Estimating soil water content from surface digital image gray level measurements under visible spectrum

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Zhu, Y., Wang, Y., Shao, M. and Horton, R. 2011. Estimating soil water content from surface digital image gray level measurements under visible spectrum. Can. J. Soil Sci. 91: 69–76. Determining soil water content (SWC) is fundamental for soil science, ecology and hydrology. Many methods are put forward to measure SWC, such as drying soil samples, neutron probes, time domain reflectrometry (TDR) and remote sensing. Sampling and drying soil is time-consuming. A neutron probe cannot determine SWC of surface soil accurately because neutrons escape when they are emitted near soil surface and TDR is, to some extent, influenced by soil salinity and temperature. Remote sensing can obtain SWC over a large area across a range of temporal and spatial scales. Complicated terrain and atmospheric conditions often make remote sensing data unreliable. Determining SWC from surface gray level (GL) measurements in the visible spectrum may have advantages over other remote sensing techniques, because surface soil images can be easily acquired by digital cameras, even with complicated landforms and meteorological conditions. However, few studies use this method, and further work is required to develop the ability of visible spectrum digital images to accurately estimate SWC. In this study, 42 soil samples were collected to investigate the relationship between surface GL and SWC using computer processing of soil surface images acquired by a digital camera. After establishing an equation to describe this relationship, a simple calibrated model was developed. The calibrated model was validated by an independent set of 48 soil samples. The results indicate that surface GL was sensitive to SWC. There was a negative linear relationship between surface GL and the square of SWC for the 42 calibration soil samples (correlation coefficients >0.91). Based on this negative relationship, a model was established to estimate SWC from surface GL. The results of model validation showed the estimated SWCs by surface GL were very close to the measured SWCs (correlation coefficient =0.99 at a significant level of 0.01). Generally, SWC could be estimated from surface GL for a given soil, and the model could be used to quickly and accurately determine SWC from surface GL measurements.

Key words: Surface soil water content, surface gray level, soil surface image, visible spectrum

Zhu, Y., Wang, Y., Shao, M. et Horton, R. 2011. Estimation de la teneur en eau du sol a partir des tons de gris d’une image numérique de la surface prise dans le spectre visible. Can. J. Soil Sci. 91: 69–76. Déterminer la teneur en eau du sol (TES) est fondamental pour la science du sol, l’écologie et l’hydrologie. De nombreuses méthodes permettent de mesurer la TES, par exemple la dessication d’un échantillon de sol, la sonde à neutrons, le réflectomètre temporel et la télédétection. L’échantillonnage et le séchage sont laborieux; la sonde à neutrons ne mesure pas avec exactitude la TES de la couche superficielle de sol parce que les neutrons s’en échappent, tandis que la salinité et la température altèrent dans une certaine mesure les relevés du réflectomètre temporel. La télédétection permet d’établir la TES sur une vaste superficie à diverses échelles spatiales et temporelles. Toutefois, la complexité du relief et les conditions atmosphériques font en sorte que les données obtenues de cette manière manquent de fiabilité. Établir la TES d’après le niveau de gris (NG) de la surface dans le spectre visible pourrait présenter des avantages sur les autres techniques de télédétection, car les appareils photo numériques peuvent aisément acquérir des images de la surface du sol même quand le relief est tourné et que les conditions météorologiques laissent à désirer. Malheureusement, peu d’études ont tendance à recourir à cette technique, qu’il faudrait perfectionner pour que les images numériques prises dans le spectre visible donnent une estimation précise de la TES. Les auteurs ont recueilli 42 échantillons de sol pour examiner les liens existants entre le NG de la surface et la TES par traitement sur ordinateur des images saisies avec un appareil photo numérique. Après avoir formulé une équation décrivant ces liens, ils ont élaboré un modèle simple et l’ont étalonné. Ce modèle a été validé par un jeu indépendant de 48 échantillons de sol. Les résultats indiquent que le NG de la surface varie avec la TES. Le NG de la surface présentait une corrélation linéaire négative avec la valeur quadratique de la TES des 42 échantillons qui ont servi à l’étalonnage (coefficient de corrélation >0.91). Un modèle a été bâti à partir de cette relation négative pour estimer la TES au moyen du NG de la surface. La validation de ce modèle révèle que la TES estimée avec le NG de la surface est très près de la TES réelle (coefficient de corrélation =0.99 à un seuil de signification de 0.01). En général, on pourrait estimer la

Abbreviations: GL, gray level; NIR, near infrared; GS, surface gray level sensitivity; SWC, soil water content; TDR, time domain reflectometry; VIS, visible
Soil water content (SWC) is a fundamental parameter in soil science, hydrology, and ecology. Soil water content has an important effect on soil chemical, physical, and biological processes through changing soil hydraulic and thermal properties and reflectivity, which finally dominate plant water uptake, vegetation pattern and hydrological process (Levitt et al. 1990; Nielsen et al. 1996; Mahrt et al. 2001). Soil water content also influences soil-water process (infiltration, runoff, and sediment) on the slope by shaping initial SWC and infiltration rate. Accurate determination of SWC is crucial for describing water movement, understanding matter transport and energy exchange in soil and ecological systems, and modeling ecological and hydrological processes. In the past few decades, many methods have been used to estimate SWC (Skidmore and Dickerson 1975; Heilman and Moore 1980; Hope et al. 1983; Yates and Warrick 1987; Serbin and Or 2003; Leconte et al. 2004; Lunt et al. 2005; Urso and Minacapilli 2006). These methods include drying soil samples and using neutron probes, time domain reflectometry (TDR), and remote sensing. Drying soil samples is time consuming. Neutron probes are not accurate near the soil surface owing to the escape of the neutron particles. Time domain reflectometry is, to some extent, influenced by soil salinity and temperature. Meanwhile, remote sensing is widely used to determine SWC for ecological and hydrological processes and modeling because remote sensing datasets have the advantage of quantifying surface SWC across a range of temporal and spatial scales.

Remote sensing estimates of SWC have used microwave, near infrared (NIR) and visible (VIS) spectra (Gillies and Carlson 1995; Simmonds and Burke 1998; Mahrt et al. 2001; Sahebia et al. 2003; Whiting and Ustin 2004; Zribi et al. 2005; Cohen et al. 2005). Many studies have shown that SWC estimation using microwave remote sensing is particularly effective for large-scale and homogeneous land surfaces. Mobile NIR and VIS spectrophotometers can be used within fields and at other small scales for a relatively large range of applications. Sinha (1987) found that spectral reflectance was negatively related to soil moisture and organic matter for alluvial and lateritic soils. Mouazen and Baerdemaeker (2005) developed a statistical model to estimate SWC from measurements with a fiber-type NIR spectrophotometer. They developed an online SWC sensor to acquire real-time information of SWC for in situ soil. Furthermore, Mouazen et al. (2006) investigated the characterization of SWC using VIS–NIR spectra and classified soil spectra into different SWC groups based on partial least squares regression analysis and factorial discriminant analysis. Chang et al. (2001) investigated soil properties including SWC using NIR reflectance spectroscopy and principal components regression analyses from a large set of soil samples. They found that SWC could be successfully predicted by NIR spectroscopy. Whiting et al. (2004) predicted SWC using a Gaussian model on soil spectra, and reported that the soil moisture Gaussian model could estimate SWC based on the declining reflectance in NIR and shortwave regions, 1.2–2.5 μm, due to the fundamental water absorption at 2.8μm. The soil moisture Gaussian model provides practical SWC estimation, and has the potential for use in correcting the effect of soil moisture in hyperspectral images. These studies demonstrate the opportunity for estimating SWC from remote sensing (microwave, NIR, and VIS). However, they require relatively expensive instruments and complicated algorithms. Furthermore, remote sensing techniques are often limited to larger scales and homogenous underlying surface. In addition, complicated landform and meteorological conditions can make the retrieval of SWC unreliable. Hence, there is an urgent need to continue developing improved remote sensing methods for estimating SWC.

Soil surfaces can reflect visible light, which causes soil surfaces to show certain colors and levels of brightness. Color and brightness correspond with a unique gray level obtained via computer image processing. Consequently, surface brightness is associated with surface gray level (GL, 0–255). For a given soil, surface GL changes with SWC because soil water modifies the reflex and scattering of visible light. For this reason, measurements of soil surface GL may be used to estimate SWC. Because surface GL can be determined easily using computer image processing, measuring GL may make the estimation of SWC convenient for various scales, climate conditions, and topographical conditions. One of the advantages of using this method is the low cost of analysis and inexpensive instruments. To date, few experiments have been performed to investigate the relationship between soil surface GL and SWC. There is a need to perform precise experiments to investigate the relationship.

The objectives of this study are to investigate the relationship between surface GL and SWC, to construct a simple model to estimate surface soil moisture from soil surface GL, and to validate the model for further applications.

**MATERIALS AND METHODS**

**Model**

Surface GL increases as SWC decreases. We define a parameter \( k \) as soil surface GL sensitivity (SGS) to
describe the change of surface GL per change in soil water content. Hence, \( k \) can be expressed as:

\[
k = -\frac{dGL}{d\theta}
\]  
(1)

where GL is surface gray level, and \( \theta \) is soil water content.

Integrating Eq. 1 provides:

\[
GL = -k\cdot\theta + C_1
\]
(2)

Surface GL sensitivity is a basic soil property influenced by soil particle composition, soil surface structure, soil mineralogy and SWC. For a given soil, SGS is dominated by soil water content \( \theta \). We assume that the change in SGS per change in soil water content \( R \), acceleration of \( k \) is a constant for a given soil. Clearly, the changes in \( k \) is opposite to the changes in SWC, because the changes in \( k \) is opposite to changes in SWC. Consequently, \( R \) can be expressed as:

\[
R = -\frac{dk}{d\theta}
\]
(3)

Integrating Eq. 3 provides

\[
k = -R\cdot\theta + C_2
\]
(4)

Substituting Eq. 4 into Eq. 2 gives:

\[
GL = R\cdot\theta^2 - C_2\cdot\theta + C_1
\]
(5)

Hence, surface GL (GL) can be estimated from \( \theta \) and three coefficients \( R \), \( C_1 \) and \( C_2 \).

At soil water content \( \theta \) equal to 0, \( k \) has a maximum value \( (K, \text{maximum SGS}) \) according to Eq. 4 and at the same time surface GL reaches a maximum value \( (GL_0) \). Substituting \( \theta = 0 \) into Eqs. 4 and 5 gives:

\[
C_1 = GL_0
\]
(6)

and

\[
C_2 = K
\]
(7)

Coefficients \( C_1 \) and \( C_2 \) both have special physical meanings as maximum GL and SGS, respectively. Eq. 5 can be rewritten as:

\[
GL = R\cdot\left(\theta - \frac{K}{2R}\right)^2 + GL_0 - \frac{K^2}{4R}
\]
(8)

Clearly, as \( \theta \) is equal to \( \frac{K}{2R} \), GL has its minimum value. Then the maximum value of GL, \( GL_s \), occurs when soil is water saturated, \( \theta_s \). Hence, \( \theta_s \) and \( GL_s \) can be expressed, respectively, as:

\[
\theta_s = \frac{K}{2R}
\]
(9)

and

\[
GL_s = GL_0 - \frac{K^2}{4R}
\]
(10)

Substituting Eqs. 9 and 10 into Eq. 8 provides:

\[
GL = R\cdot(\theta_s - \theta)^2 + GL_s
\]
(11)

Eq. 11 can be rearranged to express soil water content \( \theta \) as:

\[
\theta = \theta_s - \sqrt{\frac{GL - GL_s}{R}}
\]
(12)

Combining Eqs. 9 and 10 gives:

\[
R = \frac{GL_0 - GL_s}{\theta_s^2}
\]
(13)

Substituting Eq. 13 into Eq. 12 provides:

\[
\theta = \theta_s - \theta_s\cdot\sqrt{\frac{GL - GL_s}{GL_0 - GL_s}}
\]
(14)

If \( GL_s \) and \( GL_0 \) are known for a specific soil, Eq. 14 can be used to estimate SWC from surface GL measurements. Because \( \theta_s \), \( GL_0 \), \( GL_s \) and \( GL \) can be easily obtained from gray level measurements under the visible spectrum with computer image processing, SWC estimation becomes readily obtainable.

**MATERIALS AND METHODS**

In total, 90 soil samples were collected from the southeast region of the Loess Plateau of China. Forty-two of the soil samples were used to calibrate the gray level/soil water content model, and the other 48 soil samples were used to validate the calibrated model. The textures of the soil samples are shown in Table 1. Soil samples were passed through a 2-mm sieve and dried at 108°C. The soils were then packed into small cylinders (3 cm in diameter and 1.5 cm deep), and water-saturated. Surface images of the packed soil samples were acquired with a digital camera (Sony DSC-HX1). The packed soil samples were allowed to dry. At selected times during drying, the samples were weighed to determine SWC (mass percentage), and at the same time the surface images were obtained. Data were collected in this manner in order to obtain SWC and GL values sequentially for each packed soil sample from saturation to dry soil conditions.

| Table 1. Soil texture classifications for the calibration and validation soil samples |
|---------------------------------|-----------------|-----------------|
| Classifications                | Samples for calibration | Samples for validation |
| Silt loam                      | 3                | 2                |
| Silty clay loam                 | 21               | 18               |
| Silty clay                     | 18               | 28               |
Brightness Calibration

The brightness of the background light must be accounted for during image processing. To achieve an image processing calibration, white and black color checkers (X-Rite GmbH) were placed at the corners of a set of soil sample images (Fig. 1a). The calibration is based on the following principle: With the continuous change in environmental light, the gray level of the color checker changes as well, but the color checker has a steady reflectivity. In image processing, the GLs of white and black color checkers are assigned as 0 and 255, respectively, no matter what their true values are in GL. In this case, the color checker acted as a standard reference for brightness. In the experiment, the input value of the white color checker GL (0\(\text{C1}/255\)) was observed using a line profile tool (Fig. 1b, soft Image-Pro Plus 6.0 demo version), and the output value of the white color checker GL was assigned the value 255. The input of the black color checker GL was observed and the output value of the black color checker GL was assigned a value of 0. Because output values of the films were not kept the same for each operation, the light intensities of the images were calibrated to the white and black values.

Gray Level Measurements

After brightness calibration, the original images (Fig. 1a) were transferred into gray images (Fig. 1b). In the figure, each square block (bold frame in Fig. 1a) is an image of one packed soil sample. The soil surface GL (0\(\text{C1}/255\)) was obtained by a line profile tool. The soil surface GL changes considerably, with a high variability. This high variability indicated that mineral composition, structure, and surface roughness of the soils were variable as well.

Gloss Elimination

When a soil sample was over-saturated, a film of water would form on the soil surface. The water film could reflect light to form gloss in the image, resulting in an obviously brighter than normal condition (Fig. 1a). With the gloss present, the surface GL is not the brightness of the true soil surface. A method to eliminate gloss was developed based on the range of GL values. If the range of GL values was larger than 10, the three maximum and minimum GL values were discarded in a step-wise manner until the range of the remaining GL values was less than 10. The value of 10 is from the GL comparison between soil with film and without film under same SWC. The discards of three maximum and minimum of GL values are experiential-based.

RESULTS

Statistical Characteristics of Surface Gray Level for the Soil Samples

Surface GL of a dry soil (\(\theta = 0\)) is a basic soil optical property that is dominated by soil mineral compositions, structure, and surface roughness. For a given soil, surface GL is controlled by SWC, and surface GL increases as SWC decreases. For saturated soil, the surface GL is at the minimum value. In order to describe statistical characteristics of surface GL for the soil samples, surface GL at \(\theta = 0\) (\(GL_0\)) and saturation (\(GL_s\)) were acquired by a line profile tool with computer image processing. The surface GL range (\(GL_r = GL_0 - GL_s\)) was determined. The statistical characteristics of \(GL_0\), \(GL_s\), and \(GL_r\) are shown in Table 2. Over the range of water contents, surface GL changed considerably, with a high variability. This high variability indicated that mineral composition, structure, and surface roughness of the soils were variable as well.

The mean of \(GL_r\) was 82 (ranging from 65 to 98), and the range of SWC from dry to saturation, was normally about 50%. Clearly, the value of \(GL_r\) is larger than that of saturated SWC, indicating that the surface GL was sensitive to changes in SWC.

Calibration of the Model

In the Model section, Eq. 8 was used to describe the functional relationship between surface GL and SWC. Based on Eq. 8, a simple model to estimate SWC was presented. Equation 8 was fitted to observed surface GL and SWC pairs in order to obtain parameters \(R\), \(K\) and \(GL_0\). Fitted results are shown in Table 3. Correlation coefficients \(r > 0.91\) were large, indicating that Eq. 8 described the relationship between surface GL and SWC well.

As mentioned in the Model section, Eqs. 9 and 10 can be used to calculate saturated water content (\(\theta_s\)) and surface GL range (\(GL_r\)). Hence, the calculated and the

![Fig. 1. Example image of a set of soil samples. The corners of the image (a) are either black or white color checkers. Images a and b indicate the processes for gray level acquisition for the soil samples.](image-url)
observed values of $\theta_s$ and $GL_s$ were compared. The comparisons are shown in Figs. 2 and 3. Observed $\theta_s$ and $GL_s$ were similar to calculated values derived from Eqs. 9 and 10. Differences between the observed and calculated values could have resulted from model shortcomings and from errors in the measurements of SWC and surface GL.

Validation of the Model
A simple model (Eq. 14) was presented to estimate SWC. In order to validate the model, 48 independent soil samples were examined. First, the soil samples were saturated and surface images were obtained by a digital camera. The soil samples were then allowed to dry. While drying, sequential measurements of SWC and surface GL were obtained. Using the data, the values of $\theta_s$, $GL_0$, and $GL_s$ were determined. Then surface GL ($GL$) values were used with the model to calculate SWC ($u$). Finally, the calculated SWC values were compared with the observed SWC values.

The calculated SWC values were similar to the observed SWC values (correlation coefficient, $r = 0.99$, see Fig. 4). Table 4 shows the statistical results for the linear regression between observed SWC and calculated SWC. The validation results suggested that model-estimated SWC values, based upon measured surface GL value, were accurate.

In the experiments, an equation was established to describe the relationship between SWC and surface GL. There were three key parameters $k$, $K$, and $R$, where $k$ is a variable parameter relating to SWC, and $K$ and $R$ are constants determined by soil type (including soil organic matter, soil particle composition, and soil minerals). In order to analyze how $K$ and $R$ affect the relationship between surface GL and SWC, we assigned different values to parameters $R$, $K$ and $GL_0$ and calculated surface GL changes. The results are presented in Fig. 5. When $K$ and $GL_0$ are fixed, the relative curvature increases as $R$ increases, and both saturated water content and surface GL at saturation decrease quickly (Fig. 5a). When $R$ and $K$ are fixed, the shapes of the

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<th>$K$</th>
<th>$GL_0$</th>
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Table 2. Statistical characteristics of gray level values $G_0$, $G_s$, and $G_r$

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<td>$G_r$</td>
<td>82</td>
<td>9</td>
<td>65</td>
<td>98</td>
<td>33</td>
<td>11</td>
</tr>
</tbody>
</table>

Fig. 2. Observed $\theta_s$ versus calculated $\theta_s$. For personal use only.
curves are similar with the only difference being the relative values of surface GL (Fig. 5b). Finally, when $R$ and $GL_0$ are fixed, the relative curvature decreases as $K$ increases (Fig. 5c).

**DISCUSSION**

Surface soil water content is important for soil science, hydrological, and ecological processes and modeling. The approach described for estimating surface soil moisture with surface gray level measurements under visible spectrum is a new method. The model included a parameter, $k$, which was defined as the soil surface GL sensitivity (SGS, surface GL change per change in soil water content) and it included assumptions that SGS was determined by soil water content and that the SGS change rate per soil water content (SGSR) was a constant for a given soil. With these assumptions we developed Eq. 8 to describe a relationship between surface GL and SWC. The equation included three important parameters, $R$, $K$ and $GL_0$. Based on our assumptions, these parameters are inter-related as indicated in Eqs. 9 and 10. Fitting surface GL and SWC data with Eq. 8 represented the relationship between surface GL and SWC very well. If parameter $R$ is set equal to 0 (indicating that SGS is a constant), surface GL is linearly related to SWC. Additionally, both $R$ and $K$ are logarithmically negatively related to saturated water content (see Fig. 6). This relationship indicates that for a given soil if saturated water content is relatively small, then surface GL sensitivity is relatively large.

In this study, a simple model was developed to estimate SWC. The model showed that if we determined $\theta_\alpha$, $GL_0$ and $GL_s$, we could estimate SWC from measured surface GL. In other words, these three parameters determine the relationship between surface GL and SWC. This model indicated that soil surface images could provide information on soil water content, and that SWC changes could be determined from image color and brightness under visible spectrum. As for the parameters $k$, $K$, and $R$, $R$ was very sensitive and determined the tendency (shape and speed of the curve) of surface GL with the change of SWC according to Eq. 11 and Fig. 5.

Using surface GL to determine SWC is convenient for a small scale and for complicated terrain, because soil surface images can easily be acquired with a digital camera.

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**Table 4. Linear regression parameters for observed versus calculated soil water contents, SWC**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. error</th>
<th>$t$</th>
<th>$P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>0.17</td>
<td>0.192</td>
<td>0.887</td>
</tr>
<tr>
<td>$a$</td>
<td>1.012</td>
<td>0.00634</td>
<td>159.55</td>
</tr>
</tbody>
</table>

**Analysis of variance**

<table>
<thead>
<tr>
<th></th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>$P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1</td>
<td>86723</td>
<td>86723</td>
<td>25456</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Residual</td>
<td>286</td>
<td>974</td>
<td>3.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>287</td>
<td>87697</td>
<td>306</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
camera. This method may be able to fill the gap between larger scales and point-scale. Moreover, the image of soil surface change can be obtained by video, so the method can also be used to measure SWC during rainfall. In this method, the calibration of surface GL is most important to account for the constantly changing light level and quality. Estimation error can be reduced by the use of black and white and increasing the numbers of color checkers. Furthermore, gloss elimination is possible, and is required for saturated soils, because the increase of $GL_s$ will lead to the obvious decrease of denominator ($GL_0-GL_s$), resulting in large a variation of determination result from Eq. 14. In addition, there is a vertical variation in SWC along the soil profile. In order to reduce this variation, in the study, soil cylinders with a depth of only 1.5 cm were used to loading soil samples. In this sense, the SWC retrieval was restricted to the surface 1.5 cm soil.

CONCLUSION

An equation describing the relationship between surface GL and SWC is presented. The equation was calibrated by fitting surface GL and SWC of 42 soil samples. Surface GL was negatively proportional to the square of SWC (Eq. 11). The calibrated results showed that the equation described the relationship of surface GL and SWC well. Based on the equation, a simple model (Eq. 14) with three basic parameters $u_s$, $GL_0$, $GL_s$ was developed to estimate SWC from surface GL via image analysis. The model was validated independently by another 48 soil samples. The validated model could estimate SWC from surface GL with a high level of accuracy.

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