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MANIPULATION OF HIGH SPATIAL RESOLUTION AIRCRAFT REMOTE SENSING DATA FOR USE IN SITE-SPECIFIC FARMING

G. B. Senay, A. D. Ward, J. G. Lyon, N. R. Fausey, S. E. Nokes

ABSTRACT. *Three spatial data sets consisting of high spatial resolution (1 m) remote sensing images acquired in 12 spectral bands, an on-the-go yield map, and a Digital Elevation Model were co-registered and evaluated for spatial variability studies in a Geographic Information Systems environment. Separate on-the-go yield maps were developed for 3, 5, and 12 statistically significant mean yield classes. For each yield class, the corresponding mean spectral and elevation data were extracted. The relationship between mean spectral and yield data was strongly linear (r = 0.99). Also, a strong linear relationship between mean yield and elevation data (r = 0.92) was found. The relationship between the spectral and on-the-go yield data indicated the potential of remote sensing for spatial variability studies.*
Keywords. *Remote sensing, GIS, On-the-go yield, DEM, Precision farming.*

The term "site-specific farming" or "precision farming" means carefully tailoring soil and crop management to fit the different conditions found in each field (Johannsen, 1995). Site-specific farming is a new system that may incorporate Remote Sensing (RS), Geographic Information Systems (GIS), and Global Positioning Systems (GPS) (Blackmore, 1996). Satellite remote sensing data from Landsat and SPOT have been used to distinguish crop species and locate stress conditions in the field. GIS technology is the "brain" of the precision farming system in that it facilitates knowledge-based decision making processes by allowing users to store and overlay separate map layers into a single integrated digital map. The site specific management concept is based on the ability to repeatedly locate a position within a field.

Field information can be gathered in three distinct manners: continuously, discretely, and remotely (Schueller et al., 1993). On-the-go yield measurements are a good example of a continuous system. The measurement of yield on a spatial basis has been performed by several researchers in recent years (e.g., Searcy et al., 1989; Vansichen and De Baerdemaeker, 1991). In practice, the management of local resources in agriculture commences with yield mapping. Yield maps provide basic information for the setup of nutrient balances, evaluation of equifertiles (areas of identical productivity), and enable control of the efficiency of the whole system (Schung et al., 1993).

Discrete sampling is normally performed based on an orthogonal grid system to distribute samples uniformly over the field. This method can provide the greatest information about the field since the samples (e.g., soil cores) can be analyzed for many physical and chemical properties in the laboratory. While this technique seems to do an adequate job of describing a field, it is expensive due to labor and sample analysis costs, and requires a lengthy period to obtain the data.

The use of remote sensing for describing field variation is probably the most developed method (Schueller et al., 1993). The information obtained from either aerial (e.g., aircraft) or satellite images is limited to the soil surface or plants that are growing on that surface. Either method for obtaining images must rely on the use of ground-based reference data to determine what is actually represented in the image. As remote sensing is incorporated into site-specific farming, there will be a need for operational image processing techniques in order to extract the pertinent information. Image processing techniques involving classification, algebraic manipulation, and overlaying in a GIS environment can be used to study and determine the relationships between remotely sensed data and reference data.

In agriculture, monitoring of crop growth and development and early estimates of the final yield are of general interest. Previous studies have investigated the relationship between remotely sensed data and crop yield with varying degrees of success. For example, Tucker et al. (1979) collected spectral data from twenty 2×3 m research plots on 21 data collection dates to infer final crop yields.

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Correlation coefficients between VI (vegetation index) and grain yield were low and not significant at early initial growth stages, but increased consistently to a significant high of 0.82 at maturity. They also found correlations decreased with progression of senescence. Thenkabail et al. (1994) reported that corn and soybean yield data were less correlated to satellite derived VIs than other crop variables such as Leaf Area Index (LAI) and wet biomass. In justifying the linking of remote sensing and crop growth simulation models for yield estimation, Clevers et al. (1994) reported that remote sensing alone is not capable of producing accurate yield estimations.

A review of the literature suggests there is inadequate knowledge on how to establish an appropriate reference data sampling strategy and on the use of remote sensing for spatial variability studies, i.e., to investigate relative differences in the field rather than yield forecasting. One of the weaknesses of the point sampling technique is that it may not depict the spatial variability of the field due to the generally small number of sampling points per field.

This article presents the results of a study conducted on evaluating the applications of high accuracy spatial data sets that were acquired using advanced instrumentation in a precision farming approach. In this study, yield reference data were acquired using a continuous sampling strategy (on-the-go yield) and remote sensing data were obtained from low altitude aircraft scans producing high spatial resolution (1 m) images in 12 spectral bands including the visible and infrared regions. In addition, a high accuracy (to within a 5 cm accuracy) Digital Elevation Model (DEM) of the site was used as an ancillary data set.

The study was conducted in a corn field at the Ohio Management System Evaluation Area (MSEA) site in Pike County, Ohio (Ward et al., 1994) and had the following objectives:

1. Devise an analysis strategy that will help investigate the relationships between on-the-go yield-maps, Multi-Spectral Scanner (MSS) images, and DEM data sets that were acquired using different instrumentation;
2. Assess and map the magnitude and extent of the spatial distribution of corn yield in the field;
3. Determine the relationship between on-the-go yield and MSS data; and
4. Determine the relationship between on-the-go yield and elevation data.

Site Characterization and Database Development

Site Description

The study site was located on the 260 ha Vanmeter Farm near Piketon, Ohio, centered approximately at long. 83° 02′ 00″ W and lat. 39° 02′ 30″ N. The site overlies the Scioto River Alluvial Valley Aquifer which was formed when fluvial and glacial-fluvial materials were deposited in the preglacial valley of the Teays River. Huntington, Rossburg, Nolin, and Landes silt loams (*fluventic hapludolls*) are the predominant soil series with some overlying sands that grade into gravel at a depth of 2 to 3 m. The research was performed on a 9 ha field that has been in continuous corn since 1991. Primary tillage is chisel plow and there are annual inputs of inorganic N fertilizer (about 180 kg N/ha), alachlor and atrazine herbicides, and fonofos insecticides. Mean annual precipitation at Piketon is 969 mm and in the study year (1994) there was 1002 mm of precipitation. Rainfall in April, May, June, July, and August 1994 was 168%, 81%, 64%, 121%, and 147% of long-term mean monthly values.

Soil characterization studies have been performed by the Natural Resources and Conservation Service (NRCS) and by Salchow et al. (1996). An interpretation of this information by Wu et al. (1996) is presented in figure 1.

Digital Elevation Data

A DEM (fig. 1) was developed from individual Global Positioning System (GPS) data points that were acquired by driving a Sports Utility Vehicle (SUV), equipped with a GPS receiver and datalogger, across the field prior to planting (11 May 1994). A stationary GPS receiver was located in the center of the field for differential correction purposes. Individual data points were acquired every 10 s by the GPS receiver while the SUV was driven at about 16 to 24 km/h depending on the topography of the area. This resulted in data points every 40 to 70 m. The SUV was driven parallel to the rows of corn stubble on a spacing of about 25 m between consecutive tracks. The data collection approach and mapping software was developed by the Center for Mapping at The Ohio State University. It provides elevation information with an accuracy of 0.05 m. The DEM was generated using a local coordinate system where the location of the differential GPS receiver represented the origin.

On-the-go Yield Data

The 1994 yield data of the research site were collected by a combine harvester where the magnitude of the yield was near-instantaneously recorded by an Ag Leader 2000 yield sensor. While yield data were tagged with a precise time code (s), a GPS unit was also installed to record the positional information (latitude and longitude) of the combine at that time. Positional data sets were also tagged with time codes so that the corresponding yield for a specific location could be attributed.

Positional data were collected at two locations (rover and base) for differential correction purposes. The rover was the combine harvester whose position was recorded every second with the help of a GPS receiver and computer configuration located in the combine. The second GPS receiver (base station) was located at The Ohio State University (about 100 km from the site). A fixed base station was used so that a differential correction procedure could be applied to increase the overall accuracy. Differential correction of the combined positional data was conducted using software called GPSWIN that was developed by the Center for Mapping at The Ohio State University. The accuracy of the resulting data set was approximately 3 to 5 m in the X,Y directions. After the positional data were differentially corrected, the yield data were attached to the corresponding positions using a time code common to both data sets. Positional data recorded in latitude and longitude were converted into meters using a relative local reference coordinate. The raw data, which consisted of yield estimates for areas of about 4 m × 5 m,

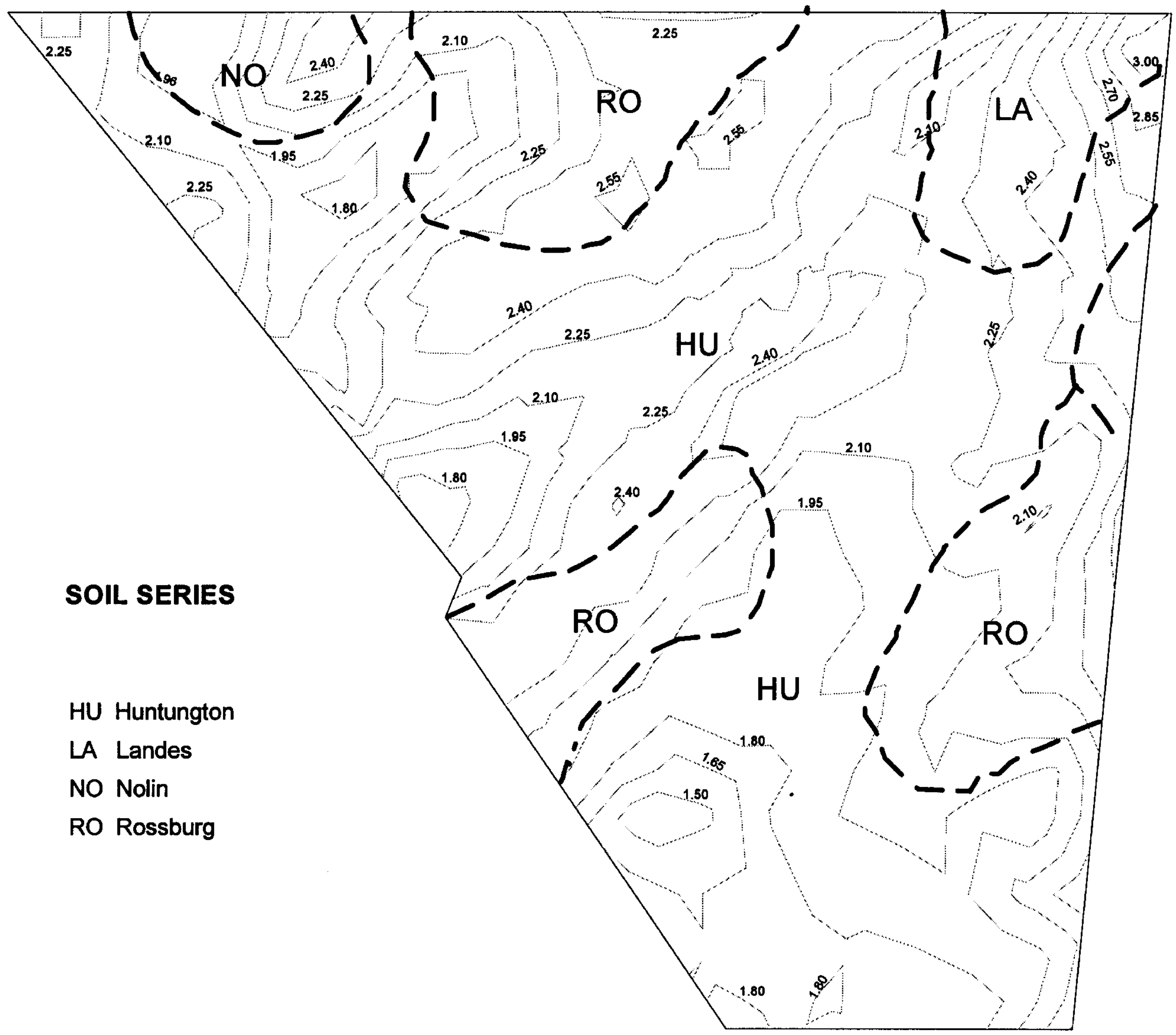

Figure 1–Soils and topographic map for the continuous corn treatment at the Ohio MSEA (elevation in m).

were processed to a yield map using the kriging geostatistical technique in ARC/INFO (ESRI, 1995).

MSS Data

Digital images of the MSEA research site (at 1 m resolution) were acquired using a multi-spectral scanner mounted on an aircraft operated by the EPA Environmental Monitoring Systems Laboratory in Las Vegas, Nevada (EMSL-LV). The scanner system used was a Daedalus Enterprises Model 1260 Instrument. The system uses a rotating mirror to direct radiated energy from the surface of the earth onto sensing detectors with an instantaneous field of view of 2.5 milliradians. The sensor has 12 spectral bands whose wavelengths include the ultraviolet, visible, near infrared, and thermal infrared. Images were obtained several times in 1994 and a cloudless or almost cloudless day occurred for each flyover. All MSS data were geocorrected and georeferenced to the Universal Transverse Mercator grid system, zone 17. All data correction and referencing was performed by the EMSL-LV.

The image which was obtained at the end of the growing season on 15 September 1994 was used in this particular study. The 15 September image was selected since it represented the most mature stage of the crop with the anticipation that the relative spatial variability of corn yield would not change much until harvest. Six bands, namely B5 (0.55-0.60 μm), B6 (0.60-0.65 μm) , B7 (0.65-0.69 μm), B8 (0.70-0.79 μm), B9 (0.80-0.89 μm), and B12 (1.55-1.75 μm) were used because of their general importance in an agricultural environment. In addition, seven Vegetation Indices (VIs) that are ratios and differences of the selected bands were also developed (see table 2).

Data Analysis

Data Co-registration

The three spatial data sets (MSS, on-the-go yield, and DEM) were co-registered to a common local coordinate system that was established for generating the DEM. The DEM was chosen as a reference since it was originally based on a local coordinate system, and also represented a very high spatial accuracy. A map-to-map co-registration was performed in ARC/INFO in a two-step procedure by first creating links for control points and then using the control-points link-file in a method called GRIDWARP, which involves the use of a least-square algorithm to fit a first order polynomial (linear) to the control points. All cells in the grid were then transformed using the fitted equation. The Root Mean Square Error (RMSE) that was associated with the transformation was about 5 m in both the X and Y directions. Road intersections and points along the field boundaries were used as control points.

During coordinate transformation, the cubic convolution resampling technique was used to determine the value of the output grid cells. Cubic convolution uses digital values of sixteen neighborhood pixels in a 4 × 4 window to calculate an output value with a cubic function where original pixels (within the window) that are farther away from the new cell have exponentially less weight than those closer to the new cell. The cubic convolution is the most accurate resampling method (ERDAS, 1991). Along with cell values, cell sizes for the DEM and on-the-go yield were set to 1.0 m to match with the MSS grid cell size. An alternative way of doing this is to set the grid cell sizes for the on the-go-yield at 5 m and degrade the DEM and the MSS data to 5 m resolution since the yield data represented an approximate 4 m × 5 m combine area. However, since spatial analysis was not intended to be done at a single grid cell or pixel level, but rather with an aggregated classes that consisted of thousands of cells, it was decided to work with a deaggregated yield map at 1 m resolution. The deaggregation approach provides equal number of cells for all spatial data sets in a given class, and simplifies presentation and interpretation of the data without affecting the results.

Yield Classification

For meaningful interpretation of the spatial variability of yield in the field, yield classes were established at three levels. Using a clustering algorithm called ISOCLUSTER that employs the migrating means technique to separate all cells into unimodal groups, and a maximum likelihood classification technique called MCLASSIFY in ARC/INFO, yield data were classified into 3 (Level I), 6 (Level II), and 12 (Level III) classes. Due to merging of clusters that were separated by less than two standard deviations the Level II classification resulted in only five out of six requested classes.

MSS and Elevation versus Yield Class Values

Yield classes were used to extract the corresponding mean MSS band digital numbers and elevation values for each class. A GIS masking technique was used to overlay yield nominal classes over the MSS images and an elevation data layer so that the mean and standard deviation of all pixels falling in a particular yield class could be queried.

Correlation statistics between class mean yield values and mean MSS parameters (bands and VIs) and between mean yield and mean elevation data were calculated. Similarly, correlation statistics between mean elevation values and mean MSS parameters, that were based on yield classes, were also calculated. For each of the mean yield classes, linear regression equations were developed between mean yield values and mean MSS parameter values.

Results and Discussion

Figures 2 and 3 show yield classification results at different aggregation levels. The spatial interpretation of the classes becomes complex as the number of classes increases (low aggregation levels). For example, at Level I (highest aggregation) where there were only three yield classes, the fragmentation (scatter) of one class in the different parts of the field was small while in Level III (not shown) a given class was scattered throughout the field and was too fragmented to be easily read. With 12 classes there were many areas in the field which were less than 0.01 ha in size.

Characteristics of the classes are reported in table 1. Band 9 (NIR) data has been reported in the table because it has the best correlation with yield (see table 2). On-the-go yield data (class mean values) varied from 5.1 to

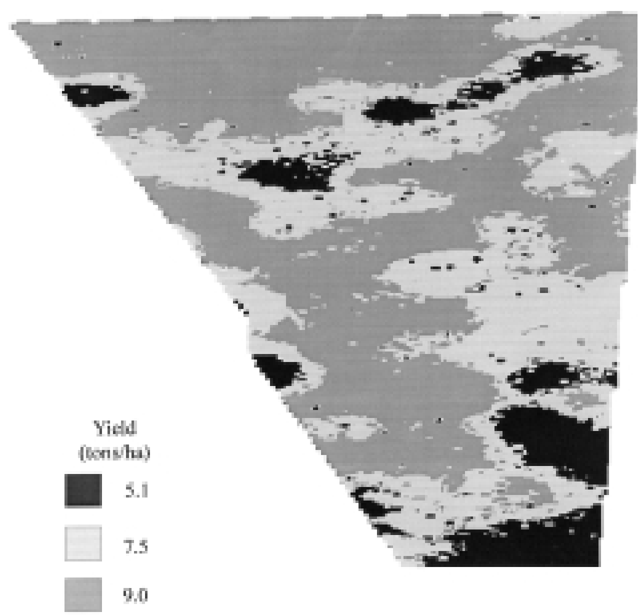

Figure 2–Spatial distribution of three yield classes.

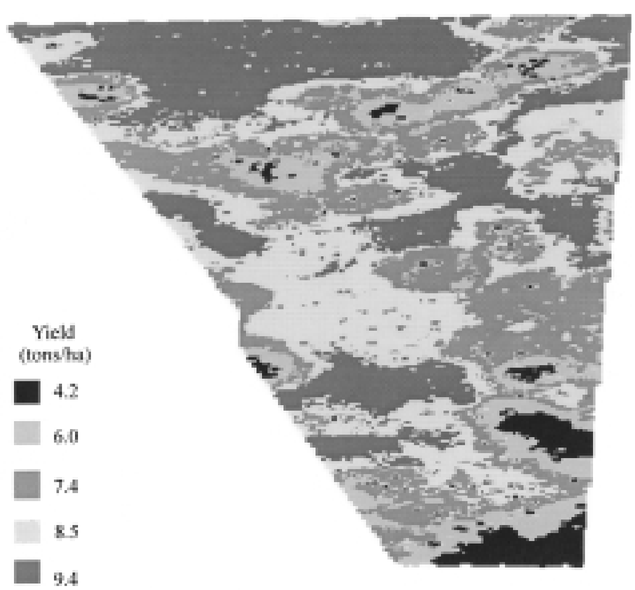

Figure 3–Spatial distribution of five yield classes.

9.05 tons/ha in the 3-class aggregation and from 3.8 to 10.4 tons/ha in the 12-class aggregation (table 1).

Correlation statistics between yield classes at three levels of aggregation and MSS parameters and between elevation and MSS parameters are shown in table 2. Histograms (not shown) and normality tests established that the yield data and spectral bands and VIs which were highly correlated to the yield data had normal distributions. Generally, highly significant linear relationships between most MSS parameters and yield and between MSS and elevation were observed. Correlation coefficients which were significant at the 0.05 level ranged from 0.74 to 0.99.

Bands 8 and 9 (near-infrared bands) were the most correlated (among individual bands) with yield data. Figure 4 shows a linear regression fit between on-the-go yield and band 9 with an R^2 of 0.99. Bands 6 and 7 (red) were the least correlated bands with yield and elevation. All VIs were significantly correlated to both yield and elevation. While bands 8 and 9 showed the highest correlations with yield in the 3-class and 5-class aggregation levels, NDVI1 and NDVI2 showed the highest correlation in the 12-class aggregation level. For all aggregation levels, NDVI1 and NDVI2 showed the highest correlation with elevation. The extent of correlation between MSS parameters and yield and between MSS and elevation decreased slightly as the aggregation level decreased (more classes). One of the reasons for the decrease of correlation with decreasing aggregation might be due to the accuracy of the co-registration of the two data sets. By producing more yield classes the size of some of the class fragments approaches the size of the positional error of the MSS data set and results in more wrong pixels being included in a particular yield class.

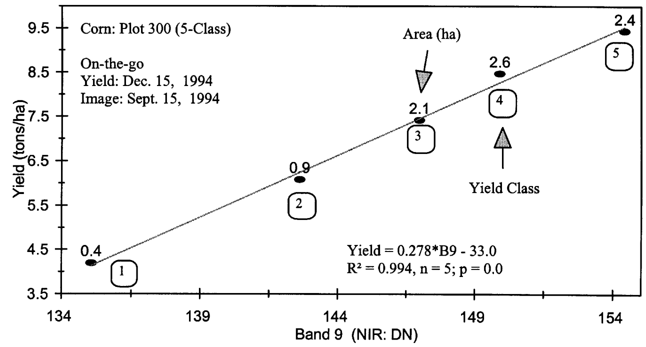

Figure 4–Regression equation between on-the-go yield and near infrared band 9.

Table 1. Basic statistics for corn yield, band 9, and elevation based on three levels of yield classes (aggregation levels)

			Yield		B9		Elevation	
Class-ID	Cell Count	Area (ha)	Mean (tons/ha)	Standard Deviation (tons/ha)	Mean (DN)	Standard Deviation (DN)	Mean (m)	Standard Deviation (m)
Level I: 3 Yield Classes								
1	10606	1.06	5.14	0.97	139	23	2.07	0.25
2	29918	2.99	7.50	0.51	147	20	2.14	0.23
3	43118	4.31	9.05	0.53	153	22	2.17	0.27
Level II: 5 Yield Classes								
1	4106	0.41	4.20	0.76	135	24	1.99	0.22
2	8642	0.86	6.08	0.46	143	22	2.12	0.25
3	20999	2.10	7.42	0.33	147	20	2.14	0.22
4	25862	2.59	8.47	0.28	150	22	2.15	0.24
5	24030	2.40	9.44	0.42	154	22	2.18	0.29
Level III: 12 Yield Classes								
1	2466	0.25	3.85	0.72	132	26	1.96	0.20
2	3759	0.38	5.27	0.34	142	21	2.07	0.25
3	4973	0.50	6.26	0.23	141	23	2.12	0.25
4	7654	0.77	6.98	0.16	147	20	2.14	0.24
5	7791	0.78	7.44	0.12	147	19	2.14	0.22
6	8181	0.82	7.84	0.11	147	19	2.16	0.22
7	8428	0.84	8.20	0.10	148	22	2.13	0.23
8	9800	0.98	8.52	0.09	150	22	2.16	0.24
9	9807	0.98	8.85	0.10	152	20	2.15	0.27
10	10826	1.08	9.21	0.11	152	20	2.18	0.29
11	7644	0.76	9.60	0.14	154	22	2.18	0.30
12	2313	0.23	10.38	0.50	169	25	2.19	0.18

General Discussion

The existence of several distinct yield classes and the high correlation between these classes and the spectral data poses two important questions: (1) what caused the distinct yield classes; and (2) how can spectral data be used as an aid to making site specific farming decisions? Unfortunately, there is no clear answer to either question. The yield classes might be due to elevation differences; soil differences; management practice inconsistencies; stresses due to weeds, insects, and disease; or a combination of several of these factors.

The importance of elevation has already been demonstrated. Elevation might influence the type of soil and soil water availability. If soil water availability is the primary reason that elevation is important then it might be expected that the results would show considerable variability from year to year. For example, at the Missouri MSEA the yield in the most productive part of the field was at least double those of the lowest yielding areas in a corn yield map study conducted for four years (Sudduth et al., 1995). They also

Table 2. Correlation matrix between yield, elevation and MSS parameters*†

	MSS Bands						Vegetation Indices (VIs)							
Classes	B5	B6	B7	B8	B9	B12	SVI1	SVI2	SND1	SND2	NDVI1	NDVI2	ND2	DEM
Yield														
3	*0.97*	–0.77	*–0.69*	1.00	1.00	*–0.90*	0.99	1.00	1.00	1.00	0.99	0.99	1.00	0.99
5	0.88	*–0.22*	*–0.06*	1.00	1.00	*–0.68*	0.98	0.99	0.99	0.99	0.98	0.98	0.99	0.92
12	0.74	*0.01*	*0.14*	0.92	0.92	–0.72	0.93	0.93	0.90	0.90	0.94	0.94	0.91	0.92
Elevation														
3	*0.91*	*–0.87*	*–0.80*	0.99	0.98	*–0.96*	1.00	1.00	0.99	0.99	1.00	1.00	0.99	1.00
5	*0.82*	*–0.28*	*–0.15*	0.94	0.94	–0.89	0.94	0.96	0.97	0.97	0.95	0.95	0.97	1.00
12	0.65	*–0.03*	*0.09*	0.82	0.81	–0.77	0.84	0.83	0.82	0.81	0.86	0.85	0.85	1.00

* Statistics in italic type were not significant at 0.05 level of significance.
† B5, B6 . . . : MSS bands. SVI1 = B8/B6; SV12 = B9/B7; SND1 = B8/B12; SND2 = B9/B12; NDVI1 = (B8 – B6)/B6 + B8); NDVI2 = (B9 – B7)/(B7 + B9); ND2 = (B9 – B12)/(B9 + B12).

reported that in wet years the highest yields occurred in the higher parts of the field while in dry years the highest yields occurred in the drainage (low) areas of the field. If the influence of elevation varies from one year to the next, its use in helping make precision farming decisions is limited. Also, several years of spatial crop data for a field would need to be collected to evaluate this factor.

Site-specific farming decisions are sometimes made based on soil spatial variability. If reference is made to the Soil Survey of Pike County (Hendershot, 1990) it is found that the whole field is mapped as a Huntington soil. However, based on several detailed studies that provided much more information than would normally be available for commercial farms, the map shown in figure 1 was developed. If this map is compared to figure 2 and 3 it can been seen that in places there is some relationship between the yield classes and soil differences. For example, the low yielding area on the west central side of the field corresponds to an area of Rossburg soil. Also, visual inspection of the field suggests that the Landes and Rossburg soils in the southeast extend much further into the field than is mapped on figure 1. These results indicate that an even more detailed field survey is needed if precision farming decisions are based primarily on soils data.

It is speculated that results shown in figures 2 and 3 reflect some management practice inconsistencies; and stresses due to weeds, insects, and disease. Inspection of the field on several occasions early in the growing season also located several small areas in the field where there were low plant populations perhaps due to variable seed and fertilizer applications. However, insufficient reference data is available to map these factors. Early in the growing season there was johnsongrass in several locations and particularly in the vicinity of the low yielding area on the west central side of the field. Johnsongrass was spot-treated with herbicides. Weed surveys on 2 August, 24 August, and 5 September 1994 found some bur cucumber in the low yielding areas on the west-central side of the field and near the southeast corner. These two locations also correspond to the areas of Rossburg soil discussed previously. On 5 September, common chickweed was found in the low yielding area just to the north of the center of the field. However, weed surveys on all these dates were inadequate to establish if weed pressures in any one of the reported locations were any more or less severe than at other locations in the field.

Based on the results of this study, it would seem that site-specific farming decisions should be based on several types of data which encompass more than one growing season. Ideally, in the future a spectral sensor will be mounted on machinery which crosses a field (plow, planter, or harvester) and will be integrated with yield, soils, and microtopography information. This type of information might then be used in conjunction with plant, environmental, and economic simulation models to determine an appropriate management practice. For example, using a stochastic approach with Groundwater Loading Effects on Agricultural Management Systems (GLEAMS), it was predicted that nitrate leaching would be highest in the low yielding Rossburg soils on the west side of the plot (Wu et al., 1996). On the other hand, the Nolin soils near the low yielding area in the north west corner had the lowest nitrate leaching. Therefore, based on environmental and yield considerations a site-specific farming decision for these two portions of the field might be different.

Conclusions

Each of the four objectives of this study was met. First, a methodology was developed to integrate and analyze three spatial data sets. The GIS environment was found effective to co-register yield maps, elevation, and remote sensing data sets with one another for spatial analysis.

The spatial variability of on-the-go yield data was mapped at three levels of aggregation. Visual interpretation of the yield classes showed that the Level 1 aggregation resulted in less fragmented classes. It was possible to identify low, medium, and high yield classes.

The large difference in yields across the field suggests that a site-specific farming strategy might be considered. This was surprising considering the small topographic changes in the field and a county soil survey which indicates there is only one soil series in this field.

The relationship between yield data and MSS parameters was determined to be strongly linear ($r = 0.99$). Near infrared bands were more strongly correlated than visible bands.

There was a strong linear relationship between yield data and elevation ($r = 0.92$). If the reason elevation was important in its influence on water availability then the establishment of a beneficial precision farming strategy for this field would be difficult.

The high correlation between the yield data and the spectral information indicates that spectral data might be useful in precision farming. How this information might be used is unclear and further research is needed. In particular, research needs to be done over multiple years on other soils and with other crops and tillage practices.

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