Soil Organic Carbon Modeling and Mapping in a Semi-Arid Environment Using Thematic Mapper Data

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Abstract
This study evaluated the effectiveness of using Thematic Mapper (TM) data for estimating soil organic carbon (SOC) content in the Zarqa Basin, Jordan, a typical semi-arid environment, and under natural surface conditions by testing a variety of statistical modeling techniques. This is essential for implementing carbon crediting programs for ameliorating the effects of global warming. Although none of the developed models was powerful in predicting SOC, a stepwise regression model was selected since it provided the lowest validation root mean square error (RMSE) of 10.4 metric tons per hectare (ton/ha). Using this model, a SOC map for the basin was constructed by applying map algebra. The total SOC content to 0.2 m depth of the basin was calculated to be 9,423,986.4 metric tons with SOC density of 26.3 ton/ha. This study suggested that, in semi-arid environments and using the statistical modeling techniques that were tested, TM-based SOC models cannot be used for implementing carbon crediting programs; however, they can estimate total surface SOC pools in large areas to within a few percent error.

Introduction
Soil carbon management and sequestration is one of several important strategies suggested by Kyoto protocol in 1997 for reducing the concentrations of carbon dioxide, the main greenhouse gas, in the atmosphere as a global warming abatement measure (UN, 1998). This, in turn, has a host of ancillary benefits, including reduced soil erosion, improved overall soil quality, reduced floods’ impacts, and improved air and water quality (Reed, 2007). Hence, many countries around the world began considering the development of policy instruments (such as carbon credits) designed to encourage owners of agricultural, grazing, and forest lands to adopt management practices that facilitate withdrawing carbon from the atmosphere and sequestering it in the soil through the natural processes of humification ( Lewandrowski et al., 2004 ). However, in order for carbon sequestered in soil to gain international acceptance as a global warming abatement measure, there is an urgent need to develop simple, accurate, rapid, and inexpensive methods for monitoring spatial and temporal changes in soil carbon stocks (Campbell et al., 2001). Direct field and laboratory measurements of soil carbon pools are very accurate, but are very costly and provide only site-specific information. Conversely, indirect estimation of carbon stock changes utilizing, among other methods, remote sensing and geographic information systems (GIS), is cost-effective and provides spatially continuous information over large areas on a repetitive basis. Therefore, to monitor soil carbon changes over large areas, indirect methods based on relationships developed at the field should be used (Post et al. 2001).

Many studies tried to model the relationship between soil organic carbon (SOC) or soil organic matter (SOM) and spectral information obtained by hyperspectral spectrometers either handheld or mounted on airplanes (e.g., Dalal and Henry, 1986; Gomez et al., 2008; Huang et al., 2007; Ingleby and Crowe, 2000) or by multispectral satellite and airborne remote sensing sensors (e.g., Aghu et al., 1990; Chen et al., 2000; Coleman et al., 1993; Huang et al., 2007; Ishida and Ando, 1999; Van Deventer, 1992; Wilcox et al., 1994; Wu et al., 2009). The use of hyperspectral spectrometers mounted on airplanes showed promising results, but that came with a high price tag of instrumentation and tasking flights across the study areas. In addition, handheld spectrometers provide discrete measurements and cover relatively small areas. Generally, studies that used multispectral satellite remote sensing systems provided poor results. The studies conducted by Chen et al. (2000) and Wilcox et al. (1994) resulted in relatively highly accurate predictions of SOC, but the study areas were relatively small with bare and dry surface conditions. Although these types of studies have their merit, as they are typically in a more controlled environment, they do not produce practical results when the goal is to study large areas repetitively under natural field conditions, which is the goal behind any carbon credit monitoring program. In addition, Aghu et al. (1990), Coleman et al. (1993), Ishida and Ando (1999), and Wilcox et al. (1994) built their conclusions on just the calibration stage and did not validate the results using a validation sample. Furthermore, Huang et al. (2007) and Wu et al. (2009) used Enhanced Thematic Mapper Plus (ETM+) imagery that were acquired after 31 May 2003. The authors of this study do not recommend using images acquired by ETM+ sensor after this date, since they suffer from missing data resulted from a permanent mechanical malfunctioning in the

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ETM + instrument (NASA, 2009). After the successful launch of Hyperion onboard Earth Observing 1 (EO-1) satellite in 2001, Foster et al. (2002) and Gomez et al. (2008) utilized Hyperion hyperspectral data to estimate SOC composition under natural field conditions. The use of Hyperion as explained by these researchers provided promising predictions of SOC, but the results relied on small-sized samples. In addition, each of these studies applied just one modeling technique; Foster et al. (2002) applied forward stepwise multiple regression and Gomez et al. (2008) applied partial least squares regression.

This study overcomes the problems associated with other studies, such as small sample size and small study area, and adds upon the previous work by applying a variety of statistical modeling techniques, and dividing the modeling process into calibration and validation stages. The study also provides models for predicting SOC content in natural field conditions using satellite-based Thematic Mapper (TM) sensor systems, which provide historical archives of imagery unmatched in quality, detail, coverage, and length (NASA, 2009). These archives constitute a valuable open-to-the-public source of indirect information, which is suitable for implementing carbon crediting programs.

The Study Area

The study area is the Zarqa Basin in Jordan (Figure 1). It covers an area of about 3,583 km² between latitudes 31°30’N and 32°30’N and longitudes 35°30’E and 36°30’E. The Zarqa Basin is a sub-watershed of the Jordan River Watershed. It comprises the Zarqa River, which is the second largest river in Jordan. The basin represents a typical semi-arid ecosystem, which is characterized by a Mediterranean climate with hot, dry summers and moderately cool, wet winters. Topography in the basin varies tremendously from 196 m below sea level along the Zarqa River in the western part of the basin to about 1,230 m above sea level close to Salt City. This variation in topography is accompanied with large variation in soil type from silty clay loam to silt loam to clay loam and silty clay. Land-use and land-cover in the basin also vary remarkably. The southwestern parts of the basin, which comprise most of the capital Amman and the Zarqa and Salt cities, are heavily urbanized. The northwestern areas are characterized by agricultural activities scattered in between forest and grazing lands. The northeastern areas are dominated by grazing lands with some dispersed agricultural activities. Barren lands characterize the southeastern parts of the basin. The basin is considered the economic heartland of Jordan; it comprises more than 50 percent of the industry and more than 60 percent of the population of Jordan (DOS, 2009). However, it is facing the threats of desertification, biodiversity loss, and pollution of air, water, and soil. Therefore, there is a need to restore its ecosystem while maintaining its development sector.

Materials and Methods

Image Description and Processing

After a thorough search of the archives of the United States Geological Survey (USGS, 2009), a cloud-free Landsat-5 TM image for path 174 and row 038, which was acquired on 30 January 2009, was downloaded. The date of the image was chosen to coincide with the fieldwork campaign carried out to collect the necessary soil samples as described in the next section. The image is in the UTM Zone 36 North coordinate system.

The ENVI 4.5 digital image processing software (ENVI, 2008) was used for processing TM data. First, bands
through 5 and 7 were stacked into one image file. Then, the image was spatially subsetted according to the borders of the Zarqa Basin, thus including only the portions of the image of interest. Finally, the ENVI® Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module (ITT, 2008) was used to correct the TM data for atmospheric effects using sun elevation of 33.4957478°, as obtained by the image information, and using the atmospheric model “Mid-Latitude Summer” and the aerosol model “Urban”, and using an average ground elevation of 0.681 km, as deduced from a local DEM.

Soil Sampling and Analysis
Using the GIS software ArcMap® 9.2 (ArcMap, 2006), 500 points were randomly generated inside the Zarqa Basin area. The locations of these points were displaced to coincide with the centers of the pixels of the processed TM imagery where they happened to exist. The generated points represented the locations of the soil samples that were intended to be taken in the field. The coordinates of these points (in the UTM Zone 36 North coordinate system) were uploaded into a handheld global positioning system (GPS) device with an accuracy of less than 5 m. By taking into consideration factors of logistics and accessibility conditions in performing the fieldwork campaign, only 333 soil samples were collected during the months from October 2008 to February 2009, using a hand probe (0.025 m in diameter) to a depth of 0.2 m (Figure 2).

Soil organic matter contents of the soil samples were determined following Walkley-Black wet combustion method (Nelson and Sommers, 1996). Knowing that SOM contains 58 percent carbon, SOC contents (in percentages) of the soil samples were calculated. However, in order to report SOC as mass per unit area (to some prescribed depth), soil bulk densities of the soil samples were first determined using core method technique (Blake and Hartge, 1986), and then, using the conversion factor “SOC (kg/kg) × Bulk Density (kg/m³) × Soil Depth (0.2 m) × 10000 / 1000”.

SOC values were tabulated in metric tons per hectare (ton/ha) to 0.2 m depth.

Soil Organic Carbon Modeling and Mapping
In this study, SOC modeling was performed using the statistical software JMP 7.0.1 (JMP, 2007). First, the soil samples were randomly split into 75 percent calibration set, which comprised 249 soil samples, and 25 percent validation set, which comprised 84 soil samples. Using the calibration set, five major statistical modeling procedures were conducted to calibrate 19 statistical models predicting SOC using the six processed TM bands as predictors. They are: (a) stepwise regression, (b) partial least squares, (c) recursive partitioning, (d) artificial neural network, and (e) combined models. The statistical model showed the best performance in the validation stage using the validation set was selected and, utilizing the digital image processing software ENVI® 4.5 (ENVI, 2008), was used to estimate SOC composition for every pixel inside the Zarqa Basin and, in turn, produce a SOC map for the area by applying map algebra (Esri, 2006). The performance of the models was evaluated according to their root mean square errors (RMSEs), coefficient of determinations (R²s), and error distribution curves. Any model that provided low RMSE and high R² with random error distribution was considered to be a successful model. But before commencing with the modeling analysis, the types of the relationships between the response and the predictors were identified by drawing scatter plots. In addition, the strengths of the relationships between the predictors and the response and among the predictors were determined by creating a correlation matrix using Pearson’s correlation coefficient (r). Correlation analysis, among other things, is useful for detecting the presence of multicollinearity, which hinders the ability to assess the importance of the independent variables (Howell, 1997). Below is a brief and concise description of the statistical modeling procedures that were calibrated and validated in this study.

![Figure 2. Locations of the soil samples in the Zarqa Basin.](image-url)
Stepwise regression (SWR) (Howell, 1997) is preferred when there is little theory to guide the selection of independent terms (predictors) that should be included in the model. It represents a subset model, at specific significance level (usually 95 percent), from the whole linear multiple regression model including all the independent terms. The first two vectors of the six latent vectors represented most of the cumulative variation in the six bands (about 95.8 percent). Using these two vectors resulted in a model, which explained only 24.1 percent of the variance in SOC. Hence, all the six latent vectors, which comprised 100 percent of the cumulative variation in the six bands, were retrieved in the SOC prediction model (Equation 2). The model explained 27.1 percent of the variation in SOC with SWR and band 3 had a negative linear effect on SOC, while band 3 had a negative linear effect on SOC.

### Results and Discussion

Image processing created an atmospherically-corrected image of retrieved surface reflectance, scaled into a 16-bit signed integer using a scale factor of 10,000. Soil analysis showed that the soil samples had SOC values varying from 1.47 to 83.75 ton/ha with a mean value of 24.66 ton/ha and a standard deviation of 15.03 ton/ha.

The correlation matrix (Table 1) and the scatter plots (Figure 3) revealed the presence of weak negative relationships between SOC and reflectance in the six processed TM bands. The correlations were found to vary from −0.14 (between SOC and band 5) to −0.27 (between SOC and band 3). Although this result coincides with the basic knowledge of remote sensing of soil properties, it states that the greater the amount of organic content in the upper portions of the soil, the greater the absorption of incident energy and the lower the spectral reflectance (Jensen, 2007), correlation weakness created difficulties in developing the required representative statistical prediction models. On the contrary, the correlations among the six bands were found to be very strong (Table 1) and vary from 0.88 to 0.99, indicating the presence of severe multicollinearity among the bands. This was taken into consideration during the modeling process.

The 19 TM-based SOC models that were resulted from the calibration stage using the calibration set of soil samples and by applying the five major statistical modeling procedures showed different characteristics as described below. The backward-selection criterion in SWR analysis was able to subset the whole six-bands model into only three-bands model (Figure 4a; Equation 1) with RMSE equals 13.76 ton/ha and R^2 equals 25.8 percent (Table 2, Model 1). The model suggested that bands 2 and 5 had positive linear effects on SOC, while band 3 had a negative linear effect on SOC.
RMSE equals 13.64 ton/ha (Figure 4b; Table 2, Model 2). The generated model suggested that band 2 had the highest positive effect in explaining SOC variation followed by band 5, while band 3 had the highest negative effect in explaining SOC variation. However, bands 1, 4, and 7 had no direct effect in predicting SOC as explained by having negligible slope factors.

Recursive partitioning analysis (Figure 4c; Table 2, Model 3) started with SOC mean of 25.39 ton/ha and standard deviation of 16.01 ton/ha with 249 counts. First SOC partitioning split was attributed to band 3 forming two separate SOC means. The partitioning split was formulated using a cut-value “If-Statement” as explained in Equation 3. The final partition tree was generated using 37 splits and ended with a prediction model that explained 57.4 percent of the variability in SOC with RMSE of 10.43 ton/ha.

\[
SOC(\text{ton/ha}) = 19.378679 + 16.009329 \times \begin{cases} 
-0.000303 \times B1 \\
+0.001808 \times B2 \\
-0.002876 \times B3 \\
+0.000391 \times B4 \\
+0.001216 \times B5 \\
-0.000411 \times B7 \end{cases}
\] (2)

Artificial neural network analysis (Figure 4d through 4g; Table 2, Models 4 through 7) produced four prediction models with \(R^2\) values varied from 28.9 percent for Model 4 with one hidden node to 62.5 percent for Model 7 with seven hidden nodes. The RMSES for these models decreased from 13.47 ton/ha for Model 4 to 9.79 ton/ha for Model 7. Hence, the higher the number of hidden nodes used in the calibration stage the higher \(R^2\) and lower RMSE produced. The first methodology for developing combined models produced four models (Figures 4h through 4k; Table 2, Models 8 through 11) with simplified architecture and \(R^2\) values varied from 27.2 percent for Model 8 with one hidden node to 50.4 percent for Model 11 with seven hidden nodes. The associated RMSES for this group of models varied from 13.63 ton/ha for Model 8 to 11.26 ton/ha for Model 11. Hence, the same result as obtained from the ANN analysis, which was the higher the number of hidden nodes used in the calibration stage the higher \(R^2\) and lower RMSE produced, can be observed.

In the second methodology for developing combined models, six linear combinations of regression functions of processed TM bands (i.e., PCs) were generated explaining 100 percent of the variations between bands (Figures 4l and 4m; Table 2, Models 12 and 13). In Model 12, the second PC was rejected through SWR analysis formulating a multiple linear regression model of three PCs with RMSE of 13.64 ton/ha and \(R^2\) of 27.1 percent (Equation 4).

\[
SOC(\text{ton/ha}) = 25.390 - 1.311 \times PC1 + 9.384 \times PC3 + 27.479 \times PC4 - 22.474 \times PC5 - 31.187 \times PC6
\] (4)

At the orthogonal rotation varimax style (Model 13), only three rotated PCs were accepted by the SWR methodology formulating a multiple linear regression model of three
rotated principal components (RPCs) with RMSE and R² of about 13.65 ton/ha and 27 percent, respectively (Equation 5).

\[
\text{SOC (ton/ha)} = 25.390 - 7.725 \times \text{RPC}_4 - 1.576 \times \text{RPC}_5 + 2.666 \times \text{RPC}_6
\]  

The third methodology for developing combined models produced six additional models (Figure 4n through 4s; Table 2, Models 14 through 19). The associated R²'s for those models generated without rotational factors (R²'s varied from 40.0 percent for Model 14 to 62.0 percent for Model 16) were larger than those generated with rotational factors (R²'s varied from 37.0 percent for Model 17 to 50.1 percent for Model 19). While, the associated RMSEs for those generated without rotational factors (RMSEs varied from 12.37 ton/ha for Model 14 to 9.85 ton/ha for Model 16) were smaller than those generated with rotational factors (RMSEs varied from 12.68 ton/ha for Model 17 to 11.29 ton/ha for Model 19). Again, the same result as obtained from the ANN analysis and the first combination method, which was the higher the number of hidden nodes used in the calibration stage the higher R² and lower RMSE produced, can also be deduced.

In the validation stage and using the validation set of soil samples, the associated RMSEs and R²s for the 19 models were found to vary from 10.44 ton/ha for Model 1 to 23.67 ton/ha for Model 7 and from 0.0 percent for Model 3 to 21.7 percent for Model 1, respectively (Table 2). Validation plots in Figure 5 provided clear view on the power of each model for predicting SOC, while error distributions in Figure 6 identified the models that produced biased trended error distributions.

Since the predicted SOC values in recursive partitioning analysis (Figure 5c; Table 2, Model 3)
were just fixed sets of means, the model could not predict SOC values beyond and in between those sets regardless of bands’ variations. Thus, the recursive partitioning model was found to be inadequate in predicting the actual SOC values. In ANN analysis (Figures 5d through 5g; Table 2), the recursive partitioning model could not predict SOC values beyond and in between those sets regardless of bands’ variations. Thus, the recursive partitioning model was found to be inadequate in predicting the actual SOC values. In ANN analysis (Figures 5d through 5g; Table 2, Model 2) and PLS (Figure 5b; Table 2, Model 2) models. Obviously, the prediction powers of these two models were not significantly different from each other as suggested by having almost similar RMSE and error distribution plots (Figures 6a and b). However, since the relationships between the processed TM bands and SOC were found to be close to linear, as shown in Figure 3, the models with non-linear algorithms were not preferred. Consequently, the PLS model was rejected. Therefore, since the SWR model (Equation 1) provided the lowest validation RMSE and the highest validation $R^2$ among all the generated models with linear relationship and relatively simple structure, as compared to the other modeling techniques, and because none of the other developed models was powerful in predicting SOC, it was preferred over the other models in this study.

The use of the SWR model for drawing the SOC map for the Zarqa Basin as shown in Figure 7, showed that the total SOC content to 0.2 m depth in the basin was about 9423986.4 tons with SOC density of about 26.3 ton/ha.

So, how accurate is the SWR model for helping the stakeholders in applying and monitoring the different carbon crediting programs? The answer depends upon how the model is to be used. Comparing the validation RMSE for the chosen SWR model of about 10.4 ton/ha to the mean annual carbon sequestration rates due to changes in

Table 2. RMSEs and $R^2$s for the Models that were Generated and Tested

<table>
<thead>
<tr>
<th>No.</th>
<th>Model</th>
<th>Description</th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>RMSE</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1</td>
<td>SWR</td>
<td>Stepwise Regression</td>
<td>13.761</td>
<td>0.258</td>
</tr>
<tr>
<td>2</td>
<td>PLS</td>
<td>Partial Least Squares</td>
<td>13.640</td>
<td>0.271</td>
</tr>
<tr>
<td>3</td>
<td>Partition</td>
<td>Recursive Partitioning</td>
<td>10.432</td>
<td>0.574</td>
</tr>
<tr>
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<td>ANN1</td>
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<td>13.470</td>
<td>0.289</td>
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<td>5</td>
<td>ANN2</td>
<td>3-nodes Artificial Neural Network</td>
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<td>0.451</td>
</tr>
<tr>
<td>6</td>
<td>ANN3</td>
<td>5-nodes Artificial Neural Network</td>
<td>10.271</td>
<td>0.387</td>
</tr>
<tr>
<td>7</td>
<td>ANN4</td>
<td>7-nodes Artificial Neural Network</td>
<td>9.790</td>
<td>0.625</td>
</tr>
</tbody>
</table>

The First Statistical Modeling Procedure (Model 1)

The Second Statistical Modeling Procedure (Model 2)

The Third Statistical Modeling Procedure (Model 3)

The Fourth Statistical Modeling Procedure (Models 4 to 7)

The Fifth Statistical Modeling Procedure (Models 8 to 19)

Combined Models (Group I)

Combined Models (Group II)

Combined Models (Group III)
farming practices such as tillage intensity and crop rotation complexity, as reported by West and Post (2002), indicated that the model is highly inaccurate. This is because none of these practices can sequester carbon at a rate greater than one ton/ha per year. The lowest ratios obtained were about 1,160 percent for a change from conventional tillage to no-till and about 2,047 percent for enhancement of crop rotation complexity. This result is not an unexpected one, since it is well known that even direct methods cannot detect annual changes in SOC pools due to their heterogeneities and dynamic nature. But after sufficient time (e.g., five to ten years) statistically significant differences in SOC could be observed in natural and planned experiments (Post et al., 2001). This, in turn, is one of the reasons for designing the carbon crediting programs in ways that operate at decadal scales. Hence, comparing the validation RMSE to the mean decadal scale carbon sequestration rates, as reported also by West and Post (2002), showed that the accuracy of the model had increased marginally. This is because these practices were found to sequester on average about 3 to 9 ton/ha over a period of 12 to 18 years associated with changes from conventional tillage to no-till and over 2 ton/ha over a period of 25 years associated with modifications in crop rotations. The lowest ratios obtained were about 112 percent for a change from conventional tillage to no-till and about 194 percent for enhancement of crop rotation complexity. This margin of error is still too high for direct application in carbon crediting programs.

Although the results of this study coincide with those obtained by other studies that utilized satellite-based multispectral sensors, the above discussion led to another question, which is: “Why did the model fail to produce accurate estimations of annual or even decadal changes in SOC?” Two issues might have degraded the quality of the developed statistical model. The first is that in many areas the soil was completely covered by different types of land-cover ranging from crop residues to grass and so forth. This obscured the sensor’s ability to see the soil itself. Hence, the spectral information content of many of the TM pixels is not directly

Figure 5. Validation plots for the models that were generated using the validation set of soil samples using (a) stepwise regression, (b) partial least squares, (c) recursive partitioning, (d) through (g) artificial neural network with 1, 3, 5, and 7 hidden nodes, (h) through (k) stepwise regression followed by artificial neural network with 1, 3, 5, and 7 hidden nodes, (l) principal components followed by stepwise regression, (m) through (p) principal components followed by stepwise regression followed by artificial neural network with 3, 5, and 7 hidden nodes, and (q) through (s) rotated principal components followed by stepwise regression followed by artificial neural network with 3, 5, and 7 hidden nodes.
related to the soil. This is consistent with the excellent fits obtained by other studies when the soil is bare and dry (e.g., Chen et al. (2000) and Wilcox et al. (1994)), which, as has been discussed earlier, contradicts the nature of carbon crediting monitoring programs. These programs are designed to be applied over large areas and under natural field conditions; since the more farmers try to store carbon through land management practices the more the soil is obscured. The second issue is that the spectral information content of many of the TM pixels in the study area is not pure, but is a mixture of different land-cover types. This might have obscured the spectral features of SOC and hence degraded the quality of the developed statistical model. These issues might be solved by utilizing satellite sensors with higher spatial resolution, such as Ikonos, QuickBird, or GeoEye, or higher spectral resolution, such as Hyperion. Additionally, errors in soil sampling and lab analysis cannot be ruled out.

Finally, another question might arise, which is: “Can this model be extended to other areas to estimate SOC pools?” Although these models are site-specific, they can be extended to similar environments to estimate total SOC pools, not to monitor carbon crediting program, taking into consideration variations that might appear as a result of changes in the factors that might affect the accumulation and decomposition of organic carbon in the soil, such as topography, land cover, soil type, land management practices, and climate. These estimates are within a few percent error as obtained by comparing the validation RMSE of the SWR model to the total SOC pools of the world grouped by soil order as reported by Eswaran et al. (1993), which showed that the error ratios obtained varied from 0.5 to 30.1 percent.

Conclusions

This study suggested that in semi-arid environments and under natural field conditions, SWR modeling procedure based on TM data was more superior in estimating spatial variations in SOC than the other modeling procedures; namely: PLS, recursive partitioning, ANN, and combined models. The SWR model had the lowest validation RMSE of 10.4 ton/ha and the highest validation $R^2$ of 21.7 percent among all the other generated models with linear
relationship and relatively simple structure. Nevertheless, the use of this model for monitoring carbon crediting programs was found to be impractical, since it could not capture small annual or even decadal variations in SOC with an acceptable error. However, although these types of models are site-specific, the calibrated SWR model could be extended to similar semi-arid environments to estimate total surface SOC pools since it could capture spatial variation in SOC to within a few percent error. In doing so, care should be taken in considering variations that might appear as a result of changes in the factors that might affect the accumulation and decomposition of organic carbon in the soil, such as topography, land-cover, soil type, land management practices, and climate. The total SOC content to 0.2 m depth of the Zarqa Basin was calculated to be 9423986.4 metric tons with SOC density of about 26.3 ton/ha.

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