

TECHNICAL NOTE

Pedology

Application and evaluation of a subaqueous soil-landscape conceptual model in the West River subestuary, Maryland

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Abstract

A soil-landscape conceptual model developed in the Rhode River subestuary of Maryland was applied to create a soil survey for the adjacent West River subestuary. The survey for the West River subestuary was completed before samples were collected there to evaluate the soil-landscape conceptual model used to generate the soil survey. The West River subestuary was then sampled along transects that crossed soil map units to compare observed soil taxa with predicted soil taxa. Observed transect samples were classified and scored based on their similarity to predicted taxa in soil map units. These data were resampled via a bootstrapping method to determine if the predictions of the West River subestuary soil survey were significantly different from random predictions. Significant information was provided by the survey, and therefore by the soil-landscape conceptual model used to generate it.

1 | INTRODUCTION

The advancement of science depends in large part on the testing of hypotheses (Fudge, 2014; Platt, 1964), which is as true in soil survey as it is in any other field of inquiry. However, not all hypotheses are created equal. Platt (1964) criticized “the eternal surveyor” among a list of scientists who rarely work with hypotheses that can be (at least in theory) disproved by experiment. Indeed, soil surveys have historically been completed without explicit hypothesis testing (Hudson, 1990), with decision making in the discipline driven largely by the informed opinions of experienced field professionals

(Arnold, 2005; Daniels, 1988). These professionals develop soil-landscape conceptual models by correlating soil profile properties with the positions of those soils throughout a landscape and are thus able to predict with some degree of accuracy soil properties at different points in the landscape where the model was developed, as well as in similar landscapes (Dokuchaev, 1967; Hudson, 1992; Ruhe, 1960). These models are tested each time they are applied to complete a soil survey by checking spatial predictions of soil properties against observations of soils sampled during a survey, adjusting the survey as needed to accommodate unexpected soil properties and carrying that experience forward as a revised

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model to complete subsequent soil surveys in similar settings (Hartung et al., 1991).

Very little work has been done to apply statistical methods and explicit hypothesis testing to soil-landscape conceptual models and the polygon-based soil surveys that they are used to create, perhaps in part because soil survey has developed more as an observational science than as an experimental science and new computational tools have needed to be developed to process complex soil data that can contain a variety of data types (e.g., rational, categorical) across different levels of organization (e.g., horizon, pedon, map unit) (Beaudette et al., 2013; Wessel et al., 2021). Most soil surveys are legend based and communicate expected properties of groups of polygons; each group of like polygons represented as a single legend entry makes up a map unit (the polygons of a map expected to contain one or more specific soil taxa) (Ditzler et al., 2017). Various statistical methods and field practices have been developed and applied to evaluate individual map units and their composition (Bigler & Liudahl, 1984; Hammer et al., 1998; Upchurch & Edmonds, 1991; Young et al., 1997), but there are few options for testing soil-landscape conceptual models and classically produced polygonal soil surveys as hypotheses that could be disproven (Arnold, 2016; Brevik et al., 2016).

Our objective in this note is to apply a soil-landscape conceptual model that was developed in one landscape to delineate map polygons and predict soil properties (i.e., taxa) in a similar landscape, treating the new soil survey as a critical hypothesis (i.e., disprovable via experiment). We outline a hypothesis testing method for soil surveys to evaluate the efficacy of the soil-landscape conceptual models used to create them and to determine if those models are applicable as part of the process of performing soil surveys of similar soil landscapes.

2 | MATERIALS AND METHODS

Rhode River, Maryland, is a brackish-water western shore subestuary of Chesapeake Bay where the first subaqueous soil survey of Chesapeake Bay was completed. A soil-landscape conceptual model was previously developed for Rhode River that describes the pedologic and geologic development of the subaqueous soils found there, as well as their general distribution as it relates to the factors and processes of soil formation (Jenny, 1941; Simonson, 1959; Wessel, 2020; Wessel et al., 2021).

The Rhode River soil-landscape conceptual model was used to complete a soil survey of West River. The most recent National Ocean Service hydrographic survey (Bond & Sturmer, 1933) was used to generate a 20-cm contour map using GIS software (Figure 1). Bathymetric (i.e., topographic) analysis was then conducted, and major subaqueous

Core Ideas

- Soil surveys can be statistically evaluated using bootstrapping statistical methods.
- A polygon-based soil survey can function as a testable hypothesis.
- A soil-landscape model developed in one setting can be evaluated in similar settings.

landforms were manually identified, delineated, and named using the same terminology as in Rhode River (Wessel et al., 2021). After landforms were identified, the relationships between soil series and subaqueous landforms observed in Rhode River were used to infer the presence and distribution of soils in West River (Figure 1) (Hudson, 1992). This soil survey (a hypothesis ready for testing) was compiled for West River before making any field visits to West River to minimize investigator bias.

Before initiation of field investigations in West River, six sampling transects were identified that crossed geomorphic landforms normal to the maximum topographic gradient. Field observation points were selected along these transects in the center of each soil map unit segment crossed, which resulted in 42 sampling points (Figure 1). At each sampling point, using appropriate methodologies (Macaulay sampler, vibracorer, or bucket auger) (Rabenhorst & Stolt, 2012), the subaqueous soil profile was examined. Soils were described to a depth of 1–2 m (or to refusal depth if shallower) using the same methods and terminology as in Rhode River (Schoeneberger et al., 2012). Profiles were then classified according to U.S. Soil Taxonomy (Soil Survey Staff, 2014; Wessel et al., 2021).

The degree to which the Rhode River soil-landscape conceptual model accurately predicted the distribution of soils across subaqueous landscapes and landforms in West River was evaluated by comparing the observed soil at each sampling point with the dominant soil series of the corresponding predicted soil map unit (all map units were consociations with no minor components). A five-point ordinal scale (Table 1) was used to evaluate how well each observed soil profile corresponded to the predicted dominant soil series with the following decreasing order of fit: (5) the observed soil matched the predicted taxonomic family and soil series; (4) the observed soil was similar to the predicted soil series; (3) the observed soil fell within the same soil taxonomic subgroup as the predicted soil; (2) the observed soil is formed from the same parent materials as the predicted soil; (1) the observed soil shares no noteworthy properties with the predicted soil. Soil “similarity” (for a score of 4) was evaluated using the Soil Survey Manual definition: “Soils having

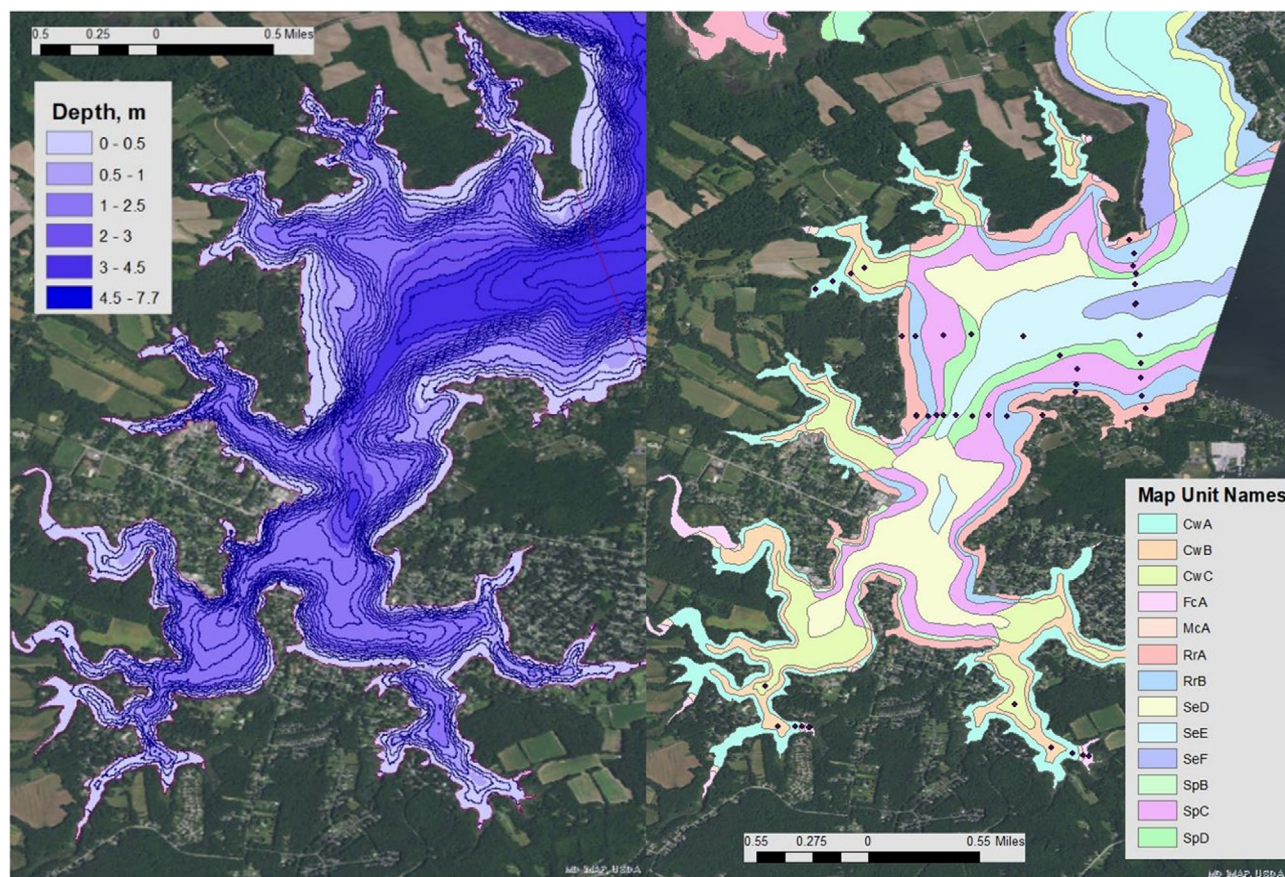


FIGURE 1 Bathymetric map (left) and soil survey of West River (right) showing targeted sampling points along six transects crossing map units. Contours are 20 cm. The first two letters of map unit names correspond to the dominant soil series (Cw = Contees Wharf, Fc = Fox Creek, Mc = Muddy Creek, Rr = Rhode River, Se = Sellman, Sp = Sand Point), and the third is a depth phase (A = 0–0.5 m, B = 0.5–1 m, C = 1–2 m, D = 2–3 m, E = 3–4 m, F = 4–5 m)

TABLE 1 The five-point ordinal scale used to score observations (soil profiles) relative to the predicted series for each soil map unit

Point score	Criteria
5	Observed soil matches predicted family and series
4	Observed soil is similar to the predicted series (i.e., shares most interpretive properties)
3	Observed soil matches the taxonomic subgroup of the predicted series
2	Observed soil is formed in the same parent materials as predicted series (i.e., Holocene mineral, Tertiary mineral, organic)
1	Observed soil shares no noteworthy properties with the predicted series and is formed in different parent materials

properties that are slightly outside the defined taxonomic limits but that do not adversely impact major land uses” (Ditzler et al., 2017); this is a necessarily biased approach that depends on the major land uses under consideration in a given landscape at a given time, and it may be particularly problematic in a subaqueous landscape where most land use interpretations have yet to be developed. This approach is not entirely algorithmic; it depends on a skilled soil scientist. Higher numbers on the scale indicated a better fit to the predicted dominant soil series in the corresponding soil map unit of the hypothesis soil survey. These 42 observation scores were then

summed to generate an observed map score for the hypothesis soil survey. The significance of this map score was then statistically evaluated using a modified bootstrapping, or data resampling, method. This method was used to test the null hypothesis:

H_0 : The distribution of observed soils in the West River landscape generates a map score that is not significantly different from a map score generated from a random selection of observed soils distributed randomly across this landscape.

A score matrix Supplemental Table (S1) was then developed using the observed soil descriptions, the predicted dominant soil series in the soil map units Supplemental Table (S2), and the five-point ordinal scale in Table 1. Location data of the observed soil descriptions were masked during this process to reduce investigator bias, and each observed soil description was given a 1–5 point value for every possible predicted soil series (this score matrix was also used to generate the observed map score once location data were unmasked, again to reduce bias). The 42 observations were resampled via bootstrapping using the GNU Octave scientific programming language (Eaton et al., 2018), randomly assigning an observed soil pedon to one of the 42 sampling points, and assigning each pairing the corresponding 1–5 point value from the score matrix. These 42 values were then summed to generate a single random map score. This process was iterated to generate a total of 10,000 random map scores using a Monte Carlo simulation approach (Kroese et al., 2014). Each of the 10,000 random map scores consisted of 42 soil observation values summed from the score matrix. The 95th percentile of these data was then selected as a significance threshold, an approach commonly used in related statistical tests to distinguish signal from noise via data resampling (Overland & Preisendorfer, 1982). This threshold and the observed map score were then used to test the null hypothesis.

3 | RESULTS AND DISCUSSION

The 42 scores for observed soils in West River were not normally distributed (Figure 2) but were illustrative of what this scoring system can reveal. Exact matches to the predicted soil series (scores of 5) were rare ($n = 2$, 5% of observations), though similar soils that shared most interpretive properties with the predicted soil series (scores of 4) were the most common result ($n = 23$, 55% of observations). This is not surprising and still meets the expectations for the map units, where slight deviations from the dominant soil series are expected to occur (e.g., finding a fine particle size class Grossic Hydrowassent where a very-fine particle size class Grossic Hydrowassent series had been mapped). Similar taxonomic variability was observed in Rhode River (Wessel et al., 2021), and previous studies have indicated that even well-defined map units in thoroughly surveyed agricultural landscapes often show substantial variability in soil families and higher taxa present (Hudson, 1990; Young et al., 1997). Several similar soil pedons (scores of 4) also matched at the subgroup level (scores of 3), but no soil pedons matched at the subgroup level while also failing to qualify as similar pedons; therefore, no observed soils received a score of 3 ($n = 0$, 0% of observations). Pedons scored as a 2 may have had parent material of the same age as the predicted soil series (e.g., Holocene) but of strongly contrasting texture and/or

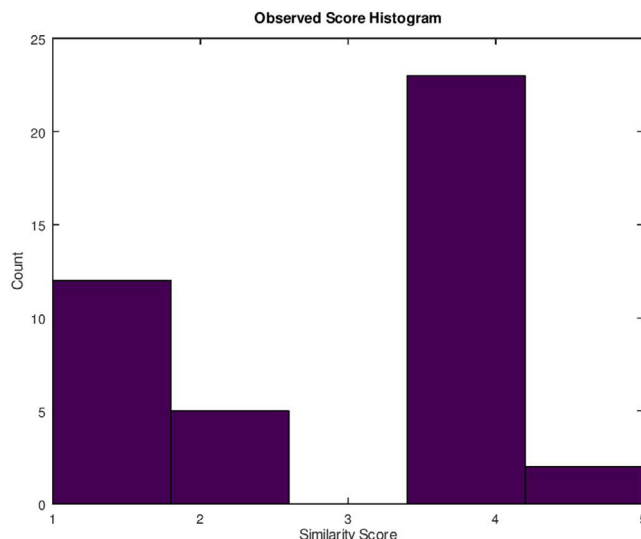


FIGURE 2 Histogram of scores from the five-point scale for the 42 cores as they corresponded to their sampling sites. Matches to the soil series were rare (5 points), though similar soils were the most common result (4 points). Some matching subgroups (3 points) were observed, but in these cases they were also similar soils, so they were given scores of 4 points. Scores of 1 point were generally where parent materials were markedly different

fluidity ($n = 5$, 12% of observations). Dissimilar inclusions with parent materials of differing age (Holocene vs. Tertiary) or different makeup (organic vs. mineral) were scored as 1 ($n = 12$, 28% of observations). Notably, some organic soils were observed in Rhode River, whereas no organic soils were observed in West River; the Fox Creek Histosol series found in Rhode River was not observed in West River. Map units mapped as submerged tidal marshes in West River (where Fox Creek soils were predicted) did contain thin organic horizons and abundant organic fragments (wood, roots, leaves); these soils also tended to contain sulfidic materials, sulfide-containing horizons that decrease to a pH of 4 or lower if allowed to oxidize, a key taxonomic criteria in subaqueous soils (Wessel & Rabenhorst, 2017) and a key feature of Fox Creek soils (Wessel et al., 2021).

An evaluation of these results using bootstrapping does enable evaluation of the soil-landscape conceptual model (Figure 3). The 95th percentile of these random map scores, the preselected significance threshold percentile, was 103. The observed map score, based on the real locations where the pedons were sampled, was 124 (out of a possible 210). The observed score exceeds the significance threshold, so the null hypothesis that our observed score would not differ significantly from a random distribution of these pedons across West River was rejected. In fact, the observed map score was higher than any of the 10,000 randomly produced map scores and would also have met a 99th percentile significance threshold. Therefore, the soil-landscape conceptual

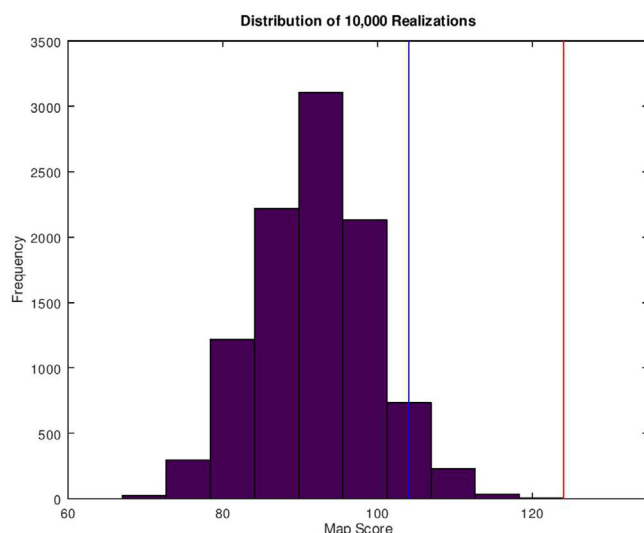


FIGURE 3 Results of resampling (bootstrapping) soil pedons across West River and summing the scores to generate 10,000 map scores for random distributions of those pedons. The blue line is the 95th percentile for these data, 103. The red line is the observed map score for the observed (real) distribution of soil cores in West River, 124

model conveys a significant amount of information relating to the distribution of soils in western shore subestuaries of Chesapeake Bay.

4 | CONCLUSION

Conventionally produced soil surveys, where map polygons are delineated based on an understanding of how soil properties change across landscapes (i.e., a soil-landscape conceptual model) and those polygons are grouped into map units of expected soil properties (i.e., taxa), can be statistically evaluated using a bootstrapping approach. In West River, observed soils were most commonly similar to predicted soils (scores of 4) and exactly matched predicted soils (scores of 5) in a few instances. The soil-landscape conceptual model used to develop this soil survey did convey significant information. The five-point scale and bootstrapping statistical method presented here should, with further refinement intended to remove remaining complexity and ambiguity in scoring soil similarity, be applicable in other landscapes to evaluate and improve soil surveys and the conceptual models used to generate them. As soil surveys are updated to account for additional observations (which can occur as land uses change and/or intensify) map unit descriptions can change, individual polygons can be reclassified into different map units, or polygons can be split, shifted, or combined. Changes may even be proposed to Soil Taxonomy (Stolt & Needelman, 2015). These changes in a soil survey or Soil Taxonomy often correspond

to changes in soil-landscape conceptual models as they are applied and reapplied in soil landscapes. This general bootstrapping approach should be useful in evaluating the value of those changes.

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AUTHOR CONTRIBUTIONS

Barret M. Wessel: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. Martin C. Rabenhorst: Conceptualization, Funding acquisition, Project administration, Resources, Software, Supervision, Writing – review & editing. Brian A. Needelman: Supervision, Writing – review & editing.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data and series descriptions are available in Wessel (2020).

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REFERENCES

- Arnold, R. W. (2005). The paradigm of pedology: How we learn what we learn. *Eurasian Soil Science*, 38(12), 1286–1289.
- Arnold, R. W. (2016). Perspectives about the national cooperative soil survey. *Advances in Agronomy*, 136, 1–26. <https://doi.org/10.1016/bs.agron.2015.11.003>
- Beaudette, D. E., Roudier, P., & O'Geen, A. T. (2013). Algorithms for quantitative pedology: A toolkit for soil scientists. *Computers & Geosciences*, 52, 258–268. <https://doi.org/10.1016/j.cageo.2012.10.020>
- Bigler, R. J., & Liudahl, K. J. (1984). Estimating map unit composition. *Soil Survey Horizons*, 25(2), 21–25. <https://doi.org/10.2136/sh1984.2.0021>
- Bond, J. A., & Sturmer, D. E. (1933). *Hydrographic survey no. 5432: Vicinity of West and Rhode Rivers*, Chesapeake Bay, Maryland. U.S. Coast and Geodetic Survey.
- Brevik, E. C., Homburg, J. A., Miller, B. A., Fenton, T. E., Doolittle, J. A., & Indorante, S. J. (2016). Selected highlights in American soil science history from the 1980s to the mid-2010s. *Catena*, 146, 128–146. <https://doi.org/10.1016/j.catena.2016.06.021>

- Daniels, R. B. (1988). Pedology, a field or laboratory science? *Soil Science Society of America Journal*, 52, 1518–1519. <https://doi.org/10.2136/sssaj1988.03615995005200050062x>
- Ditzler, C., Scheffe, K., & Monger, H. C. (Eds.). (2017). *Soil survey manual* (USDA Handbook 18). U.S. Government Printing Office.
- Dokuchaev, V. V. (1967). *Russian chernozem* (Translated from Russian into English by N. Kaner). Israel Program for Scientific Translations.
- Eaton, J. W., Bateman, D., Hauberg, S., & Wehbring, R. (2018). *GNU Octave version 4.4.1 manual: A high-level interactive language for numerical computations*. <https://www.gnu.org/software/octave/doc/v4.4.1/>
- Fudge, D. S. (2014). Fifty years of J. R. Platt's strong inference. *The Journal of Experimental Biology*, 217(8), 1202–1204. <https://doi.org/10.1242/jeb.104976>
- Hammer, R. D., Young, F. J., & Williams, F. (1998). Evaluating central tendency and variance of soil properties within map units. *Soil Science Society of America Journal*, 62(6), 1640–1646. <https://doi.org/10.2136/sssaj1998.03615995006200060022x>
- Hartung, S. L., Scheinost, S. A., & Ahrens, R. J. (1991). Scientific methodology of the national cooperative soil survey. In M. J. Mausbach, & L. P. Wilding (Eds.), *Spatial variabilities of soils and landforms* (Vol. 28, pp. 39–48). SSSA. <https://doi.org/10.2136/sssaspecpub28.c4>
- Hudson, B. D. (1990). Concepts of soil mapping and interpretation. *Soil Horizons*, 31, 63–72. <https://doi.org/10.2136/sh1990.3.0063>
- Hudson, B. D. (1992). The soil survey as a paradigm-based science. *Soil Science Society of America Journal*, 56(3), 836–841. <https://doi.org/10.2136/sssaj1992.03615995005600030027x>
- Jenny, H. (1941). *Factors of soil formation: A system of quantitative pedology* (1st ed.). McGraw-Hill.
- Kroese, D. P., Brereton, T., Taimre, T., & Botev, Z. I. (2014). Why the Monte Carlo method is so important today. *WIREs Computational Statistics*, 6(6), 386–392. <https://doi.org/10.1002/wics.1314>
- Overland, J. E., & Preisendorfer, R. W. (1982). A significance test for principal components applied to a cyclone climatology. *Monthly Weather Review*, 110(1), 1–4. [https://doi.org/10.1175/1520-0493\(1982\)110<0001:ASTFPC>2.0.CO;2](https://doi.org/10.1175/1520-0493(1982)110<0001:ASTFPC>2.0.CO;2)
- Platt, J. R. (1964). Strong inference. *Science*, 146(3642), 347. <https://doi.org/10.1126/science.146.3642.347>
- Rabenhorst, M. C., & Stolt, M. H. (2012). Subaqueous soils: Pedogenesis, mapping, and applications. In H. Lin (Ed.), *Hydropedology: Synergistic integration of soil science and hydrology* (pp. 173–204). Academic Press. <https://doi.org/10.1016/b978-0-12-386941-8.00006-x>
- Ruhe, R. V. (1960). Elements of the soil landscape. In *Transactions of the 7th International Congress of Soil Science* (Vol. 4, pp. 165–170). International Society of Soil Science.
- Schoeneberger, P. J., Wysocki, D. A., & Benham, E. C., & Soil Survey Staff. (2012). *Field book for describing and sampling soils, version 3.0*. USDA-NRCS.
- Simonson, R. W. (1959). Outline of a generalized theory of soil genesis. *Soil Science Society of America Journal*, 23(2), 152–156. <https://doi.org/10.2136/sssaj1959.03615995002300020021x>
- Soil Survey Staff. (2014). *Keys to soil taxonomy* (12th ed.). USDA-NRCS.
- Stolt, M. H., & Needelman, B. A. (2015). Fundamental changes in soil taxonomy. *Soil Science Society of America Journal*, 79(4), 1001–1007. <https://doi.org/10.2136/sssaj2015.02.0088>
- Upchurch, D. R., & Edmonds, W. J. (1991). Statistical procedures for specific objectives. In M. J. Mausbach, & L. P. Wilding (Eds.), *Spatial variabilities of soils and landscapes* (Vol. 28, pp. 49–71). SSSA. <https://doi.org/10.2136/sssaspecpub28.c5>
- Wessel, B. M. (2020). *Subaqueous soils of Chesapeake Bay: Distribution, genesis, and the pedological impacts of sea-level alternations* [Doctoral dissertation, University of Maryland]. ProQuest Dissertations & Theses Global. <https://drum.lib.umd.edu/handle/1903/26547>
- Wessel, B. M., & Rabenhorst, M. C. (2017). Identification of sulfidic materials in the Rhode River subestuary of Chesapeake Bay. *Geoderma*, 308, (Supplement C), 215–225. <https://doi.org/10.1016/j.geoderma.2017.07.025>
- Wessel, B. M., Rabenhorst, M. C., & Needelman, B. A. (2021). A subaqueous soil-landscape conceptual model to guide soil survey in Chesapeake Bay subestuaries. *Soil Science Society of America Journal*, 85(5), 1727–1740. <https://doi.org/10.1002/saj2.20305>
- Young, F. J., Hammer, R. D., & Williams, F. (1997). Estimation of map unit composition from transect data. *Soil Science Society of America Journal*, 61(3), 854–861. <https://doi.org/10.2136/sssaj1997.03615995006100030020x>

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