All particles matter: the impact of characterizing horticultural substrates[©]

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INTRODUCTION

Knowledge of substrate particle size and shape is beneficial for reasons such as increasing product efficiency, ensuring specified standards, and maximizing plant growth. Classification of aggregate materials has long been analyzed on the basis of sieve analysis. Sieves work by separating aggregate materials by a particle's 2nd smallest dimension (Allen, 1997). The material is then expressed as a cumulative or differential distribution curve which reflects the percent mass of the material retained or passed through a sieve (Weiner, 2011). Despite its simplistic nature, this is a very crude and rudimentary method of characterizing materials. There are drawbacks to sieve analysis such as: reduced efficacy in worn screens, finite number of sieves, time consuming, data subjected to human error, and no capacity for shape parameters (Rauch et al., 2002; Vaezi et al., 2012).

Since the turn of the millennium, digital analysis has gained interest in the fields of biosystems and civil engineering. The applicability of this newer technology to determine size and shape distributions of aggregate materials has been well established in these fields (Rauch et al., 2002; Vaezi et al., 2012). Engineers have recognized the advantages of digital analysis to include attributes such as large repeatability, small sample sizes, non-destructive nature, and robustness of data.

There are numerous commercially available imaging devises/programs capable of distinguishing particle size and shape. The Computerize Particle Analyzer 2 (CPA-2) is one of three units introduced by W.S. Tyler's parent company, Haver & Boecker, for use in material gradation (Figure 1). Samples are placed into a feed funnel and gradually deposited onto a vibrating channel. The particles transverse the channel and are deposited onto a conveyor system. As every particle leaves the conveyor, it passes between the imaging device and a high intensity LED backlight. The camera utilizes line-scan technology which scans a line of 2,048 pixels 20,000 times per second. By merging successive line scans, the CPA-2 can discern the outline of each particle greater than 34 microns. Utilizing this equipment could give insight to the influence of particle size and shape of container substrate characteristics. However, in order to establish the validity of new testing technology, the results must compare favorably to traditional testing techniques.

The objective of this study is two-fold: evaluate the material limitations of sieve analysis with respect to particle length to width ratio (L:W) and time, and validate the use of the CPA-2 with traditional sieve analysis using capable materials and techniques.

MATERIALS AND METHODS

Sieve limitations

In order to evaluate material limitations of sieve analysis, particles with accurate dimensions were created using 2-, 3-, and 6-mm thick acrylic sheets and a laser cutter (Zing 24, Epilog Laser, Golden, Colorado). To isolate the effect of particle L:W, the width (w) of the particles were cut equal to the height (h) of the acrylic sheets (i.e., 2 mm w × 2 mm h). Only a particle's length (l) and width will be used as descriptive values from this point forward. Eight L:W ratios, ranging from 1:1 to 8:1, were cut in each width (2, 3, and 6 mm) so that the smallest particle evaluated was 2×2 mm and the largest was 6×48 mm. Particle widths were evaluated separately. For each width, 100 particles of each L:W ratio were mixed to represent a heterogeneous mixture of 800 particles. Each heterogeneous sample was

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dispersed onto the largest sieve of a stack containing 12 sieves. The sieve sizes used were 19, 16, 12.5, 9.5, 6.3, 5.6, 4.75, 4, 3.35, 2.8, 2.36, and 2 mm. The samples were agitated using a Ro-Tap (Model B, W.S. Tyler, Mentor, Ohio) then hand sorted and counted. To observe run time effect, samples were run for 1, 2, 3, 4, and 5 mins. Each sample at each time was replicated 3 times.
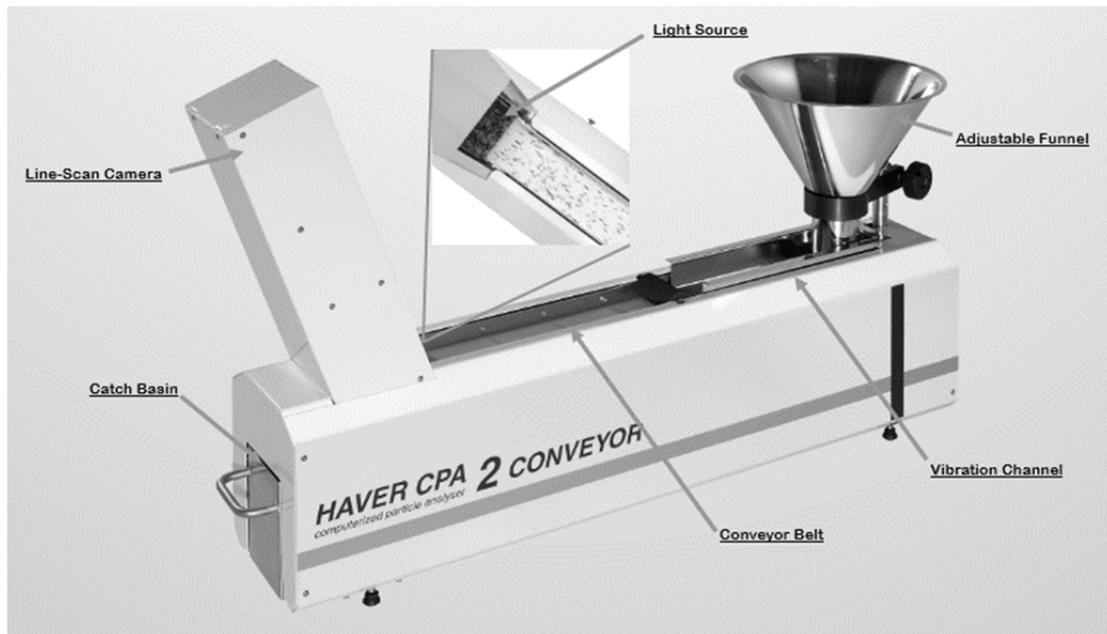

Figure 1. Tyler (Haver) computer particle analyzer 2 conveyor.

Number of particles falling within each sieve was modeled following a generalized linear model, assuming a multinomial distribution for the response (multinomial distribution with cumulative logit link). Fixed effects in the model were given by the particle L:W, runtime, and the interaction runtime by L:W. Repetitions within each time and L:W ratio were considered random effects.. All data were subjected to PROC GLIMMIX (SAS 9.4, SAS, Cary, North Carolina). All significances were at $\alpha=0.05$.

CPA-2 validation

Sieve analysis is expressed in terms of percent mass retained while the CPA-2 values are weighted by number of particles and can be sorted by standard or custom size classes. The CPA-2 obtains particle size by applying image transformation algorithms for each particle. Volume of a particle can be calculated by the CPA-2 utilizing the equivalent sphere model. If one assumes all particles have the same density, then mass equals volume. Sand is a material with a fairly consistent particle density. Given the spherical nature of the material, it is also an ideal material for sieve analysis. Three different horticultural sands were evaluated, a course, medium, and fine textured sand. Since every particle is evaluated, sample sizes were reduced by half (50 g) for the CPA-2 compared to sieve analysis (100 g). The sieve sizes and size classes used were 4, 2.8, 2, 1.4, 1, 0.71, 0.6, 0.425, 0.25, 0.18, 0.125, and 0.063 mm. The sieve samples were agitated using the same Ro-Tap for 5 min.

To compare both gradation methods, a general linear model was fitted to percent retained measured through the Ro-Tap and CPA-2. Fixed effects were sieve size, gradation method, and their interaction. Repetitions within each method were considered a random effect. Simple effect analysis was used to compare both methods within each sieve size.

RESULTS AND DISCUSSION

Sieve limitations

Similar trends in the data were recorded for each particle width (2, 3, and 6 mm). Therefore, only the results from the 3 mm particles will be discussed. The distribution of particles of equal width and height were affected by L:W (p=<0.0001), time (p=<0.0001), and the interaction term L:W*time (p=0.0011). Summation curves of the 8 L:W ratios help visualize the influences of L:W and time across sieves sizes (Figure 2). As particle L:W increases, distribution across sieves also increases. No particles with an 8:1 L:W and only a single 7:1 L:W particle reached the targeted screen (2.8 mm). The more elongated the particle, the more time is required for that particle to properly orient itself to pass through a screen. Time affects varying L:W ratio particles differently. Time's effect increases as particle L:W increases. The squarer or rounder a particle is, the weaker the effect time has on the distribution of the particle.
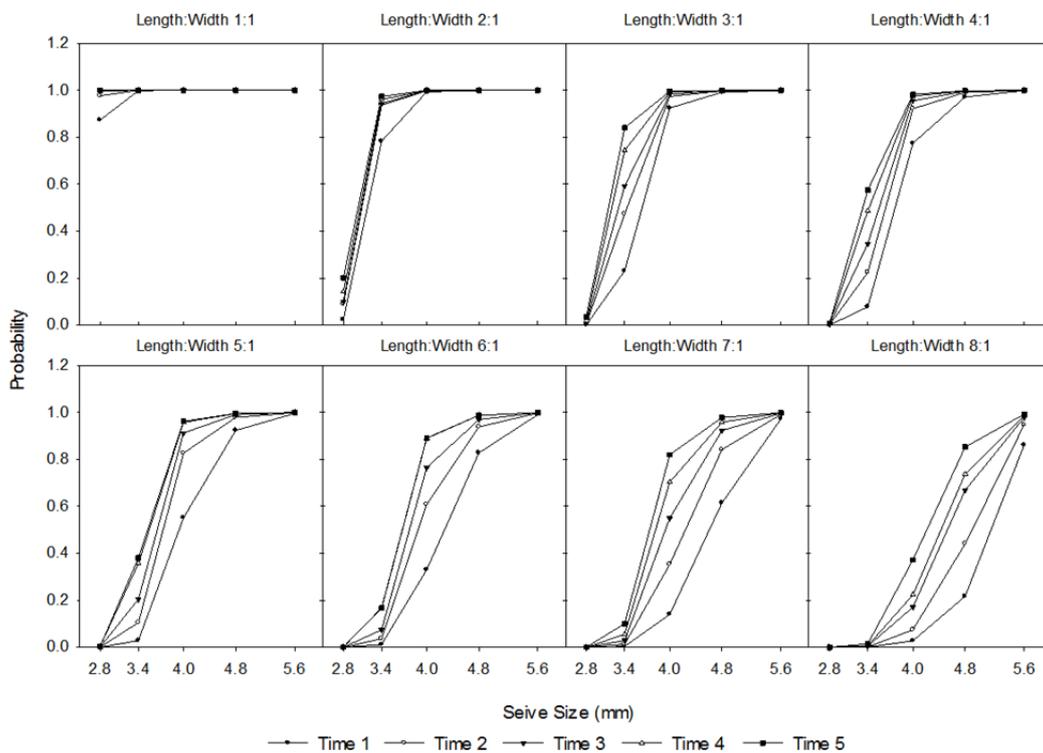

Figure 2. Predicted cumulative distribution of 3-mm particles by length: width ratio and time.

These results show three things concerning the retention of a particle on a sieve:
1) The width of the particle is the limiting dimension.
2) The length of the particle is the influential dimension.
3) Time is the variable that influences particle length effect.

The significance of these results, though simplistic in nature, directly impact horticultural substrate research. Many horticultural substrates are not spherical or cubic in nature and are not appropriate materials for sieve analysis. However, the limitations of sieve analysis are generally ignored without contemplating the implications on substrate research reproducibility. For example, seven of the eight L:W ratios were collected on the same sieve. In distribution analysis, the assumption is that all particles collected in a given sieve are the same or similar, but an 8:1 L:W particle will impart different characteristics to the substrate than a 2:1 L:W particle. In order to further substrate research, newer and more robust

technology must be utilized to better characterize the diverse and dynamic materials used as substrates.

CPA-2 validation

Differences in distributions were observed between Ro-tap and CPA-2 in all three sand textures (Figures 3-5). One source of error could have occurred in the assumption of consistent particle density due to sand's varying mineral content. Other sources of error could be attributed to particle oscillation across the measuring line, improper equipment calibration, or poor transformational data into volumetric calculations. Volumetric calculations assume that particles have a consistent specific gravity. For example, two sheets of paper, side by side, have the same specific gravity and their volume will be calculated proportionately equal. However, a ream of paper and a sheet of paper with the same projected area but different specific gravities will be calculated disproportionately on the basis of their 2-D images. This is believed to be the primary source of error in the CPA-2's distributions. A larger, flat particle will have a calculated volume higher than its mass and skew the distributions toward larger sieve sizes.

Unlike traditional sieve analysis, singular calculations like volume are only a small computation in the large array of functions the CPA-2 uses to characterize particles. From container characteristics (air, water, and bulk density) imparted by particle size and shape, to the engineering processes that created them, this instrument has immediate implications into understanding particles' effect in container production. Once the unique features of substrates are discovered, the wealth of knowledge and information could lead to many solutions to decade-long questions.
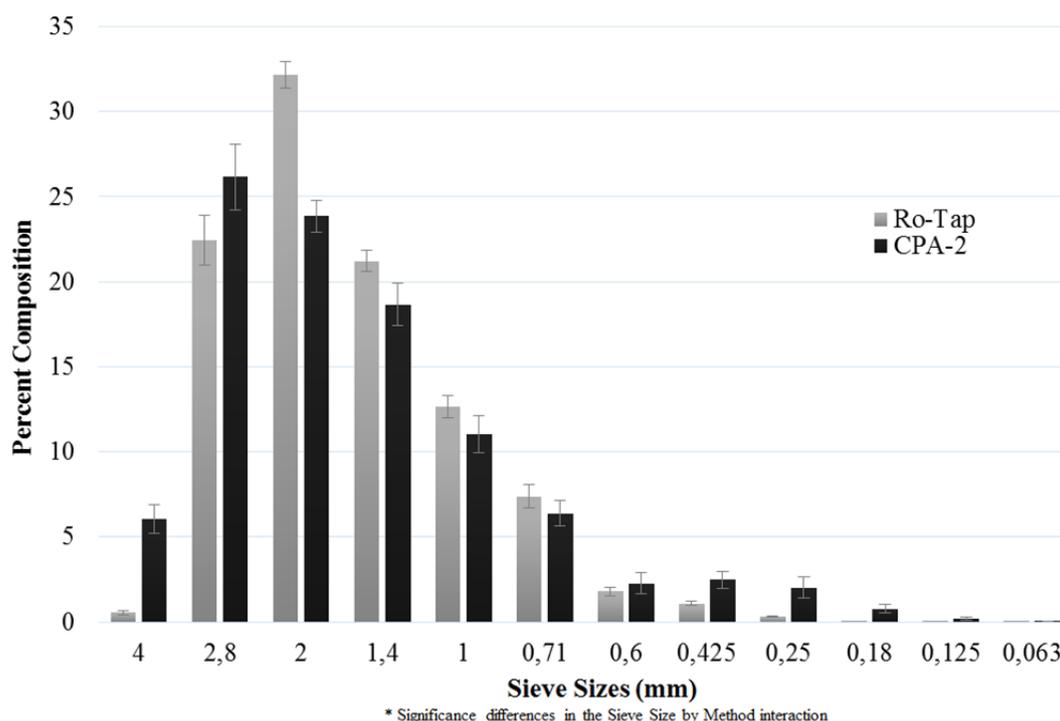

Figure 3. Differential distribution of coarse sand measured by Ro-Tap and CPA-2.
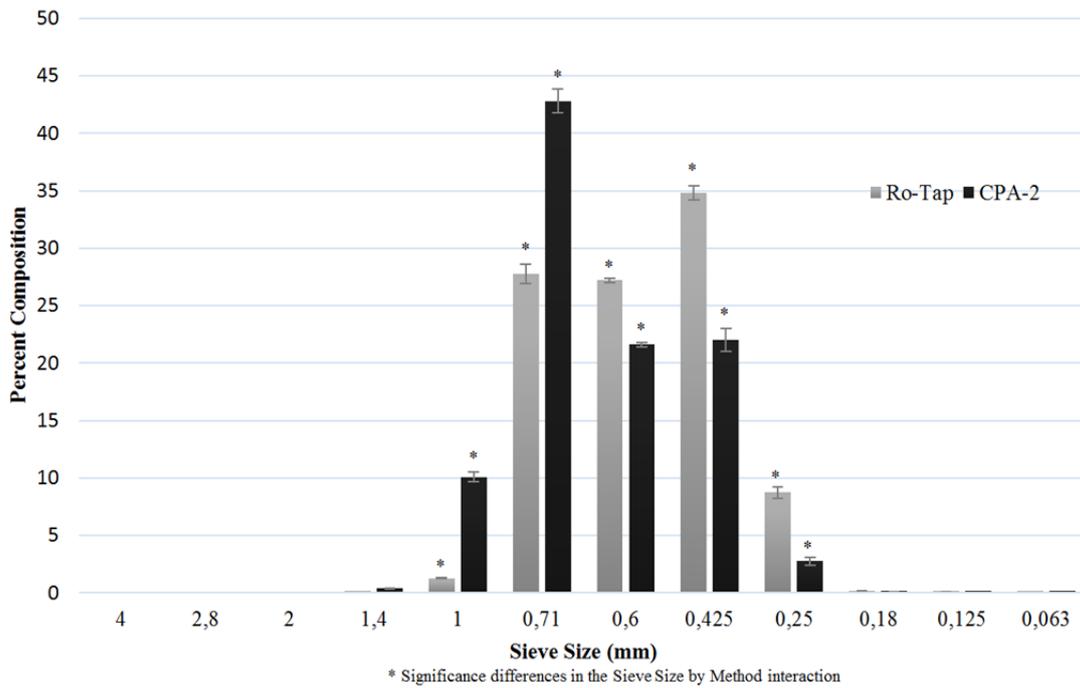
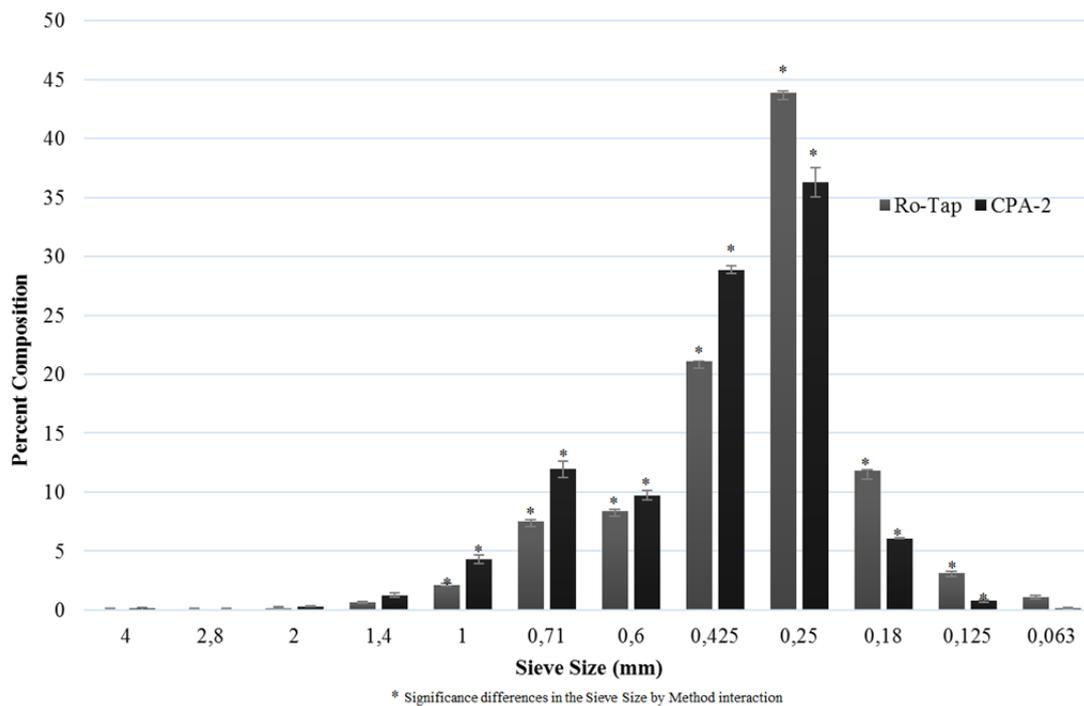Figure 4. Differential distribution of medium sand measured by Ro-Tap and CPA-2.

Figure 5. Differential distribution of fine sand measured by Ro-Tap and CPA-2.

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