Received: 28 June 2023 | Accepted: 18 March 2024 | Published online: 17 April 2024

DOI: 10.1002/saj2.20674

Soil Science Society of America Journal

ORIGINAL ARTICLE

Fundamental Soil Science

Exploratory assessment of the SLAKES method to characterize aggregate stability across diverse soil types

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Assigned to Associate Editor Aaron Lee Motschenbacher Daigh.

Abstract

Classical soil aggregate stability (AS) methods lack standardized protocols and require long measurement times. However, the fairly new SLAKES method purportedly allows for rapid AS estimation with minimal technical equipment. SLAKES has been tested on fine-textured soils but its suitability for other soil types is unknown. This study investigated SLAKES' suitability for AS measurements on silty clay, silt loam, and sandy loam soils. For each SLAKES test, three aggregates were immersed in distilled water and imaged for 10 min. SLAKES output includes disaggregation data per aggregate and three coefficients from a Gompertz function that describe slaking dynamics. Four AS descriptors obtained from SLAKES output were investigated: the averaged maximum slaking from a test (a_{SK}), the maximum slaking for each measurement (aggregate) (a_{FT}, from fitting a Gompertz function to SLAKES raw data), the averaged a_{FT} for the measurements in a test ($\overline{a}_{FT}$), and the slaking index at 10 min per measurement (SI_{600}). The a_{SK} is a direct descriptor included in the SLAKES output, while a_{FT}, $\overline{a}_{FT,}$ and SI_{600} are indirect descriptors. The SI_{600} was the most preferred SLAKES AS descriptor since it is a calculated parameter and due to its sensitivity in detecting AS status among all soil types. The sandy loam soil was the most stable from both the raw SLAKES data and fitting, albeit counterintuitive. SLAKES default measurement time was sufficient for the silty clay and silt loam soils but not for the sandy loam soil. Overall, SLAKES was a useful tool for AS measurements on fine-textured soils but was less suitable for AS measurements on the coarse-textured soil.

1 | INTRODUCTION

Physical soil health parameters such as aggregate stability (AS) are essential for improving our understanding of processes affecting agricultural productivity and environmental quality. AS measurements help assess whether or not the strength of soil aggregates is being improved through agricultural activities like tillage, manuring, crop rotation, and others (Castro Filho et al., 2002). Some of these practices tend to render soil aggregates either stable or unstable and consequently improve or degrade soil structure. For example, the topsoil structure may benefit from reduced tillage operations that favor aggregation and reduce the risk of soil erosion

Abbreviations: AS, aggregate stability; SI, slaking index; SI_{600}, slaking index at 600 s.

(Fuentes et al., 2012; Laufer et al., 2016). Thus, AS measurements may serve as a useful indicator of topsoil degradation (Deviren Saygin et al., 2012).

Despite the plethora of classical AS methods available, the quantification of this property is challenging. As stated by Le Bissonnais (1996), the existence of several AS measurement methods is "a reflection of a sustained interest in this property and a lack of satisfactory standard methodology." This methodological lapse is evident in the lack of standardized procedures and instrumentation specificity required by different methods, repeatability concerns, the measurement time, inaccuracies especially with coarse-textured soils, and the lack of affordable private providers to whom it may be outsourced (Almajmaie et al., 2017; Amézketa, 1999; Fajardo et al., 2016; Gyawali & Stewart, 2019). Additionally, AS methods depend on the type of aggregate breakdown mechanism intended to be investigated. These include breakdown due to slaking, differential swelling, raindrop impact, and physicochemical dispersion (Le Bissonnais [1996]). Existing classical AS methods include those that employ wet sieving techniques (Kemper & Roseneau, 1986; Le Bissonnais, 1996; Yoder, 1936), ultrasonic dispersion (Mentler et al., 2004), water drop impact tests (Imeson & Vis, 1984; Zhu et al., 2009), dry sieving (Mapa & Gunasena, 1995), or rainfall simulation techniques (Legout et al., 2005; Warnemuende et al., 2007). Recent years have seen the development of new AS measurement methods. For instance, Koestel et al. (2021) proposed an X-ray imaging technique for identifying aggregates within intact soils. Additionally, spectroscopic techniques have been employed for the estimation of AS and aggregate size distribution (Afriyie et al., 2020; Shi et al., 2020). Although several AS methods exist, their selection and the interpretation of measurement outcomes depend on the purpose of the measurement (Saygın et al., 2012). Moreover, challenges associated with AS measurement methods are documented in the literature. For instance, Flynn et al. (2020) posited that although the wet sieving method proposed by Yoder (1936) has been modified over time, some of the improved equipment is costly and may discourage its use. Furthermore, Ternan et al. (1996) suggested that the drop tests could overestimate the weakness of surface structures to rain impact by overestimating the energy input by concentrating on single drops. To overcome some of the above-mentioned challenges, researchers at the University of Sydney developed SLAKES, an AS assessment method that uses an image recognition algorithm and is implemented in a smartphone-based application (Fajardo et al., 2016). The SLAKES method is based on the AS in water test of Vertisols by Field et al. (1997), who investigated the coherence of the clay-sized minerals of aggregates when immersed in water using classical AS methods such as the Emerson dispersion test (Emerson, 1967; Loveday & Pyle, 1973). The Emerson test was used to classify several Australian soils, which were mostly clayey.

Core Ideas

- We tested SLAKES suitability for aggregate stability measurements across diverse soil types.
- SLAKES sensitivity depends on the slaking descriptor employed.
- SLAKES was less suitable for the sandy loam soil but suitable for the silty clay and silt loam soils.
- The default measurement time was suitable for the finer soils but not for the coarse-textured soils.

The SLAKES app measures the increase in the aggregate area continuously for 10 min as it disperses in water (Fajardo et al., 2016; Flynn et al., 2020). Slaking, which is defined as the compression of entrapped air during fast wetting (Panabokke & Quirk, 1957), is the main aggregate breakdown mechanism measured depending on related factors of aggregate size, moisture, and clay contents. Within SLAKES, a Gompertz function is fitted to the disaggregation data to model the dynamics of soil slaking as a function of time and to provide parameters from which the AS status can be inferred. The three-parameter Gompertz function is reportedly advantageous over other functions (e.g., exponential functions) because both rapid and gradual disaggregation processes can be modeled (Fajardo et al., 2016). Outputs from the SLAKES test include the disaggregation data of each aggregate and the arithmetic means of each of the three Gompertz fit parameters (a, b, and c) from all aggregates used. In effect, these parameters describe the maximum slaking (a), the initial time of fast slaking (b), and the growth rate of the aggregate area (c). All the SLAKES data per test are saved to a downloadable text file. Furthermore, SLAKES is purported to offer advantages over existing classical AS methods. These advantages include its simplicity, rapidity, reduced sample preparation, objectivity, cheapness, and the possibility to visualize continuous changes during disaggregation (Fajardo et al., 2016).

Since its development, SLAKES has been employed in a few studies focusing mostly on AS assessment of fine-textured soils (clayey and silty soils) under agricultural and natural management systems. For example, Fajardo et al. (2016) tested SLAKES on soils reflecting the agro-ecological variability of New South Wales (Australia) under different land uses. They detected significant differences between native vegetation and agricultural fields using SLAKES. They highlighted further their failure to measure AS of certain soils thought to be unstable due to their sandy and/or hydrophobic nature. Flynn et al. (2020) assessed the stability of Vertisols to tillage practices, where the SLAKES method was more sensitive to tillage practices (conventional tillage, no-till, and perennial grasslands) than the Cornell wet AS test which employs a rainfall simulator. Similarly, Bagnall and Morgan (2021) reported that SLAKES was able to detect differences between tillage treatments (conventional tillage, no-till, and perennial grass) on clay and silt-textured soils. Jones et al. (2021) also applied SLAKES in a digital soil mapping approach to assess AS in a mixed agricultural landscape in Australia.

Recently, Vanwindekens and Hardy (2023) developed the QuantiSlakeTest (QST), based on the SLAKES method, to quantitatively assess the disaggregation of silt loam soils under different tillage, organic, and inorganic fertilization schemes. The test measures the changing weight of the samples due to the mass loss upon immersion in water. They reported that generally, QST indicators correlated to soil properties and that the method could discriminate between soil management practices.

The majority of studies that have evaluated the SLAKES method were conducted on fine-textured soils, and the reliability of the method on coarse-textured soils is not well known. Additionally, the SLAKES method assumes that slaking of the aggregates reaches an asymptote after 10 min. This may not be the case for all soil types, and even for the same soil type under different management systems. Thus, it is important to evaluate if there is a need to use different measurement times for different soil types. Therefore, the objectives of the study were to (1) assess the validity of SLAKES output compared to results from fitting the Gompertz function to the same output but outside of the SLAKES app, (2) assess SLAKES sensitivity to soil type (silty clay, silt loam, and sandy loam soils) for AS measurements, and (3) examine the suitability of the default SLAKES measurement time for different soil types.

2 | MATERIALS AND METHODS

2.1 | Study area description

Soil samples were collected from three long-term experiments (LTEs) in Lanna (Sweden), Bad Lauchstädt (Germany), and Askov (Denmark), which differ in soil texture. The LTE at Lanna had a silty clay texture and was classified as an Aquic Haplocryept (Soil Survey Staff, 2014). The mean annual temperature at the site is 7.3˚C and precipitation is 636 mm (Kätterer et al., 2014). The Bad Lauchstädt LTE had a silt loam texture, and the soils were identified as Haplic Mollisol (Soil Survey Staff, 2014). The average annual temperature and precipitation are 8.7˚C and 484 mm, respectively (Naveed et al., 2014). Lastly, the Askov LTE in Denmark had a sandy loam soil texture, and the soil was classified as a Typic Hapludalf (Soil Survey Staff, 2014). The mean annual precipitation and temperature are 953 mm and 8.8˚C, respectively (Christensen et al., 2019). Table 1 shows an overview of the textural composition and organic carbon content for the three LTEs.

2.2 | Soil sampling and sample preparation

All soils were sampled at a water content corresponding to field capacity (approximately −100 hPa matric potential) except for Bad Lauchstädt, where there was a rainfall event during sampling. Samples were taken at a depth of approximately 0–15 cm with a shovel, covering an area of approximately 50 cm by 50 cm each. We sampled eight plots in Lanna, four plots in Bad Lauchstädt, and 23 plots in Askov. The differences in number of plots emanated from the layout of the LTE at each site. The Lanna LTE comprised an unfertilized and farmyard manure treatments with four replicate plots each. The Bad Lauchstädt LTE had a control and manure treatment with two crops (maize and barley), and each treatment was a long strip with no field replicates. Finally, the Askov LTE comprised four crops (grass, barley, maize, and wheat) and manure treatments with three field replicates each. Further details about the field site and each treatment plot are available in Fu et al. (2022). To account for the variations in the number of samples, we carried a higher number of tests per plot for Bad Lauchstädt as described in Section 2.3.

In total, 35 bulk samples were collected across the three sites. Collected samples were sealed in ziplock bags and transported in cooling boxes to a cold room, where they were stored at 2˚C to minimize ageing of aggregates. The samples were air-dried for not less than 72 h and passed through an 8-mm sieve for AS measurements.

2.3 | Laboratory measurements

The SLAKES setup for AS tests required a Petri dish, distilled water, sieved aggregates, an appropriate lighting system, and a smartphone with the SLAKES app installed. In this study, a Samsung Galaxy S10 smartphone was used, which had a 12-MP telephoto lens, optical image stabilization (OIS) antiblur software, a 12-MP wide-angle lens with dual aperture and dual-pixel, which also included in-built (OIS) software to reduce blurry images, and a 16-MP ultra-wide-angle lens, was used. The phone was suspended on a clamp and the experimental unit was set up following the procedure described by Flynn et al. (2020). For each test, three individual air-dried aggregates were selected based on their apparent symmetry with preference given to more rounded aggregates. The aggregates were placed at pre-marked positions in the Petri dish for a reference image to be taken in the application. The aggregates were then removed, and the Petri dish was filled with deionized water (dispersing medium), after which all three aggregates were then fully immersed in the water at the same

TABLE 1 Overview of soil texture and soil organic carbon information for the long-term experimental sites.

Long-term experimental site	SOC (g/100 g)	Clay (<2 µm) (g/100 g)	Fine silt (2–20 µm) (g/100 g)	Coarse silt (20–50 µm) (g/100 g)	Fine sand (50–100 µm) (g/100 g)	Coarse sand (100–2000 µm) (g/100 g)
Lanna (SiC)—1996 (58°21′N, 13°08′E)	1.87–2.39	38–42	24–29	17–24	2–3	6–7
Bad Lauchstädt (SiL)—1902 (51°24′N, 11°53′E)	1.57–2.00	19–21	12–14	54–56	3–4	3–5
Askov (SL)—1894 (55°28′N, 09°07′E)	1.00–1.71	9–11	6–9	11–14	11–13	51–59

Note: Year after site name denotes the year of establishment. Data are presented as range (minimum–maximum).
Abbreviations: SiC, silty clay; SiL, silt loam; SL, sandy loam; SOC, soil organic carbon.

positions used for the reference image. Afterwards, the start button of the SLAKES app was immediately pressed to commence the aggregate slaking test. By default, the SLAKES app images the disaggregation as the incremental change in aggregate area due to slaking. The SLAKES app also displays a slaking index (SI) onscreen after measurements. The displayed SI value is modeled by a Gompertz function (Equation 1) fitted to the disaggregation data, which is a function of the change in the aggregate area at various timesteps, relative to the reference aggregate area before slaking.

$$\mathrm{SI}_t = a\, e^{\left(-b\, e^{\left(-c \log_{10}(t)\right)}\right)}, \tag{1}$$

where SI_t is the slaking index at time t, with a, b, and c being parameters of the Gompertz function. The parameter a is the asymptote which represents the maximum predicted or possible slaking and reflects the AS status of the soils. Parameter b represents the initial time or fast slaking, and c represents the growth rate and is associated with the ongoing slaking of the aggregates (Fajardo et al., 2016; Jones et al., 2021). Outputs from SLAKES test include the disaggregation data of each aggregate over an exponential-like time interval, the arithmetic means of each of the three Gompertz fit parameters (a, b, and c) from all aggregates used, and a standard deviation value (Flynn et al., 2020). Each test output or data is saved to a downloadable text file. Furthermore, the displayed SI values by SLAKES are classified into three classes to reflect the AS status. Thus, tests with SI values from 0 to 3 indicate stable aggregates. Between 3 and 7, the aggregates show moderate stability and tests with SI values higher than 7 designate unstable aggregates (Fajardo et al., 2016). An unequal number of replicate tests was performed across sites due to differences in the field layouts. For Lanna and Askov, where we sampled from more plots, three replications were performed for each test, while seven replications were performed per test in Bad Lauchstädt, where we sampled from fewer plots. A summary of the total number of tests performed per site is presented in Table 2.

2.4 | Descriptive parameters of slaking

For clarity and a better understanding of AS status based on the SLAKES output, four different descriptors of slaking are introduced here. The SLAKES displayed SI value (arithmetic mean of the Gompertz parameter a per test of three aggregates) directly obtained from the SLAKES app is denoted as "a_{SK}" from hereon. Additionally, we derived other indirect AS descriptors from the raw SLAKES outputs. For instance, to investigate the reproducibility of the a_{SK} descriptor, we fitted the Gompertz function to the disaggregation data of each aggregate in Microsoft Excel to obtain the "a_{FT}" parameter.

TABLE 2 Number of conducted tests and percentage of aggregate stability tests corresponding to the three stability classes per soil type.

Soil type	Total N	Stable (0%–3%)	Moderately stable (3%–7%)	Unstable (>7%)
Lanna (SiC)	32	71.9	21.8	6.30
BadLauchstädt (SiL)	51	21.6	54.9	23.5
Askov (SL)	118	59.3	10.2	30.5

Abbreviations: N, number of tests; SiC, silty clay; SiL, silt loam; SL, sandy loam.

The a_{FT} parameter is the expected asymptote of each disaggregation data and represents the maximum possible slaking. A distinction is made between a_{SK} and a_{FT} in that, while the former is a direct and an averaged parameter depicting maximum slaking in a test of three aggregates, the latter is an indirect parameter and a unique value depicting maximum slaking of individual aggregates. The a_{FT} of the three aggregates in a test was averaged to obtain the "$\overline{a}_{FT}$" descriptor. All things being equal, the a_{SK} and $\overline{a}_{FT}$ values should correspond since the latter was obtained by fitting the Gompertz function to the same dataset as used internally by SLAKES to generate the a_{SK}. Furthermore, "SI_{600}" (previously introduced by Flynn et al. [2020]), which is an indirect AS descriptor, was calculated from the raw SLAKES output in the present study. SI_{600} is the maximum slaking index at the end of the SLAKES test and was calculated from Equation (2).

$$SI_{600} = \frac{A_{600} - A_0}{A_0}, \tag{2}$$

where SI_{600} refers to the observed slaking at 600 s, A_0 is the initial area of the aggregate, and A_{600} is the final aggregate area after 600 s of slaking. This describes the change in the area of the aggregate from a reference image over 10 min of wetting (Bagnall & Morgan, 2021). Thus, it was the observed slaking at 600 s and was computed per aggregate. The assessment of AS for each SLAKES measurement of three aggregates in the same Petri dish is simply referred to as a test, while the assessment of AS of each aggregate is referred to as a measurement from hereon.

2.5 | Data analysis

To model the dynamics of disaggregation, Gompertz functions were fitted to the disaggregation data in Microsoft Excel. Initial estimates of the model parameters were guestimated based on the observed data to predict the SI values for each measurement or aggregate. The parameter *a* was based on the SI_{600}, parameter b on the initial observed SI value, and parameter c on the slope of the data. Using the nonlinear *Solver* algorithm in Microsoft Excel, the model parameters were optimized by minimizing the sum of squared errors between the observed and predicted disaggregation data. The sensitivity of a_{FT} and SI_{600} to soil type was tested using the Kruskal–Wallis rank sum test. To test the significance of the differences in AS between soil types for the a_{FT} and SI_{600} descriptors, Dunn's post hoc test was used for pairwise comparisons. The statistical significance level was considered at a p-value < 0.05. The strength of the linear relationship between a_{SK} and $\overline{a}_{FT}$ descriptors was assessed with the Pearson correlation coefficient. The data analyses and graphical presentation were performed with SigmaPlot 14.5 (Systat Software Inc.).

3 | RESULTS AND DISCUSSION

3.1 | Distribution of a_{SK} across soil types

Before assessing SLAKES data legitimacy, the spread and range of a_{SK} were investigated for each soil type (Figure 1). Additionally, the percentage of tests that conformed to the three AS classes was assessed per soil type. Furthermore, the a_{SK} values from the present study were also compared to the maximum value of 7.3 reported by Jones et al. (2021). From Figure 1, it is evident that a_{SK} is sensitive to soil type, where generally, most tests from the silty clay and silt loam soils showed few incidences of aggregate instability ($a_{SK} \geq 7$) compared to the sandy loam soil which showed a higher incidence of aggregate instability ($a_{SK} \geq 7$). Table 2 shows that the silty clay soil had the highest (71.9%) and lowest (6.30%) percentages of stable and unstable AS status, respectively. The sandy loam soil had a higher percentage (59.3%) of stable AS status compared to the silt loam soil (21.6%) and a comparatively higher percentage of unstable AS status (30.5%) than the latter (23.5%).

The observation of more stable sandy loam AS status compared to the silt loam soil is counterintuitive and could be attributed to higher amounts of coarse sand particles in the sandy loam soil (which do not disaggregate) than in the silty loam soil (Table 1). According to Lado et al. (2004), although AS increases with clay content, clay content and mineralogy may increase slaking. They found that dried aggregates slaked extensively when wetted rapidly despite the increase in clay content. From Tables 1 and 2, it is evident that the higher clay content of the silt loam soil did not translate to a more stable AS status. Furthermore, the susceptibility of finer soil particles, mostly silt, to soil structural deterioration is well-documented in the literature (Fernández-Ugalde et al., 2009;

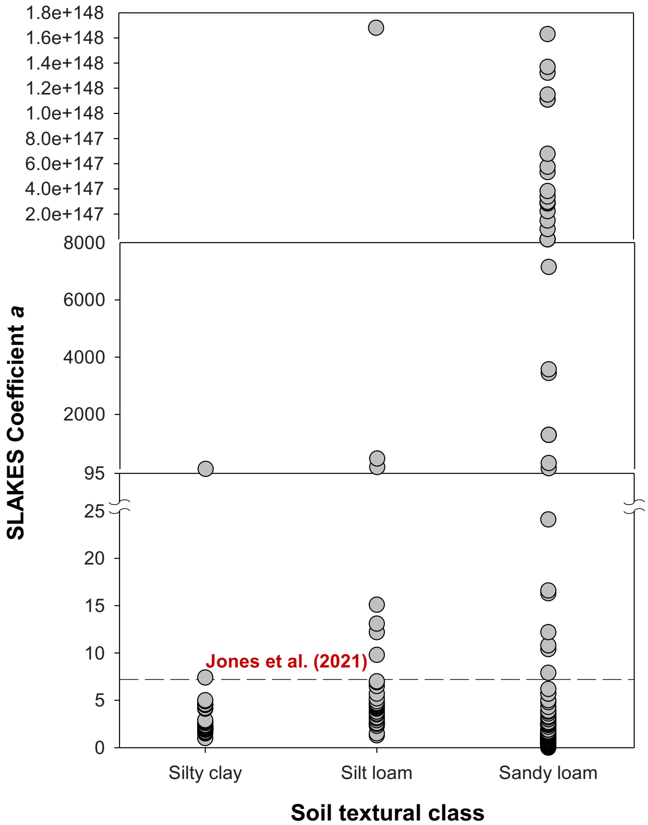

FIGURE 1 The spread and range in the SLAKES parameter *a* (a_{SK}) for three soil types. The broken line is the maximum slaking reported by Jones et al. (2021). The continuous horizontal lines within the plot depict the range in a_{SK} values (0–95, 95–8000, and 8000–1.8e+148). Axes break in the plot goes from 25 to 95.

Vasiliniuc & Patriche, 2009). Thus, the lower silt content of the sandy loam soil as well as the factors discussed above possibly explains the higher percentage of stable tests for the sandy loam soil compared to the silt loam soil.

From Figure 1, extremely high a_{SK} values were observed, and these were suspected to be outliers. Outlying a_{SK} values were identified by graphing the data for each soil type (boxplots not shown). For the silty clay soil, a single outlier with an a_{SK} of 97 was found. The silt loam soil type had three outliers with a_{SK} values of 161, 459, and 1.68E+148. Lastly, 26 outliers with a_{SK} values greater than 1000 were observed for the sandy loam soil. Although such high values theoretically reflect unstable AS tests, in principle, they afford little understanding. Therefore, for all soil types, we defined a threshold of 1000 above which tests with larger a_{SK} values were considered outliers.

The findings of Flynn et al. (2020) concur with the current study, where they reported larger a_{SK} (parameter *a*) values for some tests than others. They attributed this to inaccurate modeling of the disaggregation parameters, where a_{SK} is extrapolated by the fitted Gompertz function outside the observed data. Such extrapolation could be attributed to slow disaggregation, possibly due to high antecedent moisture contents and larger soil particles (e.g., small stones). Thus, with the default SLAKES measurement duration, only a part of the disaggregation process is measured, and the subsequent modeling of the disaggregation dynamics may lead to extrapolations of SI outside the observed data. Therefore, these observations raise concerns about the validity of the a_{SK} as the most descriptive AS indicator across soil types. We assess the reproducibility of SLAKES output and the possibility to obtain more reliable AS descriptors than a_{SK} in subsequent sections. Two factors can influence the SLAKES output: (i) the dynamics of disaggregation and (ii) the data quality and the accuracy of the automated fitting of the Gompertz function to test data within the SLAKES app. This will be addressed in Section 3.2.

3.2 | Slaking dynamics and the reproducibility of SLAKES outputs

3.2.1 | Evaluation of the disaggregation process and the modeled dynamics of disaggregation

Following up on Section 3.1, we assessed the reliability of the a_{SK} descriptor obtained from the SLAKES app. To do this, we examined the data recorded at the measurement level (each aggregate separately) rather than at the test level (all three aggregates per test together). Consequently, the Gompertz function was fitted to the disaggregation data of each aggregate to obtain a_{FT}. Thereafter, the progression of aggregate breakdown was visualized per aggregate (three per test) by plotting the SI values against time on a log scale. The $\overline{a}_{FT}$ values were calculated for comparison with a_{SK} for every test. Figure 2 shows selected test examples which highlight unexpected disaggregation dynamics and their potential influence on the computed a_{SK} values.

For the silty clay example (Figure 2a–c), disaggregation proceeded well for two of the three measurements (Figure 2a,b), where both the periods of fast and slow disaggregation could be identified. Moreover, the a_{SK} (2.9) did not correspond to the $\overline{a}_{FT}$ (7.2). From Figure 2c, there is an apparent extrapolation of disaggregation outside the observed data. Consequently, a higher a_{FT} was obtained from the Gompertz model fit to this data compared to the two other measurements (Figure 2a,b), due to the continuous rise of the curve and the resultant poor modeling of the asymptote in the former. Furthermore, due to the range in the a_{FT} values of the three measurements (Figure 2a–c), different AS statuses (stability classes) may be defined depending on which measurements are considered. For instance, averaging the a_{FT} from Figure 2a,b will result in a different AS status than the average for all three measurements in the test. The silt

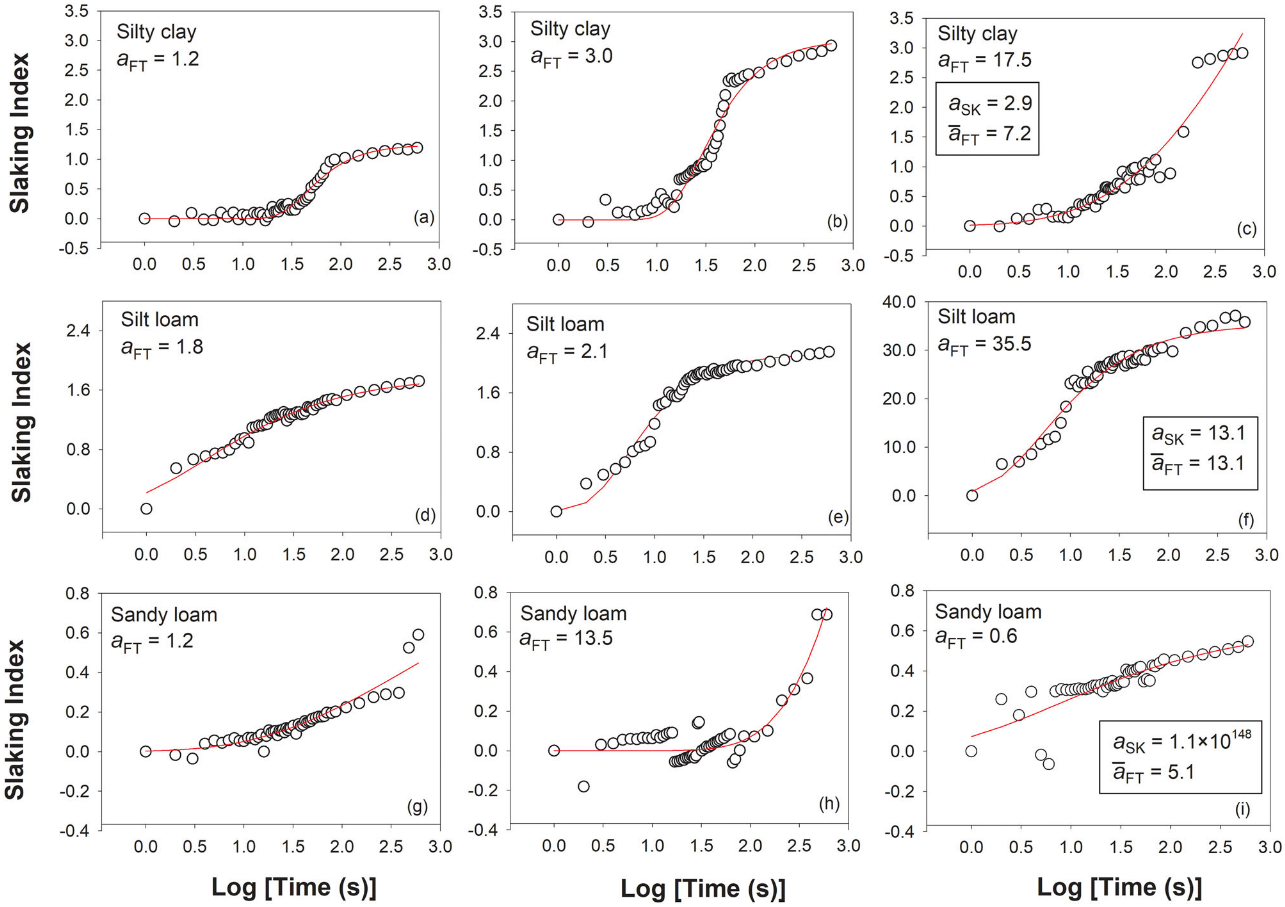

FIGURE 2 Disaggregation data visualized with selected test examples consisting of three aggregate measurements from the same test—for the silty clay (a–c), silt loam (d–f), and sandy loam soil (g–i). The a_{SK} is the parameter a from SLAKES internal Gompertz function fitting per test, while the $\bar{a}_{FT}$ is the averaged parameter a from the fitting of the Gompertz function to disaggregation data per test outside the SLAKES app. The a_{SK} and $\bar{a}_{FT}$ values are compared in a box in the last plot for each test: (c) silty clay, (f) silt loam, and (i) sandy loam tests. Plot (f) has a different scale due to a higher range in slaking indices compared to (d) and (e). All other measurements visualized have the same scale within the test. The open circles show slaking index at given time steps on the log scale, while the red curves represent the fitted Gompertz function to the disaggregation data.

loam example (Figure 2d–f) showed better disaggregation dynamics of the three soil type examples presented. Thus, the observed disaggregation data showed almost no incidence of extrapolation beyond the measurement period. Unsurprisingly, the fitted Gompertz functions to data modeled the disaggregation dynamics satisfactorily and the a_{SK} value was consistent with the $\bar{a}_{FT}$ value for the test.

However, it is noticeable that Figure 2f has a higher range in slaking indices (SI) compared to Figure 2d,e. This may be due to the misidentification of the actual disaggregated area. For instance, detached particles may float away from the main mass of a disaggregated aggregate with turbid fluid in between them. SLAKES may misrecognize the turbid fluid as part of the disaggregated mass, resulting in a larger estimated area and consequent high SI values. Such high SI values influence the modeled asymptote (Gompertz parameter a value) of affected measurements and consequently, the computed a_{SK}. Nonetheless, SLAKES averages the asymptote from all three measurements, regardless of the presence of larger SI values. Similar to the observation made for the silty clay example, averaging a_{FT} values of two of the measurements (Figure 2d,e) will result in a different AS status compared to the $\bar{a}_{FT}$ value from all three measurements in the test.

Among the three soil types, the sandy loam example (Figure 2g–i) showed the most obvious extrapolation beyond the observed data for all three measurements. This suggests that SLAKES default measurement time may be insufficient for the test. Additionally, disaggregation was variable and proceeded rather sporadically, such that the periods with fast and slow rates of aggregate breakdown could not be identified (Figure 2g–i). Furthermore, modeling the dynamics of disaggregation was challenging as seen from the poor Gompertz function fits to the data. The occurrence of several high a_{SK} values within the present study (Figure 1) and especially for the sandy loam soil offers little confidence in the use of the parameter as the most descriptive of the AS status. A comparison of the a_{SK} and $\bar{a}_{FT}$ descriptors revealed differences where, for example, the calculated $\overline{a}_{FT}$ value of 5.1 significantly differed from the a_{SK} value of 1.1E+148 (Figure 2g–i). This gives credence to suspected inaccuracies in the computed a_{SK} values, especially for those tests with high a_{SK}.

Therefore, the three test examples presented highlight problems with SLAKES interpretation of disaggregation based on the a_{SK} descriptor. This notwithstanding, the silt loam example shows the possibility to obtain reproducible results from the SLAKES output. Since only three test examples are presented here, the observations may not be limited to these examples but also apply to other tests. We assess further the extent of our observations in Section 3.2.2 by comparing the a_{SK} and $\overline{a}_{FT}$ descriptors for all tests to filter out tests where the a_{SK} and $\overline{a}_{FT}$ values do not correspond with each other.

3.2.2 | Comparison of a_{SK} and $\overline{a}_{FT}$ across soil type

The relationship between the a_{SK} and $\overline{a}_{FT}$ of all tests was initially assessed for each soil type. Extremely weak correlations were observed in general; however, the best correlation was observed for the silty clay soil (r = 0.23), while the silt loam (r = −0.02) and sandy loam soils (r = −0.03) showed weak negative correlations. Such weak correlations may be attributed to outlying a_{SK} values (Section 3.1) which could not always be reproduced from disaggregation data (Section 3.2.1) leading to different $\overline{a}_{FT}$. Additionally, the low correlations could be attributed to the poorly modeled dynamics of disaggregation and problems with the averaging of parameters within SLAKES (Section 3.2.1). Due to these observations from the entire datasets, a selection of tests with a_{SK} < 75, 50, and 25 was compared to their corresponding $\overline{a}_{FT}$. For the silty clay soil, correlations between the two descriptors were identical for the three selected datasets (a_{SK} < 75, 50, and 25). This correlation was stronger (r = 0.98) compared to the correlation found for the entire datasets. Furthermore, correlations between a_{SK} and $\overline{a}_{FT}$ of selected silt loam tests were equally identical for all three a_{SK} thresholds (r = 0.29) and were better than the initial correlation from all tests. Nonetheless, the $\overline{a}_{FT}$ of one test was observed to be more than ten times larger than the a_{SK}. Removing this test resulted in a substantial improvement in the correlation between descriptors (r = 0.94). Lastly, correlations between a_{SK} and $\overline{a}_{FT}$ for the selected sandy loam tests were equally identical for the three a_{SK} thresholds (r = −0.06). Similarly, extremely large $\overline{a}_{FT}$ than a_{SK} were observed for three tests ($\overline{a}_{FT}$ > 17,091,349). Excluding these tests equally improved the correlation (r = 0.61) between descriptors.

Figure 3 shows the correlation between a_{SK} and $\overline{a}_{FT}$ after the removal of tests with extreme $\overline{a}_{FT}$ as described above. For the silty clay soil (Figure 3a), there was a strong positive correlation between a_{SK} and $\overline{a}_{FT}$ (r = 0.98). The majority of the tests were below the maximum slaking value of 7.3 observed by Jones et al. (2021). The silt loam soil (Figure 3b) also showed a strong correlation between the two descriptors (r = 0.94). However, some of these values were higher than the reported maximum in the literature. Lastly, the results from the sandy loam soil (Figure 3c) showed a moderate correlation (r = 0.61) between the two descriptors with major deviations from the 1:1 line. Due to the disparity between a_{SK} and $\overline{a}_{FT}$ values for the sandy loam soils, it is unclear which of the two descriptors more accurately characterizes the soil AS status. Furthermore, even after the removal of obvious outliers, the a_{SK} descriptor showed some high values, possibly due to errors from the sporadic disaggregation, misrecognized area of disaggregated measurements due to shadows, and the poorly modeled disaggregation dynamics within the SLAKES app (Sections 3.1 and 3.2.1). Therefore, describing the AS of soils studied presently using the a_{SK} descriptor could lead to wrong conclusions.

Due to the above-mentioned problems with the a_{SK} and $\overline{a}_{FT}$ descriptors, we focus on AS descriptors at the measurement level in subsequent sections, thus, assessing the AS based on the a_{FT} and SI600 descriptors. Although the a_{FT} descriptor provides useful insights into the disaggregation process and a means to model the expected asymptote for each measurement, its direct use for AS assessment may not be accurate due to the underlining Gompertz function fitting problems (Section 3.2.2). Therefore, a goodness-of-fit parameter was employed to investigate the quality of the fit by the Gompertz function. To this end, the SLAKES data were filtered based on the quality of the fits. This is described in detail under Section 3.2.3.

3.2.3 | Quality of fit by Gompertz function to disaggregation data

The validity of the a_{FT} descriptor was investigated based on the quality of the fitted Gompertz function to disaggregation data. Furthermore, the a_{FT} descriptor allows the estimation of the bias between the observed and fitted disaggregation for every measurement. To assess the quality of the Gompertz function fits to the disaggregation data, the coefficient of determination (R^2) was employed as a goodness-of-fit metric. An arbitrary maximum R^2 value of 0.95 was set for data filtering. Based on visual inspection, the majority of fitted measurement curves with R^2 values greater or equal to 0.95 had a sigmoid shape, showing evidence for both fast and slow disaggregation processes. These were mostly silty clay in texture (plots not shown here). However, there were some differences between the observed and predicted disaggregation data, mostly for the sandy loam soil.

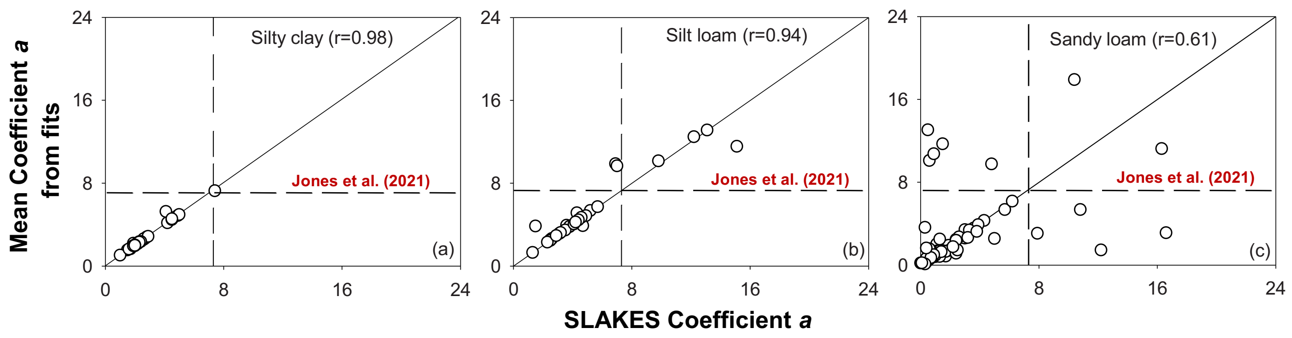

FIGURE 3 Comparison between the SLAKES parameter a (a_{SK}) and the mean parameter a values obtained from fitting the Gompertz function to disaggregation data ($\overline{a}_{FT}$). Only the a_{SK} values less than 25 and their corresponding averaged $\overline{a}_{FT}$ values are shown for each soil type. Vertical and horizontal broken lines depict the maximum reported slaking index of 7.3 by Jones et al. (2021). The r denotes Pearson's correlation coefficient.

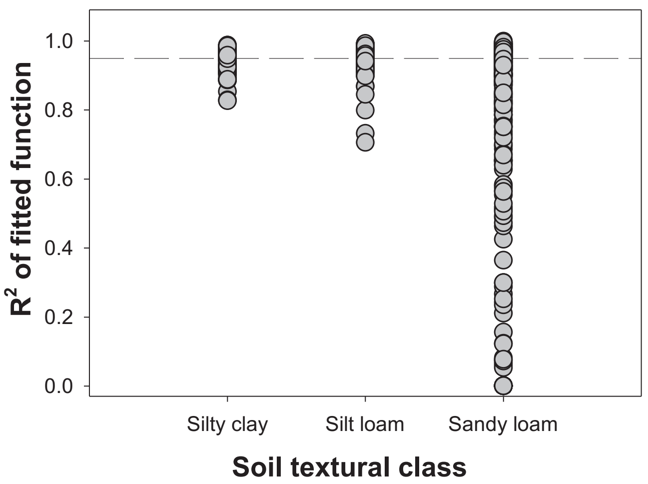

FIGURE 4 Distribution of the R^2 as the indicative parameter of the quality of the fitted Gompertz function to SLAKES disaggregation data. The horizontal broken line in the plot corresponds to an R^2 of 0.95, which is set as a threshold to select well-fitted data by the function.

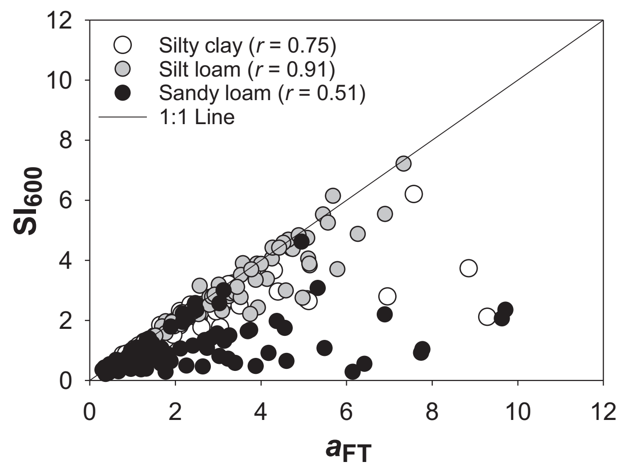

FIGURE 5 Comparison between SI_{600} and a_{FT} of each aggregate using the final filtered dataset. SI_{600} is the slaking index of each measurement at 10 min of measuring; a_{FT} is the parameter a from the fits of the Gompertz function to disaggregation data of every individual aggregate. The r denotes Pearson's correlation coefficient.

Across all soil types, several measurements had R^2 values below the set threshold. Nevertheless, some measurements with R^2 below the set threshold were seemingly well-fitted by the model in some cases. Fajardo et al. (2016) also observed low R^2 values for low-slaking samples (five measurements per test) and attributed this to the range in values over the R^2 parameter. Additionally, the present study found extremely low R^2 values in the sandy loam soil compared to the threshold (Figure 4). It was also impossible to fit the Gompertz function to some disaggregation data from the sandy loam soil and hence an R^2 of 0 was set for these. As the R^2 values alone may not necessarily translate to good fits and vice versa, the Gompertz function fits (predicted) to the disaggregation data (observed) was visually inspected for each measurement. Therefore, the criteria for data selection for further analysis included measurements with an R^2 value of 0.95 and disaggregation data that are well-fitted by the Gompertz function.

3.2.4 | Comparison of SI_{600} and a_{FT}

Prior to assessing the relationship between the SI_{600} and a_{FT} of selected measurements using the criteria described in Section 3.2.3, both descriptors were first compared for all measurements across soil types. In general, weak correlations were observed across soil types; thus, $r = 0.05$ for the silty clay, $r = 0.03$ for silt loam, and $r = -0.08$ for the sandy loam soils (plot not shown). However, a comparison between SI_{600} and a_{FT} of selected measurements based on the R^2 yielded better correlations. From Figure 5, the a_{FT} and SI_{600} descriptors generally compare well for silty clay and silt loam measurements with some deviations. The largest deviation between the descriptors was found in the sandy loam soils ($r = 0.51$). The silty clay soil showed a strong correlation ($r = 0.71$), and the silt loam soil was the strongest ($r = 0.91$). Furthermore, the a_{FT} values were generally larger than the SI_{600} values, likely due to the incomplete measurement of the

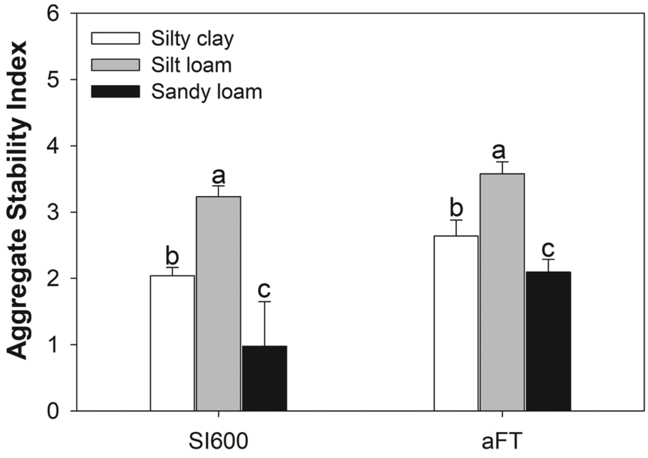

FIGURE 6 SLAKES sensitivity to aggregate stability across soil types assessed using the SI_{600} and a_{FT} descriptors. The SI_{600} is the slaking index at 10 min of measurements, while the a_{FT} is the parameter a from the fits by the Gompertz function of disaggregation data per measurement. Different letters indicate significant differences of either SI_{600} or a_{FT} between soil types.

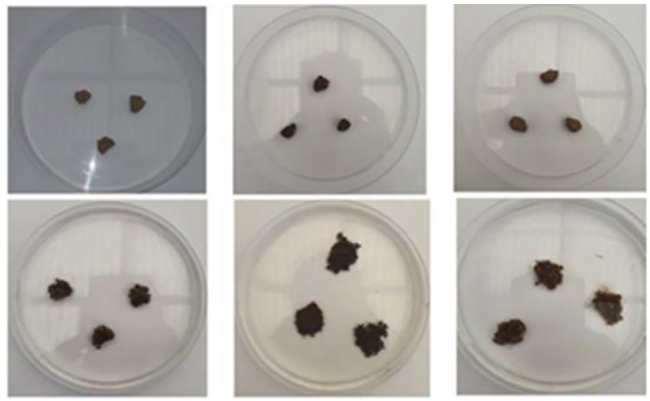

FIGURE 7 Visualization of aggregates before (top image) and after (bottom) 10 min of immersion in water. Left—silty clay (Lanna), middle—silt loam (Bad Lauchstädt), and right—sandy loam (Askov).

disaggregation process in function of the SLAKES default measurement time. Similarly, Flynn et al. (2020) found that the SI_{600} values were smaller compared to other descriptors of AS and this is consistent with the present findings. Furthermore, the a_{FT} is a modeled parameter from the Gompertz function and is subjected to challenges when fitting this function. Conversely, the SI_{600} is an observed index that is representative of the actual slaking at 600 s. Therefore, we consider the latter as being more reliable and a better descriptor of the AS status.

3.3 | Sensitivity of the SI_{600} and a_{FT} AS descriptors to soil type

Since the a_{SK} and $\bar{a}_{FT}$ parameters were found to be inaccurate for describing the AS status, their sensitivity to soil type was not assessed. Therefore, to address the second study objective on the sensitivity of SLAKES to soil type, the Kruskal–Wallis test with soil type as a factor was performed independently for the SI_{600} descriptor based on the final selected measurements (Sections 3.2.3 and 3.2.4). The sensitivity of the a_{FT} descriptor from the corresponding measurements was also assessed merely for comparison to the performance of SI_{600} but not for drawing any conclusions. As shown in Figure 6, both the a_{FT} and SI_{600} descriptors exhibited statistically significant differences for all pairwise comparisons among the three soil types ($p < 0.001$).

Overall, SLAKES sensitivity varied with soil type. However, the magnitude of these differences between soil types depended on the AS descriptor considered. As observed from Section 3.2.1 with the a_{SK} descriptor, Figure 6 also depicts the sandy loam soil as the most stable soil type based on the comparatively low range in SI values of both SI_{600} and a_{FT} descriptors. However, this observation is counterintuitive and may be misleading. The sandy loam soil had comparatively lower amounts of clay, silt, and soil organic carbon contents (Table 1) which are known factors for improving AS (Chaney & Swift, 1984; Tisdall & Oades, 1982) compared to the other soil types. A likely explanation for this could be due to SLAKES default measurement period which may be insufficient for the sandy loam tests which may disaggregate slowly and thus, only the slow disaggregation process may be captured by the end of the test. Despite the data optimization and selection of less extreme measurements for further analysis, results from this study (Figure 6) suggest that the SLAKES method may be less suitable and requires modification for AS assessment for the coarse-textured soil.

3.4 | Dynamics of disaggregation: Why 10 min?

The Emerson test, one of the original methods based on which the SLAKES method originates, was developed for specific Australian soils (mostly clayey). According to Emerson (1991), all air-dried aggregates used in the Emerson test slaked completely between 3 and 47 s of measuring. Thus, under 1 min of measuring, the asymptote could already be reached for those measurements. The present study considered three different soil textures using the default 10-min measurement time in SLAKES. From previous discussions (Section 3.2.1), disaggregation was variable with soil type. For example, sandy loam aggregates generally disaggregated sporadically, silty clay aggregates broke down progressively and the aggregates from the silt loam site showed an intermediate rate of disaggregation. Figure 7 shows selected test examples depicting the area of aggregates before and after SLAKES tests for the silty clay, silt loam, and sandy loam soils, respectively. Visually, the silty clay test (Figure 7a)

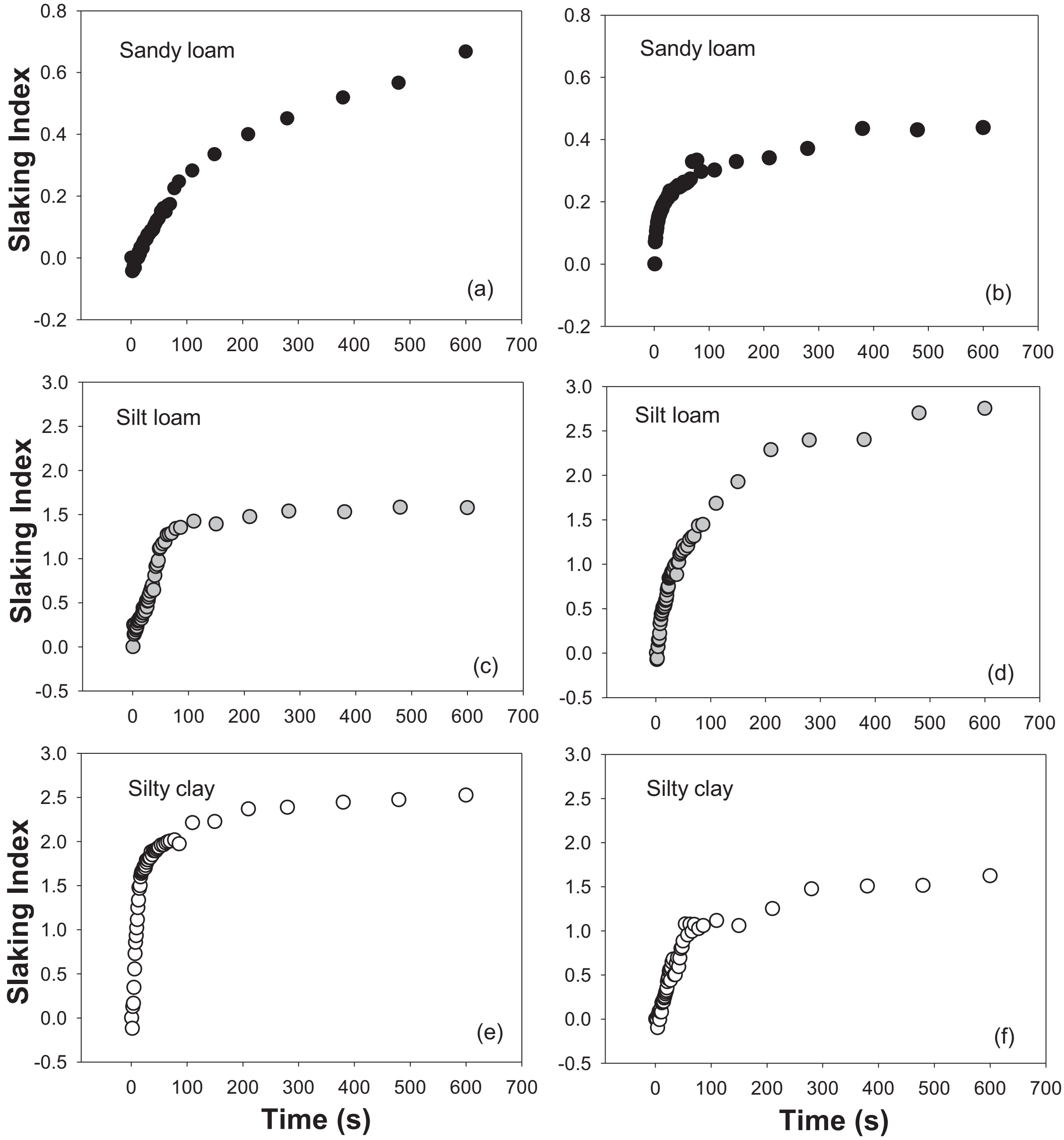

FIGURE 8 Suitability of SLAKES default measurement time visualized with two measurements per soil type. The range in slaking indices goes from −0.5 to 3.0 for the silty clay and silt loam soils and from −0.2 to 0.8 for the sandy loam soil over 10-min measurement duration.

appeared to be the most stable of the three tests as evidenced by the comparatively small increase in the initial aggregate area at the end of the 10-min default SLAKES test.

Apart from the high a_{SK} obtained from the raw output of all tests, high values in the initial time or fast slaking (parameter b of the Gompertz function) were observed, especially from the sandy loam soil. Due to the large range of the data, parameter b cannot be reasonably interpreted. The parameter c of the Gompertz function, which depicts the growth rate and is associated with the ongoing slaking of the aggregate, was found to be variable between soils. The sandy loam soil had the highest mean parameter c value (12.2), followed by the silt loam soil (0.97) and the silty clay soil (0.93). However, there was no statistically significant difference in the c parameter between soil types. The disaggregation process concerning the default measurement time was examined by plotting SI against time for each measurement. Visual assessment of these time series plots showed trends of expected further disaggregation where the SI values continue to increase, indicating that the disaggregation continues longer than the default 10-min measurement time. This observation was predominant in the sandy loam and in some cases, the silt loam measurements (Figure 8). This expected further disaggregation beyond SLAKES default measurement time was also reported by Flynn et al. (2020), who considered such observations to be small and within range of parameter *a* values within their dataset. However, the magnitude of such further expected disaggregation (parameter *c*) varies with soil type and may be larger for some soils than others as seen in the present study. Additionally, this trend in the data contradicts laboratory observation, where the sandy loam measurements showed nearly complete disaggregation upon immediate aggregate immersion compared to measurements from the silty clay and silt loam soils. Furthermore, selected examples of silty clay measurements (Figure 8) depicted that about 5 min into the test, nearly constant slaking indices are obtained. Thus, the asymptote may already be reached allowing for twice as many SLAKES tests to be made considering the default SLAKES measurement time. Considering the maximum observed slaking time by Emerson (1991) (<1 min), SLAKES default measurement time may be suitable for clayey soils. However, the 10-min measurement time was unsuitable for the sandy loam soil due to the instances where disaggregation was expected to continue for a longer period than the default measurement time. Thus, disaggregation may continue until the aggregate is completely destroyed and a final area is reached.

4 | CONCLUSIONS AND RECOMMENDATIONS

The SLAKES method can rapidly assess the stability of the three investigated soil types (silty clay, silt loam, and sandy loam) with little setup requirements and technological needs. However, the best use and interpretation of the SLAKES outputs require a thorough assessment of all descriptors of slaking (a_{SK}, a_{FT}, and SI_{600}). Repeatability and accuracy concerns prohibited the use of the raw output for statistical analysis. This was due to cases of extrapolated SI beyond SLAKES default measurement time, problems with the automated fits by Gompertz to disaggregation data within the SLAKES app and the resultant inconsistent results when compared to Gompertz parameters obtained from the fitting of individual measurement disaggregation curves. Although the a_{SK} descriptor provided some insight into the AS of the soils studied, inaccuracies and Gompertz fitting problems prevented its adoption. We propose the use of the SI_{600} from individual measurements as this descriptor is the most reflective of the AS status.

For a better comparison between predicted and observed parameters describing slaking, we recommend that the developers of the SLAKES app should include parameters of the Gompertz function (parameters *a*, *b*, and *c*) for each measurement (aggregate). This will allow the assessment of how well the fits by Gompertz function outside the SLAKES app compares to what SLAKES directly estimates and will help boost confidence for the acceptance or rejection of the outputs from SLAKES. Generally, SLAKES showed sensitivity to soil type. According to the SLAKES outputs, the sandy loam soil was the most stable soil which is counterintuitive and suggests that further investigations be conducted to ascertain if the SLAKES method is suitable for AS measurements on coarse-textured soils.

Furthermore, the SLAKES default 10-min measurement time was found to be unsuitable for the sandy loam soil especially. The kinetics of disaggregation were found to be variable where nearly constant SI values could be obtained after 5 min for the silty clay soil, while an apparent extension of the default measurement time seemed necessary for the sandy loam soils. The suitability of the measurement time could be better assessed if SLAKES is equipped with a feature that allows user-defined measurement time based on the experience with the type of samples investigated rather than a default measurement time. Additionally, problems of further disaggregation could be addressed with this feature where measurement errors can be identified from an infinite extrapolated disaggregation, while samples that may require more time may benefit from such time extension. Overall, SLAKES has the potential to determine the AS status of soil, however, the current setup requires some modification for even greater adoption. Given its cheapness, rapidity, and useful information it provides, there is a great appeal to a wide range of stakeholders involved in physical soil health research.

AUTHOR CONTRIBUTIONS

Diana Vigah Adetsu: Data curation; formal analysis; investigation; methodology; visualization; writing—original draft. **Emmanuel Arthur**: Conceptualization; formal analysis; methodology; resources; supervision; writing—review and editing. **Yuting Fu**: Resources; writing—review and editing. **Wim Cornelis**: Methodology; supervision; writing—review and editing. **Mathieu Lamandé**: Conceptualization; formal analysis; methodology; supervision; writing—review and editing.

ACKNOWLEDGMENTS

Our gratitude goes to Dr. Ines Merbach and the staff from UFZ and Dr. Sofia Delin from SLU who helped with soil sampling and provided relevant information for the Bad Lauchstädt and Lanna LTEs, respectively. We also acknowledge Dr. Johannes Jensen, Dr. Bent Christensen, and Henning Thomsen for the information on Askov LTE.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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REFERENCES

Afriyie, E., Verdoodt, A., & Mouazen, A. M. (2020). Estimation of aggregate stability of some soils in the loam belt of Belgium using mid-infrared spectroscopy. *Science of the Total Environment*, *744*, 140727. https://doi.org/10.1016/j.scitotenv.2020.140727

Almajmaie, A., Hardie, M., Acuna, T., & Birch, C. (2017). Evaluation of methods for determining soil aggregate stability. *Soil and Tillage Research*, *167*, 39–45. https://doi.org/10.1016/j.still.2016.11.003

Amézketa, E. (1999). Soil aggregate stability: A review. *Journal of Sustainable Agriculture*, *14*(2–3), 83–151. https://doi.org/10.1300/J064v14n02_08

Bagnall, D. K., & Morgan, C. L. S. (2021). SLAKES and 3D scans characterize management effects on soil structure in farm fields. *Soil and Tillage Research*, *208*, 104893. https://doi.org/10.1016/j.still.2020.104893

Castro Filho, C., Lourenço, A., De F Guimarães, M., & Fonseca, I. C. B. (2002). Aggregate stability under different soil management systems in a red latosol in the state of Parana, Brazil. *Soil and Tillage Research*, *65*(1), 45–51. https://doi.org/10.1016/S0167-1987(01)00275-6

Chaney, K., & Swift, R. S. (1984). The influence of organic matter on aggregate stability in some British soils. *Journal of Soil Science*, *35*(2), 223–230. https://doi.org/10.1111/j.1365-2389.1984.tb00278.x

Christensen, B. T., Thomsen, I. K., & Eriksen, J. (2019). *The Askov long-term experiments: 1894–2019—A unique research platform turns 125 years* (DCA Report No. 151). DCA.

Deviren Saygın, S., Cornelis, W. M., Erpul, G., & Gabriels, D. (2012). Comparison of different aggregate stability approaches for loamy sand soils. *Applied Soil Ecology*, *54*, 1–6. https://doi.org/10.1016/j.apsoil.2011.11.012

Deviren Saygın, S., Cornelis, W. M., Erpul, G., & Gabriels, D. (2012). Comparison of different aggregate stability approaches for loamy sand soils. *Applied Soil Ecology*, *54*, 1–6. https://doi.org/10.1016/j.apsoil.2011.11.012

Emerson, W. W. (1967). A classification of soil aggregates based on their coherence in water. *Soil Research*, *5*(1), 47–57. https://doi.org/10.1071/SR9670047

Emerson, W. W. (1991). Structural decline of soils, assessment and prevention. *Soil Research*, *29*(6), 905–921. https://doi.org/10.1071/SR9910905

Fajardo, M., Mcbratney, A. B., Field, D. J., & Minasny, B. (2016). Soil slaking assessment using image recognition. *Soil and Tillage Research*, *163*, 119–129. https://doi.org/10.1016/j.still.2016.05.018

Fernández-Ugalde, O., Virto, I., Bescansa, P., Imaz, M. J., Enrique, A., & Karlen, D. L. (2009). No-tillage improvement of soil physical quality in calcareous, degradation-prone, semiarid soils. *Soil and Tillage Research*, *106*(1), 29–35. https://doi.org/10.1016/j.still.2009.09.012

Field, D. J., Mckenzie, D. C., & Koppi, A. J. (1997). Development of an improved Vertisol stability test for SOILpak. *Soil Research*, *35*(4), 843–852. https://doi.org/10.1071/S96118

Flynn, K. D., Bagnall, D. K., & Morgan, C. L. S. (2020). Evaluation of SLAKES, a smartphone application for quantifying aggregate stability, in high-clay soils. *Soil Science Society of America Journal*, *84*(2), 345–353. https://doi.org/10.1002/saj2.20012

Fu, Y., de Jonge, L. W., Moldrup, P., Paradelo, M., & Arthur, E. J. G. (2022). Improvementsin soil physical properties after long-term manure addition depend on soil andcrop type. *Geoderma*, *425*, 116062. https://doi.org/10.1016/j.geoderma.2022.116062

Fuentes, M., Hidalgo, C., Etchevers, J., De León, F., Guerrero, A., Dendooven, L., Verhulst, N., & Govaerts, B. (2012). Conservation agriculture, increased organic carbon in the top-soil macro-aggregates and reduced soil CO_2 emissions. *Plant and Soil*, *355*(1), 183–197. https://doi.org/10.1007/s11104-011-1092-4

Gyawali, A. J., & Stewart, R. D. (2019). An improved method for quantifying soil aggregate stability. *Soil Science Society of America Journal*, *83*(1), 27–36. https://doi.org/10.2136/sssaj2018.06.0235

Imeson, A. C., & Vis, M. (1984). Assessing soil aggregate stability by water-drop impact and ultrasonic dispersion. *Geoderma*, *34*(3–4), 185–200. https://doi.org/10.1016/0016-7061(84)90038-7

Jones, E. J., Filippi, P., Wittig, R., Fajardo, M., Pino, V., & Mcbratney, A. B. (2021). Mapping soil slaking index and assessing the impact of management in a mixed agricultural landscape. *Soilless*, *7*(1), 33–46. https://doi.org/10.5194/soil-7-33-2021

Kätterer, T., Börjesson, G., & Kirchmann, H. (2014). Changes in organic carbon in topsoil and subsoil and microbial community composition caused by repeated additions of organic amendments and N fertilisation in a long-term field experiment in Sweden. *Agriculture, Ecosystems & Environment*, *189*, 110–118.

Kemper, W. D., & Rosenau, R. C. (1986). Aggregate stability and size. In A. Klute (Ed.), *Methods of soil analysis: Part 1—Physical and mineralogical methods* (pp. 425–442). ASA, SSSA. https://doi.org/10.2136/sssabookser5.1.2ed.c17

Koestel, J., Fukumasu, J., Garland, G., Larsbo, M., & Nimblad Svensson, D. (2021). Approaches to delineate aggregates in intact soil using X-ray imaging. *Geoderma*, *402*, 115360. https://doi.org/10.1016/j.geoderma.2021.115360

Lado, M., Ben-Hur, M., & Shainberg, I. (2004). Soil wetting and texture effects on aggregate stability, seal formation, and erosion. *Soil Science Society of America Journal*, *68*(6), 1992–1999. https://doi.org/10.2136/sssaj2004.1992

Laufer, D., Loibl, B., Märländer, B., & Koch, H.-J. (2016). Soil erosion and surface runoff under strip tillage for sugar beet (*Beta vulgaris* L.) in Central Europe. *Soil and Tillage Research*, *162*, 1–7. https://doi.org/10.1016/j.still.2016.04.007

Le Bissonnais, Y. (1996). Aggregate stability and assessment of soil crustability and erodibility: I. Theory and methodology. *European Journal of Soil Science*, *67*(1), 11–21. https://doi.org/10.1111/ejss.4_12311

Legout, C., Leguédois, S., & Le Bissonnais, Y. (2005). Aggregate breakdown dynamics under rainfall compared with aggregate stability measurements. *European Journal of Soil Science*, *56*(2), 225–238. https://doi.org/10.1111/j.1365-2389.2004.00663.x

Loveday, J., & Pyle, J. (1973). *The Emerson dispersion test and its relationship to hydraulic conductivity* (Technical paper no. 15). CSIRO Division of Soils, CSIRO.

Mapa, R. B., & Gunasena, H. P. M. (1995). Effect of alley cropping on soil aggregate stability of a tropical Alfisol. *Agroforestry Systems*, *32*(3), 237–245. https://doi.org/10.1007/BF00711712

Mentler, A., Mayer, H., Strauß, P., & Blum, W. E. H. (2004). Characterisation of soil aggregate stability by ultrasonic dispersion. *International Agrophysics*, *18*(1), 39–45.

Naveed, M., Moldrup, P., Vogel, H.-J., Lamandé, M., Wildenschild, D., Tuller, M., & De Jonge, L. W. (2014). Impact of long-term fertilization practice on soil structure evolution. *Geoderma*, *217*, 181–189. https://doi.org/10.1016/j.geoderma.2013.12.001

Panabokke, C. R., & Quirk, J. P. (1957). Effect of initial water content on stability of soil aggregates in water. *Soil Science*, *83*(3), 185–196. https://doi.org/10.1097/00010694-195703000-00003

Shi, P. U., Castaldi, F., Van Wesemael, B., & Van Oost, K. (2020). Vis-NIR spectroscopic assessment of soil aggregate stability and aggregate size distribution in the Belgian Loam Belt. *Geoderma*, *357*, 113958. https://doi.org/10.1016/j.geoderma.2019.113958

Soil Survey Staff. (2014). *Keys tosoil taxonomy*. USDA-NRCS.

Ternan, J. L., Williams, A. G., Elmes, A., & Hartley, R. (1996). Aggregate stability of soils in central Spain and the role of land management. *Earth Surface Processes and Landforms*, *21*(2), 181–193. https://doi.org/10.1002/(SICI)1096-9837(199602)21:2⟨181::AID-ESP622⟩3.0.CO;2-7

Tisdall, J. M., & Oades, J. M. (1982). Organic matter and water-stable aggregates in soils. *Journal of Soil Science*, *33*(2), 141–163. https://doi.org/10.1111/j.1365-2389.1982.tb01755.x

Vanwindekens, F. M., & Hardy, B. F. J. S. (2023). The QuantiSlakeTest, measuring soil structural stability by dynamic weighing of undisturbed samples immersed in water. *SOIL*, *9*(2), 573–591. https://doi.org/10.5194/soil-9-573-2023

Vasiliniuc, I., & Patriche, C. (2009). Soil structural degradation risk in Horoiata basin (Tutova Hills). *Present Environment and Sustainable Development, NR*, *3*, 2009.

Warnemuende, E. A., Patterson, J. P., Smith, D. R., & Huang, C.-H. (2007). Effects of tilling no-till soil on losses of atrazine and glyphosate to runoff water under variable intensity simulated rainfall. *Soil and Tillage Research*, *95*(1–2), 19–26. https://doi.org/10.1016/j.still.2006.09.001

Yoder, R. E. (1936). A direct method of aggregate analysis of soils and a study of the physical nature of erosion losses. *Agronomy Journal*, *28*(5), 337–351. https://doi.org/10.2134/agronj1936.00021962002800050001x

Zhu, Z. L., Minasny, B., & Field, D. J. (2009). Measurement of aggregate bond energy using ultrasonic dispersion. *European Journal of Soil Science*, *60*(4), 695–705. https://doi.org/10.1111/j.1365-2389.2009.01146.x

How to cite this article: Adetsu, D. V., Arthur, E., Fu, Y., Cornelis, W., & Lamandé, M. (2024). Exploratory assessment of the SLAKES method to characterize aggregate stability across diverse soil types. *Soil Science Society of America Journal*, *88*, 1086–1099. https://doi.org/10.1002/saj2.20674