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GIS and Remote Sensing for Detecting Yield Loss in Cranberry Culture[1]

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Abstract: The primary goal of our research is to develop key elements of a precision agriculture program applicable to high-value woody perennial crops, such as cranberries. These crop systems exhibit tremendous variability in crop yields and quality as imposed by variations in soil properties (water availability and nutrient deficiency) that lead to crop stress (disease development and weed competition). Some of the variability present in the growing environment results in persistent yield losses as well as crop-quality reductions. We are using state-of-the-art methodologies (GIS, GPS, remote sensing) to identify and map spatial variations of the crop. Through image-processing methods (NDVI and unsupervised classification), approximately 65% of the variation in yield was described using 4-m multispectral satellite data as a base image.

Key words: database analysis, GIS, perennial crop management, remote sensing, unsupervised classification, yield loss, yield mapping.

The concept of precision agriculture identifies alternative approaches to farm management (Anonymous, 1997). Over the past few decades the definition of ''management units'' has changed from a ''whole-farm'' approach to a ''prescribed'' field-specific and even site-specific treatments. Use of the Global Positioning System (GPS) and Geographical Information System (GIS) to develop georeferenced maps for various crop and soil properties provides growers and field professionals with a new set of management and communication tools (Anderson et al., 1999). Recently, those state-of-the-art technologies have become more common in the management of the field crops, such as soybeans, corn, and wheat (Adamsen et al., 1999; Lelong et al., 1998; Towner and Servilla, 2000).

Johnson et al. (2000) demonstrated through remote sensing and GIS how wine grape quality varies across a vineyard and how growers could capture that variation in a segmented harvest. The result was a more uniform product. This approach is underutilized in other perennial crops such as blueberries and cranberries, although some research is being conducted in citrus orchards (Craig et al., 2000) and in forestry (Everitt et al., 1999). Growing perennial crops involves long-term sustainable management of soils, soilborne pathogens, water, and nutrient inputs. Production costs are typically calculated on a per-acre basis, and these base costs are not greatly influenced by yield per acre. Spatial variation in water stress, nutrient availability, and pathogen pressure causes spatial variations in crop response to grower-controlled inputs (i.e., fertilizers, fungicides) and in potential yield. Those effects are most likely to have a persistent cumulative influence on the spatial distributions of yield in perennial crops. Therefore, significant opportunities exist for improving efficiency of agricultural perennial systems by better understanding and utilizing existing spatial variation of farm resources and historical crop data.

In this paper we examine methods of GIS, GPS, and remote sensing for mapping and analyzing crop loss in cranberry farming on both a whole-field and within-field basis. Cranberries are a low-growing, intensively managed perennial crop indigenous to the sandy wetland soils found in the Pine Barrens region of New Jersey. The berries develop on fruiting uprights along a network of vegetative horizontally growing shoots called runners and are harvested from September through October. Currently, New Jersey has approximately 1,500 ha of cranberry beds. Yields vary from 5,000 to 60,000 kg/ha nationally and average approximately 17,000 kg/ha. The value of cranberries fluctuates in a range from $0.22 to $1.32 per kg. At the low end of this range cranberry production must be maintained at a minimum of 23,000 kg/ha to remain profitable. Average cranberry yields in New Jersey increased from approximately 16,000 kg/ha in 1993 to 20,000 kg/ha in 2000, with yield from some beds reaching 60,000 kg/ha. Variation within a single bed can be as high as 200-fold, and much of this variation is not yet quantified. Therefore, great potential exists for cranberry production to increase yield through improved farm management (Brightman, 1998). There is an opportunity to invest in precision management for enhancing cranberry profitability by increasing yields and reducing chemical inputs as opposed to acreage expansion. Taking into consideration the perennial nature and high value of this crop as well as its situation on wetlands, the implementation of precision agriculture methodologies for cranberry farms should bring tremendous economic and ecological benefits to producers, industries, and the public. In this paper we investigate methods to detect and map crop-limiting factors through remote sensing and GIS.

Materials and Methods

Study area: Commercial cranberry beds located in the Pinelands of southern New Jersey were used in this

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study. Cranberries are planted on hydric soils of Atsion (820 ha), Berryland (196 ha), and Manahawkin (86 ha) series, which correspond to Aeric Alaquods, Typic Alaquods, and Terric Haplosaprists, respectively. Specific features of these soils are sandy texture; high groundwater table (0.2-0.45 m in summer); and low pH (3-5), nitrogen content, and cation exchange capacity (CEC<10 mg-eq/g). Soil organic content typically increases progressively for the Atsion, Berryland, and Manahawkin series from 2% to 10%.

Cranberry GIS: Over the past 2 years we have developed a GIS database for New Jersey cranberry growers. Fruit delivery data from 1993 to 2000 was provided by Ocean Spray, Inc., a growers' cooperative. Data for each year included information on cranberry cultivar, amount of delivered and useable berries, TACY (mg of anthocyanin per 100 grams of fruit), and amount of unusable fruit. Cranberry bed outlines were digitized on screen using 1995 USGS 1-meter color infrared digital aerial photography in ArcView 3.2 (ESRI Inc., Redlands, CA) GIS software. The color infrared images, provided in digital format with 1-m ground resolution, were sufficiently detailed to easily delineate bed boundaries (Barrete et al., 2000). All of the imagery and base maps are in the UTM coordinate system (NAD 83, zone 18N). Each bed in the database was given a unique code that integrates the bed identification number and owner. Data linked to each bed in the GIS include the total bed yield (barrels) for each growing season from 1993 to 2000 and the cultivar. From the GIS, a relative yield per hectare was calculated for each bed in the study area (Table 1). Three varieties (Ben Lear, Early Black, and Stevens) are most commonly grown in the area and in the present study comprised 277 beds grown on approximately 479 ha.

Imagery: An IKONOS I multispectral satellite image (Space Imaging Inc., Thornton, CO) collected on 13 July 2000 was used as a base image in this study. The image is composed of 4 bands, i.e. Blue, Green, Red, and Near Infrared (NIR). The bands range in width from 65.8 to 95.4 nm and are centered at 480 nm (Blue), 550 nm (Green), 664 nm (Red), and 805 nm (NIR). The imagery was ortho-rectified by Space Imaging, Inc and projected in the UTM NAD83 (zone 18N) coordinate system with 4-m ground resolution.

Image analysis: Two ratios were calculated from the image data for further analysis. The normalized difference vegetative index (NDVI) (Jensen, 2000) and the structurally independent pigment index (SIPI) (Peñuelas et al., 1995) were used to detect variation in the surface reflectance of the cranberry beds:

$$NDVI = (NIR - Red)/(NIR + Red) \quad (1)$$

$$SIPI = (NIR - Blue)/(NIR - Red) \quad (2)$$

where NIR, Red, and Blue are spectral reflectance of the corresponding bands. These indices were calculated using the software package IMAGINE 8.4 (ERDAS, Inc., Atlanta, GA). An unsupervised classification using the Iterative Self-Organizing Data Analysis (Tou and Gonzalez, 1974) algorithm is performed on the color-IR imagery, and each of the index files to cluster the digital reflectance numbers into 20 statistically based classes. Image pixels are clustered based on similarity of their spectral reflectance or indices. This method uses no *a priori* knowledge about spectral signatures of the features on the image to determine classes. The information required as input to this classification scheme includes a number of clusters or classes, a convergence threshold, maximum percent of pixels left unchanged after each iteration, and maximum number of iterations run. All pixels in an image are assigned to a class.

The results of the unsupervised classification were then opened as a layer in the cranberry GIS in ArcView 3.2 with the Image Analyst Module 1.1 (ESRI, Redlands, CA) installed. A total of three unsupervised classifications were examined (i.e., classifications of NDVI, SIPI, and the raw imagery). The number of pixels for each of the 20 classes in a particular bed is extracted from the image. From this, the percentage of each class within each bed for the whole farm is computed. A correlation analysis between total individual bed yield at harvest for each of the three cultivars and the area of each pixel class in a bed is done using COSTAT ver. 5.034 (CoHort Software, Inc.) to determine significant relationships between the spectral data and yield. Pixel classes are identified in this manner as having either significantly positive, significantly negative, or no correlation with bed yield. These classes are then mapped as a georeferenced layer in the cranberry GIS.

TABLE 1. Data summary from cranberry GIS.

Property	1993	1994	1995	1996	1997	1998	1999	2000
Total harvested area (ha)	929	964	1,008	1,005	1,050	1,076	964	885
Number of beds	471	499	509	515	537	535	504	475
Average bed size (ha)	1.98	1.94	1.98	1.94	1.94	2.02	1.90	1.86
Maximum bed size (ha)	13.03	13.03	13.03	13.03	13.03	13.03	13.03	13.03
Minimum bed size (ha)	0.16	0.16	0.16	0.16	0.12	0.12	0.12	0.12
Number of growers	19	19	20	19	20	20	19	15
Average yield (ton/ha)	16.5	22.7	17.3	17.3	21.7	19.2	24.9	20.1
Maximum yield (ton/ha)	41.2	59.1	40.3	43.3	48.5	45.9	63.2	52.5
Minimum yield (ton/ha)	0.03	1.03	0.02	0.20	0.10	0.12	0.12	1.62

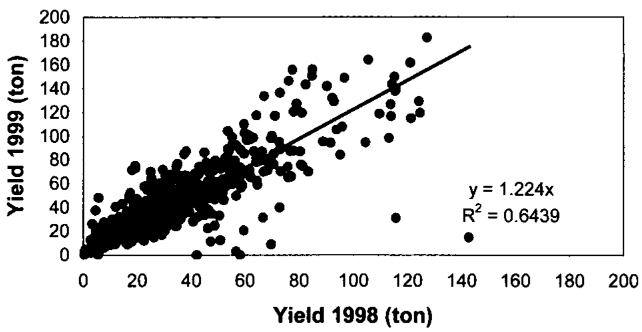

FIG. 1. A relationship between total yields in 1998 and 1999. Data from all yielding beds included in Cranberry GIS are combined.

The results were verified by selecting specific beds and ground-truthing the patterns produced in the analyses. This was done using a variety of field methods including visual observations, berry counting, plant density measurements, pathogen isolations, elevation mapping, soil texture analysis, and soil moisture mapping. All sampling locations were georeferenced with GPS (Trimble Pathfinder Pro XR2, Trimble Navigation Limited), and corresponding maps were created using geostatistical techniques of inverse-distance weighting and kriging (Gotway et al., 1996; Isaaks and Srivastava, 1989) with GS+ (Gamma Design Software, MI).

RESULTS

For all cultivars there was a high correlation between yields from sequential years for the same beds. The relationship between yields in 1998 and 1999 for all beds included in the cranberry GIS shows a high correlation (Fig. 1). Correlation coefficients for the 2000 yield with yields of preceding years are significant going back to 1993 (i.e., 0.740, 0.815, 0.722, 0.710, 0.628, 0.636, and 0.740 for 1999, 1998, 1997, 1996, 1995, 1994, and 1993, respectively).

To more accurately capture cranberry yield trends over time and space, yield values were normalized for each cultivar. The individual bed yield for a given year is divided by the average yield for the specific cultivar for that specific year. In this way beds with different yielding potentials were compared in a single yield map. The normalized yields were projected as data layers across 8 years (Fig. 2), and the yield trend was calculated from the data as a regression line over time. A negative slope indicates a decline in yield for a particular bed (shown in blue), positive slope indicates an increase in yield (shown in red), and no change in yields is shown in green. The results of this analysis were then projected onto a map showing the distribution of yield trends (Fig. 3).

The analysis of the imagery involved several steps. First, the whole image plate provided by Space Imaging, Inc. was included into an unsupervised classification. The image comprised not only areas occupied by cranberry bogs but also roads, forests, and water reservoirs. The unsupervised classifications set for 20 classes were run for the raw image, a Normalized Difference Vegetation Index (NDVI), or Structural Independent Pigment Index (SIPI), and the area occupied by each pixel class in each cranberry bed was calculated. The correlation between the area of each pixel class and total bed yields was generally low and not significant (>0.05). As a result, the analyses were run again but a mask was developed so that only areas under cranberry beds were included in the classification. The masking improved the results; however, the correlations still were not sufficient and a subjective inspection of the classes revealed very little information (data not shown). Masks (areas of interest) were developed for each individual cultivar so that three cultivars (Early Black, Stevens, and Ben Lear) could be examined separately. The results were greatly improved (Table 2), with several classes showing strong correlations with yield (negative or positive). As evident from Table 2, each cultivar demonstrates correlations with slightly different classes. Thus, Stevens and Early Black cultivars show strong and significant correlations with high classes of NDVI (classes 16-20). Correlation of Ben Lear with the same classes is also high but not significant, probably because of small sampling size. However, Ben

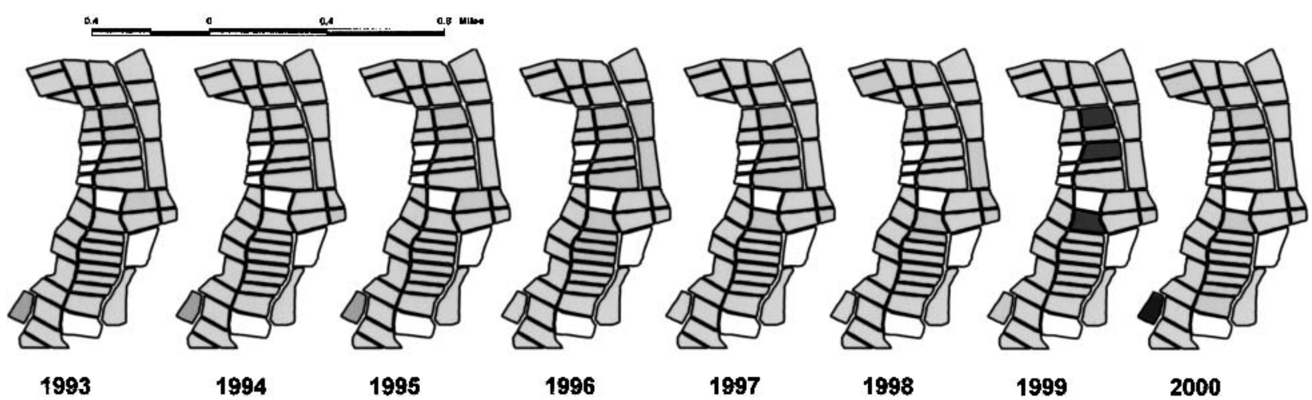

FIG. 2. Patterns of production across a range of cranberry beds over an 8-year period. Yields were standardized by first calculating the yearly average for each cultivar and then dividing bed yield by the cultivar average. Color palette represents statistical deviation from the cultivar average for that season (see legend for Fig. 3).

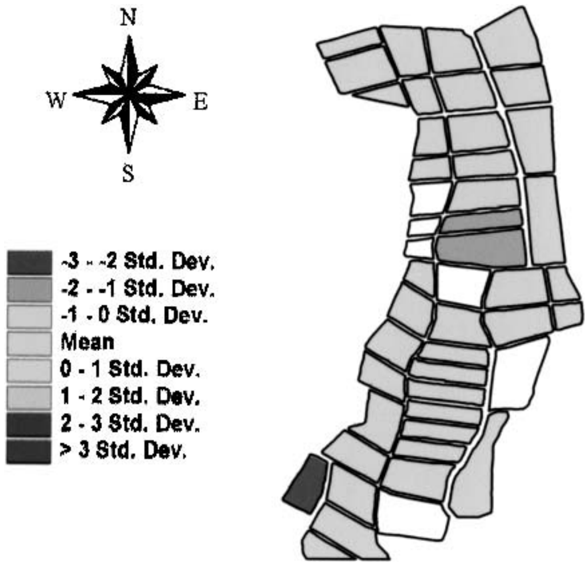

FIG. 3. Yield trends over 1993-2000 period calculated from the yield data presented in Fig. 2. Beds colored in blue represent decreasing yields; yields from the beds colored green are stable or unchanged over 8 years.

Lear shows high and significant negative correlations with the classes of low NDVI (classes 1-8). The unsupervised classifications of raw imagery and SIPI index were processed in the same way as NDVI and yielded similar results.

Pixel class data also were subjected to a multiple stepwise regression, which helped to increase correlation with cranberry yield (r^2 became 0.741, 0.711, and 0.425 for Stevens, Ben Lear, and Early Black, respectively). A strong relationship was found between the observed

TABLE 2. Correlation coefficients between bed yields (1999–2000 average) and % area of the individual classes derived with unsupervised classification of NDVI from IKONAS multispectral imagery (2000).

Class #	Stevens n = 53	Ben Lear n = 28	Early Black n = 157
1	−0.23	0.50*	−0.36*
2	−0.23	−0.40*	−0.37*
3	−0.44*	−0.43*	−0.33*
4	−0.41*	−0.49*	−0.36*
5	−0.54*	−0.59*	−0.39*
6	−0.59*	−0.52*	−0.42*
7	−0.63*	−0.48*	−0.47*
8	−0.66*	−0.42*	−0.45*
9	−0.71*	−0.33	−0.47*
10	−0.80*	−0.29	−0.48*
11	−0.73*	−0.10	−0.47*
12	−0.52*	−0.08	−0.38*
13	−0.30*	−0.10	−0.21*
14	−0.12	0.06	0.13
15	0.16	0.17	0.39*
16	0.48*	0.30	0.53*
17	0.68*	0.32	0.54*
18	0.76*	0.33	0.48*
19	0.68*	0.36	0.43*
20	0.60*	0.25	0.30*

yields for the cultivar Stevens and the yields predicted based on multiple regression from classes 1, 6, 10, 11, 16, 17, 18, and 19. Thus, using satellite multi-band imagery through unsupervised classification of NDVI up to 74% variation in the yield can be explained for Stevens and Ben Lear cultivars. Only about 42% of yield variation was explained for Early Back cultivar, which might be due to several reasons: (i) larger sampling size for this cultivar; (ii) beds with this cultivar tend to be the oldest planted and often exhibit a biannual bearing pattern; and (iii) this cultivar may contain significant genetic diversity, whereas Stevens and Ben Lear show lower levels of genetic diversity.

The results of the correlation analysis (Fig. 4) for the relationships between the unsupervised classification and cranberry yields were visualized as maps using AreView (Fig. 5A, B). Figure 5A shows results of the unsupervised classification for a group of beds where each of the 20 classes is represented by a distinct color shade. Then every class was assigned in one of the three groups, namely having significantly positive, negative, or no significant correlation with yield based on the information from Table 2 for each cultivar. Those three groups are colored differently in Figure 5B.

Yield maps, derived from the remotely sensed data, were verified for some beds with berry counting close to harvest. Figure 6 shows the contour of a 2000 yield map developed by kriging the data from 216 sampling locations superimposed on a map derived by unsupervised classification of the same-year multispectral satellite imagery. A generally good correspondence of the areas with low yield to pixels with the classes negatively correlated with yield can be noted. However, unsupervised classification of the remotely sensed data provides more detail maps than one can obtain even from very dense ground sampling. A correlation between remotely sensed and ground-sampled data is usually decreased by error of geographical co-registration of the imagery and sampling locations, which combines GPS error and

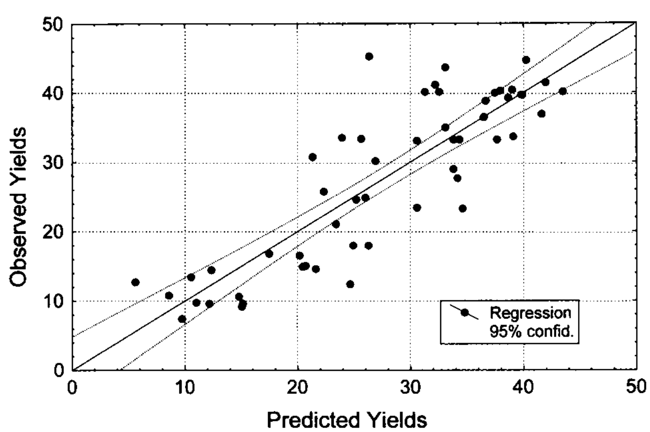

FIG. 4. A relationship between cranberry yields observed in the field (for 79 Stevens' beds) and predicted by multiple stepwise regression of the data derived with unsupervised classification of NDVI from multi-band satellite imagery (IKONOS I).

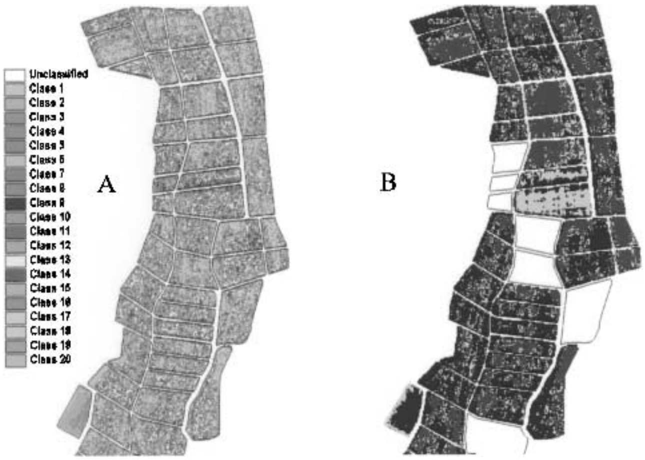

FIG. 5. Distribution of yield potential within cranberry beds. A) Unsupervised classification of multispectral IKONOS I imagery. B) Pixels colored red positively correlated with yield, blue are negatively correlated with yield, and green shown no significant correlation. Figure demonstrates where yield losses occurred.

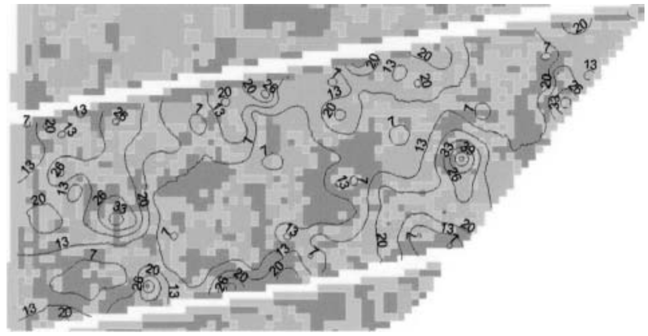

FIG. 6. Contour yield (ton/ha) map (2000) kriged from the results of berry counting on 216 locations. Color map is developed from unsupervised classification of IKONOS I imagery (see caption for Fig. 5).

image-processing error (Salvador, 1999). Besides, maps developed from the ground-sampled point data have an error due to biased sampling locations.

Discussion

The availability of detailed and accurate yield data that can be related to specific fields or beds has provided the opportunity to develop an agricultural GIS that can be used to track yield trends. In the case of cranberry, we have found that yields show a high correlation between years. This high correlation suggests that in cranberries most of the beds exhibit constant rankings through the years, with slight fluctuations due to variation in management inputs, bud set, and weather conditions. When examined separately, the three cultivars examined in this study differed in yield potential and yielding pattern. For example, Early Black shows a biennial bearing pattern, with yields from a same bed changing almost two-fold in consecutive years. Nevertheless, for such beds high correlation exists between yields in alternate years. Based on the finding that the ranking of beds is constant, the analysis of historical data may be useful in targeting beds for remediation or replanting.

We suspect that areas within a bed that are producing poorly are likely to recur at the same places and possibly increase in size. Thus, yield maps as well as maps of yield trends could be used to identify problem beds. Diagnostic methods also need to be developed to identify the factors limiting yield. Very often these yield-limiting factors are not readily apparent, which makes it difficult to locate low-yielding areas of a bed without the remote sensing and GIS tolls described here.

The combination of detailed yield records with remotely sensing data has provided the opportunity to detect and map yield variation within a cranberry bed. Using this approach, crop losses that are not readily visible to the naked eye (such as chronic injury from Phytophthora root rot, water stress, or nutrient deficiency) can be located (Pozdnyakova et al., 2002). The map E.I.C. 2002 presented in Figure 3 helps identify beds where the ranking has either changed (increased or decreased) or remained the same. For example, two beds in the center show a declining yield (colored blue in Fig. 3). Using the classified remote sensing data (Fig. 5B, large areas of these beds were found to be in decline. Thus, one method identifies a problem bed and the second method shows the distribution of yield loss within the bed. Each type of disease, nutrient deficiency, or drainage problem does not necessarily have a unique spectral fingerprint; therefore, ground-based diagnostics are necessary. In practice, scouting techniques that use handheld computers with georeferenced maps and GPS will be used to guide the scout to problem areas and provide a medium for reporting to the grower.

Different methods were used to process the image data. Ratio-based methods, such as NDVI and SIPI, work well because variations in radiance that may occur across the image will be minimized. NDVI worked very well in this analysis; however, other methods may be superior (Huete, 1988; Stoms and Hargrove, 2000). This type of analysis is limited by the spectral and spatial characteristics of the imagery being used. For example, multispectral imagery obtained from the IKONOS satellite contains four broad spectral bands with a ground resolution of 4 m. Other platforms, such as airborne hyperspectral imagery contain greater numbers of spectral bands with reduced bandwidth. In the future, additional images will be taken throughout the season to determine the optimum number of images needed and the optimum timing in terms of crop phenology.

Ultimately, this technique will be used not only to visualize the yield potential within the beds but also to monitor yield changes within beds over time through image change analysis (Kadmon and Harari-Kremer, 1999). This approach will provide the technical underpinning to create a bed-management tool that also can be used as an annual report card for monitoring progress in various treatment regimes.

Crop yield models and canopy-specific weather data will be combined with the remotely sensed data to provide accurate yield predictions (Hartkamp et al., 1999). Management plans will be developed under a GIS and implemented using GPS-guided scouts and machinery (Fleischer et al., 1999). Ultimately, growers will be able to access historical and current yield maps derived from remotely sensed data. These yield maps combined with treatment maps will be a viable tool for day-to-day cranberry management and provide a means for evaluating crop management techniques through crop change detection.

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