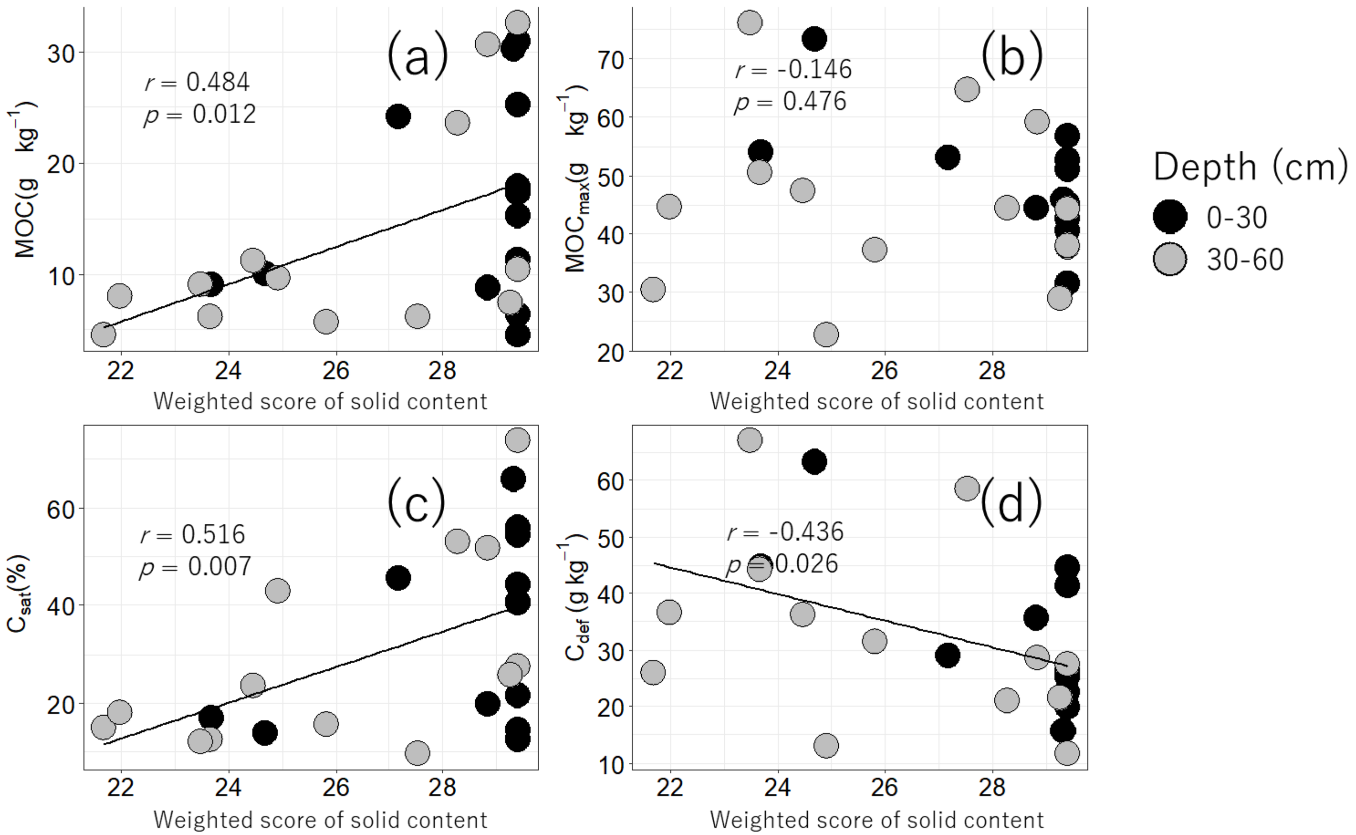

Figure 6-11. Scatter plots showing relationship between carbon sequestration conditions and weighted score of solid content in lowland soils

a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}).

Solid line shows significant correlation.

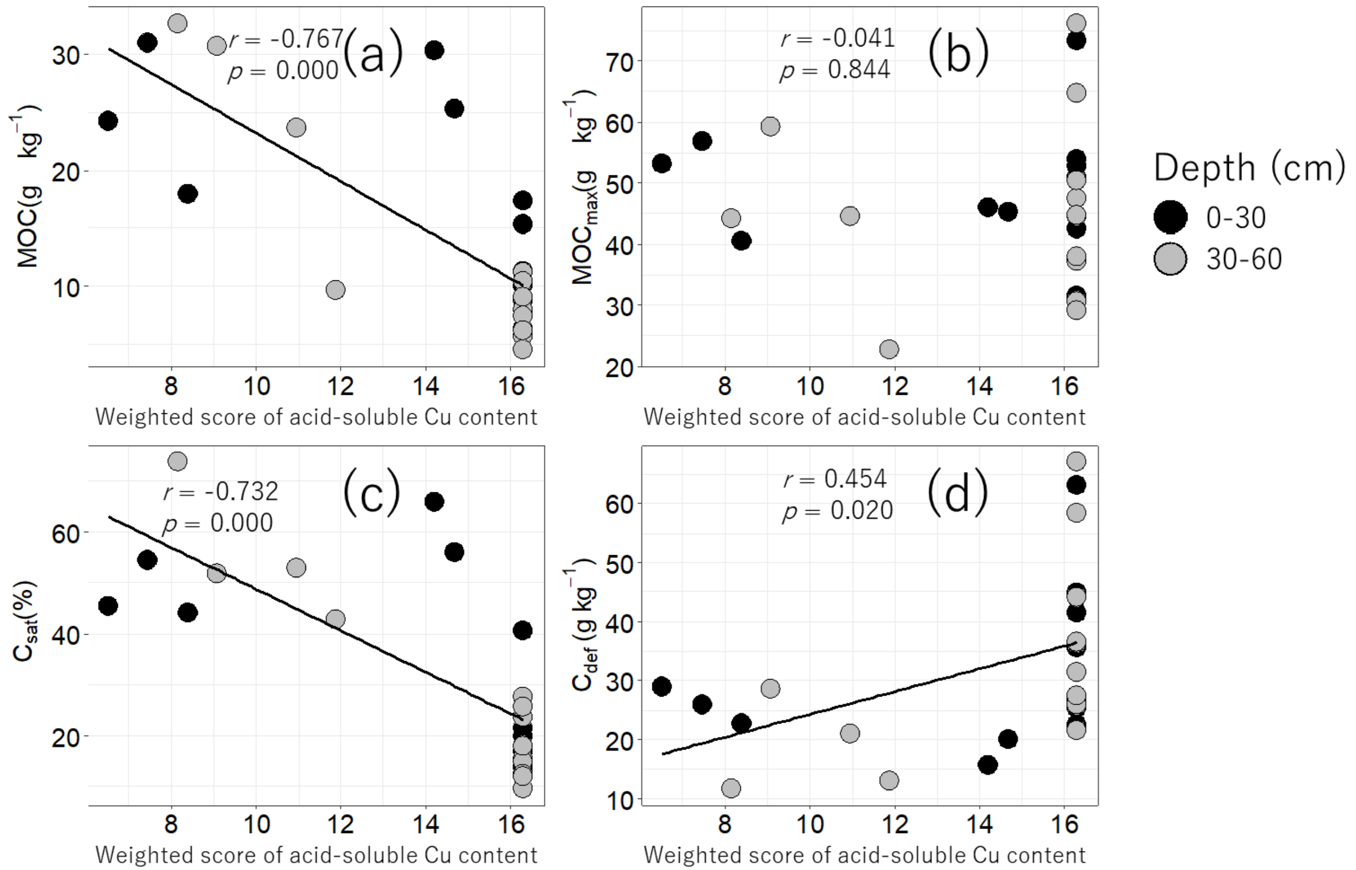

Figure 6-12. Scatter plots showing relationship between carbon sequestration conditions and weighted score of acid-soluble Cu content in lowland soils a) Mineral-associated organic carbon (MOC), b) Maximum mineral-association organic carbon (MOC_{max}), c) C saturation ratio (C_{sat}), and d) C deficiency (C_{def}). Solid line shows significant correlation.

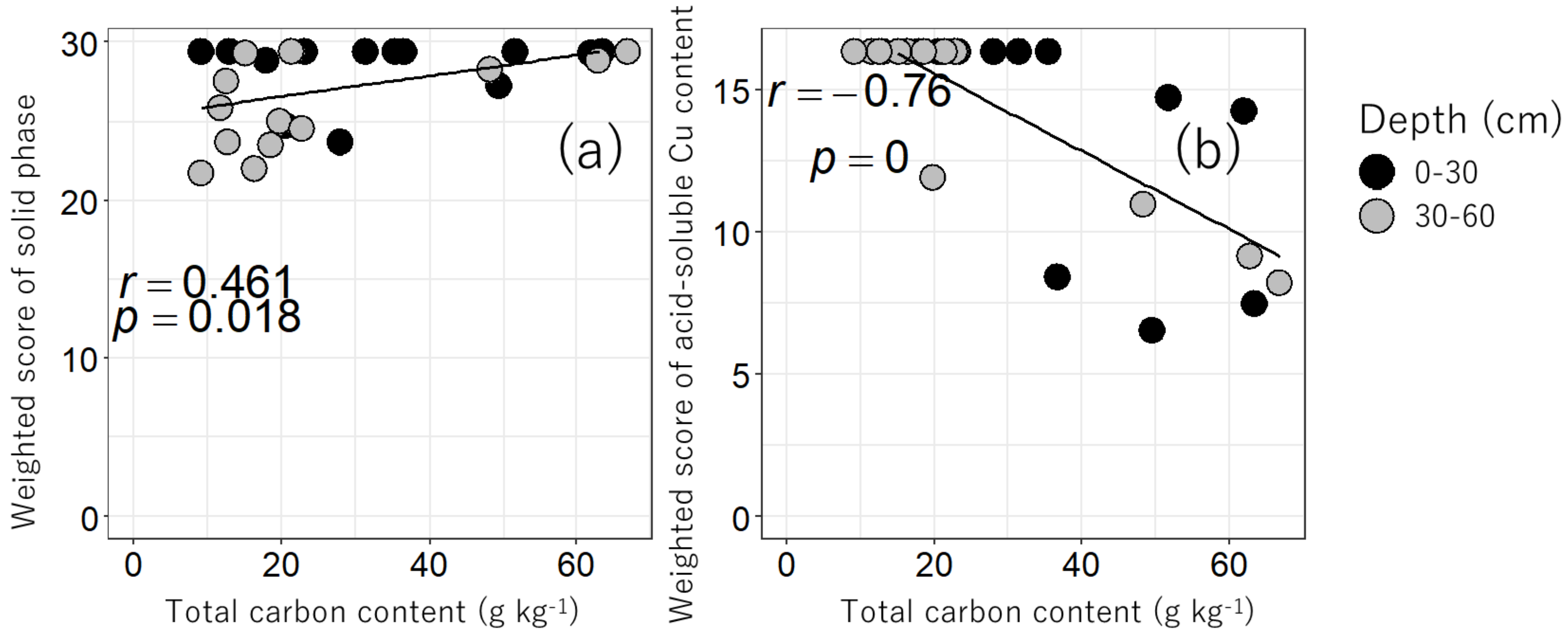

Figure 6-13. Scatter plots showing relationship between Total carbon and weighted scores

a) Weighted score of solid content, b) Weighted score of acid-soluble Cu content.

Solid line shows significant correlation.

6.4. Discussion

6.4.1. Comparison of long-term soil carbon sequestration capacity with previous studies

The mean C_{sat} value at 0–30 cm depth for arable land worldwide was estimated to be 43 ± 2% (Georgiou et al. 2022). This value was higher for peat soils but lower than the global mean for all soil types. However, peat soils exhibited a greater proportion of POM compared to other soil types (Zhao et al. 2023). Consequently, when estimating MOC, it is important to note that assuming the proportion of MOC to total carbon content for mineral soils may overestimate the MOC in peat soils. Furthermore, target sites in this study focused on fine-grained soil (Table 5-1), which resulted in relatively higher MOC_{max} than data set in the Georgiou et al. (2022) integrating data of various texture soils.

Among the three soil types examined, excluding peat soils, MOC was significantly lower in Andosols compared to Andosols with alluvial deposits (Table 6-1). However, the absence of ultrasonic dispersion led to underestimations of the clay-silt fraction and MOC_{max} in Andosols, potentially resulting in overestimated C_{sat} and underestimated C_{def}. These underestimations may be attributed to various factors, such as carbon adsorption on amorphous or less-crystalline mineral surfaces (Beare et al. 2014), mesopore complexity (Mayer et al. 2004, McCarthy et al. 2008, Chevallier et al. 2010), or complex formation and precipitation involving aluminum (Scheel et al. 2007). Thus, the estimations for C_{sat} and C_{def} in Andosols presented in this chapter are likely to be highly uncertain.

To address these uncertainties, particularly for peat soils and Andosols, future tasks should focus on improving analytical methods for soil texture and refining MOC measurements.

In terms of sampling depths, MOC and C_{sat} were inferred to be higher at 0–30 cm, likely due to the influence of soil structure development driven by organic matter input and tillage. This finding is consistent with results reported by Burger et al. (2023).

6.4.2. Relationship of long-term soil carbon storage capacity to Soil Quality Index and soil physicality

In all soil types, except for non-mineral soils, the SQI was significantly negatively correlated with both MOC and C_{sat} only at the 30–60 cm depth (Figs. 6-2b, f). This may be attributed to the weighted scores of exchangeable calcium content and acid-soluble copper content, which showed negative correlation coefficients with MOC and C_{sat} (Figs. 6-4b, f; 6-8b, f), outweighing the influence of the positive correlation coefficients observed for solid content scores (Figs. 6-6b, f). The significant negative correlation between SQI and both MOC and C_{sat} at the 30–60 cm depth (Figs. 6-2b, f) is likely due to the lower exchangeable calcium content and higher solid content at this depth compared to the 0–30 cm depth (Table 5-3). The deduction of scores for exchangeable calcium and the solid content resulted in greater variation.

Despite the significant negative correlations observed at the 30–60 cm depth, the absolute values of the correlation coefficients were less than 0.3 (Figs. 6-2b, f). This suggests that improving soil quality (SQI) and enhancing long-term soil carbon storage (MOC and C_{sat}) should be addressed as separate issues.

Focusing on Brown Lowland soils, where the accuracy of soil texture and MOC_{max} measurements was ensured compared to other soil types, no correlation was observed between SQI or the weighted score of exchangeable calcium content with MOC, MOC_{max}, C_{sat}, or C_{def} (Figs. 6-9 and 6-10). Conversely, the weighted score of the solid content showed significant positive correlations with MOC and C_{sat} and a significant negative correlation with C_{def} (Figs. 6-11a, c, d). Similarly, the weighted score of acid-soluble copper content demonstrated significant negative correlations with MOC and C_{sat} and a significant positive correlation with C_{def} (Figs 6-12a, c, d). Total carbon content showed significant positive and negative correlations with the weighted scores of the solid content and acid-soluble copper content, respectively (Figs. 6-13a, b). Therefore, it can be inferred that MOC, determined from total carbon content, also exhibited significant positive and negative correlations with the weighted scores of the solid content and acid-soluble copper content, respectively. Furthermore, as MOC_{max} showed no significant correlation with the weighted scores of the solid content and acid-soluble copper content, it can be assumed that C_{sat} and C_{def}, derived from a combination of MOC and MOC_{max}, displayed similar correlations with these scores and MOC (Figs. 6-11 and 6-12).

These relationships can be explained by the fact that in fields with high total carbon content, the solid content score was higher (indicating less solid content) due to improved soil structure resulting from organic matter application (Šimanský et al., 2019). Additionally, the lower limit of acid-soluble copper content decreased (Table 3-1), which may have reduced the decline in the acid-soluble copper content score.

Even when focusing solely on Brown Lowland soils, no correlation was found between SQI and either C_{sat} or C_{def} (Figs. 6-9c, d). This suggests that improving soil quality and enhancing long-term soil carbon storage conditions should be addressed independently, consistent with the approach taken for all soil types except for non-mineral soils.

Based on the evidence presented, the following mechanisms may define the relationship between SQI and C_{sat}. First, as the increase in C_{sat} from organic matter input is expected to slow as saturation approaches (Georgiou et al. 2022), the relationship with SQI may vary depending on the level of C_{sat}. In this study, the estimated C_{sat} level was relatively low compared to the global mean for arable soils, and the estimates may have overestimated C_{sat} in Peat soils and Andosols. Therefore, the actual C_{sat} levels in these soil types may be much lower than expected.

It is plausible to suggest that there is no direct correlation between SQI and C_{sat}. This is because organic matter application has been shown to partially improve SQI and increase C_{sat}. However, while organic matter application strongly influences C_{sat}, it makes only a modest contribution to SQI improvement. As a result, in arable lands with low C_{sat} levels, such as those studied here, there is little concern about carbon saturation. Instead, organic inputs aimed at enhancing SQI could also help reduce environmental impacts simultaneously.

6.5. Conclusion

To develop a diagnostic indicator for assessing the adequacy of the carbon cycle in soils, C_{sat}, the saturation rate of MOC, was estimated using values from existing literature and relational equations. In Chapter 5, the relationships between MOC_{max}, C_{sat}, and both the SQI and MDS scores were analyzed using soil data from two depths. The findings revealed that C_{sat} posed minimal concerns regarding saturation and showed no correlation with SQI. This suggests that efficient carbon sequestration can be compatible with organic inputs aimed at improving SQI.

However, future steps should focus on reducing the uncertainties in C_{sat} estimation by refining the analytical methods for soil texture and directly measuring MOC in practice.

7. General discussion

7.1. Significance of soil quality assessment of arable land

A comparison was conducted between fields cultivated with wheat for six years and those cultivated with potatoes for three years. Soil physical and chemical properties were considered when calculating Soil Quality Index (SQI). Furthermore, SQI was used to assess crop productivity during years with unfavorable climatic conditions for crop growth. The findings indicated that improving soil quality could mitigate the likelihood of yield reductions caused by adverse weather conditions.

Total soil carbon content is often used as a key indicator to evaluate soil quality (Bünemann et al. 2018). In regional comparisons, increasing soil organic matter content in agricultural land aligns with the results of this study indirectly (Qiao et al. 2022, Pan et al. 2009, Renwick et al. 2021, Kane et al. 2021). However, in within-field comparisons, soil organic matter content was found to be higher in areas with unstable yields than in those with stable yields (Leuthold et al. 2024). This highlights the importance of considering differences in scale when interpreting these results. This study did not show direct correlation between SQI and MOC converted from total carbon (Fig. 6-1a). However, indirect correlation was found between exchangeable calcium content with highest impact on SQI and total carbon (Fig. 4-4). This indicates that scoring function may round off the variation of the exchangeable calcium content value which meets the reference value.

In all cases, exchangeable calcium content and solid content were identified as important factors in calculating SQI, with exchangeable calcium content assigned the greatest weighting. In the Tokachi region, crop rotation systems commonly involve potatoes, wheat, sugar beet, and beans. However, soil pH is often managed at lower levels to prevent potato common scab, resulting in reduced lime applications. Consequently, a lower score for exchangeable calcium content may indicate a deficiency relative to diagnostic reference values. Thus, soil quality could be effectively improved by supplementing calcium with neutral materials. Calcium has been shown to enhance crops' tolerance to environmental stress (Palta 2010), suggesting that sufficient calcium addition could stabilize high yields.

In contrast, the solid content exhibited a relatively narrow range of scores between fields, with limited influence on reductions in SQI scores. Soil physical properties were found to improve with organic matter applications, which increased total carbon content. Given the significant correlation between total carbon content and cation exchangeable capacity (which determines the reference value for exchangeable calcium content), it was inferred that improving soil physical properties may indirectly enhance the score for exchangeable calcium content.

Other parameters identified as MDS either Chapter 4 or 5 had different scale of inter-field variation depending on the study case and relatively poor impact on SQI. However, those parameters were important to construct optimized MDS to assess the soil quality in this region. According to the Japan Meteorological Agency (2024), Japan has been experiencing a notable upward trajectory in temperature, with intermittent fluctuations. While no discernible long-term trend in annual precipitation has been observed, the frequency of heavy rain and short-duration intense rainfall events has been increasing. Projections indicate, with a high degree of confidence, that these trends will persist in the future. Under the RCP2.6 scenario for the Tokachi region—representing a world in which the Paris Agreement's 2°C target was achieved, with global average temperatures at the end of the 21st century approximately 2°C higher than pre-industrial levels—the mean annual temperature is projected to rise by about 1.6°C. Additionally, the frequency of short-duration heavy rain is expected to increase by approximately 1.7 times, while the annual maximum snow depth is predicted to decrease by around 12% (Obihiro Weather Station & Sapporo District Meteorological Office 2022). These projections suggest with a high degree of certainty that the risks of both drought and water damage will increase, posing significant challenges for agricultural production. To maintain stable crop yields under such conditions, it will be essential to improve soil physical properties related to permeability and drainage, ensure adequate nutrient supply to crops, and enhance their stress tolerance. Improvements in the physical and chemical properties of soils, coupled with enhancements in overall soil quality, are critical for adapting to future climate change.

Conversely, while it may be challenging to detect the impact of enhanced soil quality on yields under favorable weather conditions, it is evident that soil management strategies aimed at optimizing soil physicochemical properties can significantly mitigate the risk of yield losses due to adverse weather. This study demonstrated that the SQI could serve as a valuable tool for assessing the effectiveness of soil management practices and guiding targeted improvement strategies. However, it should be noted that the correlation between yield and SQI in the inferior climate year did not prove a causal relationship that SQI improvement mitigated risk of yield decrease and contributed to yield stability under climate change. The causal relationship needs to be proved by long-term organic material experiment field comparing SQI and yield variation with and without SQI improvement by organic material.

7.2. Issues to be addressed in establishing an efficient soil data collection system

In the United States, soil quality evaluation methods have been developed using over 1,500 soil samples from long-term experiments and local fields. From 39 candidate parameters reflecting soil quality, 12 were selected based on four criteria: 1) sensitivity to management, 2) measurement accuracy, 3) relevance to soil functions, and 4) ease of sampling and cost. This approach, known as the Cornell Comprehensive Assessment of Soil Health (Idowu et al. 2008, Moebius-Clune 2016), serves as a robust model. Additionally, the Soil Health Institute has recommended three parameters—soil organic carbon content, carbon mineralization potential, and water-resistant aggregates—based on literature, sensitivity to management practices, cost, and scalability (Bagnall et al. 2023).

In Japan, it is crucial to compile data on the physicochemical properties of agricultural soils and determine appropriate parameters and reference values for soil quality evaluation based on specific goals. To facilitate this, existing data collection systems should be leveraged, sampling and measurement processes should be streamlined, and efficient data collection strategies must be developed.

This study identified a potential method to simplify soil quality evaluation at the 30–60 cm depth by analyzing soil penetration resistance and surface soil thickness. The Tokachi Agricultural Cooperative Federation collects and links data on chemical properties and soil texture from disturbed soil to farmers' information, which could facilitate the analysis of relationships between SQI and yield. However, parameters such as macropore ratio and solid content require undisturbed soil sampling, which is labor-intensive and requires expertise. Developing a pedotransfer function (Reidy et al. 2016) to estimate undisturbed soil structure from disturbed soil could enable accurate crop productivity evaluations using SQI with reduced labor (Mamehpour et al. 2021).

Enhancing SQI accuracy would create a virtuous cycle of data-driven field improvement, increased awareness of data collection's importance, and an established system for accumulating data. Although the number of cases was limited, this study found that the coefficient of variation for SQI was smaller than that for Minimum Data Set or weighted scores, demonstrating its robustness against annual variability (Tables 4-7, 5-6). Moreover, yield variation showed a greater correlation with weather factors than soil factors.

Annual variations in bulk density and solid content were minimal in unplowed fields but more pronounced when comparing plowed and unplowed fields. To standardize soil quality comparisons, it is advisable to ensure consistent plowing conditions during sampling. When comparing fields with differing tillage practices, soil nutrient status might be more accurately reflected by calculating nutrient content per soil volume (nutrient content per soil weight multiplied by bulk density). Using this metric could make SQI more robust against annual fluctuations, although the effort required to measure bulk density should be weighed against its benefits.

7.3. Development from soil quality to assessment of soil health

This study aimed to assess the sustainability of the carbon cycle through soil as part of a broader soil health evaluation. A continuous application trial of compost and crop residues estimated that a combined input of 4.3 Mg C ha^{-1} year^{-1} is required to maintain soil carbon storage (a soil carbon storage rate of 0 Mg C ha^{-1} year^{-1}) in a four-year crop rotation system on Andosols in Hokkaido, Japan (Koga 2017). Using a carbon coefficient of 0.45 based on Sekiya (2013), this carbon input was converted into an organic matter input of 9.6 Mg ha^{-1} year^{-1}. In contrast, a 30-year trial of continuous organic matter application on low-humic Andosols in the Tokachi region estimated the required organic matter input to maintain soil carbon sequestration at only 2.5 Mg ha^{-1} year^{-1} (Nakatsu and Tamura 2008). These findings suggest that long-term organic matter application may reduce the rate of soil organic matter decomposition. One possible explanation for this difference is the varying decomposition rates of carbon in organic matter, with long-term trials potentially leading to an accumulation of persistent carbon, such as mineral-associated organic carbon (MOC).

To evaluate the extent of MOC accumulation, the MOC saturation (C_{sat}) estimations from previous studies (Chapter 6) indicated that saturation levels were not a concern and showed no correlation with the SQI. As organic matter input increases, the rate of C_{sat} increase is expected to slow as saturation is approached (Georgiou et al. 2022). However, C_{sat} appeared to have little influence on SQI, suggesting that C_{sat} and SQI are independent variables. This finding implies that organic matter inputs aimed at improving SQI—at least up to the point where C_{sat} approaches saturation—can achieve dual benefits: climate change adaptation and mitigation through soil carbon sequestration and enhanced soil quality. This approach could therefore contribute to overall soil health improvement. The minimum organic matter input required to achieve this balance can be determined using C_{sat} and SQI as indicators.

Future research should address two key areas. First, methods for analyzing the soil texture of Andosols need refinement. Second, Csat levels should be evaluated by directly measuring MOC to improve accuracy.

Techniques have been developed to apply biochar, a carbonized biological material, to agricultural land as an efficient means of soil carbon sequestration. However, the impact of such techniques on crop productivity must be carefully considered. Koga et al. (2017) applied wood-derived biochar, a form of persistent organic matter, to ordinary Andosols in the Tokachi region at rates of 0, 10, 20, and 40 Mg ha^{-1} over four years (equivalent to 0, 8.45, 16.9, and 33.8 Mg C ha^{-1} over four years). After four years of crop rotation, no significant differences in crop yield were observed. However, changes in soil carbon sequestration were -3.55, 4.89, 13.4, and 29.9 Mg C ha^{-1} over four years, respectively, with sequestration efficiency increasing alongside higher carbon input.

The organic matter in biochar was primarily in the form of particulate organic matter (POM), which had minimal impact on mineral-associated organic matter (MAOM) saturation (Cooper et al. 2020, Shi et al. 2021). However, biochar exhibited characteristics such as high pH, high CN ratio, and low nitrogen content. Over-application of biochar for carbon sequestration could potentially hinder crop productivity by raising soil pH and increasing the risk of nitrogen starvation. To balance crop productivity with soil carbon sequestration, it would be prudent to avoid excessive reliance on biochar and instead apply moderate amounts of organic matter that include nitrogen and phosphate, such as compost. Additionally, using diagnostic tools such as the SQI and C_{sat} can help assess nutrient availability and carbon sequestration status, facilitating the determination of optimal organic matter input. Regarding the fractionation of POM and MAOM, size fractionation was found to be a more straightforward method compared to density fractionation. However, fine biochar particles (<53 μm) that are originally classified as POM could potentially be misidentified as MAOM during size fractionation. It is essential to ensure that soil samples containing biochar are properly fractionated to avoid overestimating MAOM.

The theoretical upper limit for MOC storage is often estimated based on clay and silt content (Hassink 1997, Six et al. 2002, Georgiou et al. 2022). However, determining whether MOC is saturated or whether storage and decomposition have reached equilibrium can be challenging when no further changes in MOC content are observed. This difficulty arises because the decomposition rate of organic matter varies depending on climate and soil type. Moreover, achieving the theoretical upper limit for MOC storage is considered a difficult goal in practice (Wiesmeier et al. 2020). To address these challenges, methods assuming ideal and near-saturated MOC storage in undisturbed ecosystems, such as forests and grasslands with minimal carbon input and output, have been widely used to estimate soil organic carbon storage potential in countries like China, France, and New Zealand (Angers et al. 2011, Chen et al. 2019, McNally et al. 2017, Wiesmeier et al. 2015).

In Japan, a country-scale dataset has organized the relationship between soil organic carbon content, reactive metal content, and the phosphorus absorption coefficient for various agricultural soil types. This research has suggested that MAOM content can potentially be estimated using the phosphorus absorption coefficient (Ichinose et al. 2024). However, the soil carbon storage potential in agricultural lands and its relationship with crop productivity remain unresolved. This study did not consider the biological process and properties of input organic material due to accumulated data items, which was the limitation and the future issue of the discussion.

It is hoped that future research will address this issue and lead to the development of a soil diagnostic method that balances carbon storage and crop productivity. This could be achieved by conducting paired sampling of forest and grassland soils adjacent to agricultural land and analyzing the relationship between SQI and C_{sat}.

8. Conclusion

This study aimed to calculate the Soil Quality Index (SQI) by integrating scores of both favorable and unfavorable soil physicochemical properties for a quantitative evaluation of soil quality in 90 wheat fields over six years and 76 potato production fields over three years in the Tokachi region. The exchangeable calcium content and solid content were identified as critical parameters for SQI calculation in both wheat and potato fields, highlighting the importance of assessing both physical and chemical soil properties. In particular, reductions in SQI scores due to exchangeable calcium content were primarily caused by deficiencies relative to reference values, suggesting that calcium supplementation using neutral materials is important for improving soil quality. However, lime application was often reduced to maintain low soil pH as a countermeasure against common scab.

Through the comparison with two study case in Tokachi region and the crop report by the Tokachi Agricultural Experiment Station, the correlation between SQI and yield was more pronounced in years with unfavorable weather, indicating that weather impacts crop yields more strongly than soil quality. Thus, improving soil quality is a vital strategy for adapting to future climate change. Additionally, the correlation between surface SQI and yield in wheat fields during unfavorable weather years was stronger in non-Andosols with thin surface soils. In potato fields, the correlation with yield was evident across all soil types when SQI was adjusted to account for surface soil thickness. These findings suggest that assessing surface soil thickness is more critical for predicting crop productivity than evaluating SQI at depths of 30–60 cm.

A comparison of SQI and soil physicochemical properties over different study years in the same fields showed that SQI was more stable over time than any single soil property. Furthermore, yield variability was more influenced by annual factors, such as weather, than by soil factors.

To develop a method for assessing soil health aimed at achieving sustainable material cycling on local and global scales, mineral-associated organic carbon saturation (C_{sat}) was estimated as an indicator of long-term carbon sequestration. Using measurements and literature-based relationships, the study explored the relationship between C_{sat}, SQI, and soil physicochemical properties. Despite inherent uncertainties in C_{sat} estimation, it was found that carbon saturation was not a significant concern in agricultural lands. Moreover, the findings suggested that improving SQI through organic matter inputs could effectively enhance carbon sequestration. This highlights the dual potential of SQI to facilitate climate change adaptation and contribute to mitigation through increased carbon storage.

To advance this work, accumulating data on crop yields and soil physicochemical properties, alongside establishing an efficient soil data collection system, would be highly beneficial. This could involve measuring surface soil thickness and developing equations to estimate soil physical properties from disturbed soil samples. Additionally, the development of a soil diagnostic method capable of proposing management strategies for both climate change adaptation and mitigation would be advantageous. This approach should include the measurement of C_{sat}, the identification of factors contributing to estimation uncertainty, and an analysis of its relationship with SQI.

9. Summary

The term “soil quality” refers to the sustainable functioning of soil, including its ability to support crop yields. It encompasses a variety of physical and chemical properties. However, in Japan, a method to identify the most important properties and calculate an overall evaluation value for a field has not yet been developed. Consequently, the prioritization of improvements across multiple fields and the order of items requiring improvement in individual fields have not been quantitatively analyzed.

The objective of this study was to calculate a Soil Quality Index (SQI) that quantifies soil quality based on soil physicochemical properties. A Minimum Data Set (MDS) was constructed by selecting soil physicochemical properties that were most representative of inter-field variability. Each MDS item was assigned a score that decreased with greater deviation from the soil diagnostic reference value. These scores were weighted based on inter-field variability, and the SQI was calculated as the sum of the weighted scores for each field.

The study calculated SQI values for 90 wheat fields over six years and 76 potato fields over three years in the Tokachi region. The necessity of assessing both physical and chemical properties was demonstrated as exchangeable calcium content and solid content were identified as highly weighted, important items for SQI calculation. The correlation between SQI and yield was stronger in years with unfavorable weather conditions, suggesting that weather had a greater impact on crop yields than soil quality. This underscores the importance of improving soil quality to adapt to future climate change.

Additionally, mineral-associated organic carbon saturation (C_{sat}) was estimated as an indicator of long-term soil carbon storage capacity using previous literature values and established relational equations. The results showed minimal concerns about carbon saturation and no correlation between C_{sat} and SQI, suggesting that effective carbon storage can be achieved through organic matter inputs aimed at improving SQI.

Looking ahead, it would be beneficial to establish an effective soil data collection system that includes measuring surface soil thickness to further analyze the relationship between SQI and C_{sat}. Moreover, the development of a soil diagnostic method capable of proposing soil management strategies for both climate change adaptation and mitigation is expected.

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11. Appendix

List of table and figure titles

Supplementary Table 1. Original data in chapter 4

ID	year	crop	cultivar	soil_type	elevation	product_yield	grain_protein	pH_H2O	Ava_P	P_absorbance	CEC	Ca	Mg	K	Mg_K	Ca_Mg	CaS	BaS	B	Mn	Zn	Cu	TC	TN	Ava_N	sand	silt	clay	solid	bulk_density	pore_pF1.5	water_holding_capacity_pF1.5_3.0	Tillage_layer_depth	tl_minmax	gravel_content	rock_depth	Ca_score	solid_score	K_score	pore_pF15_score	B_score	weighted_Ca_score	weighted_solid_score	weighted_K_score	weighted_pore_pF15_score	weighted_B_score	SQI	seed_days	growth_days	seed_amount	Base_N_fert	Former_N_fert	Later_N_fert	Total_N_fert
1	2019	wheat	Yumechikara	Brown Lowland soil	50	741.4	14.79	5.63	1157.4	9250	28.7	4491	736	381	4.5	4.4	55.9	71.5	0.41	181.5	8.4	3.67	31.7	2.4	6.44	20.2	42.8	36.9	39.7	1.1	19.3	5.1	60.0	0.9			1.0	1.0	0.8	1.0	0.8	38.7	26.3	12.1	11.3	6.6	94.9	262	307	8.0	4.8	10.6	4.2	19.6
2	2019	wheat	Yumechikara	Andosol	145	714.1	14.72	6.08	141.8	19870	25.9	2918	450	491	2.1	4.7	40.2	52.9	0.67	46.6	4	0.38	31.0	2.3	4.63	48.4	29.6	21.9	32.9	0.9	13.1	12.7	60.0	0.9			0.8	0.9	0.6	0.7	1.0	32.2	24.0	9.4	7.7	8.0	81.3	262	309	8.5	3.2	7.4	0.0	10.6
3	2019	wheat	Yumechikara	Andosol	166	718.3	17.25	5.44	214.1	18070	26.6	2492	362	385	2.2	5	33.4	43.2	0.88	147.3	2.28	0.4	42.8	3.1	6.27	40.2	36.4	23.5	38.8	1.1	13.5	6.6	35.0	0.0			0.7	0.8	0.8	0.7	1.0	27.5	20.3	12.0	7.9	8.0	75.7	267	304	9.0	5.6	8.2	0.0	13.8
4	2019	wheat	Yumechikara	Andosol	81.6	548.2	14.37	5.94	93.2	21900	29.3	2692	390	332	2.7	5	32.7	41.7	0.56	53.2	3.97	0.28	50.8	4.2	5.48	48.1	30	21.9	31.6	0.9	16.9	11.9	60.0	0.9			0.8	0.9	0.9	0.8	1.0	29.7	25.0	13.9	9.9	8.0	86.5	263	306	10.0	10.4	0.0	0.0	10.4
5	2019	wheat	Yumechikara	Brown Lowland soil	62	736.0	16.51	4.71	412.9	6470	14.5	1653	330	177	4.4	3.6	40.7	54.6	0.42	125.9	3.71	5.48	11.1	1.1	4.25	43.9	28.1	27.9	53.0	1.4	7.0	6.8	60.0	0.9			1.0	0.8	1.0	0.4	0.8	37.6	19.8	15.3	4.1	6.7	83.6	267	301	9.0	4.8	6.3	0.0	11.1
6	2019	wheat	Yumechikara	Brown Lowland soil	141	749.6	18.67	5.38	754.2	6210	15.2	2188	365	258	3.3	4.3	51.3	66.8	0.54	68.7	4.72	2.02	16.9	1.4	5.98	56.3	19.5	24.1	44.2	1.2	11.8	15.3	60.0	0.9		58.0	1.0	0.9	1.0	0.6	1.0	38.7	23.8	15.3	6.9	8.0	92.7	260	313	6.0	4.0	5.6	8.4	18.0
7	2019	wheat	Yumechikara	Brown Lowland soil	141	343.7	19.97	5.31	650.8	4520	11.9	1622	227	221	2.4	5.1	48.7	62.2	0.42	48.9	3.66	1.84	12.5	1.0	5.41	69.6	11.8	18.6	51.4	1.4	14.2	14.3	41.0	0.2		25.0	1.0	0.8	1.0	0.7	0.8	38.7	20.5	15.3	8.3	6.7	89.5	260	313	6.0	4.0	5.6	8.4	18.0
8	2019	wheat	Yumechikara	Andosols with alluvial deposit	180.4	473.1	16.53	5.59	345.1	17050	36.3	5259	460	254	4.2	8.2	51.7	59.5	0.75	48.7	2.42	0.4	55.7	3.8	6.77	42	27	31	40.3	1.1	12.7	8.7	39.0	0.1		40.0	0.9	0.7	1.0	0.6	1.0	36.0	19.6	15.3	7.4	8.0	86.4	261	310	10.0	0.0	3.2	3.2	6.3

Detailed description is shown in List 1 as the next page

List 1. Description of the Supplementary Table 1

column_name	meaning	unit
ID	ID	
year	Harvest year	
crop	Crop name	
cultivar	Cultivar	
soil_type	Soil type	
elevation	Elevation	m
product_yield	Product yield	g m^{-2}
grain_protein	Grain protein	%
pH_H2O	$pH(H_2O)$	
Ava_P	Available_phosphate	mg P_2O_5 kg^{-1}
P_absorbance	Phosphate_absorption_coefficient	mg P_2O_5 kg^{-1}
CEC	Cation exchange capacity	$cmol_c$ kg^{-1}
Ca	Exchangeable Ca content	mg CaO kg^{-1}
Mg	Exchangeable Mg content	mg MgO kg^{-1}
K	Exchangeable K content	mg K_2O kg^{-1}
Mg_K	Mg/K	equivalent ratio
Ca_Mg	Ca/Mg	equivalent ratio
CaS	Lime saturation	%
BaS	Base saturation	%
B	Hot-water dissolved boron content	mg kg^{-1}
Mn	Easily reductive manganese	mg kg^{-1}
Zn	Acid-soluble zinc	mg kg^{-1}
Cu	Acid-soluble copper	mg kg^{-1}
TC_%	Total carbon	%
TC	Total carbon	g kg^{-1}
TN_%	Total nitrogen	%
TN	Total nitrogen	g kg^{-1}
Ava_N	Hot-water extractive nitrogen	mg $100g^{-1}$
sand	Sand content	%
silt	Silt content	%
clay	Clay content	%
solid	Solid phase	
bulk_density	Bulk density	Mg m^{-3}
pore_pF1.5	Macropore ratio	$\times\ 10^{-2}$ m^3 m^{-3}
water_holding_capacity_pF_1.5_3.0	Available moisture	$\times\ 10^{-2}$ m^3 m^{-3}
Tillage_layer_depth	Surface soil thickness	cm
tl_minmax	Year standardized penetration depth	
gravel_content	Gravel content	kg kg^{-1}
rock_depth	Gravel emmergence depth	cm
Ca_score	Exchangeable calcium content score	
solid_score	Solid phase score	
K_score	Exchangeable potassium content score	
pore_pF1.5_score	Macropore score	
B_score	Hot-water dissolved boron content score	
weighted_Ca_score	Weighted exchangeable calcium content score	
weighted_solid_score	Weighted solid phase score	
weighted_K_score	Weighted exchangeable potassium content score	
weighted_pore_pF1.5_score	Weighted macropore score	
weighted_B_score	Weighted hot-water dissolved boron content score	
SQI	Soil quality index	
seed_days	Sowing date	DOY
growth_days	Growth days	days
seed_amount	Sowing rate	g m^{-2}
Base_N_fert	Basal nitrogen fertilization rate	gN m^{-2}
Former_N_fert	Supplemental nitrogen fertilization rate before emergence of flag leaf	gN m^{-2}
Later_N_fert	Supplemental nitrogen fertilization rate after emergence of flag leaf	gN m^{-2}
Total_N_fert	Total nitrogen fertilization rate	gN m^{-2}

Supplementary Table 2. Original data in chapter 5

ID	year	crop	cultivar	soil_type	depth	pH_H2O	Ava_P	P_absorbance	CEC	TC	TN	sand	silt	clay	solid	bulk_density	pore_pF1.5	water_holding_capacity_pF1.5_3.0	gravel_content	Ca_score	Cu_score	Solid_score	weighted_Ca_score	weighted_Cu_score	weighted_solid_score	SQI	MOC	MOCmax	Csat	Cdef	yield_per_area	yield_cul_mean	relative_yield	depth_tillage_layer	SQI_0_60_ave	depth_weighted_SQI	simple_correction_SQI
01	2020	Potato	Sayaka	Peat soil	0-30	5.37	403.1	1825.0	48.52	181.32	11.18	33.34	27.76	38.87	18.17	0.44	35.01	12.10	1.25	9.46	1.00	0.73	51.34	16.30	21.37	89.01	58.7	57.3	102.4	-1.4	3483.0	3957.1	88.0	47.0	90.6	70.6	83.7
01	2020	Potato	Sayaka	Peat soil	30-60	5.28	367.6	1843.0	53.26	187.77	11.51	25.25	28.89	45.84	28.68	0.63	5.40	12.56	1.94	8.55	1.00	1.00	46.40	16.30	29.40	92.10	60.7	64.3	94.5	3.5							
02	2020	Potato	Sayaka	Andosol	0-30	6.18	156.7	2073.0	32.92	79.08	5.32	38.23	31.68	30.07	28.71	0.77	24.76	11.12	0.49	10.00	0.23	1.00	54.30	3.73	29.40	87.43	25.6	53.1	48.2	27.5	4176.3	3957.1	105.5	100.0	87.1	87.1	87.4
02	2020	Potato	Sayaka	Andosol	30-60	5.95	122.3	2147.0	31.65	73.29	4.98	37.74	27.71	34.54	29.07	0.77	28.53	2.85	0.52	9.66	0.30	1.00	52.44	4.89	29.40	86.73	23.7	53.5	44.3	29.8							
03	2020	Potato	Sayaka	Andosol	0-30	5.44	173.1	1987.0	28.16	68.70	5.15	40.22	27.94	31.82	27.31	0.72	30.37	3.99	0.08	4.45	0.59	1.00	24.15	9.55	29.40	63.10	22.2	51.4	43.2	29.2	3055.8	3957.1	77.2	35.0	61.7	36.6	44.2
03	2020	Potato	Sayaka	Andosol	30-60	5.41	142.6	2107.0	29.55	69.69	5.12	38.80	30.30	30.89	34.61	0.87	8.66	8.82	0.10	4.60	0.60	0.87	24.99	9.78	25.48	60.25	22.5	52.6	42.8	30.1							
04	2020	Potato	Sayaka	Andosol	0-30	5.92	76.5	1997.0	19.3	18.90	1.71	44.46	30.30	25.22	38.95	1.07	5.55	7.58	0.09	7.60	1.00	0.77	41.28	16.30	22.64	80.23	6.1	47.7	12.8	41.6	4553.7	3957.1	115.1	100.0	80.5	80.5	80.2
04	2020	Potato	Sayaka	Andosol	30-60	5.92	52.4	2103.0	20.03	17.18	1.55	48.69	26.80	24.49	36.31	0.99	8.39	7.92	0.09	7.39	1.00	0.83	40.14	16.30	24.29	80.73	5.6	44.1	12.6	38.6							
05	2020	Potato	Sayaka	Andosols with alluvial deposit	30-60	5.34	505.6	1284.0	34.53	60.56	4.05	30.37	27.45	42.17	39.30	0.96	7.12	3.55	0.87	10.00	0.99	1.00	54.30	16.07	29.40	99.77	29.5	59.9	49.3	30.3							
05	2020	Potato	Sayaka	Andosols with alluvial deposit	0-30	5.45	979.2	1385.0	34.55	53.78	3.67	34.71	26.93	38.33	31.38	0.81	22.95	5.83	1.24	10.00	1.00	1.00	54.30	16.30	29.40	100.00	26.2	56.1	46.7	29.9	3478.5	3957.1	87.9	18.0	99.9	30.0	36.0
06	2020	Potato	Sayaka	Andosol	0-30	5.79	78	2005.0	17.56	22.18	1.96	48.93	28.86	22.19	23.49	0.69	37.77	5.79	0.32	7.07	1.00	0.94	38.38	16.30	27.62	82.30	7.2	43.9	16.3	36.7	3744.6	3957.1	94.6	41.0	79.2	55.1	67.5
06	2020	Potato	Sayaka	Andosol	30-60	5.8	61.3	2048.0	15.55	20.68	1.82	55.79	23.15	21.04	20.05	0.59	45.59	5.32	0.02	7.49	0.73	0.80	40.69	11.88	23.58	76.14	6.7	38.0	17.6	31.3							
07	2020	Potato	Sayaka	Andosol	30-60	5.84	68.7	1825.0	20.67	28.13	2.25	48.78	28.63	22.57	37.79	1.02	7.26	6.77	0.08	7.28	0.74	0.79	39.52	12.11	23.34	74.97	9.1	44.0	20.7	34.9							
07	2020	Potato	Sayaka	Andosol	0-30	6	139.7	1839.0	19.89	30.22	2.44	40.98	31.36	27.64	26.86	0.74	34.16	3.85	0.25	8.95	0.94	1.00	48.58	15.37	29.40	93.35	9.8	50.7	19.3	41.0	3754.7	3957.1	94.9	100.0	84.2	84.2	93.4

Detailed description is shown in List 2 as the next page

List 2. Description of Supplementary Table 2

column_name	meaning	unit
ID	ID	
year	Harvest year	
crop	Crop name	
cultivar	Cultivar	
soil_type	Soil type	
depth	Elevation	cm
	Product yield	g m^{-2}
	Grain protein	%
pH_H2O	$pH(H_2O)$	
Ava_P	Available_phosphate	mg P_2O_5 kg^{-1}
P_absorbance	Phosphate_absorption_coefficient	mg P_2O_5 kg^{-1}
CEC	Cation exchange capacity	$cmol_c$ kg^{-1}
Ca	Exchangeable Ca content	mg CaO kg^{-1}
Mg	Exchangeable Mg content	mg MgO kg^{-1}
K	Exchangeable K content	mg K_2O kg^{-1}
Mg_K	Mg/K	equivalent ratio
Ca_Mg	Ca/Mg	equivalent ratio
CaS	Lime saturation	%
BaS	Base saturation	%
B	Hot-water dissolved boron content	mg kg^{-1}
Mn	Easily reductive manganese	mg kg^{-1}
Zn	Acid-soluble zinc	mg kg^{-1}
Cu	Acid-soluble copper	mg kg^{-1}
TC	Total carbon	g kg^{-1}
TN	Total carbon	g kg^{-1}
Ava_N	Hot-water extractive nitrogen	mg $100g^{-1}$
sand	Sand content	%
silt	Silt content	%
clay	Clay content	%
solid	Solid phase	
bulk_density	Bulk density	Mg m^{-3}
pore_pF1.5	Macropore ratio	$\times$ 10^{-2} m^3 m^{-3}
water_holding_capacity_pF1.5_3.0	Available moisture	$\times$ 10^{-2} m^3 m^{-3}
Ca_score	Exchangeable calcium content score	
Solid_score	Solid phase score	
Cu_score	Acid-soluble copper content score	
weighted_Ca_score	Weighted exchangeable calcium content score	
weighted_solid_score	Weighted solid phase score	
weighted_Cu_score	Weighted acid-soluble copper content score	
SQI	Soil quality index	
MOC	Mineral-associated organic carbon content	g kg^{-1}
MOCmax	Maximum MOC content	g kg^{-1}
Csat	Csat	%
Cdef	Cdef	%
yield_per_area	Yield	g m^{-2}
yield_cul_mean	Cultivar-adjuted yield	%
relative_yield	Yield ratio to the regional average	%
depth_tillage_layer	Surface soil thickness	cm
SQI_0_60_ave	SQI in 0-60 cm	
depth_weighted_SQI	Depth corrected SQI	
simple_correction_SQI	Simple corrected SQI	

Supplementary Table 3. Correlation coefficients between MDS candidates in chapter 4

p value	pH (H_2O)	Available phosphate content	Exchangeable Ca content	Exchangeable Mg content	Exchangeable K content	Mg/K	Ca/Mg	Lime saturation percentage	Base saturation percentage	Hot-water dissolved B content	Easily reducible Mn content	Acid-soluble Zn content	Acid-soluble Cu content	Solid content	Bulk density	Macropore	Available moisture
Available phosphate content	1.00																
Exchangeable Ca content	< 0.05	1.00															
Exchangeable Mg content	0.72	0.86	< 0.05														
Exchangeable K content	1.00	1.00	1.00	< 0.05													
Mg/K	1.00	1.00	0.07	1.00	< 0.05												
Ca/Mg	0.20	1.00	< 0.05	1.00	1.00	1.00											
Lime saturation percentage	< 0.05	0.08	< 0.05	< 0.05	1.00	1.00	< 0.05										
Base saturation percentage	< 0.05	< 0.05	< 0.05	< 0.05	1.00	1.00	0.86	< 0.05									
Hot-water dissolved B content	1.00	1.00	0.43	1.00	1.00	1.00	1.00	1.00	1.00								
Easily reducible Mn content	1.00	< 0.05	1.00	0.15	1.00	1.00	1.00	1.00	0.40	1.00							
Acid-soluble Zn content	0.64	< 0.05	< 0.05	< 0.05	1.00	1.00	1.00	< 0.05	< 0.05	< 0.05	0.99						
Acid-soluble Cu content	< 0.05	1.00	0.89	1.00	1.00	1.00	0.21	1.00	1.00	1.00	1.00	1.00					
Solid content	0.33	< 0.05	0.55	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	< 0.05				
Bulk density	0.64	0.08	< 0.05	0.30	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	< 0.05	< 0.05			
Macropore ratio	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.12	1.00		
Available moisture	1.00	1.00	0.15	< 0.05	1.00	1.00	1.00	1.00	1.00	1.00	0.14	1.00	1.00	1.00	1.00	1.00	
Year standardized penetration depth	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.41	0.21	1.00	1.00
r value																	
Available phosphate	-0.015																
Exchangeable Ca content	0.502	0.144															
Exchangeable Mg content	0.344	0.336	0.799														
Exchangeable K content	0.197	0.260	0.317	0.610													
Mg/K	0.145	-0.069	0.429	0.256	-0.483												
Ca/Mg	0.394	-0.139	0.599	0.044	-0.181	0.315											
Lime saturation percentage	0.614	0.426	0.692	0.478	0.165	0.284	0.484										
Base saturation percentage	0.566	0.501	0.621	0.497	0.250	0.200	0.336	0.983									
Hot-water dissolved B content	0.184	-0.032	0.364	0.214	0.038	0.188	0.294	0.291	0.251								
Easily reducible Mn content	-0.063	0.547	0.231	0.404	0.163	0.057	-0.151	0.315	0.368	0.045							
Acid-soluble Zn content	0.349	0.498	0.460	0.453	0.215	0.184	0.189	0.578	0.581	0.501	0.329						
Acid-soluble Cu content	-0.478	0.306	-0.334	-0.201	-0.055	-0.110	-0.391	-0.013	0.093	-0.115	0.273	0.019					
Solid content	-0.376	0.445	-0.355	-0.298	-0.169	-0.145	-0.267	0.103	0.171	-0.146	0.197	-0.071	0.574				
Bulk density	-0.349	0.425	-0.440	-0.378	-0.213	-0.182	-0.308	0.088	0.165	-0.185	0.157	-0.108	0.600	0.977			
Macropore ratio	0.098	0.199	0.029	-0.038	0.047	-0.122	0.163	0.074	0.074	-0.137	-0.001	0.145	-0.018	-0.410	-0.302		
Available moisture	-0.103	-0.145	-0.405	-0.475	-0.250	-0.145	-0.129	-0.135	-0.113	0.011	-0.407	-0.105	0.163	0.161	0.250	0.014	
Year standardized penetration depth	0.217	-0.247	0.190	0.261	0.101	0.140	-0.043	0.024	0.018	0.100	0.038	0.019	-0.137	-0.366	-0.392	-0.164	-0.309

p value was corrected with Holm's method

Supplementary Table 4. Correlation coefficients between MDS candidates in chapter 5

p value	pH (H_2O)	Available phosphate content	Exchangeable Ca content	Exchangeable Mg content	Exchangeable K content	Mg/K	Ca/Mg	Lime saturation percentage	Base saturation percentage	Hot-water dissolved B content	Easily reducible Mn content	Acid-soluble Zn content	Acid-soluble Cu content	Solid content	Bulk density	Macropore
Available phosphate content	< 0.05															
Exchangeable Ca content	< 0.05	< 0.05														
Exchangeable Mg content	0.18	< 0.05	< 0.05													
Exchangeable K content	< 0.05	0.09	< 0.05	< 0.05												
Mg/K	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05											
Ca/Mg	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.23										
Lime saturation percentage	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.17	< 0.05									
Base saturation percentage	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.75	0.15	< 0.05								
Hot-water dissolved B content	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.58	0.53							
Easily reducible Mn content	< 0.05	0.30	< 0.05	0.98	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05						
Acid-soluble Zn content	< 0.05	< 0.05	< 0.05	< 0.05	0.72	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.83					
Acid-soluble Cu content	0.29	< 0.05	0.22	0.73	0.17	0.80	0.08	< 0.05	< 0.05	0.17	< 0.05	< 0.05				
Solid content	0.74	0.12	< 0.05	0.72	0.26	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.99	0.11			
Bulk density	< 0.05	0.71	< 0.05	0.08	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	< 0.05	0.34	< 0.05	< 0.05		
Macropore ratio	0.06	0.13	0.75	0.37	0.47	0.20	< 0.05	< 0.05	< 0.05	0.61	0.68	0.28	0.13	< 0.05	< 0.05	
Available moisture	0.71	0.08	0.74	0.24	< 0.05	< 0.05	0.44	0.11	0.06	0.12	< 0.05	0.66	0.12	< 0.05	< 0.05	0.81
r value																
Available phosphate content	-0.388															
Exchangeable Ca content	-0.243	0.496														
Exchangeable Mg content	-0.093	0.407	0.774													
Exchangeable K content	0.367	-0.118	-0.271	-0.143												
Mg/K	-0.388	0.242	0.674	0.643	-0.621											
Ca/Mg	-0.240	0.204	0.397	-0.222	-0.202	0.083										
Lime saturation percentage	0.399	0.322	0.474	0.430	0.137	0.095	0.147									
Base saturation percentage	0.498	0.238	0.286	0.401	0.297	-0.022	-0.099	0.956								
Hot-water dissolved B content	-0.360	0.454	0.563	0.452	-0.195	0.501	0.156	0.038	-0.043							
Easily reducible Mn content	0.432	-0.072	-0.236	-0.002	0.478	-0.281	-0.343	0.251	0.402	-0.149						
Acid-soluble Zn content	-0.193	0.637	0.447	0.417	-0.025	0.205	0.166	0.351	0.284	0.436	-0.015					
Acid-soluble Cu content	0.074	0.202	-0.086	0.024	0.095	-0.017	-0.122	0.389	0.458	0.095	0.343	0.381				
Solid content	0.023	0.107	-0.162	-0.025	0.079	-0.147	-0.184	0.142	0.206	-0.240	0.182	-0.001	0.110			
Bulk density	0.193	0.026	-0.291	-0.122	0.204	-0.302	-0.246	0.189	0.288	-0.353	0.299	-0.066	0.150	0.967		
Macropore ratio	0.131	0.105	0.022	-0.062	0.050	-0.089	0.152	0.176	0.153	0.036	0.028	0.076	0.104	-0.622	-0.516	
Available moisture	-0.026	-0.121	-0.023	-0.081	-0.146	0.147	0.053	-0.110	-0.132	0.108	-0.149	-0.031	0.109	-0.431	-0.427	-0.017

p value was corrected with Holm's method

Supplementary Table 5. ANOVA table for yield, analyzing year, cultivar, and soil type as a between-subjects factor

		Degrees of freedom	Sum of squares	Mean Square	*F* value	*p* value	
Potato	Year	2	1939565	969783	2.5	0.0908	.
	Cultivar	2	6341047	3170524	8.19	0.00076	***
	Soil type	3	762713	254238	0.66	0.58216	
	Year x Cultivar	4	3281665	820416	2.12	0.09045	.
	Year x Soil type	4	411820	102955	0.27	0.89864	
	Cultivar x Soil type	2	184019	92010	0.24	0.78927	
	Year x Cultivar x Soil type	2	700759	350380	0.91	0.41037	
	Residual	56	21680900	387159			
Wheat	Year	2	459964	229982	17.35	0.000036	***
	Soil type	3	43710	14570	1.1	0.37	
	Year x Soil type	2	36438	18219	1.37	0.27	
	Residual	21	278430	13259			

.: $p < 0.1$, ***: $p < 0.001$

Supplementary Table 6. Results of multiple comparison test with *p*-values corrected using Holm's method on surface soil thickness

p value	Brown Lowland soil	Andosols with alluvial deposits	Andosols
Andosols with alluvial deposits	1.000		
Andosols	1.000	1.000	
Peat soils	0.004	0.164	0.001