Mapping the total phosphorus concentration of biosolid amended surface soils using LANDSAT TM data

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ABSTRACT

Conventional methods for soil sampling and analysis for soil variability in chemical characteristics are too time-consuming and expensive for multi-seasonal monitoring over large-scale areas. Hence, the objectives of this study are: 1) to determine changes in chemical concentrations of soils that are amended with treated sewage sludge; and 2) to determine if LANDSAT TM data can be used to map surface chemical characteristics of such amended soils. For this study, we selected two fields in NW Ohio, designated as F34 and F11, that had been applied with 34 and 11 ton acre^{-1} of biosolids, respectively. Soil samples from a total of 70 sampling locations across the two fields were collected one day prior to LANDSAT 5 overpass and were analyzed for several elemental concentrations. The accumulation of Ba, Cd, Cu, S and P were found to be significantly higher in the surface soils of field F34, compared to field F11. Regression equations were established to search for algorithms that could map these five elemental concentrations in the surface soils using six, dark-object-subtracted (DOS) LANDSAT TM bands and the 15 non-reciprocal spectral ratios derived from these six bands for the May 20, 2005, LANDSAT 5 TM image. Phosphorus (P) had the highest R^2 adjusted value (67.9%) among all five elements considered, and the resulting algorithm employed only spectral ratios. This model was successfully tested for robustness by applying it to another LANDSAT TM image obtained on June 5, 2005. Our results enabled us to conclude that LANDSAT TM imagery of bare-soil fields can be used to quantify and map the spatial variation of total phosphorous concentration in surface soils. This research has significant implications for identification and mapping of areas with high P, which is important for implementing and monitoring the best phosphorous management practices across the region.

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1. Introduction

Application of treated sewage sludges (biosolids) to agricultural land has become a prominent and acceptable method of waste disposal in recent years. Biosolids are known to improve soil physical characteristics (Epstein et al., 1975; Wei et al., 1985), increase the organic matter and cation exchange capacity and supply the nutrients required for crop growth (Sommers, 1977; Singh and Agrawal, 2008). However, the potential for excess application of biosolids, resulting in a build up of nitrogen, phosphorus (Mantovi et al., 2005), zinc, copper, lead (Mantovi et al., 2005; Udom et al., 2004; Nyamangara and Mzezewa, 1999) and cadmium (Bergkvist et al., 2003) in the surface soils of agricultural fields continues to be an area of concern. Accumulation of phosphorus at high concentrations is a major environmental concern, as it affects the water quality of lakes and rivers in the event of runoff (Shober and Sims, 2003). Hence, there is an increasing need to continuously monitor the extent of soil contamination in biosolid-applied fields. Even though conventional methods of soil sampling and testing are being used for this purpose, they are often expensive, time-consuming and unsuitable for mapping soil contamination over large areas.

Remote sensing has been used as an alternative method for determining and mapping the physical and chemical characteristics of the soil. High resolution aerial imagery was used to map the organic carbon (Chen et al., 2000), clay content (Sullivan et al., 2005), organic matter and Bray-1 phosphorus concentration (Varvel et al., 1999) in bare soils. Dematte et al. (2003) reported that chemical variations in soil resulting from fertilizer applications can be detected, based on the intensity of reflectance. Several studies showed the use of spectral reflectance to determine the soil color (Post et al., 2000), texture and particle size distribution (Chang et al., 2001), soil moisture (Lobell and Asner, 2002), iron oxides (Ji et al., 2002), carbonates (Ben-Dor and Banin, 1990), clay (Ben-Dor and Banin, 1995), organic carbon (Dalal and Henry, 1986; Morra et al., 1991; Reeves et al., 2002) organic matter (Henderson et al., 1992) and soil phosphorus (Bogrekci and Lee, 2005, 2007).

The addition of soil contaminants as a result of biosolid application tends to be concentrated in surface soil samples (Mantovi et al., 2005; Bergkvist et al., 2003; Udom et al., 2004; Nyamangara and Mzezewa,

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1999). Consequently, the focus of this study was to determine the use of remote sensing to map chemical variability in bare soils. The objectives of this study were: 1) to determine changes in elemental concentrations of soils amended with biosolids; and 2) to use LANDSAT TM data to map these elemental concentrations of the soils when they are not covered by vegetation (bare).

2. Materials and methods

2.1. Soil sampling and chemical analysis

Two adjacent agricultural fields, F34 and F11, that received a cumulative amount of 34 ton acre^{-1} (76 Mg hac^{-1}) and 11 ton acre^{-1} (25 Mg hac^{-1}) of Class B biosolids on a dry weight basis during the period of 1985–2002 were selected for this study (Fig. 1). Soil samples were collected at 0, 30, and 50 cm depths from each of the 70 sampling locations across the two fields. These fields were selected because they are representative of large areas of northwest Ohio where land application of biosolids has become an important agricultural practice. The soil samples were collected on May 19 of 2005, one day prior to LANDSAT over pass, and the sampling locations were marked using a Trimble GeoExplorer (Trimble Navigation Limited, CA, USA) global positioning system (GPS) receiver. The collected soil samples were dried and passed through a 2 mm sieve. The moisture content of the surface soil samples was measured using the gravimetric method. The source of sewage sludge for the agricultural fields in the study area was the Oregon Waste Water Treatment Plant (OWWTP). The basic composition of the sewage sludge of OWWTP is typical of the bio-solids produced in Ohio, which is regulated within the limits set by the U.S. Environmental Protection Agency (USEPA) under the part 503 rule (USEPA, 2002).

Soil samples (approximately 0.5 g) were digested with concentrated HNO$_3$, according to USEPA method SW846-3051A (USEPA, 1998) using a Mars Xpress microwave digestion unit (CEM, Matthews, NC, USA). The digested solution was filtered and then analyzed for As, B, Be, Ca, Cd, Cr, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Pb, S, Se, Si and Zn concentrations using inductively coupled plasma-optical emission spectrometry (ICP-OES) (IRIS Intrepid II, Thermo Scientific, Waltham, MA, USA). Quantification was achieved using matrix matched high and low concentration standards for each element. Internal quality controls and blanks were run every ten samples in order to quantify cross-contamination and recovery efficiencies.

Analysis of variance (ANOVA) was used to compare the accumulation of each element in the F34 and F11 fields using SAS version 9.1 statistical software (SAS Institute Inc., Cary, NC, USA). An alpha level of 0.05 was used to determine the significance.

2.2. LANDSAT data acquisition and analysis

The LANDSAT image frames of May 20 and June 5, 2005, covering the study area were downloaded soon after soil sampling. They were then processed with the ER Mapper image processing software, a commercial product of Earth Resources Mapping, Inc. The study area was located within the LANDSAT overpass region of Path 20, Row 31. The natural color image of the study area, overlaid with outlines of the fields permitted for Class B biosolid applications, is shown in Fig. 1. The locations of all the 70 soil sampling points collected one day prior to LANDSAT 5 overpass were also shown separately in Fig. 1 on the natural color image of the study area. The study site was dry, without any vegetation, implying that image spectral reflectances represent the spectral reflectance of soil. The procedure for developing the GIS database of the Class B biosolid permitted fields in Wood and Lucas counties of northwest Ohio was reported in detail by McNulty (2005).

Based on the locations of the 70 soil samples, the dark object subtracted (DOS) pixel values corresponding to the LANDSAT TM bands
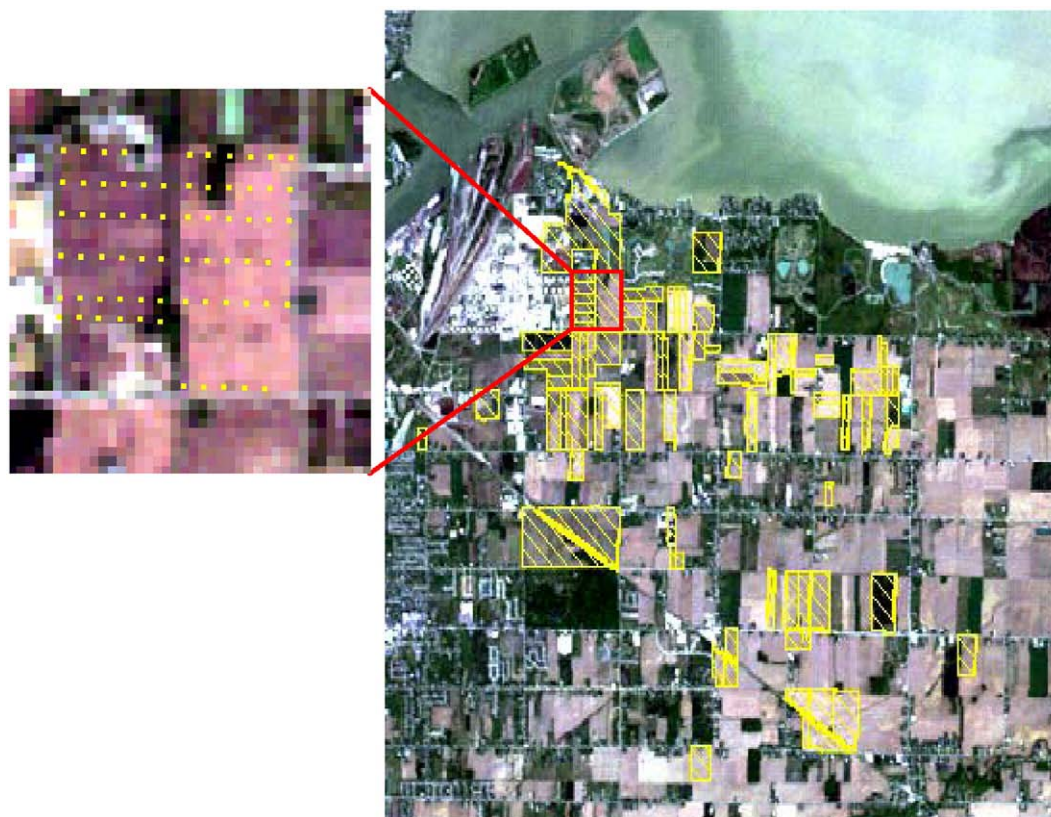
Fig. 1. The LANDSAT 5 TM natural color image (TM bands 1, 2, and 3 displayed as BGR, respectively) obtained on May 20, 2005 showing the eastern part of Lucas County in northwest Ohio; this area drains into Lake Erie, which is towards the northern side (top) of the image. The fields permitted for Class B biosolid application in the area are outlined in the image. The fields marked with red borders are the experimental fields used in this study. Soil sampling locations of the study area were shown as yellow dots in the insert image.

1–5 and 7 were derived from the original May 20, 2005 image. The spectral range of these LANDSAT TM bands are as follows: band 1: 450–520 nm; band 2: 520–600 nm; band 3: 630–690 nm; band 4: 760–900 nm; band 5: 1550–1750 nm; and band 7: 2080–2350 nm. The dark object of each spectral band is defined as one value less than the minimum digital number found in all the pixels of the image (Vincent et al., 2004). The detailed procedure for DOS and its effects on removal of atmospheric haze was given in Vincent (1997) and Vincent et al. (2004). From the DOS-corrected digital number (DN) values of the six LANDSAT single bands, 15 non-reciprocal spectral ratios were calculated. These spectral ratios are: $R_{2,1}$; $R_{3,1}$; $R_{3,2}$; $R_{4,1}$; $R_{4,2}$; $R_{4,3}$; $R_{5,1}$; $R_{5,2}$; $R_{5,3}$; $R_{5,4}$; $R_{7,1}$; $R_{7,2}$; $R_{7,3}$; $R_{7,4}$; $R_{7,5}$ where R represents the ratio and the numbers represent the LANDSAT TM band numbers (Vincent, 1997). The spectral ratios were calculated using the MINITAB statistical software (MINITAB Inc., State College, PA, USA).

2.3. LANDSAT TM best spectral ratio model development and validation

The relationships between the chemical concentrations of the surface soil samples and the DOS DN values corresponding to the six single bands and the 15 non-reciprocal spectral ratios were developed by regression analysis. Using the MINITAB regression analysis component the best subsets regression was employed, and only the top two models with the highest R^2 adjusted values were chosen to report for each number of variables. The best subsets procedure was used for sequentially entering independent variables one at a time to improve the regression equation's predictive ability. The reported models from the best subset regression output were tested for autocorrelation with a Durbin–Watson (DW) statistical test (Durbin and Watson, 1951). This tests for autocorrelation in the input parameters. Finally, the model which had the highest R^2 adjusted and that also passed the DW test was selected as the best model for given inputs. This procedure was reported in detail elsewhere by Vincent (2000) and Vincent et al. (2004). The identified best model was then applied to the same May 20, 2005, LANDSAT image, which was used in developing the model to map the elemental concentration of the surface soils. The model was also applied and validated using the June 5, 2005, LANDSAT image, which was obtained 17 days after the soil sampling. In the LANDSAT images that were applied with the best model, masks were created to limit the display to only bare soil fields.

2.4. Laboratory spectral data acquisition and analysis

A Fieldspec Pro spectroradiometer (ASD Inc., Boulder, CO, USA) with a spectral range of 350–2500 nm was used to obtain the reflectance spectra of the collected soil samples in the laboratory, with a quartz–tungsten–halogen (QTH) lamp as a light source. Diffused light from the 100 W Lowell Pro-Light was used to illuminate the soil samples that
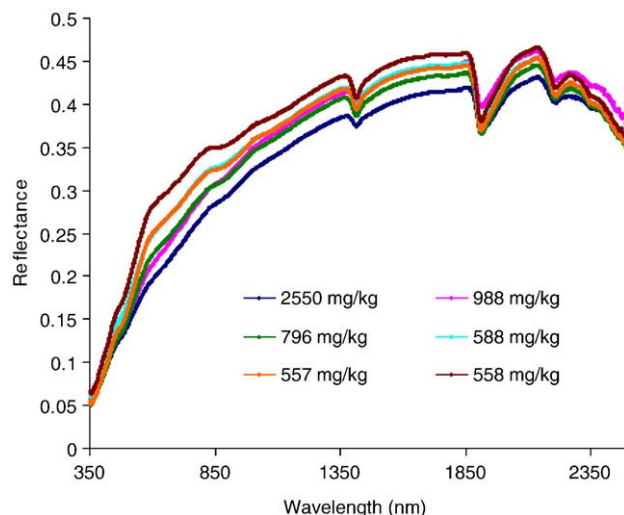

Fig. 2. Averaged (n=35) spectral reflectance of the soil samples collected at 0, 30 and 50 cm depths in F34 and F11 treated fields. Also given are the averaged total P concentrations (in mg/kg) corresponding to the soil samples. The spectral reflectance of the soils decrease with increase in P concentration. The surface soil samples of field F34 have high P concentration (2550 mg/kg) and low spectral reflectance throughout the spectral range, compared to the rest of the soil samples.

were placed in a Petri plate at 45° angles, when spectra were collected in the laboratory. The fore-optics of the spectroradiometer was aligned vertically, and the height of the fore-optics was adjusted so that reflected light only from the surface of the soil samples filled the field of view (FOV) of the instrument. The height of the foreoptics was kept constant throughout the experiment at 20 cm from the surface of each soil sample. The same experimental setup was used to obtain the spectra of all the soil samples collected at 3 different depths from each field. Calibration spectra of a white Spectralon panel (Labsphere Inc., North Sutton, NH) were acquired before recording the soil spectra. The spectral recording software in the spectroradiometer was set in such a way that each reflectance spectrum recorded was obtained by collecting and averaging 20 individual reflectance spectra. Each spectrum was normalized by dividing it by the measured spectrum of the standard (Spectralon panel). The configuration of the ASD spectroradiometer consists of three detectors, each collecting spectra from the 350–1050, 900–1850, and 1700–2500 nm spectral regions, respectively. The spectra collected by these detectors within the instrument are not spliced together. Hence, each normalized spectrum was splice-corrected with the ASD View Spec software (ASD Inc., Boulder, CO). Individual spectral measurements of the soil samples corresponding to the three sampling depths in each of the fields were then averaged to overcome the spectral variations.

3. Results

3.1. Soil chemical concentration

The chemical concentration of the soils at 0, 30 and 50 cm depths and the moisture content of the surface soils in both the F34 and F11 treated fields are shown in Table 1. Among all the chemicals that were

Table 1
Chemical concentration of soils applied with 34 ton acre^{-1} (F34) and 11 ton acre^{-1} (F11) of Class B biosolids

Treatment	Soil depth (cm)	Ba (mg/kg)	Cd (mg/kg)	Cu (mg/kg)	S (mg/kg)	P (mg/kg)	Moisture (%)
F34	0	161 (±28.5)	5.7 (±0.5)	55 (±5)	405 (±57)	2550 (±625)	9.7 (±7.3)
	30	103 (±16.7)	5.7 (±0.46)	37 (±5.1)	197 (±55)	796 (±439)	
	50	97 (±14.4)	5.6 (±1.1)	35 (±6.1)	154 (±31)	557 (±103)	
F11	0	98 (±19.1)	3.6 (±1.9)	37 (±6.6)	265 (±68)	988 (±303)	5.5 (±2.5)
	30	100 (±13.3)	3.5 (±0.9)	31 (±5.1)	165 (±49)	588 (±177)	
	50	99 (±13.5)	3.7 (±0.9)	31 (±4.9)	132 (±51)	558 (±149)	

The given values are means±standard deviation of 35 replicates.

Table 2
Best spectral ratio input models for phosphorous, copper, and sulfur that pass the Durbin–Watson test along with the values of R^2 adjusted and SE (standard error)

Chemical	Best spectral ratio model	R^2 adjusted (%)	SE (mg/kg)
Phosphorus	4156 − 1690 (R51) + 2257 (R73)	67.9	531.2
Copper	75 − 17.9 (R51) + 21.9 (R73)	59	6.9
Sulfur	507 − 14.7 (R51) + 214 (R73)	49.3	66.8

Note: The models developed for Cd and Ba did not pass the Durbin–Watson test at 5% level of significance.
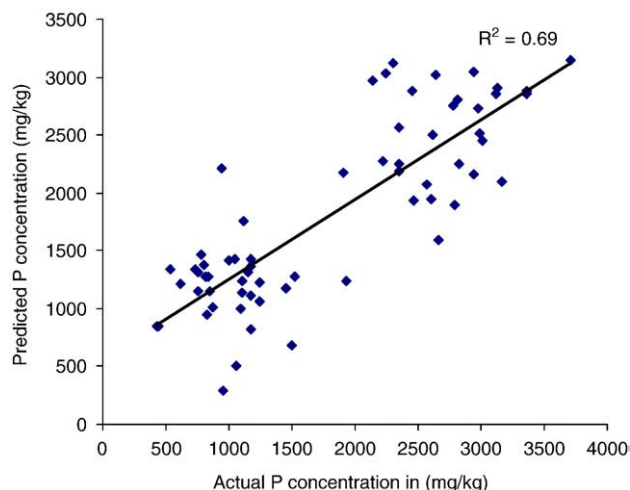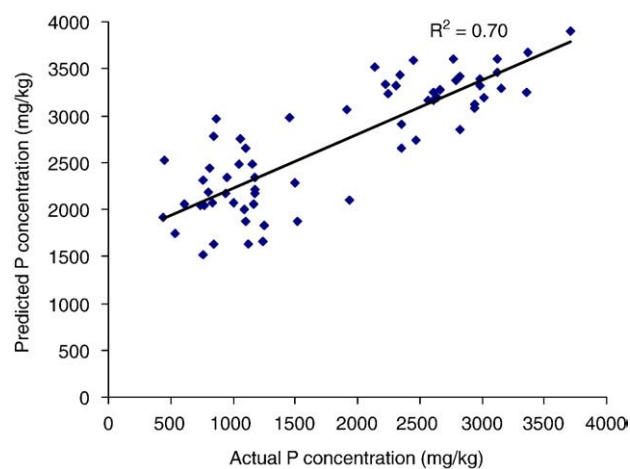
Fig. 3. Actual versus predicted P concentration (in mg/kg) of surface soil samples using the dark object subtracted best P spectral ratio model being applied to the LANDSAT 5 TM frame of May 20, 2005, which was also used for developing the model.

analyzed, the accumulation of Ba, Cd, Cu, S and P were significantly ($p<0.05$) higher in the surface soils of F34, compared to F11 (Table 1). There was no significant difference in the chemical concentrations at 30 and 50 cm depths among the F34 and F11 soils. Also, the moisture content of the surface soils in both the fields was similar (Table 1). The soils were of the prevalent latty silty clay type with surface soils having 40–55% of clay and 3–5% of organic matter (Soil Survey Staff, 2007).

3.2. Spectral reflectance of soil samples

The averaged spectral reflectances of the F34 and F11 soils obtained at 0, 30 and 50 cm depths are shown in Fig. 2. The reflectance of the soil samples gradually increases from 350 nm to about 2200 nm, then decreases to about 2500 nm. There is a broad, shallow reflectance minimum between 600 and 1100 nm (centered about 850 nm), which is likely due to trace amounts of iron present in the soils. The two absorption bands (reflectance minima) near 1400 and 1900 nm in the spectra are due to the in-situ soil moisture. All the soil samples that were used in obtaining the spectra in the laboratory were dried and passed through a 2 mm sieve to minimize the effects of soil moisture and particle size on the spectra.

Fig. 4. Actual versus predicted P concentration (in mg/kg) of surface soil samples using the dark object subtracted best P spectral ratio model being applied to the LANDSAT 5 TM frame of June 5, 2005.
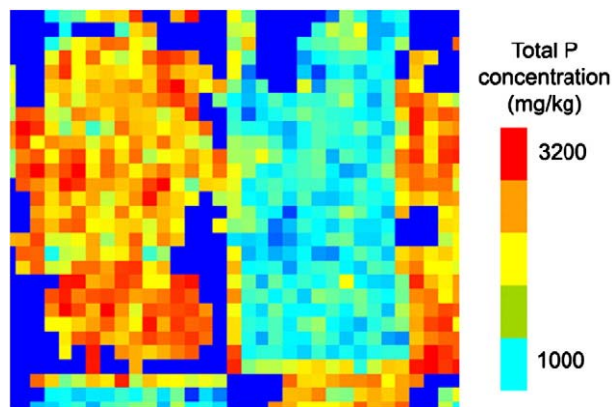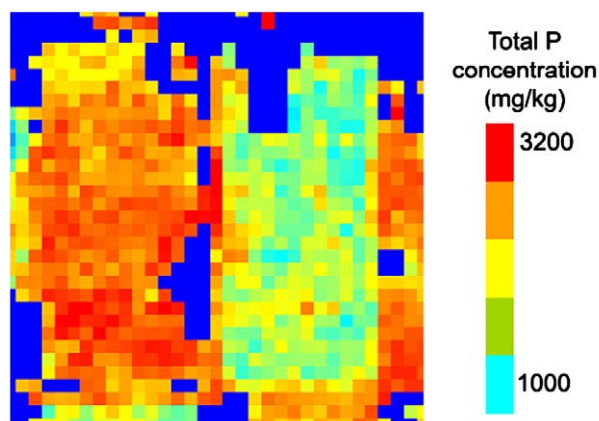

Fig. 5. Image showing the total P concentration (mg/kg) in surface soil samples of fields F34 (left side of the image) and F11 (right side of the image), displayed as red (high P content) to turquoise (low P content), obtained by applying the best P spectral ratio model to the LANDSAT 5 TM frame of May 20, 2005 which was also used for developing the model.

3.3. LANDSAT spectral ratio model

Regression equations were established to determine the chemical concentrations of Ba, Cd, Cu, S and P, which are significantly ($p<0.05$) higher in the surface soils of F34 compared to F11, using the DOS-corrected six TM bands and the 15 non-reciprocal spectral ratios. The best spectral ratio input models that pass the DW test of significance along with their R^2 adjusted and standard error values are given in Table 2. None of the single band models passed the DW test. Phosphorus had the highest R^2 adjusted value (67.9%) among the chemical attributes that passed the DW test (Table 2) and are considered for mapping P with LANDSAT TM data. Hence, only the P results were shown in this paper. The P values obtained from chemical analysis of the 70 surface soil sampling locations versus the predicted values of P for the same locations obtained by applying the P spectral ratio model $P(mg/kg)=4156-1690(R51)+2257(R73)$ to the May 20, 2005, LANDSAT TM frame is given in Fig. 3. The P spectral ratio model was also applied to the June 5, 2005 LANDSAT image frame and the predicted P values were plotted against the P values obtained by the soil analysis (Fig. 4). The model performed well in predicting the P concentrations of surface soil when applied to either of the LANDSAT TM images.

The application of the best P spectral ratio model to the LANDSAT 5 TM frame of May 20, 2005, which was also used in developing the model, is shown in Fig. 5. The redder color in this image corresponds to higher amounts of P in surface soil. Fig. 6 shows the image of the

Fig. 6. Image showing the total P concentration (mg/kg) in surface soil samples of fields F34 (left side of the image) and F11 (right side of the image), displayed as red (high P content) to turquoise (low P content), obtained by applying the P spectral ratio model to the LANDSAT 5 TM frame of June 5, 2005.
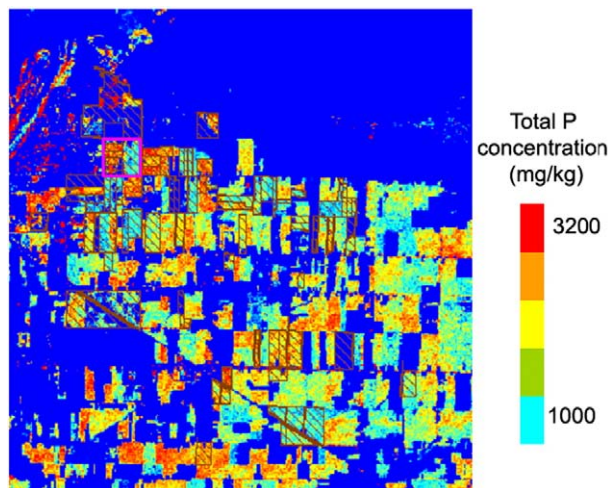
Fig. 7. The total P concentration (mg/kg) in surface soil samples of the bare soil fields in the eastern part of the Lucas County of northwest Ohio, which is a part of the drainage basin of Lake Erie, which is located at the northern side (top) of the image. The image is obtained by applying the P spectral ratio model to the LANDSAT 5 TM frame of May 20, 2005 which was used for developing the model. The fields permitted for Class B biosolid application in the vicinity are outlined in the image. The fields marked with a pink border are the experimental fields used in this study. Not all of the permitted fields in this image would have recently received sewage sludge, and some non-permitted fields could have recently received other types of fertilizers.

same spectral ratio model that was developed using the LANDSAT 5 frame of May 20, 2005, being applied to the LANDSAT 5 frame of June 5, 2005. Note that the P concentration in the F34 field is significantly higher than the F11 field in both the images (Figs. 5 and 6). The application of the best P spectral ratio model to the May 20, 2005, LANDSAT TM image, showing the part of the watershed that drains into Lake Erie, is given in Fig. 7. The fields outlined in this figure are permitted for Class B biosolid application.

4. Discussion

The analytical results showed that the accumulation of P in surface soil samples of F34 was about 2.6 times higher than for the F11 soils. This confirms the report of Chang et al. (1983) that five continuous years of biosolids application in two California soils at 0, 22.5, 45 and 90 ton per hectare increased the total P concentration of surface soil (0–15 cm) from 515–540 mg/kg to 1092–1312, 1657–2163 and 2617–3470 mg/kg, respectively. Similarly Maguire et al. (2000) reported that the concentration of total soil P in surface soils (0–20 cm) of biosolid amended soils was 738 mg/kg, or nearly double the values in unamended soils, where the total soil P was 403 mg/kg. High concentrations of Cd and Cu in the surface soils of F34 compared to F11 agree with the reports of Nyamangara and Mzezewa (1999), that the long-term application of biosolid increases the accumulation of Cd and Cu in the surface soils.

Our spectral results showed that the intensity of spectral reflectance (from 350–2500 nm spectral range) decreases with increases in P concentration of the soils (Fig. 2) agreeing the results of Bogrekci and Lee (2005). Bogrekci and Lee (2005) also showed that the removal of P and other nutrients from soils through leaching results in an increase in the spectral reflectance of soils. In our study, the reflectance of the soil samples (Fig. 2) decreased more in the NIR region compared to the visible region. Bogrekci and Lee (2007) found a good relationship between reflectance and P concentration with coefficients of determination of 0.93, 0.95 and 0.76 for total, Mehlich-1 and water soluble P. The reflectance of F34 surface soil samples is low compared to the rest of the soil samples and this can be attributed to its high total P concentration of 2550 mg/kg (Fig. 2).

LANDSAT TM data can be used to estimate and map some chemical characteristics of soils, such as total phosphate content, as shown in this study. Our results enabled us to conclude that remotely sensed imagery of bare soil fields can be used to quantify and map the spatial variation of total P concentration in surface soils. The technology is simple enough to be applied to the entire watershed. The P spectral ratio model was more robust and reliable than the single band input models and can be applied to bare soil fields with low (<13%) soil moisture.

Nanni and Dematte (2006) have successfully employed LANDSAT TM data to estimate the sand, silt, clay, organic matter, cation exchange capacity (CEC) and sum of cations in Brazilian soils. They derived spectral reflectance values from the corrected LANDSAT image to develop multiple regression equations in order to estimate the different physical and chemical characteristics of the soils; however, no soil maps were presented in that study (Nanni and Dematte, 2006). Our study is significant because it represents the first successful effort in using LANDSAT TM data to estimate and map P concentration in surface soils. We also successfully validated the P spectral ratio model by applying to another LANDSAT image obtained on June 5, 2005.

Aerial imagery was used to map the organic carbon (Chen et al., 2000), clay content (Sullivan et al., 2005), organic matter and Bray-1 phosphorus concentration (Varvel et al., 1999) and LANDSAT TM imagery was used to estimate the physical and chemical properties (Nanni and Dematte, 2006) of surface soils in the previous studies. However, the algorithms developed in these studies were based on the reflected image intensity values of the soils, which required correction for atmospheric haze with atmospheric models before applying the algorithms to another date. The P spectral ratio model developed in our study is based on the DOS-corrected spectral ratios and is more robust than any model that could be derived from a combination of single spectral bands. Vincent et al. (2004) showed that the DOS spectral ratio models were more robust than single band models and can be applied with reasonable accuracy to different times of data collection, though their subject was cyanobacteria blooms in lakes or streams, and the present study is about P concentrations in bare soils on dry land.

By applying our P spectral ratio model, we can identify and map the P concentration in surface soils as a result of biosolid application. Because P accumulation in soils can also result from the application of biosolids, animal manures, and man-made fertilizers, this research has significant implications in identifying the fields with high concentrations of surface soil P, thus helping in the implementation of P-based management practices on agricultural fields, with an aim toward reduction of P runoff into nearby surface water bodies.

Shober and Sims (2003) reported that twenty-four of the states and territories in the United States now have regulations to restrict the land application of biosolids, based on phosphorus concentration in soil. Thirteen of these 24 states have established actual numerical limits for soil test phosphorus (STP), with an aim to cease the application of biosolids once these limits are reached. As the total soil P and STP are linearly related to each other (Allen and Mallarino, 2006), our P spectral ratio model can be used to monitor P levels in surface soils. One limitation of this P model is that it was developed using bare soil fields that had a low surface soil moisture (<13%); thus, we have no evidence that this model will be accurate for fields with soil moisture contents greater than that value. In the future we will be examining this P model on fields with higher moisture contents. Further, we will test the model to determine the P concentration in surface soils of other soil types in this region, though the soils tested were of the prevalent type (Latty Silty Clay).

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