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RELATIONSHIP BETWEEN SOIL MOISTURE CONTENT IN PADDY FIELD AND ITS IMAGE TEXTURE

Siti Khairunniza Bejo*, Nor Hafizah Sumgap, Siti Nurul Afiah Mohd Johari

Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

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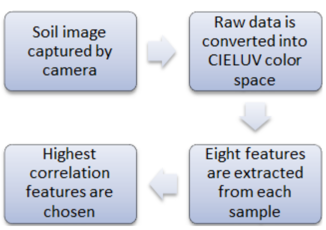
*Corresponding author
skbejo@upm.edu.my

Graphical abstract



Abstract

The aim of this study is to identify the relationship between soil moisture content and its image texture. Soil image was captured and converted into CIELUV color space. These images were later used to develop two dimensional gray level co-occurrence matrix. Eight texture features extracted from gray level co-occurrence matrix namely mean, variance, homogeneity, dissimilarity, entropy, contrast, second moment and correlation was used for the analysis. The results has shown that the image texture properties can be used to relate with soil moisture content, where variance, homogeneity, dissimilarity, entropy, contrast, second moment and correlation gave significant responds to the moisture content. The highest value of correlation was gathered from entropy with *r* = -0.522.

Keywords: Soil moisture content, texture, image processing

1.0 INTRODUCTION

This study was focusing on soil moisture content in paddy field. Water is important variable in planting paddy crops and it has different water requirement for different growing stages of paddy i.e. vegetative, reproductive and ripening phases [1]. Currently there are several methods used to measure soil moisture content. The conventional method is gravimetric method where soil sample was taken to laboratory oven dried for 24 hours to get the mass of water pore [2]. However this method is time consuming and not suitable if moisture content need to be measured multiples times day by day. There are several available in-situ measurements which can give reading of soil moisture content in short period and repeatable. However the used of sensor is limited since it depends on the technical specification provided by manufacturers. Besides that, leaving the sensor in field for too long and without any supervision might cause damage to it or being stolen by others. Soil particles are having different size depend on the amount of mineral particles that bind them together. The soil texture can be separated into three major groups which are sand (biggest soil separates), silt (medium soil separates) and clay (smallest soil separates). Particles of sand, silt, and clay have its own standing physical characteristics in term of size, shape, specific area, number and size of pore, water holding capacity, and absorptive capacity. When these three different soil textural groups mixed, its characteristics are different. It can be classified to three class i.e. coarse textured soil, medium textured soil, and fine textured soil. A fine textured soil may hold more water as the pore size is smaller with higher water potential compared to coarse textured soil where water is drained quickly. Knowing that soil naturally has different texture, therefore capturing an image of soil will give a different image texture. The variation of soil particles shape and size will produce different pattern in each image captured. For example, a fine textured soil which contains more clay particles give a smooth texture surface compared to a coarse textured soil with larger sandy particles. There are several texture features can be extracted from soil image such as mean, variance, homogeneity, entropy, contrast, second moment and correlation [3]. These parameters can be extracted from grey scale of soil image by using computer programming and it can be used to find relationship with soil moisture content.

Han and Hayes [4] reported that grey level co-occurrence matrices (8x8) for dark and light soils were different. Burks *et al*. [5] used color co-occurrence method texture statistics for discriminating different weed species and soil. It was found that texture statistics could be used in a generalized square distance classifier to discriminate between the data classes [6]. Meyer *et al*. [7] used texture features second moment, entropy and homogeneity extracted from grey image of soils and plants where soils classification accuracy is 97%. Entropy and second moment texture features of the grey scale image of sludge had been used to predict sludge moisture content using neural network where the decreasing in moisture increased the sludge uniformity, but decreased the image entropy. Bodun *et al*. [8] reported that grey level co-occurrence matrices for sludge varied with the change of soil moisture. Roy and Shibusawa [9] found that contrast and correlation features had negative responses to moisture content and energy feature had positive response to moisture content.

Based on the literature, it can be seen that the image texture gave response to moisture content. However, it response to the soil in the paddy field have not yet being explored. This condition gave high motivation to perform this research.

2.0 EXPERIMENTAL

2.1 Data Collection

Two hundred and forty two soil samples were collected from the Sawah Sempadan, Selangor paddy field which had been plowed after harvesting. Auger or excavating was used to take surface soil approximately 100g from each plot at 10-15 cm depth. It was then stored in a plastic bag and tied tightly to prevent any moisture loss during transporting from field to laboratory which took approximately 2 hours to arrive.

2.2 Image Acquisition

Before the soil samples were taken into oven for oven dry process, a digital image of each sample was captured using digital camera (Canon EOS400D) with the resolution of 7.0 Megapixels and saved in a RGB color in JPEG format. The camera is set to capture in single shooting mode with standard picture style, automatic white balance and ISO standard is 800. The camera has been setup on a tripod at 40 cm height in a constant position and lens aperture under control lighting environment as shown in Figure 1. The lighting was setup around soil sample to avoid any possible shadow appear on soil. All lights and tripod were set on a black board to minimize reflection and no flash was used. The soil sample was placed in a black box at the center of camera focusing area with the size of area cover by soil is at 1000x1000 pixels.

2.3 Measuring Moisture Content

In this study, the actual value of soil moisture content was measured using gravimetric method. Gravimetric method measure soil moisture content on a weight based where the weight of water in sample is divide by the dry weight of the soil sample. The American Society for Testing and Materials (ASTM) standard for gravimetric methods in laboratory test were used to determine the soil moisture content. The samples were placed in a can and weighted before oven dry at 105°C for 24 hours. It is then weighted again to get the mass of dry soil. At this temperature, all moisture in soil will be evaporated but it not burning any soil organic matters. This is important to make sure the weight loss after oven dry is the weight of moisture in soil only. Th sture content determination is as

$$w = \frac{M_{ms} - M_d}{M_d - M_c} \times 100 \quad (1)$$

Where,

w = moisture content

M_{ms} = mass of moisture soil

M_d = mass of dry soil

M_c = mass of can

Figure 1 Image acquisition

2.3 Image Texture

All of the textural analysis was done using the gray level co-occurrence matrix (GLCM) of soil image in CIELUV color. CIELUV color was used as it gave the best result for mean image intensity relation with moisture content [10]. The GLCM calculates how often a pixel with gray level (gray scale intensity), value *i* (value in column) occurs horizontally adjacent to a pixel with the value *j* (value in row). The GLCM describe here is used for a series of second order texture calculations. The second order measures consider the relationship between groups of two pixels in the original image, normally use neighboring pixels. There are eight textural properties i.e., mean, variance, homogeneity, dissimilarity, entropy, contrast, second moment and correlation. These textural properties are defined as follow:

i. Mean

$$\mu = \sum_{i,j=0}^{N-1} i(P_{i,j}) \quad (2)$$

ii. Variance

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\ (i-\mu_i)^2 \quad (3)$$

iii. Homogeneity

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad (4)$$

iv. Dissimilarity

$$\sum_{i,j=0}^{N-1} P_{i,j}\ |i-j| \quad (5)$$

v. Entropy

$$\sum_{i,j=0}^{N-1} P_{i,j}\ (-\ln P_{i,j}) \quad (6)$$

vi. Contrast

$$\sum_{i,j=0}^{N-1} P_{i,j}\ (i-j)^2 \quad (7)$$

vii. Second Moment

$$\sum_{i,j=0}^{N-1} P_{i,j}^2 \quad (8)$$

viii. Correlation

$$\sum_{i,j=o}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(i-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \quad (9)$$

Where;
i = row number
j = column number
N = the total number of pixel
P*i,j* = the probability for the pixel at *i, j*

These texture properties then were analyzed using Pearson Correlation to find the significant relation between image texture properties with soil moisture content.

3.0 RESULTS AND DISCUSSION

The textural analysis was done using the gray scale image of CIELUV and being analyzed using ENVI software for different texture parameter. There are eight texture properties had been tested i.e. mean, variance, homogeneity, dissimilarity, entropy, contrast, second moment and correlation. Table 1 shows the results distribution for each texture property with respective moisture content.

It can be seen that each property give different effect to soil image. For example, the value for mean, variance, dissimilarity, entropy and contrast are increasing when the value of moisture content decreasing. The increasing in texture properties value indicates that there are high variations in gray level of image matrices which mean the texture become irregular. Meanwhile, the value for homogeneity, second moment and correlation are decreasing as the moisture content decrease. As the value is approaching zero, the gray level becomes closer and constant which indicate smoother texture [3].

The result of Pearson correlation value for image texture properties with moisture content shows that only mean (r = -0.041) did not give significant correlation. Homogeneity (r = 0.474), second moment (r = 0.510), and correlation (r = 0.264) provide significant positive correlation. Meanwhile, variance (r = -0.444), dissimilarity (r = -0.456), entropy (r = -0.522), and contrast (r = -0.428) provides significant negative correlation. From the result, entropy and second moment are the two properties which have higher correlation. The negative *r* values indicate that when the value of entropy is increase, it shows more uncertainty in the image. This is because the coarse soil gives more variation to gray levels in image matrices. Therefore, it can be said that when the soil roughness is increasing, the soil moisture content is increasing too. It is known that the bigger size of soil aggregate can hold higher moisture content.

Table 1 Correlation between moisture content and image texture

Image Texture (N=242)	**r**
Mean	-0.041
Variance	-.444**
Homogeneity	.474**
Dissimilarity	.456**
Entropy	-.522**
Contrast	-.428**
Second moment	.510**
Correlation	.264**

** Correlation is significant at the 0.01 level (2-tailed).

4.0 CONCLUSION

The relationship between soil moisture content and its image texture has been studied in this research. Based on the eight features extracted from the image tested i.e. mean, variance, homogeneity, dissimilarity, entropy, contrast, second moment and correlation, it shown that entropy has highest correlation with soil moisture with *r* = -0.522. The entropy measure disorder or complexity of an image and the high entropy image has high contrast from one pixel to its neighbor. Meanwhile, the decreasing in second moment value represents the highest level of non-homogeneity which indicates a spread of values in co-occurrence matrix or coarse image texture. In summary, it can be concluded that the image texture properties can be used to relate with moisture content of soil taken from paddy field.

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