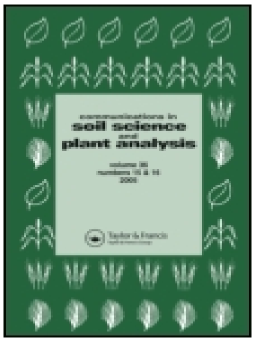

Taylor & Francis
Taylor & Francis Group

Communications in Soil Science and Plant Analysis

ISSN: 0010-3624 (Print) 1532-2416 (Online) Journal homepage: https://www.tandfonline.com/loi/lcss20

Bare Soil Reflectance to Characterize Variability in Soil Properties

M. Mzuku, R. Khosla & R. Reich

To cite this article: M. Mzuku, R. Khosla & R. Reich (2015) Bare Soil Reflectance to Characterize Variability in Soil Properties, Communications in Soil Science and Plant Analysis, 46:13, 1668-1676, DOI: 10.1080/00103624.2015.1043463

To link to this article: https://doi.org/10.1080/00103624.2015.1043463

Published online: 11 Jul 2015.

Communications in Soil Science and Plant Analysis, 46:1668–1676, 2015

ISSN: 0010-3624 print / 1532-2416 online
DOI: 10.1080/00103624.2015.1043463

Bare Soil Reflectance to Characterize Variability in Soil Properties

M. MZUKU,[1] R. KHOSLA,[2] AND R. REICH[3]

[1]Department of Agricultural Engineering and Land Planning, Botswana College of Agriculture, Gaborone, Botswana
[2]Department of Soil & Crop Sciences, Colorado State University, Fort Collins, Colorado, USA
[3]Department of Forest, Rangeland, and Water Stewardship, Colorado State University, Fort Collins, Colorado, USA

*Remote sensing allows for the rapid and inexpensive acquisition of soil reflectance data. Knowing what soil parameters have the greatest influence on bare soil imagery will facilitate better use of remote sensing for precision crop management. The objectives of this study were (i) to determine measured soil properties that are most influential on remotely sensed bare soil reflectance and (ii) to select which spectral band or combination of spectral bands is best for describing individual soil properties. This study was conducted on three study sites located in northeastern Colorado. All sites were in irrigated continuous corn (*Zea mays *L.) cropping systems. Remotely sensed imagery was acquired by aircraft prior to planting. Soil samples were collected and analyzed for bulk density, soil color (moist and dry), organic matter, organic carbon, soil texture, and cone index. Principal component analysis (PCA) was performed for the green, red, and near-infrared (NIR) bands of the imagery. Least-squares regression analysis was used for analyzing relationships between remote sensing data and soil data. Across study sites, the first principal components of the green, red, and NIR bands were found to have significant statistical relationships with organic carbon and sand, silt, and clay fractions. Individual spectral bands explained a significant portion of the variability in soil moisture, moist soil color, dry soil color, organic carbon, sand, silt, and clay. Results from this study support the use of remote sensing for assessment of soil variability.*

Keywords Bare soil, reflectance, variability

Introduction

Remote sensing of bare soil can potentially quantify soil information by recording the electromagnetic energy reflected by the soil surface. The proportion of energy reflected by a particular surface is due, in part, to the physical composition of the surface (Avery and Berlin 1992). Ocular color variations observed on a bare soil surface are affected by soil properties such as organic matter, soil texture, and soil moisture, to name a few (Hoffer 1978). Acquiring soil information using remote sensing is advantageous for precision agricultural applications because the data collected are in digital format, are georeferenced,

Received 16 September 2014; accepted 3 November 2014.
Address correspondence to Raj Khosla, Department of Soil & Crop Sciences, Colorado State University, 1170 Campus Delivery, Fort Collins, CO 80523-1170, USA. E-mail: Raj.Khosla@colostate.edu

and provide complete coverage of the entire field. For these reasons, remote sensing data can easily be input into a geographic information system (GIS) to be combined with other GIS layers and/or to be statistically modelled. To fully exploit the utility of bare soil imagery for precision agriculture, it would be advantageous to identify the soil properties that are most influential on bare soil imagery reflectance.

Characterization of soil variability is of immense value to precision agricultural practices. Many commercially employed methods, such as grid soil sampling, to characterize soil variability are intrusive, costly, and unsuitable for precision agriculture practices where characterizing small-scale spatial variability is paramount. Remote sensing has been studied as a nonintrusive alternative to grid-soil sampling and analysis. Soil reflectance has been shown in several studies to be significantly correlated with soil organic matter (Page 1974; Krishnan et al. 1980; Stoner et al. 1980; Coleman and Montgomery 1987; Coleman and Tadesse 1995). Soil moisture content has also been shown to significantly influence the spectral reflectance in the 400- to 1100-nm wavelength (Bowers and Hanks 1965; Skidmore, Dickerson, and Shimmelpfennig 1975; Lobell and Asner 2002) as well as in the 1100- to 2500-nm wavelength (Lobell and Asner 2002).

Unlike organic matter and soil moisture, the relationship between soil texture and reflectance has not been clearly established from in-field studies. Ben-Dor et al. (2003) stated that soil albedo is affected by soil physical properties. For example, surface roughness affects albedo; soils that have coarse surface textures are spectrally "rough" and therefore reflect less incident radiation. Laboratory studies have demonstrated significant relationships between soil texture and spectral reflectance; however, few studies have shown any relationship between reflectance in the 400- to 1100-nm wavelength from aerial imagery and soil texture. Horvath, Post, and Kelsey (1984) found that finer textured soils generally have greater reflectance. In a more recent study, Ray et al. (2004) showed that silt content is significantly correlated with certain spectral indices derived from IKONOS imagery. Both studies suggest that particle-size distribution significantly affects aerial reflectance. However, the degree to which soil texture affects aerial imagery remains uncertain. Because remote sensing imagery has been shown to be useful as a basis for precision nutrient management (e.g., Fleming et al. 1999; Khosla et al. 2002), we are interested in determining the soil properties that affect the reflectance characteristics of soil as detected by aerial remote sensing. The objectives of this study were (i) to identify measured soil properties that are most influential on remotely sensed bare soil reflectance and (ii) identify the spectral bands best suited for characterizing individual soil properties.

Materials and Methods

Study Sites

The study was conducted on three continuous maize irrigated sites in northeastern Colorado. Study site I was a furrow-irrigated site while study sites II and III were irrigated using center-pivot sprinkler irrigation systems. Study site I was mapped as having Ascalon (fine-loamy, mixed, superactive, mesic, Ardic Argiustoll), Haverson (fine-loamy, mixed, superactive, calcareous, mesic Aridic Ustifluvent), Otero (coarse loamy, mixed, superactive, calcareous, mesic Aridic Ustorthent), Nunn (fine smectitic, mesic, Aridic Argiustoll), and Olney (fine loamy, mixed, superactive, mesic Ustic Haplargid) soil series (USDA 1980). Study site II was located on a field that was mapped as having Albinas (fine-loamy, mixed, superactive, mesic Pachic Argiustoll), Ascalon (fine-loamy, mixed, superactive, mesic, Aridic Argiustoll), and Haxton (fine- loamy, mixed, superactive, mesic

Pachic Argiustoll) soil series (USDA 1981). These soils are characterized as being very deep and well drained and have accumulated carbonates in the soil solum. The Ascalon series occurs on upland positions and is formed from calcareous parent material. The Haxtun series consists of eolian deposits that overlay buried soil, occurring in drainages and depressions. The Albinas series is alluvial and occurs on fans and terraces. Study site III was mapped as Valentine (mixed, mesic, Typic Ustipsamment) and Dwyer (mixed, mesic, Ustic Torripsamment) series (USDA 1968).

Measurements and Soil Analyses

Remotely sensed bare soil imagery was acquired by aircraft on a residue-free, conventionally tilled field after field preparation and prior to planting. Spatial resolution of the imagery was 1 m. Imagery was captured in three bands (green, red, NIR) using a DuncanTech MS 3100 (Redlake MASD Inc., San Diego, CA). Geometric correction was performed in ERDAS Imagine 8.6 using image-to-image registration with a root mean square error less than 1 pixel for all images. Images were then radiometrically corrected in ERDAS Imagine using the histogram minimization method (Chavez 1975).

Prior to planting, georeferenced soil samples were collected using a Giddings truck-mounted hydraulic soil sampling probe. Georeferenced soil sample locations were determined using Farm GPS (Red Hen Systems Inc., Fort Collins, CO). A nonaligned systematic sampling strategy with sampling density of 2.5 samples per hectare was employed to locate the sample positions. Soil sample sizes were 33, 86, and 74 soil sample cores per field for sites I, II, and III, respectively. A Trimble Ag 114 differentially corrected GPS unit was used to navigate to the sample locations. Soil samples were collected from both the surface and subsurface. Surface samples consisted of the top 10 cm of the sample core, while subsurface samples were taken at 30-, 60-, and 90-cm soil depths. Soil samples were oven dried to a constant weight. Bulk density of each sample was determined using the method of Donahue, Miller, and Shickluna (1983). Soil color was determined for both moist and dry surface samples using a Munsell color chart (USDA 1954); Schoeneberger et al. 1998). Organic matter and organic carbon content was determined using the methods described by Nelson and Sommers (1996). Soil texture was determined using the hydrometer method (Gee and Bauder 1986). Cone indices were measured with an electronic cone penetrometer at soil depths of 0, 5, 10, 15, and 20 cm.

Statistical Analysis

For objective (i), S-Plus (Insightful Corporation 2003) was used to run principal component analysis (PCA) to compress the remote sensing data by reducing the number of dimensions without much loss of information. The number of principle components will be less than or equal to the number of original bands associated with the imagery. The PCA transforms the data in such a way that the first principle component has the largest possible variance, that is, it accounts for as much of the variability in the data as possible, and each succeeding component in turn has the greatest possible variance, given that it is uncorrelated with preceding components (Campbell 2002). To identify the measured soil properties that are most influential in determining overall reflectance of the bare soil images, first principal component (PC-1) was considered the response variable and was regressed on all measured soil properties (predictor variables) using least-squares regression analysis (SAS Institute 2001).

For objective (ii), we were interested in determining what combination of spectral bands could be used to explain the variability in the soil properties measured in this study. Each measured soil property was considered a response variable that was individually regressed on each spectral band and combination of bands (predictor variables) using Proc R-Square (SAS Institute 2001). Best-fit models were chosen based on a combination of Akaike's information criterion and the coefficient of determination. Models were further evaluated using cross-validation. This technique is used to evaluate the predictive power of a model; it utilizes the available data set for both training (model building) and testing (model validation). Stone (1977) and Shao (1993) provide more detailed information on cross validation procedures.

Results and Discussion

Soil Properties Affecting Imagery

The PCA was performed on remote sensing data using the green, red, and NIR bands from each study site. The first principal component (PC-1) explained 98 percent of the variability in the remote sensing data for all three study sites. Using regression analysis to assess the relationships between measured soil properties and remote sensing, PC-1 was regressed on all measured soil properties. Results of the regression analysis are presented in Table 1. At study site I, results revealed that there was a significant relationship between PC-1 and organic carbon, sand, silt, and clay. At study site II, it was found that significant relationships existed between PC-1 and organic carbon, sand, silt, clay, soil moisture, and

Table 1
Coefficient of determination R^2 associated with regressing PCA-1 against measured soil properties; only soil properties significant at $P \leq 0.05$ are listed

Study site	Soil property	R^2
I	Organic carbon	0.20
	Sand	0.34
	Silt	0.39
	Clay	0.30
II	Porosity	0.07
	Moisture	0.56
	Organic carbon	0.52
	Sand	0.25
	Silt	0.42
III	Bulk density	0.04
	Moisture	0.15
	Organic carbon	0.23
	Sand	0.18
	Silt	0.12
	Clay	0.17

porosity. At study site III, PC-1 was significant with organic carbon, sand, silt, clay, and soil moisture. Of the three study sites, site II had the strongest relationships (i.e., more variability explained) between PC-1 and measured soil properties, which may be because study site II had pronounced variability in topography and therefore more variability in soil properties across the field. Across study sites, PC-1 was found to have significant statistical relationships with organic carbon as well as the sand and silt fraction. Of all soil properties measured in this study, four soil properties (organic carbon, sand, silt, and clay) had the greatest influence on the variability in reflectance as measured by remotely sensed imagery. These results are encouraging with regard to site-specific management because soil texture and organic carbon both have profound influence on soil productivity. It is important to note that the sites used in this study had a wide range of soil types between study sites. Although the sites were all located in the western Great Plains and had similar relief, this study shows the utility and reliability of using remote sensing of bare soil to assess in-field variability in organic carbon, and soil texture for precision crop management.

Spectral Bands and Individual Soil Properties

Results of the all-possible regressions procedure are presented in Table 2. Overall, similar trends were observed across all study sites. Remote sensing spectral bands were significant in explaining the variability in soil moisture, moist soil color, dry soil color, organic carbon, sand, silt, and clay at all sites ($P < 0.05$). These results were not surprising because these soil properties (i.e., soil moisture, organic carbon, sand, silt, and clay) are known to affect ocular color variation in bare soil. In the case of dry and moist soil color, remote sensing imagery will logically detect variations in these two parameters, and hence a discussion of the significance of these two soil parameters (dry and moist soil color) would be redundant.

Study site II had the strongest relationships between soil properties and spectral bands, with coefficients of determination as high as 0.72 (Table 2 and Figure 1). Scatter plots of predicted versus observed values and histograms of the residuals are presented for soil organic carbon and soil moisture from study site II (Figure 1). Results from study site II along with results from the other sites are promising because they illustrate the utility of bare soil reflectance for characterizing soil properties. Study site II exhibited more topographic variation than the other two study sites, which likely influenced the relationship between soil reflectance and measured soil properties. Topographic variation will cause differential solar reflectance (Campbell 2002). Remote sensing scientists often regard topographic variation as a phenomenon that requires correction prior to any meaningful image interpretation of the imagery is made (Riano et al. 2003). In this study, the topographic variability likely enabled the image from site II to have greater expression of soil properties.

Variability in bulk density, porosity, and cone index were not well explained by remote sensing spectral bands. This does not mean, however, that these properties do not affect spectral reflectance. On the contrary, these properties most likely do affect bare soil reflectance. The poor relationships observed between spectral bands and bulk density, porosity, and cone index are most likely because of the coarse spectral resolution (i.e., only three bands: green, red, NIR) of the remote sensing platform used in this study. Perhaps future studies will investigate the use of hyperspectral remote sensing for detecting variability in these properties.

Table 2

Coefficient of determination and best predictor variables (spectral bands and combination of bands), as determined by all possible regressions procedure, for all measured soil properties by site year

Site												
Year	ρb[a]–1	R^2	ρb 2	R^2	ρb 3	R^2	ρb 4	R^2	Φ[b] 1	R^2	Φ 2	R^2
I	r[c],g	0.01ns	ir, g	0.03 ns	ir, r, g	0.11 ns	r, g	0.12 ns	ir, g	0.02 ns	ir, r, g	0.11 ns
II	R	0.03ns	ir, g	0.08 ns	ir, g	0.06 ns	ir, r, g	0.12 ns	ir, g	0.08 ns	ir, g	0.06 ns
III	ir, r, g	0.04ns	ir, r, g	0.03 ns	ir, r, g	0.10 ns	ir, r, g	0.03 ns	ir, r, g	0.03 ns	ir, g	0.08 ns
Year	Φ3	R^2	Moisture	R^2	Color 1[d]	R^2	Color 2[e]	R^2	O.C.	R^2	Sand	R^2
I	r, g	0.12 ns	ir, r, g	0.22*	r, g	0.33*	ir, r	0.02 ns	ir	0.35*	ir, r, g	0.51*
II	ir, g	0.11 ns	ir, r, g	0.72*	ir, r	0.65*	ir, r	0.57*	ir, r, g	0.62*	ir, g	0.27*
III	ir, g	0.03 ns	ir, r, g	0.25*	ir, r	0.31*	ir, g	0.17*	ir, g	0.18*	ir, r, g	0.33*
Year	Silt	R^2	Clay	R^2	CI[f] 1	R^2	CI 2	R^2	CI 3	R^2	CI 4	R^2
I	ir, r, g	0.58*	ir, r, g	0.37*	ir, r, g	0.15 ns	ir, r	0.35 ns	ir, r, g	0.29 ns	ir, r, g	0.26 ns
II	ir, g	0.38*	r, g	0.09*	ir, r, g	0.05 ns	r, g	0.01 ns	r, g	0.01 ns	ir, r, g	0.00 ns
III	ir, g	0.20*	ir, g	0.18*	ir, r, g	0.02 ns	ir, r, g	0.13 ns	ir	0.08 ns	ir, g	0.05 ns

*Significant at $P < 0.05$.

[a] ρb, soil bulk density. Numbers following bulk density correspond to the following depths: 1, surface; 2, 30 cm; 3, 60 cm; and 4, 90 cm.

[b] Φ, soil porosity.

[c] ir, near infrared band: r, red band; g, green band.

[d] Color 1, moist soil color.

[e] Color 2, dry soil color.

[f] CI, cone index (soil compaction). Numbers following cone index correspond to the following depths: 1, surface; 2, 5 cm; 3, 10 cm; and 4, 15 cm.

Note. ns, not significant ($P > 0.05$).

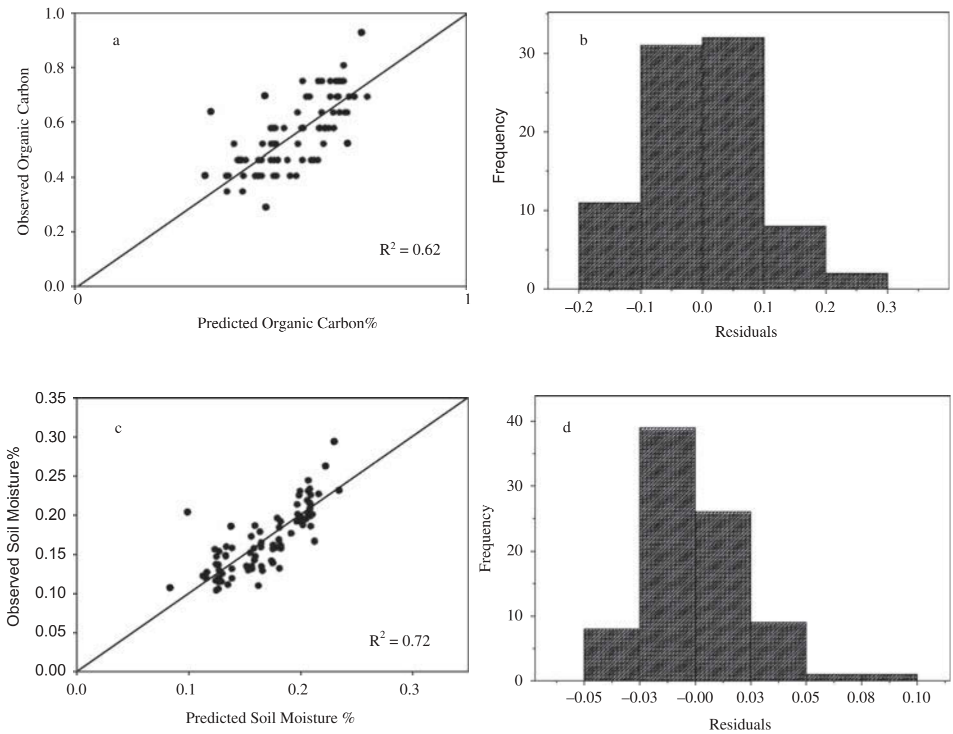

Figure 1. Scatter plots and corresponding residual histograms generated through cross validation for soil organic carbon (a and b) and soil moisture (c and d) for study site II. An idealized line has been superimposed on the scatter plots to aid in visual interpretation.

Regression analysis of PCA-1 against soil properties and soil properties against individual spectral bands both seem to suggest that soil texture (sand, silt, and clay), organic carbon, and soil moisture are the most influential soil properties on spectral reflectance in the visible and NIR regions of the electromagnetic spectrum and hence these properties can be characterized using bare soil reflectance.

Conclusions

In this study, the relationships between measured soil properties and bare soil spectral reflectance were investigated. The first principal components of three remotely sensed images were regressed against several measured soil properties. Significant relationships were found between the first principal component and organic carbon and soil texture. This finding is very promising with regard to the use of remote sensing for precision agriculture. From our results we conclude that both organic matter and soil texture are the primary factors affecting bare soil reflectance for the sites used in this study. Regression analysis of individual soil properties against remote sensing spectral bands indicated that remote sensing may be used for quantifying soil moisture, moist soil color, dry soil color, organic carbon, sand, silt, and clay. Furthermore, our findings increase our understanding of remote sensing bare soil in lieu of intensive grid-soil sampling for characterizing variability of these soil properties.

References

Avery, T. E., and G. L. Berlin. 1992. *Fundamentals of remote sensing and airphoto interpretation*, 5th ed. Englewood Cliffs, NJ: Prentice-Hall.

Ben-Dor, E., N. Goldlshleger, Y. Benyamini, M. Agassi, and D. G. Blumberg. 2003. The spectral reflectance properties of soil structural crust in the 1.2–2.5 μm spectral region. *Soil Science Society of America Journal* 67: 289–99.

Bowers, S. A., and R. J. Hanks. 1965. Reflection of radiant energy from soils. *Soil Science* 100: 130–38. doi:10.1097/00010694-196508000-00009

Campbell, J. B. 2002. *Introduction to remote sensing*, 3rd ed. New York: Guilford.

Chavez, P. S. 1975. Atmospheric, solar, and M.T.F. corrections for ERTS digital imagery. In *Proceedings of the American Society of Photogrammetry*, 724–932. Bethesda, MD. American Society of Photogrammetry and Remote Sensing.

Coleman, T. L., and O. L. Montgomery. 1987. Soil moisture, organic matter, and iron content effects on the spectral characteristics of selected vertisols and alfisols of Alabama. *Photogrammetric Engineering and Remote Sensing* 53 (12): 1659–63.

Coleman, T. L., and W. Tadesse. 1995. Differentiating soil physical properties from multiple band DOQ data. *Soil Science* 160: 81–91. doi:10.1097/00010694-199508000-00001

Donahue, R. L., R. W. Miller, and J. C. Shickluna. 1983. *Soils: An introduction to soils and plant growth*, 5th ed. Englewood Cliffs, NJ: Prentice-Hall.

Fleming, K. L., D. G. Westfall, D. W. Wiens, L. E. Rothe, J. E. Cipra, and D. F. Heermann. 1999. Evaluating farmer developed management zone maps for precision farming. In *Precision Agriculture: Proceedings of the Fourth International Conference ASA, CSSA, and SSSA*, ed. P. C. Robert, R. H. Rust, and W. E. Larson, 335–43. Madison, WI: ASA, CSSA, and SSSA.

Gee, G. W., and J. W. Bauder. 1986. Particle size analysis. In *Methods of soil analysis, part I*, ed. A. Klute, 404–8. Madison, WI: SSSA.

Hoffer, R. M. 1978. Biological and physical considerations in applying computer-aided analysis techniques to remote sensor data. In *Remote sensing: The quantitative approach*, ed. P. H. Swain and S. M. Davis, 227–89. New York: McGraw-Hill.

Horvath, E. H., D. F. Post, and J. B. Kelsey. 1984. The relationships of Landsat digital data to the properties of Arizona rangeland. *Soil Science Society of American Journal* 48: 1331–34.

Insightful Corporation. 2003. *S-plus version 6.2.*. Seattle, WA: Insightful Corporation.

Khosla, R., K. Fleming, J. A. Delgado, T. Shaver, and D. G. Westfall. 2002. Use of site specific management zones to improve nitrogen management for precision agriculture. *Journal of Soil and Water Conservation* 57 (6): 515–18.

Krishnan, P., J. D. Alexander, B. J. Butler, and J. W. Hummel. 1980. Reflectance technique for predicting soil organic matter. *Soil Science Society of American Journal* 44: 1282–85.

Lobell, D. B., and G. P. Asner. 2002. Moisture effects on soil reflectance. *Soil Science Society of America Journal* 66: 722–27.

Nelson, D. W., and L. E. Sommers. 1996. Total carbon, organic carbon, and organic matter. In *Methods of soil analysis, part 3: Chemical methods*, ed. D. L. Sparks, 961–1010. Madison, WI: SSSA.

Page, N. R. 1974. Estimation of organic matter in Atlantic coastal plain soils with a color difference meter. *Agronomy Journal* 66: 652–53.

Ray, S. S., J. P. Singh, G. Das, and S. Panigrahy. 2004. Use of high resolution remote sensing data for generating site-specific soil management plan. *International Archives Photogramm., Rem Sens., and Spatial Informatics Sciences* XXXV-B7: 127–32.

Riano, D., E. Chuvieco, J. Salas, and I. Aguado. 2003. Assessment of different topographic corrections in landsat-TM data for mapping vegetation types (2003). *IEEE Transactions on Geoscience and Remote Sensing* 41 (5): 1056–61. doi:10.1109/TGRS.2003.811693

SAS Institute. 2001. *Statistical analysis software version 8*. Cary, NC: SAS Institute.

Schoeneberger, P. J., D. A. Wysocki, E. C. Benham, and W. D. Broderson. 1998. *Field book for describing and sampling soils*. Lincoln, NE: National Soil Survey Center.

Shao, J. 1993. Linear model selection by cross-validation. *Journal of the American Statistical Association* 88: 486–94. doi:10.1080/01621459.1993.10476299

Skidmore, E. L., J. D. Dickerson, and H. Shimmelpfennig. 1975. Evaluating surface-soil water content by measuring reflectance. *Soil Science Society of America Proceedings* 39: 238–42.

Stone, M. 1977. Asymptotics for and against cross-validation. *Biometrika* 64: 29–35. doi:10.1093/biomet/64.1.29

Stoner, E. R., M. F. Baumgardner, L. L. Biehl, and B. F. Robinson. 1980. *Atlas of soil reflectance properties* (Research Bulletin 962). West Lafayette, IN: Purdue University.

USDA. 1954. *Munsell Soil Color Charts*. Baltimore, MD: Munsell Color Company.

USDA. 1968. *Soil Survey of Morgan County, CO*. Washington, DC: USDA Soil Conservation Service.

USDA. 1980. *Soil Survey of Weld County*, *Southern Part, CO*. Washington, DC: USDA Soil Conservation Service.

USDA. 1981. *Soil Survey of Yuma County, CO*. Washington, DC: USDA Soil Conservation Service.