Identification and quantification of soil redoximorphic features by digital image processing

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Abstract

Soil redoximorphic features (SRFs) have provided scientists and land managers with insight into relative soil moisture for approximately 60 years. The overall objective of this study was to develop a new method of SRF identification and quantification from soil cores using a digital camera and image classification software. Additional objectives included a determination of soil moisture effects on quantified SRFs and image processing effects on interpretation of SRF metrics. Eighteen horizons from selected landscapes in the Central Claypan Area, northcentral Missouri, USA were photographed from exposed soil cores under controlled light conditions. A 20 cm² area was used for SRF quantification following a determination of the initial gravimetric water content of horizon faces. Overall color determination accuracy was 99.6% based on Munsell soil color measurements. Rewetting of air-dry horizon faces by successive application of 1 mL of deionized water demonstrated little change in identified SRFs after seven applications. Mean change in identified Low Chroma and High Chroma SRFs between the seventh and tenth rewetting sequences was 2% (SD±4) and 0.03% (SD±0.3), respectively. However, ten of eighteen horizons contained a greater area of Low Chroma after ten rewetting sequences compared to the same horizon at the initial moisture state. Metrics characterizing SRF boundaries, shapes, number of SRFs, and mean area of SRFs were sensitive to post-classification image smoothing. Methods demonstrated by this study provide an opportunity to better integrate pedology with other related earth sciences by allowing standardized quantification of SRFs as well as a determination of human error associated with current visual estimates.

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1. Introduction

Color is the most cited attribute used for soil classification and land use decisions by people around the world (Barrera-Bassols and Zinck, 2003). Human perception of color is dependent on both a physical stimulus (e.g., reflected wavelengths striking receptors within the eye) and the processing of nerve impulses within the brain. The latter of these represents a subjective, psychological aspect of color perception that is dependent on an individual’s color experiences and varies among multiple observers (Thompson, 1995). While color references have been adopted to aid in transfer of soil color knowledge (e.g., Munsell soil color charts), the lack of a standardized, objective color perception by humans remains a notable source of error when describing and classifying soils. Reliable land management decisions based on interpretations of soil color and color patterns (e.g., soil redoximorphic features) require accurate, concise measurements.

Soil redoximorphic features (SRFs) are micro- (surface and interiors of soil structural units) and macro-morphological (horizon and profile) features formed by oxidation-reduction chemical reactions mediated by microbes in association with saturated and anaerobic conditions within soil profiles and landscapes. Examples of SRFs include accumulations and depletions of Fe and/or Mn in soil profiles relative to the surrounding soil matrix (Schoeneberger et al., 2002). The identification of SRFs is typically performed in the field by color descriptions and has been relied upon by many hydrology and pedology investigations. Examples of SRF use include documenting wetland soil morphology (Blume and Schllicting, 1985), correlating soil water and oxygen content with soil color (Evans and Franzmeier, 1988), studying altered drainage effects on soil morphology (James and Fenton, 1993), correlating subsurface flow paths with soil color (Brouwer and Fitzpatrick, 2002), and documenting restrictive, subsurface horizon effects on hillslope hydrology (Calmon et al., 1998).

More recently, measured and predicted water table depths have been correlated with SRF estimates of presence and abundance made by human observers (Gentner et al., 1998; He et al., 2003; Morgan and Stolt, 2006). These findings suggest that SRF estimations made in the
field by human observers can substitute for monitoring soil water regimes in legal designations of wetlands (Vepraskas and Caldwell, 2008a,b). However, imprecise measurements (e.g., lack of repeatable color recognition in the field by one or multiple observers), unknown accuracy (e.g., error associated with areal estimates), and undefined representative elementary areas (see VandenBygaart and Protz, 1999) remain. Increasing confidence in land management actions based on SRF interpretations requires more defendable methods for quantification.

Digital image processing techniques, often used in soil micromorphology, have provided useful tools for quantifying various soil attributes. A method for quantifying micromorphological features based on color was demonstrated by Protz et al. (1992). In this study, multi-channel images (e.g., red, green, and blue color values, hereafter RGB) of soil thin sections were used to quantify soil voids, organic material, mineralogy, and SRFs (Protz et al., 1992). Additional use of remote sensing software by Terribile and FitzPatrick (1992; 1995) demonstrated the usefulness of image classification algorithms for identifying and quantifying mineralogy from soil thin sections. Adderley et al. (2002) refined digital image processing of soil thin sections by converting RGB to Munsell colors to aid in feature identification. Aydemir et al. (2004) reexamined the use of remote sensing software and indicated that identification of mineralogy from soil thin sections by automated classification algorithms was very similar to manual, point-counting methods. Drawbacks to these methods include initial subjective decisions regarding color values that constitute particular morphologic/mineralogical features, time and equipment required to prepare soil thin sections, number of samples that can be processed, and limits on the areal size of samples analyzed.

Objective color determinations are possible and have been a focus of selected soil classification, mineralogy, and pedotransfer studies. Chromometers, spectrometers, and digital cameras have been used to accurately determine Munsell and RGB color values (Fernandez and Schulze, 1987), examine moisture effects on soil color (Shields et al., 1968), document accuracy of soil color descriptions (Cooper, 1990; Post et al., 1993; Shields et al., 1966), examine iron oxide contents of soils (Levin et al., 2005), and predict soil organic matter content (Kirshnan et al., 1980; Sudduth and Hummel, 1991; Viscarra Rossel et al., 2008). However, these studies have relied on disturbed (e.g., sieved) soil samples, prohibiting the quantification of color patterns formed in situ.

The use of digital cameras to objectively identify pedon color has been recently attempted. van Huyssteen et al. (2006b) demonstrated the use of digital camera and digital image analysis to quantify soil color from 10 excavated soil pits. The authors documented disagreement between visually interpreted colors and colors determined from digital image processing. Validation of this methodology showed only one Munsell Hue (i.e., 7.5YR) was accurately reproduced by digital image capture (van Huyssteen et al., 2006a), thus limiting the extension of this method to the continuum of soil colors often observed. Additionally, image analysis did not objectively discriminate SRFs from the matrix soil color during image processing and could not quantify potential error due to varying light conditions and camera setup among soil pits (van Huyssteen et al., 2006b).

Increased use of soil morphology for predicting hydrology at the soil profile and landscape scales, quantitative methods used in soil micromorphology, and various soil color measurement devices motivate the development of new SRF identification and quantification methods. Such a method can simultaneously advance emerging, interdisciplinary sciences relying on soil morphology. For example, Hydropedology seeks to better link pedology, soil physics, and hydrology through use of quantitative hydromorphological data (Lin, 2003; Lin et al., 2008). Moving from descriptive pedological studies and soil profile descriptions to a more quantitative science is needed, resulting in data more amenable to statistical testing and pedotransfer functions. This advance will promote more holistic studies of soil by integrating quantitative data already produced by the fields mentioned above and many other related earth sciences (e.g., ecology and geology).

This purpose of this study is to demonstrate the usefulness of readily available digital camera equipment and remote sensing software to the field of pedology. The overall objective of this research is to develop and document standardized SRF identification by color from soil cores under controlled light conditions through supervised image classification. The use of soil cores, as opposed to soil thin sections or soil pits, is highlighted to demonstrate a less destructive and more time efficient method of obtaining quantitative, morphological measurements of SRFs formed in situ. Additional objectives are to quantify accuracy of this image classification approach and the effects of moisture and post-classification image processing on selected SRF metrics.

2. Materials and methods

2.1. Study area and soil sampling

Two study sites were selected, Field 1 and 2, located within 2 km of Centralia, MO, USA (39° 13´ 58´´ N, 92° 07´ 57´´ W). Study sites and soil core locations were chosen to match locations with existing order one soil surveys and previous soil characterization data. Each field is managed for grain production and has been cropped using a corn–soybean rotation with minimum tillage (Field 1) and no-tillage (Field 2). Additional site history, management practices, conservation measures, and geomorphic setting is detailed by Kitchen et al. (2005), Lerch et al. (2005), and Myers et al. (2007).

Soil series described at these sites included Putnam and Adco (fine, smectitic, mesic Vertic Albaqualf) as well as Mexico and Leonard (fine, smectitic, mesic Vertic Epiaqualf). Cumulic Mollisols (Argiudolls) were also identified at each site. Soils described at the two study sites form a succession of summit (Putnam, Adco), shoulder (Mexico), backslope (Leonard), and footslope (Argiudolls) landscape positions. This soil catena is typical of the northcentral Missouri Claypan Region (Myers et al., 2007). Examples of SRFs identified for these soil series include Fe and Mn concentrations, depletions, and concretions (USDA-NRCS, 1995). Three soil series (Putnam, Mexico, and Leonard) meet criteria for designation as a likely hydric soil (USDA-NRCS, 2009). Seasonal perched water tables and lateral flow above a large clay content argillic horizon (i.e., claypan) have been observed for these soils (Blanco-Canqui et al., 2002; Jamison and Peters, 1967).

We extracted 8-cm diameter, 120-cm long soil cores on 31 Oct., 2008 and 1 Nov., 2008 from the two study sites. A total of six cores, three from each study site, were used in this study (Table 1). Soil cores were stored in capped polyethylene terephthalate glycol plastic tubing, transported to a controlled temperature room within 8 h of collection, and stored at 0 °C. Soil cores were removed from storage 24 h prior to core preparation and image capture.

2.2. Core preparation and image capture

A total of 18 horizons (3 horizons per core) were chosen for analysis to capture a range of horizon designations, depths, and textural classes (Table 1). Each horizon was prepared for digital photography separately. Soil cores were cut into 23-cm long segments and manually split lengthwise along structural voids, avoiding contact and smearing of exposed ped faces. This preparation produced two exposed horizon faces (Fig. 1). Prior horizon designations for the study sites were confirmed following splitting of cores. An initial gravimetric water content of one horizon face was determined for each core by collecting 1 to 2 g of soil, avoiding the central portion of the exposed face used for image capture (Fig. 1). The remaining horizon face was allowed to air-dry, followed by a determination of gravimetric water content using the methods specified above.
Hereafter, these two types of horizon faces will be referred to as Initial and Air-dry, respectively.

A Nikon D80 digital camera, containing a 3872×2592 pixel image sensor, and a Nikkor 60 mm f/2.8 lens were used to obtain digital images of horizon faces. Two Nikon Wireless Speedlights were radially mounted to the end of the camera lens at 90° and 270°, angled 30° toward the optical axis, and used as light sources. A manual flash output level was chosen to insure repeatable exposure for all images. The camera body was mounted to a tripod and placed 25 cm from each horizon face, measured from the end of the camera lens housing. Individual pixel size was 700 µm² based on this camera setup distance. All digital images were captured in a dark laboratory room. A manual white balance was performed for each image by photographing a standard 18% gray card. Manual white balance was performed separately for each day of photography. A 20 cm² (1610×1610 pixels) region of interest (ROI) was chosen for SRF image capture and processing.

The file format of final stored digital images was RAW (digital negative file) in RGB color space. This file format excluded use of automated image compression and white balance algorithms (e.g., JPEG). A manual white balance was performed for each image by photographing a standard 18% gray card. Manual white balance was performed separately for each day of photography. A 20 cm² (1610×1610 pixels) region of interest (ROI) was chosen for SRF identification (Fig. 1). An image of each horizon face was acquired immediately after the initial and air-dry gravimetric water content samples were taken, producing two images of the same horizon at differing water contents (Table 1).

**Table 1**

<table>
<thead>
<tr>
<th>Soil series/great group</th>
<th>Sample</th>
<th>Horizon</th>
<th>Depth of image center (cm)</th>
<th>Textural class</th>
<th>Water content (g g⁻¹)</th>
<th>Initial</th>
<th>Final</th>
<th>Air-dry</th>
<th>Rewetted</th>
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<td></td>
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<td>0.22</td>
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<td></td>
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<td>0.03</td>
<td>0.16</td>
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</tr>
<tr>
<td></td>
<td>33–00</td>
<td>Bt1</td>
<td>19</td>
<td>SIC</td>
<td>0.31</td>
<td>0.36</td>
<td>0.07</td>
<td>0.25</td>
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<tr>
<td></td>
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<td>Bt3</td>
<td>49</td>
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<td>0.28</td>
<td>0.05</td>
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<td>SIL</td>
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<td>0.22</td>
<td>0.02</td>
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<td>27–03</td>
<td>Eg2</td>
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<td>SICL</td>
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<td>0.21</td>
<td>0.02</td>
<td>0.14</td>
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<tr>
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<td>Btg1</td>
<td>99</td>
<td>SIC</td>
<td>0.25</td>
<td>0.24</td>
<td>0.02</td>
<td>0.19</td>
<td></td>
</tr>
</tbody>
</table>

* SIL, silt loam; SICL, silty clay loam; SIC, silty clay; C, clay.

A series of wetting and rewetting sequences were performed on the Initial and Air-dry horizon faces, respectively, to quantify the effects of increasing soil moisture on horizon color and identified SRFs. A single wetting/rewetting sequence included the application of 1 mL of deionized water followed by image capture 10 min after application time. Water was applied as a fine mist at a 25 cm distance from the horizon face. A 10 min time period after wetting was chosen to avoid possible glistening effects of applied water on the horizon face. The camera and core setup was stationary for the entire wetting/rewetting sequence. Six wetting sequences were performed on the Initial horizon face followed by a determination of the final gravimetric water content. Ten rewetting sequences were performed on the Initial horizon face followed by a determination of the rewetted gravimetric water content. Number of wetting and rewetting sequences chosen was determined by monitoring color values from a subset of test horizon faces until the difference in mean RGB value was less than 2% between successive applications. Gravimetric water contents were determined by methods previously specified. Mean color value of each horizon face was quantified in 8-bit RGB color space (0 to 255 possible values per color) during wetting/rewetting sequences. Comparison of SRFs from images during wetting/rewetting sequences was also performed following digital image processing.

**2.4. Supervised image classification procedures**

A supervised image classification procedure using Munsell soil color charts and existing definitions of SRFs (Schoeneberger et al., 2002) was developed to create an objective and repeatable SRF

![Fig. 1. Prepared horizon face and 20 cm² region of interest chosen for image analysis.](image-url)
identification method for all horizon images. The range of Munsell colors chosen for supervised classification procedures was based on a total of 165 profile and 2332 SRF color descriptions made by trained soil scientists for soil series in Missouri matching those found at the study site (Missouri Cooperative Soil Survey, 2008).

A total of 238 Munsell soil colors (10 R, 2.5–10 YR, 2.5–5 Y) from a new, never used Munsell soil color chart, version 2000, were photographed twice using the same camera and light settings described above. This produced two sets of Munsell soil color images. The first set of Munsell color images were used as a training data set to define mean RGB values of the 238 Munsell soil colors. A rectangular ROI was created for each photographed Munsell color and a mean RGB value was determined from pixel values falling inside the ROI. A total of 238 spectral signatures were created from this data set.

The second set of Munsell soil color images was only used for an accuracy assessment, ensuring use of separate data sets to generate spectral signatures (i.e., first set of Munsell soil colors) and determine classification accuracy (i.e., the second set of Munsell soil colors). Each pixel from the second set of Munsell soil color images was assigned to one of 238 possible spectral signatures created from the first set of Munsell soil color images using a supervised image classification. A minimum distance algorithm was used for this classification assignment based on the smallest calculated Euclidean distance. Euclidean distances (hereafter, spectral difference values) were calculated as the difference between the candidate pixel’s RGB value (i.e., image being classified) and the spectral signatures’ RGB values. Two files were produced from each image classification, one containing each pixel’s assigned spectral signature and the other containing the corresponding spectral difference value. See Leica (2005) for further details on supervised image classification procedures, algorithms, and files produced.

Accuracy of this classification procedure was determined from 50 randomly located pixels per Munsell soil color. An error matrix was produced to determine accuracy of Munsell soil color groups and the KHAT statistic. Accuracies were calculated by dividing the diagonal produced to determine accuracy of Munsell soil color groups and the strong agreement between classification procedures, algorithms, and files produced.

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Color of horizon faces was determined by supervised image classification and SRFs were identified from groupings of Munsell soil colors. A total of 238 Munsell soil colors were categorized into five color groups including High Value, Low Chroma, High Chroma, Matrix, and Low Value/Chroma. Color groups were defined by ranges of Munsell Value and Chroma across all Hues photographed (Table 2). Color groups were based on ranges of Munsell Value and Chroma recommended by Schoeneberger et al. (2002) for SRF identification and 2332 SRF color descriptions previously made for matching soil series (Missouri Cooperative Soil Survey, 2008). Color groups allowed for more efficient quantification of SRFs and remaining soil features as opposed to interpretation of individual Munsell soil colors. Additional terminology from Schoeneberger et al. (2002) analogous to our color groups is presented in Table 2. However, we did not infer chemical compositions of color groups used for SRF identification (e.g., Fe or Mn content).

| Color groups | Code | Hue | Value | Chroma | Soil redoximorphic terminology
<table>
<thead>
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<tr>
<td>High Value</td>
<td>HV</td>
<td>All</td>
<td>8</td>
<td>≤8</td>
<td>Redox depletions</td>
</tr>
<tr>
<td>Low Chroma</td>
<td>LC</td>
<td>All</td>
<td>7–4</td>
<td>2–1</td>
<td>Fe and/or Mn redox concentrations</td>
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<tr>
<td>High Chroma</td>
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<td>All</td>
<td>7–3</td>
<td>8–4</td>
<td>Fe and/or Mn redox concentrations</td>
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<td>Low Value/Chroma</td>
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<td>All</td>
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<td>1</td>
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<td></td>
<td>M</td>
<td>All</td>
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</tbody>
</table>


Table 2: Groupings of Munsell soil colors used for identification of soil redoximorphic features.
3. Results

3.1. Water content and wetting/rewetting effects on color

Mean initial gravimetric water content of horizon faces was 0.27 g g\(^{-1}\) (SD±0.05) and ranged from 0.21 to 0.37 g g\(^{-1}\). Eleven of eighteen Initial horizon faces increased in water content following six wetting sequences (Table 1). Mean change in water content following six wetting sequences was 0.02 g g\(^{-1}\) (SD±0.04). Textural class of horizon faces that did not increase in water content was silt loam, with the exception for one silty-clay loam horizon. Mean air-dry gravimetric water content was 0.04 g g\(^{-1}\) (SD±0.02) and ranged from 0.01 to 0.07 g g\(^{-1}\). Mean change in water content of Air-dry horizon faces following ten rewetting sequences was 0.16 g g\(^{-1}\) (SD±0.04).

Examination of 8-bit RGB values of horizon faces studied \((n=18)\) during the wetting sequence indicated no increasing or decreasing trend occurred for Field 1 (Fig. 2a) and Field 2 samples. However, changes in 8-bit RGB values were observed between individual wetting sequences. Mean percent change in 8-bit RGB values following six wetting sequences was \(-0.1\%\) (SD±0.8) and ranged from \(-1.7\%\) to 1.9%. Mean 8-bit RGB color of horizon faces was observed to decrease during rewetting of Air-dry horizon faces. This trend was observed for Field 1 (Fig. 2b) and Field 2 horizon faces. Mean percent change in 8-bit RGB values following the ten rewetting sequences was \(-15.9\%\) (SD±2.7). Mean change in 8-bit RGB color values was \(-14.9\%\) (SD±2.8) following seven rewetting sequences; whereas, the mean change between the seventh and tenth rewetting sequence was \(-1.0\%\) (SD±0.9). Slight movement of soil particles was visually observed during rewetting/rewetting sequences, indicated by the appearance and disappearance of small voids (i.e., reworking of the soil fabric due to physical impact of water mist).

\[\text{Fig. 2. Change in mean 8-bit RGB color value for Field 1 samples during (a) wetting and (b) rewetting sequence. Mean RGB is calculated for each image over all pixels within the 20 cm}^2\text{ area. Each pixel's value is calculated by the sum of red, blue, and green 8-bit color values, then divided by three. Sample numbers are described in Table 1.}\]

3.2. Classification accuracy

Examination of the error matrix produced from a total of 11,900 pixel assessments indicated overall accuracy was 99.6%. Color group accuracies ranged from 98% to 100%. Twenty-one and 22 pixels of 2800 total Matrix pixels were misclassified as Low Chroma and Low Value/Chroma, respectively (Table 3). The KHAT statistic was 0.99, indicating strong agreement between training and reference data sets.

3.3. Supervised image classification and post-classification processing

An example of SRF identification by color groups is presented in Fig. 3. Total time to complete digital image processing per file after image capture was 12 min. Time to import one image from the digital camera, select the ROI, and export of the file to image classification software was 5 min. (Fig. 3a). Time to perform one supervised image classification was 5 min. (Fig. 3b and c). Time to complete post-classification processing including color grouping (Fig. 3d), thresholding of voids (Fig. 3e), production of the final classified image (Fig. 3f), and post-classification smoothing was 2 min.

An example of color grouping for a subarea identified in Fig. 3a is presented in Fig. 4. Variability of Munsell Hue (Fig. 4a), Value (Fig. 4b), and Chroma (Fig. 4c) are shown for one High Chroma SRF prior to classification. Munsell Hue was observed to vary more than Value and Chroma for identified SRFs. Fig. 4d shows the classified image prior to post-classification smoothing, highlighting a ‘salt-and-pepper’ effect on SRF identification due to pixel-by-pixel image classification.

3.4. Wetting/rewetting effects on SRF identification

Low Chroma was identified for all horizon faces. Percent area of Low Chroma identified from Initial Field 1 horizon faces ranged from 0.09 to 35% (Fig. 5a); whereas, percent Low Chroma of Initial Field 2 horizon faces ranged from 0.2 to 41%. Four of five horizons containing the greatest Low Chroma were designated as Eg horizons and percent area ranged from 18 to 41%. Small changes in percent Low Chroma between wetting sequences were observed for all horizon faces (Fig. 5a). The mean percent change in Low Chroma after six wetting sequences was \(1\%\) (SD±4.2).

High Chroma was identified for 16 of 18 Initial horizon faces. Percent area of High Chroma from Initial Field 1 horizon faces ranged from 0.008 to 20%; whereas, percent High Chroma of Initial Field 2 horizon faces ranged from 0.004 to 4% (Fig. 6a). Mean percent change in High Chroma after six wetting sequences was \(-0.3\%\) (SD±0.3). No consistent increasing or decreasing trends were observed for all color groups and horizons during the wetting sequences.

Sixteen of eighteen Air-dry horizon faces contained a greater percent Low Chroma compared to matching Initial horizon face and the mean difference was 29% (SD±0.3). Percent area of Low Chroma identified from Air-dry Field 1 horizon faces ranged from 3 to 80% (Fig. 5b); whereas, percent Low Chroma from Air-dry Field 2 horizon faces decreased from 0.21 to 0.37 g g\(^{-1}\).
faces ranged from 2 to 87%. All horizon faces with identified High Chroma (16 of 18) showed a greater identified percent area for Air-dry horizon faces compared to the matching Initial horizon face. Mean difference between Air-dry and Initial percent High Chroma for matching horizon faces was 5% (SD ± 6).

Decreasing trends in percent Low Chroma (Fig. 5b) were observed for 17 of 18 Air-dry horizon faces during the rewetting sequences. Mean reduction in percent Low Chroma after the seventh rewetting sequence was 23% (SD ± 24). Mean reduction in percent Low Chroma between the seventh and tenth wetting sequence was 2% (SD ± 4). A decreasing trend in identified High Chroma during rewetting sequences was also observed (Fig. 6b). A mean reduction of 3% (SD ± 5) for percent High Chroma occurred after seven rewetting sequences. Mean reduction in percent High Chroma between the seventh and tenth rewetting sequence was 0.03% (SD ± 0.3).

One horizon face, sample 33–2, increased in percent Low Chroma after ten rewetting sequences (15 to 38%). Visual inspection of the rewetted images for sample 33–2 did not reveal possible explanations for this change (e.g., glistening effect due to water on horizon face). However, quantification of classified Munsell colors prior to color grouping indicated the Air-dry horizon face was dominated by Munsell Value 4 and 5 and Chroma 3. Following rewetting sequences, color was dominated by Munsell Value 4 and Chroma 2, resulting in greater area grouped as Low Chroma. An associated reduction in the Matrix color group further highlighted this effect on final percent color groups. No increase in percent High Chroma for sample 33–2 occurred during the rewetting sequences.

All 18 horizons contained identified Low Chroma areas for the Initial horizon face and the Air-dry horizon face after ten rewetting sequences. Greater Low Chroma area occurred for 10 of 18 horizon faces after ten rewetting sequences compared to the matching Initial horizon faces. Differences in Low Chroma ranged from −11 to 33%. No significant linear trend between differences in percent Low Chroma and differences in gravimetric water content of Initial horizon faces and the matching Air-dry horizon face after ten rewetting sequences was found (p = 0.3). Percent High Chroma was more similar between the Initial horizon face and the Air-dry horizon face after ten rewetting sequences. Mean difference in percent High Chroma between these matching horizons was 0.8% (SD ± 1.9).

3.5. Post-classification smoothing effects

An example of post-classification smoothing effects on SRF patch geometry from a subarea identified in Fig. 3a is shown in Fig. 7. Generalized effects of post-classification smoothing were an elimination of isolated (1–4 pixel) patches (Fig. 7a) by the 3 × 3 window (Fig. 7b), simplification of individual patch boundaries and shapes by the 4 × 4 and 5 × 5 windows (Fig. 7c and d), and an increase of patch connectedness by the 6 × 6 window (Fig. 7e).

A trend of reduced Low Chroma and High Chroma percent area was identified for the 18 Initial horizon faces as window size of post-classification smoothing increased. However, reductions in percent area were small compared to reductions in total number of patches (Table 4). Mean number of Low Chroma patches from Initial horizon faces not smoothed was 6095 (SD ± 4329). Mean number of Low Chroma patches was 3411 (SD ± 2348) and 1350 (SD ± 966) after use of the 3 × 3 and 6 × 6 majority filter window size, respectively. Greater than one-third of Low Chroma and two-thirds of High Chroma patches were eliminated following use of the 3 × 3 majority filter window (Table 4), indicating a large number of isolated pixels existed after supervised classification and color grouping. Mean area of Low Chroma patches was 0.04 mm² (SD ± 0.04) and mean area of High Chroma patches 0.01 mm² (SD ± 0.14) for Initial horizon faces not smoothed. Mean area of Low Chroma and High Chroma patches increased to 0.13 (SD ± 0.13) and 0.08 mm² (SD ± 0.14), respectively, following the use of 6 × 6 majority filter window. This represented more than a doubling of mean Low Chroma area and quadrupling of mean High Chroma area (Table 4). These increases were attributed to elimination of small, isolated patches.
Edge density of Low Chroma and High Chroma was 3.2 (SD±2.7) and 0.6 mm/mm² (SD±1.1), respectively, for 18 Initial horizon faces with no post-classification smoothing. Following use of the 6×6 majority filter, Low Chroma edge density was 1.0 mm/mm² (SD±0.9) and High Chroma edge density was 0.1 mm/mm² (SD±0.2). Percent reduction in edge density mirrored percent reduction in number of patches for both Low Chroma and High Chroma (Table 4). Mean shape contiguity of Low Chroma increased from 0.4 (SD±0.05) to 0.6 (SD±0.04) when the classified image was smoothed by the 6×6 majority filter window. Mean shape contiguity of High Chroma patches was 0.2 (SD±0.06) and 0.6 (SD±0.10) for the 18 Initial horizon faces prior to smoothing and following use of a 6×6 majority filter window, respectively. Greater percent increase in High Chroma shape contiguity with increasing majority filter window size was observed compared to Low Chroma (Table 4).

4. Discussion

4.1. Use of soil cores for SRF identification

The method described here allows a relatively rapid, non-destructive, and accurate assessment of SRF occurrence from soil cores. This method may also be viewed as a quantitative version of site reconnaissance as recommended by Lindbo et al. (2008). Additionally, evaluations of SRF metrics over varying ROIs are possible, allowing a determination of a representative elementary area (REA) for SRF descriptions (Vandenbygaart and Protz, 1999). Subsequent REA analyses can provide guidance on sampling methods required to meet specific objectives (e.g., accurate determinations of percent Low Chroma using the smallest sampling area possible). Excessive site disturbance and sampling effort may then be avoided if an REA analysis indicates coring of a specific diameter is sufficient as opposed to pit excavation. While this study quantified a 20 cm² area, additional image processing indicated up to a 40 cm² area (2277×2277 pixels) can be quantified from 8 cm diameter cores. In addition to accurate SRF determinations, new findings within the field of micropedology are expected from more detailed investigations of classified images produced by this method.

This method noticeably differs from existing methods used to quantify soil morphology due to no use of additional preparation (e.g., plastic impregnation, thin sectioning). Texture of soils, lack of any significant rock fragments within soil profiles, lack of large roots, and ambient soil moisture conditions allowed cores to be quickly prepared in the laboratory for digital photography. Preparation of soil cores by simply breaking along the structural units allowed us to quantify SRFs formed in situ and located on ped surfaces. Any attempts to further prepare horizon faces (e.g., manually smooth an exposed horizon) are expected to bias expression and quantification of SRFs, changing areal extent and shapes of individual features. This bias may vary with textural classes of soil studied. Methods presented here were developed after attempts to prepare faces with high speed cutting saws proved unreliable due to smearing of large clay-content horizons. Previous attempts to use a digital camera within a soil pit by van Huyssteen et al. (2006b) relied on manual smoothing of pit

Fig. 4. Results of supervised image classification for Munsell (a) Hue, (b) Value, (c) Chroma, and (d) the final classified image based on color groups listed in Table 2. Subarea is noted in Fig. 3a.

Fig. 5. Change in Low Chroma color group for Field 1 samples during (a) wetting and (b) rewetting sequence. Sample numbers are described in Table 1.
faces. However, these authors did not quantify this effect on soil colors. Standardized preparation of exposed faces, in addition to consistent lighting conditions, remains a challenge when attempting to objectively quantify color from soil pits in the field.

4.2. Advantages of digital photography and image processing

A known accuracy for color recognition is an immediate benefit of this method. This accuracy determination is necessary when interpreting SRF descriptions and using resulting data to make quantitative predictions. Our accuracy determination was based on five color groups chosen to meet our objectives of demonstrating SRF identification from existing color definitions and descriptions of the soil series studied here. However, the creation of 238 spectral signatures during supervised classification setup allows any combination of colors to be used in image analysis to address specific study objectives. Thus, this method could be used for other quantitative assessments beside SRF descriptions (e.g., identification and quantification of void space, root morphology, krotovinas, etc.).

Additional error matrices constructed to determine accuracies of unique Value/Chroma combinations (e.g., Munsell Value and Chroma 4/3 across all Hues) indicated an overall accuracy of 98.8% and a KHAT statistic of 0.99. Only one Value/Chroma combination (8/1) was accurate for less than 90% of pixels evaluated. This accuracy allowed further investigation of classified images to understand trends in SRFs (e.g., sample 33- -2 during rewetting sequence). Overall accuracy of unique Munsell Hue, Value and Chroma (e.g., 10YR 4/3) was 74.2% and the KHAT statistic was 0.74. A determination of nearest neighbors in RGB color space for the 238 Munsell soil colors used in this study indicated color determinations using these methods are most accurate.

Table 4

<table>
<thead>
<tr>
<th>Metric</th>
<th>Majority filter window size</th>
<th>3 x 3</th>
<th>4 x 4</th>
<th>5 x 5</th>
<th>6 x 6</th>
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<tbody>
<tr>
<td>Low Chroma Area (%)</td>
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<td>−0.5</td>
<td>−1.1</td>
<td>−1.1</td>
<td>−1.5</td>
</tr>
<tr>
<td># of patches</td>
<td>−45</td>
<td>1.1</td>
<td>3.7</td>
<td>3.7</td>
<td>3.7</td>
</tr>
<tr>
<td>Mean patch area</td>
<td>61</td>
<td>110</td>
<td>189</td>
<td>189</td>
<td>247</td>
</tr>
<tr>
<td>Edge density</td>
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<td>68</td>
<td>56</td>
<td>56</td>
<td>74</td>
</tr>
<tr>
<td>Shape contiguity</td>
<td>30</td>
<td>44</td>
<td>59</td>
<td>59</td>
<td>65</td>
</tr>
<tr>
<td>High Chroma Area (%)</td>
<td>0.2</td>
<td>−0.2</td>
<td>−0.3</td>
<td>−0.3</td>
<td>−0.3</td>
</tr>
<tr>
<td># of patches</td>
<td>71</td>
<td>81</td>
<td>88</td>
<td>88</td>
<td>92</td>
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<tr>
<td>Mean patch area</td>
<td>151</td>
<td>213</td>
<td>344</td>
<td>344</td>
<td>454</td>
</tr>
<tr>
<td>Edge density</td>
<td>58</td>
<td>84</td>
<td>78</td>
<td>78</td>
<td>87</td>
</tr>
<tr>
<td>Shape contiguity</td>
<td>128</td>
<td>149</td>
<td>184</td>
<td>184</td>
<td>204</td>
</tr>
</tbody>
</table>

*a Absolute difference.  
*b Percent difference.

Fig. 6. Change in High Chroma color group for Field 2 samples during (a) wetting and (b) rewetting sequence. Sample numbers are described in Table 1.

Fig. 7. Geometry of a High Chroma color group based on (a) the final classified image, (b) a 3 x 3 majority filter window size, (c) a 4 x 4 majority filter window size, (d) a 5 x 5 majority filter window size, and (e) a 6 x 6 majority filter window size. Subarea is noted in Fig. 3a.
sensitive to differences in Hue. This sensitivity combined with
scattering of light from rough, horizon faces is reflected in the large
variability of Hue for classified images (see Fig. 4). While this method
relied on RGB color space, an additional step of converting pixel values
to other available color spaces (e.g., CIELAB, Viscarra Rossel et al.,
2006) prior to digital image processing may increase accuracies for
individual Munsell soil colors.

The use of classified images produced from this method with GIS
software affords many opportunities within the field of quantitative
soil morphology. Our image classification process allowed the
identification of soil voids by spectral difference values. While metrics
reported here were for Low Chroma and High Chroma, it is possible to
to quantify void areas, shapes, and boundaries. Occurrence of SRFs
within a specified distance of soil voids can be determined (e.g.,
percent Low Chroma within 0.1 to 1 mm of voids), thus possible
indicators of soil moisture regime can be also be quantified (Bouma,
1983). Associations of SRFs with root channels can be measured and
used for study of wetland soil/plant interactions (Vepraskas, 2001).
Contrast of SRFs with the surrounding matrix, an attribute currently
described by field soil scientists (Schoeneberger et al., 2002), can be
accurately quantified for specified distances. The combination of
spatial analyses with multiple metrics produced for SRFs affords
future opportunities to quantitatively explore relationships previously-
described qualitatively.

Image classification allows a larger number of SRF metrics to be
calculated than reported here (e.g., fractal dimension, proximity
indices, contagion; Turner et al., 2001). Metrics chosen for this study
allowed for a simple investigation of post-classification smoothing
effects. However, this type of investigation is critical to understanding
how post-classification smoothing can affect interpretation of SRF
metrics. Whether a SRF reflects current versus relict moisture regimes
can be based on the determination of diffuse versus sharp boundaries
(Vepraskas, 2001) and may be of interest for particular soils. A
determination of edge density quantifies this SRF morphology
attribute. A choice of no post-classification smoothing or a small
majority filter window size may be most appropriate when
determining SRF edge density. However, a dual objective to assess
the mean area of the most dominant SRF patches may not be met due
to inclusion of isolated pixels. Determining what metric may best
address a particular study objective, what effect post-classification
smoothing will have on metric values, and what is the variability of
metrics across soil moisture conditions are critical information needs
at the beginning of any study using SRFs.

4.3. Importance to soil classification and land management decisions

Our results indicated guidelines used for soil descriptions may be
better defined and more consistently applied by integration of digital
photography and image classification. The U.S. Department of
Agriculture Soil Survey Manual states two soil water states should be
used for color descriptions: ‘moist’ and ‘dry.’ Whereas the ‘dry’ state is
considered air-dry, the ‘moist’ state is determined when the color does
not change upon additional moistening (Soil Survey Division Staff,
1993). Our use of a digital camera and 8-bit RGB color space indicated
this strict condition may never be met. Up to a 17% change in 8-bit RGB
color value was observed for an individual wetting sequence despite
the relatively large percent saturation (0.87 ± 0.21) of these horizons.
The contribution of reworked soil particles and increasing water
content to changes in RGB color values for horizons used in this study
is unknown. Difficulty in precisely determining the ‘moist state’ of a
given soil by human observers will likely continue, drawing attention
to possible effects and biases on soil descriptions and SRF identifica-
tion. Greater transferability of SRF descriptions may be possible if more
specific guidelines are used for ‘moist’ state used (e.g., <5% change in
8-bit RGB color after 5 applications of 1 mL of water) and horizon
color is objectively determined.

The rewetting of Air-dry horizon faces showed that 8-bit RGB color
value was quickly reduced after four rewetting applications and values
were relatively stable following the seventh water application.
Percent area of Low Chroma and High Chroma during rewetting
sequences was also generally stable between the seventh and tenth
water application (≤2% change in percent area). However, large
differences in Low Chroma between the Initial horizon faces and
matching horizon faces following ten rewetting sequences existed
(−11 to 33%). These results point to the important consideration of
rainfall patterns, profile recharge, and antecedent soil moisture
conditions when choosing a time period to perform soil descriptions
and/or digital image capture. Time of year effects (i.e., moisture status
of soil) on SRF determinations may significantly impact attempts to
predict soil saturation and frequency (He et al., 2003; Vepraskas and
Caldwell, 2008a,b), causing variable results for the same horizon.

Our results indicate that an objective quantification of ‘moist’ SRFs
from same pedon/horizon at two different initial moisture contents
may result in two widely different SRF descriptions. These findings,
viewed in context of the potential error associated with color
perception by humans, point to the low precision and high
uncertainty possible in current field descriptions of soil. Previous
accuracy determinations of human color perception showed that
ranges of perceived Munsell Value and Chroma were 0.5 to 2 units and
0.5 to 1.75 units within the tested color, respectively (Shields et al.,
1966). Post et al. (1993) documented 52% agreement of Munsell color
determinations by soil scientists for 41 soil samples. Additionally,
Sánchez-Maralhón et al. (2005) showed that color fading of Munsell
soil color charts occurs over time by as much as 1 unit in Hue, Value,
and Chroma, resulting in references that do not truly represent their
intended color.

The combined factors mentioned above are expected to cause
error in field determinations of SRF presence by color, as well as areal
estimates. Examination of an individual SRF feature shows significant
variation in color and complex geometry at fine scales (Fig. 4). The
ability of trained soil scientists to determine individual feature
boundaries and ignore interior portions of features not meeting SRF
definitions (e.g., Munsell Chroma 3 versus 2) while making accurate
areal determinations is unknown. Increased complexity of SRF
geometry and decreasing size of individual features will likely
increase error in areal estimates. Mean area of Low Chroma and
High Chroma patches identified from Initial horizon faces was
<0.05 mm² prior to use of image smoothing. A notable contribution
that this method can make to current land management decision
making is the quantification of error associated with SRF determina-
tions for a range of soil, SRFs, and soil scientists. Quantifying this error
will allow functional relationships among monitored water table
depths, saturation frequencies, and SRFs to be correctly made using
structural analyses, as opposed to incorrect applications of regression
techniques (Webster, 1997).

5. Conclusions

This study demonstrated the successful integration and applica-
tion of methods previously developed in soil micromorphology,
remote sensing, and digital photography to the field of pedology. The
use of image classification allowed us to accurately determine colors
and quantify color patterns formed in soil (i.e., SRFs) for a defined area
(20 cm²) from 8-cm soil cores, reducing time associated with use of
soil thin sections. This method allows new quantitative measures of
SRFs and spatial relationships within soil horizons to be made,
promoting future interdisciplinary studies among soil hydrologists,
chemists, physicists, and pedologists. Wetting/rewetting of horizon
faces for this method showed that widely different SRF estimations
can result for the same horizon at different soil moisture conditions.
Inaccurate predictions of soil saturation frequency from functional
relationships between measured water table depths and SRFs are
possible due to this variation. Examination of post-classification smoothing effects on classified images points to the importance of matching metrics and image processing methods with specific research objectives. Possible confounding effects of image processing on SRF interpretations can be avoided at the beginning of any study by this examination of smoothing effects on metrics. Finally, this method allows error associated with human estimations of SRFs to be quantified. Such assessments remain a critical information need so that confidence in the use of SRF descriptions for land management decisions is properly placed.

Application of this method to differing soils may be dependent on textural class, ability to extract soil cores (e.g., subsurface restrictions due to rock fragments and roots), and soil moisture conditions. Use of this method for soils similar to those reported here is recommended for relatively moist conditions (e.g., following profile recharge). Cores used in this study were conducive to separation along structural units due to relatively moist conditions during sampling. This method is recommended, when possible, as a quantitative site reconnaissance technique for SRF investigations. Images produced here can be used in REA analyses to determine a representative sampling unit for pedological research, potentially reducing unnecessary pit excavation and increased sampling effort.

Acknowledgements


Leica Geosystems Geospatial Imaging, LLC (Leica), 2005. ERDAS Field Guide, Leica Geosystems Geospatial Imaging, LLC, St. Gallen, Switzerland.


