Spatial Modeling using Remote Sensing, GIS, and Field Data to Assess Crop Yield and Soil Salinity

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Abstract. A comprehensive salinity monitoring program has been conducted in a portion of the Arkansas Valley in southeastern Colorado from 1999 to the present. This area was selected for study because it provides a good illustration of a salinity-affected area. The main objective of this presentation is to utilize spatial statistical modeling using information from remote sensing, GIS, GPS, along with field data to develop salinity maps and predict yield. The approach presented in this paper involves integrating remotely sensed data with topographical data (elevation, slope, and aspect) and field data (water table fluctuation, groundwater salinity, soil texture, yield data, and soil salinity) to establish and validate the appropriate spatial techniques to accurately predict crop yield in relation to soil salinity. For the field scale study, several fields were selected to represent different irrigation systems, soil types, and crop patterns. In each field, 7 to 15 wells were installed. At these fields, water table depth, groundwater salinity, soil salinity, and yield samples are collected regularly during the growing season. In addition to field data collection, a satellite image from IKONOS on July 11was acquired. It has four bands (blue, green, red, and infrared) with a 4-meter spatial resolution. In this study, trend surface models, which describe the large-scale spatial variability, have been developed based on the lowest values Akaike Information Criterion Corrected (AICC) and high R^2. P-Value of each related variable and for all the related variables together should be less than 0.05 to guarantee a strong relation among the variables. Also, P-Value from Moran should be greater than 0.05 to guarantee that there is no autocorrelation among the residuals.

1 Introduction

1.1 Overview:

Soil salinity is a severe environmental hazard which increasingly impacts crop yields and agricultural production. Salinity refers to the presence in soil and water of various electrolytic mineral solutes in concentrations that are harmful to many agricultural crops (Hillel 2000). Natural salinization or primary salinization results form the long-term influence of natural processes. In contrast, human-induced salinization or secondary salinization is the result of salt stored in the soil profile being mobilized by extra water from human activities such as irrigation (Szabolcs 1989). On average, 20% of the world's irrigated lands are affected by salts, but this figure increases to more than 30% in countries such as Egypt, Iran and Argentina (Ghassemi et al. 1995).

Remote sensing data has great potential for monitoring dynamic processes, including salinization. Remote sensing of surface features using aerial photography, videography, infrared thermometry and multispectral scanners has been used intensively to identify and map salt-affected areas

(Robbins and Wiegand 1990). Multispectral data acquired from platforms such as the Landsat, SPOT, and the Indian Remote Sensing (IRS) series of satellites, have been found to be useful in detecting, mapping, and monitoring salt-affected soils (Dwivedi and Rao 1992). However, the digital analysis of multispectral data using the spectral response pattern of salt-affected soils is plagued by misclassification. In order to improve the detectability of these soils and other natural features using remote sensing data, various image transforms have been developed. These transforms not only enhance the detectability of these features, but also aid data compression resulting in substantially reduced computational time and cost. Hill and Donald (2003) and Wilhelm et al. (2000) used vegetation indices to estimate ground pattern. Wiegand et al. (1994) carried out a procedure to assess the extent and severity of soil salinity in fields in terms of economic impact on crop production and effectiveness of reclamation efforts. Golovina et al. (1992) made an effort to automate methods of air photo interpretation in order to speed up and make the interpretation process more objective when compiling maps of soil salinization. Srivastava et al. (1997) made a scheme of image processing and GIS techniques using false color, vegetation indices, density slicing, overlaying, and supervised classification and applied it on IRS-1B LISSS II data. Band ratios of visible to near-infrared and between infrared bands have proven to be better for identifying salts in soils and salt-stressed crops than individual bands (Craig et al., 1998; Hick and Russell, 1990; and Hick et al., 1984).

The integration of remotely sensed data, Geographic Information Systems (GIS), and spatial statistics provides useful tools for modeling large-scale variability to predict the distribution, presence, and pattern of exotic and native plant species as well as soil characteristics (Kalkhan et al. 2000). This integration also provides tools for assessing the landscape-scale structure of forest and rangelands (Chong et al. 2001). Large sample size can provide better estimates of the variable of interest; however, collecting field data can be time consuming and self-limiting (Scheaffer et al. 1990; Olsen and Schreuder 1997).

The approach presented in this research involves integrating remotely sensed data with topographical data (elevation, slope, and aspect) and field collected data (water table fluctuation, groundwater salinity, soil texture, yield data, soil salinity) to establish the appropriate spatial techniques and the way in which these techniques should be applied to accurately predict crop yield in relation to salinity. The approach is being tested on data collected in the lower Arkansas River Valley in Colorado. Most data indicate that the main factor influencing yield in this region is salinity. In some cases, yield is being reduced by a combination of soil salinity, poor irrigation water, high water table, and groundwater salinity.

1.2 The Problem in the Arkansas River:

The Arkansas River is one of the most saline rivers of its size in the United States. Salinity levels, measured as dissolved solid concentrations, increase from 300 mg/L near Pueblo to over 4,000 mg/L at the Colorado-

Kansas border (Ghassemi et al. 1995). According to data collected between April 1990 and March 1993, concentrations increased 183%, or about 30 mg/L per mile, from Las Animas on the western edge of John Martin Reservoir to Coolidge, Kansas. The water of the Arkansas is used to irrigate crops in the river valley, and farmers are facing decreasing crop yields due in part to these high levels of salinity. In some areas, land is being taken out of production due to unsustainable crop yields. It was estimated that in 1977 over 200,000 acres in the Arkansas Valley were being irrigated with water that contains salinity concentrations greater than 1,400 mg/L (Miles 1977).

2 Site Description and Data Preparation and Utilization

2.1 Site Description:

The area of study is located in southeastern Colorado primarily in Otero County. Data has been collected in several fields during the last five years. The fields were selected to represent different cases. The first field (#7) is 260 acres located west of Highway 207 and south of the Arkansas River. The soil type is loam, and the field is irrigated with a center pivot. Alfalfa has been cultivated in the field since 1999. 13 wells have been installed in this field. The second field (#17) is located south of the Rocky Ford Canal and west of Highway 71. The field covers 97 acres and is irrigated with a furrow system through gated pipes. The soil type is sandy loam. Field 17 was planted with corn in 1999, 2000, and 2001. Onions were planted in 2002 and left fallow in 2003. We have 11 wells in this field. The third field (#20) is 9.8 hectares. The soil type is loam, and the field is irrigated with a furrow system through gated pipes. Corn was planted in 2001, onions in 2002, and wheat in 2003. The fourth field (#40) is located north of the town of Swink, about 1.5 miles north of Highway 50 and east of County Road 25. 20.2 acres of the field are irrigated, and 18 acres are not irrigated. The soil type is sandy clay loam. The field is irrigated with a furrow system through gated pipes. The field was planted with corn in 1999, 2000, and 2001. It was left fallow in 2002 and 2003. The fifth field (#80) is 23.4 acres. The soil type is clay loam. The field is irrigated with furrow irrigation through siphons. Corn was planted in the field in 1999, 2000, and 2001. The field was left fallow in 2002 and planted with sorghum in 2003.

2.2 Field data collection:

A comprehensive salinity monitoring program has been conducted in the Arkansas Valley from 1999 to the present. Field data on variables that can affect salinity or crop yield are being collected. The fields for the study were selected to represent a variety of scenarios with different soils, irrigation systems, and irrigated crops. Examples of data being collected are: water table fluctuation, groundwater salinity, soil salinity, crop samples, evapotranspiration, rainfall, and soil texture. During the growing season, data pertaining to water table, groundwater salinity, rainfall, and evapotranspiration are collected on a weekly basis. For one month after the season is finished data are collected bi-weekly. Data is collected monthly during the rest of the year. Soil salinity is usually measured three times during the irrigation season: at the beginning, middle, and end of the season. Soil salinity is measured by using a EM38 and taking a vertical and horizontal reading, and these readings are transferred to dS/m (decicemns per meter units) using a calibration equation. In addition to EM38, soil samples are collected for each field (from 12 to 20 positions) at four depths (1 foot, 2 feet, 3 feet, and 4 feet) and analyzed in the laboratory using a Hatch salinity kit. Crop samples are collected in the form of number of plants, green leaf area, biomass, and grain yield.

2.3 Spatial Statistical Modeling:

All the above data from the topology data to the field data to the remote sensing data can be integrated together with spatial statistical modeling. Spatial statistical modeling has the power to detect the relation among many variables. With the help of the Splus program, researchers are able to read the data in the right format, take the weighted distance of the data, and check which variables have relation with stepwise regression. With the ordinary least squares method (OLS) we can decide the best model to use. The best model should have the smallest value of AICC (Akaike Information Criterion Corrected) and higher value of R^2. Also, a small value for P (less than 0.05) to guarantee that the selected variables have strong relation with both yield and salinity, and high value for P from Moran (> 0.05) to make sure that there is no autocorrelation in the residuals.

3 Methodology and Procedure

Many variables effect yield production either directly or indirectly, such as soil salinity, groundwater salinity, water table, and soil texture. In our study area, salinity is the main factor influencing yield, but other variables might have either direct or indirect effects. The main objective of this paper is to predict yield from the related variables such as soil salinity, groundwater salinity, water table, topology data (elevation, aspect, and slope), and texture type (sand, clay, and silt). Also, yield will be predicted from the IKONOS image. The same will be done with salinity. Therefore, all the variables which might influence either yield or salinity will be tested with stepwise and ordinary least squares (OLS) regression analysis to select the best model. The best model should include only the variables which have strong relation to either yield or salinity.

Yield and salinity will be predicted from the IKONOS image only for the sub-basin and tested for two fields. The main benefit of predicting yield and salinity from an image is that it can give a general estimation without any fieldwork, saving money and effort. Then, salinity will be predicted from the collected field data of groundwater salinity and water table, and yield will be predicted from salinity, groundwater salinity, and water table. Yield and salinity will also be predicted from topology data (elevation, aspect, and slope) and from soil texture classification (sand, clay, and silt).

The sets of bands, which should be used with each predicted variable, must be carefully selected. The following table describes the IKONOS data. The designation and principal applications can be used as guidelines when making predictions from remote sensing data.

Table 1: Description of IKONOS data.

Type	Width (μm)	Spatial Resolution	Designation and Principal Application
Band1 (Blue)	0.45-0.53	4 m	Water penetration
Band2 (Green)	0.52-0.61	4 m	Vegetation for vigor assessment.
Band3 (Red)	0.64-0.72	4 m	Vegetation discrimination.
Band4 (NIR)	0.77-0.88	4 m	Healthy vegetation and water bodies.

Table 1 shows that all IKONOS bands can be used for predicting yield. Since both IKONOS images used in this study were taken during the growing season, they are suitable for predicting crop yield.

4 Analysis and Results

The criterion that will be followed in selecting the best model to predict either yield or salinity will be based on the following:

1. Smallest value of AICC (Akaike Information Criterion corrected).
2. Higher Multiple R^2.
3. Small P-Value (less than 0.05) of each related variable and for all the related variables together to guarantee a strong relation among the variables.
4. High P-Value (2-side) of Moran (larger than 0.05) to guarantee that there is no autocorrelation in the residuals.
5. Smallest Residual Standard error.

The analysis used in this paper was based on the field scale only. It cannot be applied to the sub-basin scale because the study area encompasses a total of five fields, one planted with alfalfa, one not covered by the image, and a third in which the corn crop was damaged by cows. The collected data from the remaining two corn fields are not enough to describe the sub-basin.

The following examples show how the spatial model can be applied to predict either yield or salinity from all different variables in different cases. The first case uses the bands of the IKONOS image to predict yield, eliminating the need for collecting field data. This method can give good results if the field has no weeds. The second case predicts yield from the indices of the IKONOS image. Sometimes the indices work better than the bands. The third case predicts yield based on water table, groundwater salinity, and soil salinity. The fourth case predicts yield from the soil texture (sand, clay, and silt).

Soil salinity will be predicted from the IKONOS images. Although the field is covered by the plant material, the vegetation can be used as a reflection of salinity since there is a strong relation between crop and soil salinity. However, salinity will not be predicted from the image indices since most of these indices are designed for vegetation. Salinity will be predicted from the water table and groundwater salinity. The parameters that produce the best model such as R2, P-Value, etc. are summarized in the form of tables to make it easy to compare the models.

Table 2: Parameters for selecting the best model for predicting yield in four different cases in Field 17

Case (1): Predict Yield from IKONOS Bands (B4)		
AICC	122.09	
	Coeff.	P-Value
Intercept	-215.07	0.0221
B4	0.4544	0.0001
R^2	0.78	
P-Value	0.0001	
P-Value (2-Side) Moran	0.6867	
Residual Standard Error	34.37	

Case (2): Predict Yield from Soil Salinity		
AICC	133.4	
	Coeff.	P-Value
Intercept	-326.6	0.1479
Soil Salinity	75.4	0.0183
R^2	0.4421	
P-Value	0.0183	
P-Value (2-Side) Moran	0.4936	
Residual Standard Error	55	

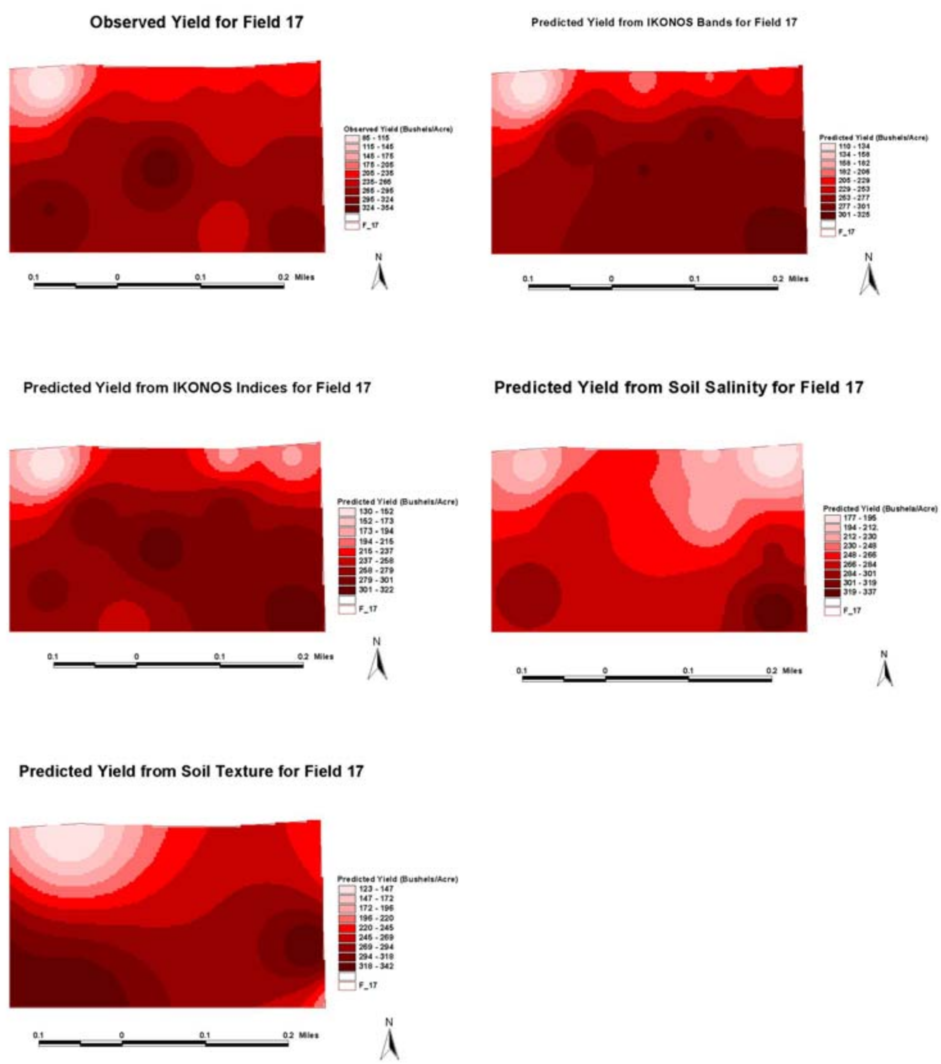
Case (3): Predicted Yield from IKONOS Indices (IR/R) and 1st PCA		
AICC	128.15	
	Coef.	P-Value
Intercept	291.8	0.0037
(IR/R)	21.6	0.05
1st PCA	-0.83	0.039
R^2	0.7347	
P-Value	0.0026	
P-Value (2-Side) Moran	0.4653	
Residual Standard Error	40	

Case (4): Predict Yield from Soil Texture (Sand and Silt)		
AICC	131.6	
	Coef.	P-Value
Intercept	-2179.9	0.006
Sand	32.04	0.0035
Silt	23.83	0.0032
R^2	0.644	
P-Value	0.0096	
P-Value (2-Side) Moran	0.615	
Residual Standard Error	46.36	

It is clear from the above table, that for the first case which predicts yield from the IKONOS bands, band 4 (the infrared band) has a very strong relation with yield. This is determined from the P-value (0.0001), which is very small, and the R^2 (0.78), which is high. Also, the P-Value (2-Side) Moran 0.6867 is larger than 0.05, which means that there is no autocorrelation in the residuals. The values of AICC (122.09) and residual standard (34.37) error are the smallest among all the trials for this case.

The second case, which represents the predicted yield from soil salinity, shows that soil salinity has a strong relation with yield even though the R^2 (0.4421) is not as high but the value of P (0.0183) is less than 0.05. If the P-Value is less than 0.05 we can accept a lower value of R^2 based on our interest in the variables.

Figure 1: The observed and predicted yield maps for four different cases in Field 17



The third case, which represents the prediction of yield from the IKONOS indices, shows that there is a good relation between yield with (IR/R) and the 1st PCA (first principal component analysis). Even though the P-value of (IR/R) is borderline, the P-value of the overall variables is very small 0.0026. Also the value of 1st PCA is less than 0.05, which supports the selection. The P-value (2-side) Moran 0.465 is larger than 0.05, which confirms that there is no autocorrelation in the residuals. Also the value of R^2 is high which makes this model the best of all the trials of different IKONOS indices.

The fourth case, which represents the prediction of yield from soil texture, shows that sand and silt have a strong relation with yield where the P-value for them is 0.0035 and 0.0032 respectively. The P-value of the overall variables is very small 0.0096 and the P-value (2-side) Moran 0.615 is larger than 0.05, which means that there is no autocorrelation in residuals and R^2 0.615, which is high.

Table 3: The observed and predicted yield and its percentage error for four different cases in Field 17.

Case (1): Predict Yield from IKONOS Bands (B4)					**Case (2): Predict Yield from Soil Salinity**			
#	Observ.	Predict.	% of Error		#	Observ.	Predict.	% of Error
1	316	309	2.2		1	316	327	-3.5
2	281	300	6.8		2	281	284	-1.1
3	226	212	6.2		3	226	177	21.7
4	248	289	-16.5		4	248	282	-13.7
5	251	298	-18.7		5	251	218	13.1
6	225	234	-4		6	225	211	6.2
7	355	302	14.9		7	355	265	25.4
8	209	193	7.7		8	209	251	-20.1
9	292	294	-0.7		9	292	284	2.8
10	281	282	-0.4		10	281	286	-1.8
11	85	96	-12.9		11	85	203	-138.8
12	327	285	12.4		12	327	296	9.5

Case (3): Predict Yield from IKONOS Indices (IR/R) and 1st PCA					**Case (4): Predict Yield from Soil Texture (Sand and Silt)**			
#	Observ.	Predict.	% of Error		#	Observ.	Predict.	% of Error
1	316	318	-0.6		1	316	283	10.4
2	281	297	-5.7		2	281	294	-4.6
3	226	190	15.9		3	226	243	-7.5
4	248	286	-15.3		4	248	278	-12.1
5	251	295	-17.5		5	251	268	-6.8
6	225	188	16.4		6	225	250.7	-11.4
7	355	322	9.3		7	355	268	24.5
8	209	240	-14.8		8	209	218	-4.3
9	292	248	15.1		9	292	320	-9.6
10	281	294	-4.6		10	281	211	24.9
11	85	130	-52.9		11	85	136	-60
12	327	285	12.8		12	327	325	0.6

Table 3 shows the error percentages of observed and predicted yield for the four different cases. From this table we can determine that the error percentage is acceptable when we take into account the errors involved in the collection and analysis of the crop samples. All errors are less than 25% and the majority of them are around 10% to 15%. Sample 11 seems to be an outlier since it is the smallest of all the collected samples and the error is significantly high in the four different cases. A couple of reasons for this sample's high error are: 1) This is a high salinity area and there could be weeds growing that are more tolerant to salt than the crop, and 2) The crop in this spot is not homogeneous which makes it difficult to collect a consistent sample.

Table 4: Parameters of selecting the best model for predicting salinity in two different cases in Field 17.

Case (1): Predict Salnity from IKONOS Bands (B4)				**Case (2): Predict Salinity from Water Table**		
AICC	19.7			AICC	133.4	
	Coef.	P-Value			Coef.	P-Value
Intercept	4.59	0.0021		Intercept	8.93	0
B4	0.003	0.0173		Water Table	-0.63	0.0027
R^2	0.45			R^2	0.6113	
P-Value	0.0173			P-Value	0.0027	
P-Value (2-Side) Moran	0.26			P-Value (2-Side) Moran	0.38	
Residual Standard Error	0.483			Residual Standard Error	0.4053	

The first case, which represents the prediction of soil salinity from the IKONOS image bands, shows that band 4 (the infrared band) has the strongest relation with salinity among the four bands. The R^2 value of 0.45 is not very high but it is acceptable since the P-value of 0.0173 is less than 0.05. The P-value (2-side) Moran of 0.0173 is less than 0.05, which assures that there is a strong relation with the selected variable. The AICC value of 19.7 and the residual standard error of 0.483 are the least among all the trials that were evaluated.

The second case, which represents the prediction of salinity based on the water table, shows a strong relation. The P-value of 0.0027 is less than 0.05, which assures that there is a strong relation between salinity and water table. When the model contains only one selected variable, the P-value of the selected variable is the same value of the overall variable, in this case 0.0027. The P-value (2-side) Moran is larger than 0.05 which assures that there is no autocorrelation in the residuals. The AICC value of 133.4 and the residual standard error of 0.4053 are the smallest among all the trials evaluated.

Figure 2: Observed and predicted salinity in Field 17

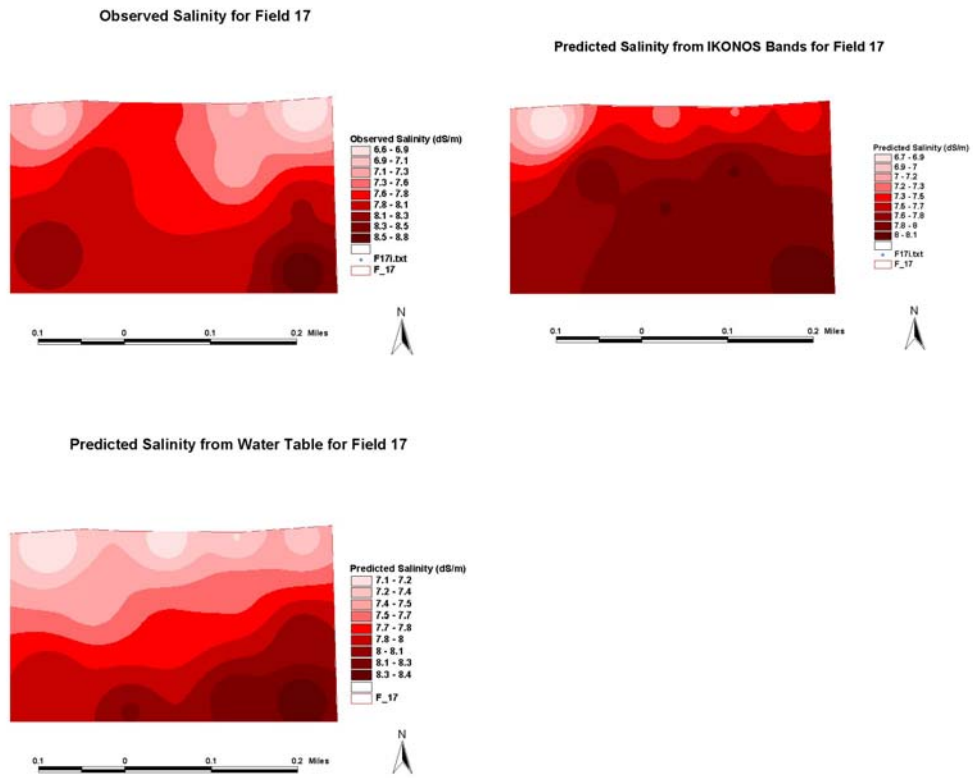


Table 5: The observed and predicted salinity and its percentage error for two different cases in Field 17.

Case (1): Predict Yield from IKONOS Bands (B4)					**Case (2): Predict Yield from Water Table**			
#	Observ.	Predict.	% of Error		#	Observ.	Predict.	% of Error
1	8.81	8.16	7.34		1	8.81	8.49	3.63
2	8.13	7.89	2.95		2	8.13	8.15	-0.25
3	6.68	7.48	-11.98		3	6.68	7.37	-10.33
4	8.08	7.89	2.35		4	8.08	8.34	-3.2
5	7.22	8.02	-11.08		5	7.22	7.7	-6.6
6	7.13	7.37	-3.37		6	7.13	7.26	-1.82
7	7.85	8.02	-2.17		7	7.85	7.79	0.76
8	7.67	7.35	4.17		8	7.67	7.14	6.91
9	8.1	7.96	1.73		9	8.1	7.48	7.65
10	8.1	7.99	1.36		10	8.1	8.21	-1.36
11	7.03	6.75	3.98		11	7.03	7.11	-1.38
12	8.26	7.78	5.81		12	8.26	8	3.15

The above data shows that highest percent error is -11.98% indicating that the selected model is efficient. Table 5 shows that the percent error in sample # 11 is very small while it was very high when predicting yield. This supports the conclusion about the difficulty in collecting consistent yield samples in high salinity spots. However when measuring soil salinity it does not matter what the condition of the crop is (scattered or vigorously growing).

5. Summary and Conclusion

When predicting either yield or salinity from IKONOS bands, band 4, which is the infrared band, has the strongest relation to both yield and salinity. This means that salinity can be predicted from the image even though the crop covers the area. The crop itself can be used as an indicator for salinity. It can be concluded also that the indices play an important role in predicting yield and in some cases they might be more valuable than using the bands. This is clearly shown when we try to predict yield from the IKONOS indices, they show a strong relation with yield and both (IR/R) and 1^{st} PCA. P-value of (IR/R) and 1^{st} PCA were 0.05 and 0.039 respectively which means that there is a strong relation between both of these variables with yield. Though the P-value of (IR/R) was 0.05 which is marginal, the P-value (0.0026) of the two variables together is very small and R^2 0.7347 is high, this assures the strong relation of both (IR/R) and 1^{st} PCA with yield.

In the case when we predict yield from water table, groundwater salinity, and soil salinity, soil salinity shows the strongest relation to yield with a very small P-value of 0.0183 and an R^2 of 0.4421. This means that soil salinity shows a strong relation to yield as expected. When predicting soil salinity from water table and groundwater salinity, water table shows a very strong relation to soil salinity with a P-value of 0.0027and an R^2 0.611. This means that groundwater salinity does have an effect on soil salinity but not as strong as water table.

In the case when we predict yield from soil texture, sand and silt show a very strong relation with yield with P-values of 0.0035 and 0.0032, respectively. The P-value from the two variables together was 0.0096, which assures this strong relation as well as an R^2 value of 0.644. It can be concluded that grain size of the soil particles can affect yield.

Some other trials were done with topology (elevation, aspect, and slope) but these variables did not appear to have an effect on either salinity or yield. The trials show very poor values of R^2 (less than 0.1). Also, soil texture was found to play a marginal role in predicting either yield or salinity. When percent sand, clay or silt has an effect on either yield or salinity, the effect is not as strong as that of water table or groundwater salinity.

The tables showing the summary of the observed and predicted values have small values for percent error. The average is around 10 %, which is very acceptable when trying to predict yield and salinity from remote sensing data and the other field data such as water table or groundwater salinity. Large values in the percent error mainly appear when there are a low number of yield samples. Most instances of medium and high yield, errors are less than 20%. The reason for the presence of high error with the small yield values is that those samples were taken in areas of the field with high salinity.

The overall conclusion is that using of stepwise regression and ordinary least squares in selecting the best models for different variables seems to be efficient. Also, the main advantages of using the stepwise and ordinary least squares models appears to be very significant when the traditional methods do not give satisfactory results.

References

Chong, G.W., Reich, R.M., Kalkhan, M.A., and Stohlgren, T.J. (2001). "New approaches for sampling and modeling native and exotic plant species richness." *Western North American Naturalist*, 61, 328-335.

Craig, J. C., Shih, S. F., Boman, B. J., & Carter, G. A. (1998). *Detection of salinity stress in citrus trees using narrow-band multispectral imaging.* ASAE paper no. 983076. ASAE Annual International Meeting, Orlando, FL, USA, 12–16 July 1998. 10 pp.

Dwivedi, R.S., and Rao, B.R.M., (1992). "The selection of the best possible Landsat TM band combination for delineating salt-affected soils." *International Journal of Remote Sensing*, 13, 2051–2058.

Ghassemi, F., Jackeman, A.J., and Nix, H.A. (1995). *Salinization of land and water resources: human causes, extent, management and case studies.* CAB International, Wallingford Oxon, UK.

Golovina, N.N., Minskiy, D.Ye., Pankova, I., and Solov'yev, D.A. (1992). "Automated air photo interpretation in the mapping of soil salinization in cotton-growing zones." *Mapping Sciences and Remote Sensing*, 29, 262-268.

Hick, P.T., and Russell, W.G.R. (1990). "Some spectral considerations for remote sensing of soil salinity." *Australian Journal of Soil Research*, 28, 417–431.

Hick, P.T., Davies, J.R., and Steckis, R.A. (1984). "Mapping dryland salinity in Western Australia using remotely sensed data." *Satellite remote sensing: review and preview*, Remote Sensing Society, Reading, UK, 343–350.

Hill, Michael J., and Donald, Graham E. (2003). "Estimating spatio-temporal patterns of agricultural productivity in fragmented landscapes using AVHRR NDVI time series." *Remote Sensing of Environment*, 84 (3), 367-384.

Hillel, D. (2000). *Salinity management for sustainable irrigation: integrating science, environment, and economics.* The World Bank: Washington D.C.

Kalkhan, M. A., Stohlgren, T. J., Chong, G. W., Lisa, D., and Reich, R. M. (2000). "A predictive spatial model of plant diversity: integration of remotely sensed data, GIS, and spatial statistics" *Paper presented at the Eighth Biennial Remote Sensing Application Conference (RS 2000), April 10-14, 2000,* Albuquerque, NM.

Metternicht, G.I. and Zinck, J.A. (1997). "Spatial discrimination of salt- and sodium-affected soil surfaces." *International Journal of Remote Sensing*, 18, 2571–2586.

Miles, D.L. (1977). *Salinity in the Arkansas Valley of Colorado.* U.S. Environmental Protection Agency, Interagency Agreement, Colorado State University, EPA-1AG-D4-0544, Fort Collins, CO.

Olsen, A., R. and Schreuder, H.T. (1997). "Perspectives on large-scale natural resources surveys when cause-effect is a potential issue." *Environ. and Ecol. Stat.,* 4, 167-180.

Peck, A.J., Thomas, J.F., and Williamson, D.R. (1983). "Salinity issues, effects of man on salinity in Australia." *Water 2000 Consultants Report, no. 8*. Canberra: Australian Government Publishing Service.

Postel, S. (1999). *Pillar of Sand: Can the Irrigation Miracle Last?* W.W. Norton and Co., New York, NY.

Robbins, C.W., and Wiegand, C.L. (1990). "Field and laboratory measurements." *Agricultural Salinity Assessment and Management*, American Society of Civil Engineers, New York.

Scheaffer, R.L., Mendenhall, W., and Ott, L. (1990). *Elementary survey sampling,* 4^{th} ed., PWS-Kent Publishing Company, Boston, MA.

Srivastava, A., Tripathi N. K., and Gokhale, K. V. G. K. (1997). "Mapping groundwater salinity using IRS-1B LISS II data and GIS techniques." *International Journal of Remote Sensing*, 18 (13), 2853-2862

Szabolcs, I. (1989). *Salt-Affected Soils.* CRC Press, Boca Raton, FL.

Wiegand, C.L., Rhoades, J.D., Escobar, D.E., and Everitt, J.H. (1994). "Photographic and videographic observations for determining and mapping the response of cotton to soil salinity." *Remote Sensing of Environment*, 49, 212-223.

Wilhelm, W.W., Ruwe, K., and Schlemmer, M.R. (2000). "Comparison of the three leaf area index meters in a corn canopy." *Crop Science,* 40, 1179-1183.