Estimating Soil Salinity from Remote Sensing Data in Corn Fields

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Abstract: This paper describes an approach to develop soil salinity maps using remotely sensed data. This approach is applied to an ongoing salinity monitoring program in a portion of the Arkansas Valley in southeastern Colorado. The approach involves integrating remote sensing data from Ikonos, GIS, and spatial analysis. The collected soil salinity data is tied to the corresponding values from the satellite image bands. The stepwise regression method is applied to find the best correlation between soil salinity data and corresponding pixel values on the satellite image bands. Two regression methods were tested with the combinations of variables: ordinary least squares (OLS) and spatial autoregressive (SAR). The results show that, the green band, the near infrared band, and the near infrared band divided by the red band ratio are strongly related to soil salinity. When these variables were introduced to the OLS model, the analysis of residuals suggested that there might be some spatial dependency based on the Lagrange multiplier test. When the same variables were introduced to the SAR model, the likelihood ratio test indicated that the SAR model was a significant improvement over the OLS model. Also the SAR model has a smaller value of Akaike Information Corrected Criteria (AICC).

1. Introduction

Soil salinity is a severe environmental hazard (Hillel 2000) that impacts the growth of many crops. Worldwide, salinization problems are spreading at a rate of up to 2 million hectares a year, which offsets a good portion of the increased productivity achieved by expanding irrigation (Postel 1999). Natural salinization, or primary salinization, results from the long-term influence of natural processes. Human-induced salinization, or secondary

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salinization, is the result of salt stored in the soil profile being mobilized by extra water provided by human activities such as irrigation (Szabolcs 1989).

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). It was estimated that in 1977 over 200,000 acres in the Arkansas Valley were being irrigated with water that contained salinity concentrations greater than 1,400 mg/L (Miles 1977). Gates et al. (2002) established that salts were returned from the irrigated valley to the Arkansas River at an estimated average rate of about 740 kg/week per irrigated hectare. Goff et al. (1997) noted that the degradation of the quality of surface and groundwater in the lower Arkansas River Valley is closely related to extensive agricultural diversions and usage, and the consumption of irrigation water by evapotranspiration increases salinity in return flows.

Remotely sensed data has a great potential for monitoring dynamic processes, including salinization. The ability to predict soil salinity accurately from remote sensing data is important because it saves labor, time, and effort when compared to field collection of soil salinity data (Robbins and Wiegand 1990). Remote sensing of surface features with aerial photography, videography, infrared thermometry, and multispectral scanners has been used intensively to identify and map salt-affected areas (Robbins and Wiegand 1990).

Metternicht and Zinck (1997) combined digital image classification with field observation of soil degradation and laboratory analysis to map salt and sodium-affected areas in the semiarid valleys of Cochabamba, Bolivia. Multispectral data acquired from platforms such as 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) noted that the digital analysis of multispectral data using the spectral response pattern of salt-affected soils is plagued by misclassification, and in order to improve the detectability of these soils and other natural features using remote sensing data various image transforms must be developed. These transforms not only enhance the detectability of these features, but also aid data compression resulting in substantially reduced computational time and cost (Dwivedi and Rao 1992). 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). Srivastava et al. (1997) studied the accuracy of mapping shallow groundwater depth and salinity using remote sensing data. They formulated a methodology involving image processing and GIS techniques using false color, vegetation indices, density slicing, overlaying, and supervised classification and applied the methodology to IRS-1B LISSS II data. In their study, groundwater depth and salinity maps were based on reflectance variations of vegetation above the ground surface, and they assert that the species of vegetation found in an area and vegetation densities can provide evidence of shallow groundwater conditions. Wiegand et al. (1994) assessed the extent and severity of soil salinity in fields in terms of economic impact on crop production and effectiveness of reclamation efforts. Their study emphazised practical ways of combining image analysis capabilities, spectral observations, and ground truth to map and quantify the severity of soil salinity and its effects on crops. Golovina et al. (1992) made an effort to automate methods of interpreting aerial photos in order to speed up the interpretation process and make it more objective. They stated that automated analysis is capable of performing a more complex evaluation of the quantitative degree of salinization than visual interpretation.

The integration of remotely sensed data, Geographic Information Systems (GIS), and spatial statistics provides useful tools for modeling variability to predict the distribution, presence, and pattern of 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). Kalkhan et al. (2000) incorporated trend surface analysis to estimate the probability of exotic species richness. They found that Landsat TM bands 1, 2, 5, 6, and 7, elevation, slope, and aspect were significant predictors. Thomas et al. (1997) presented a rapid, cost-efficient methodology to link plant diversity surveys from plots to landscapes using unbiased site selection based on remotely sensed information. Utset et al. (1998) used a calibrated Four-Electrode Probe (FEP) for inexpensive and indirect determinations of salinity-sensor electrical conductivity (EC) in a plot in Cauto Valley, Cuba. Their cross-validation analysis showed that EC semivariograms obtained from FEP measurements can characterize the soil EC spatial variation in a similar way to semivariograms of laboratory-measured soil EC.

In this paper, we evaluate the relationship between soil salinity and satellite imagery. These relationships are evaluated using multiple regression models that are capable of accounting for any spatial dependency in the residuals. The best model is then used to produce salinity maps.

2. Site Description and Data Collection

The study area (Figure 1) for this project is located in southeastern Colorado, primarily in Otero County. This region was selected because it provides a good illustration of a salinity-affected area. The salinity monitoring program is applied on the sub-region scale and on the field scale. For the sub-region scale, salinity readings are taken twice each growing season in approximately 69 fields with an EM-38 salinity probe (Gates et al. 2002). This EM-38 data is collected at between 60 and 120 points in each field depending on the field's area. In each of these fields, there is one monitoring well where groundwater level and groundwater salinity readings are taken during the year. For the field scale, fields with different irrigation systems, soil types and crop types were selected. In each of these fields, salinity readings are taken three times during the growing season. Each field also contains between 7 and 15 monitoring wells. At the field scale, the following readings are taken: soil salinity, water table fluctuation, and groundwater salinity, rainfall, estimates of irrigation water quality and quantity, and evapotranspiration. Yield samples are also taken. Figure 1 shows the map of the study site along with the Ikonos satellite imagery that was acquired in 2001. The image covers part of the study area. The dominant irrigated fields were alfalfa, corn, cantaloupe, and onion. Five fields were selected for field scale study (7, 17, 20, 40 and 80). Three of these fields were planted with corn (17, 40, and 80) and are described in this paper. The other two fields (7 and 20) are excluded from this discussion because field 7 was planted with alfalfa and field 20 was not covered by the image.

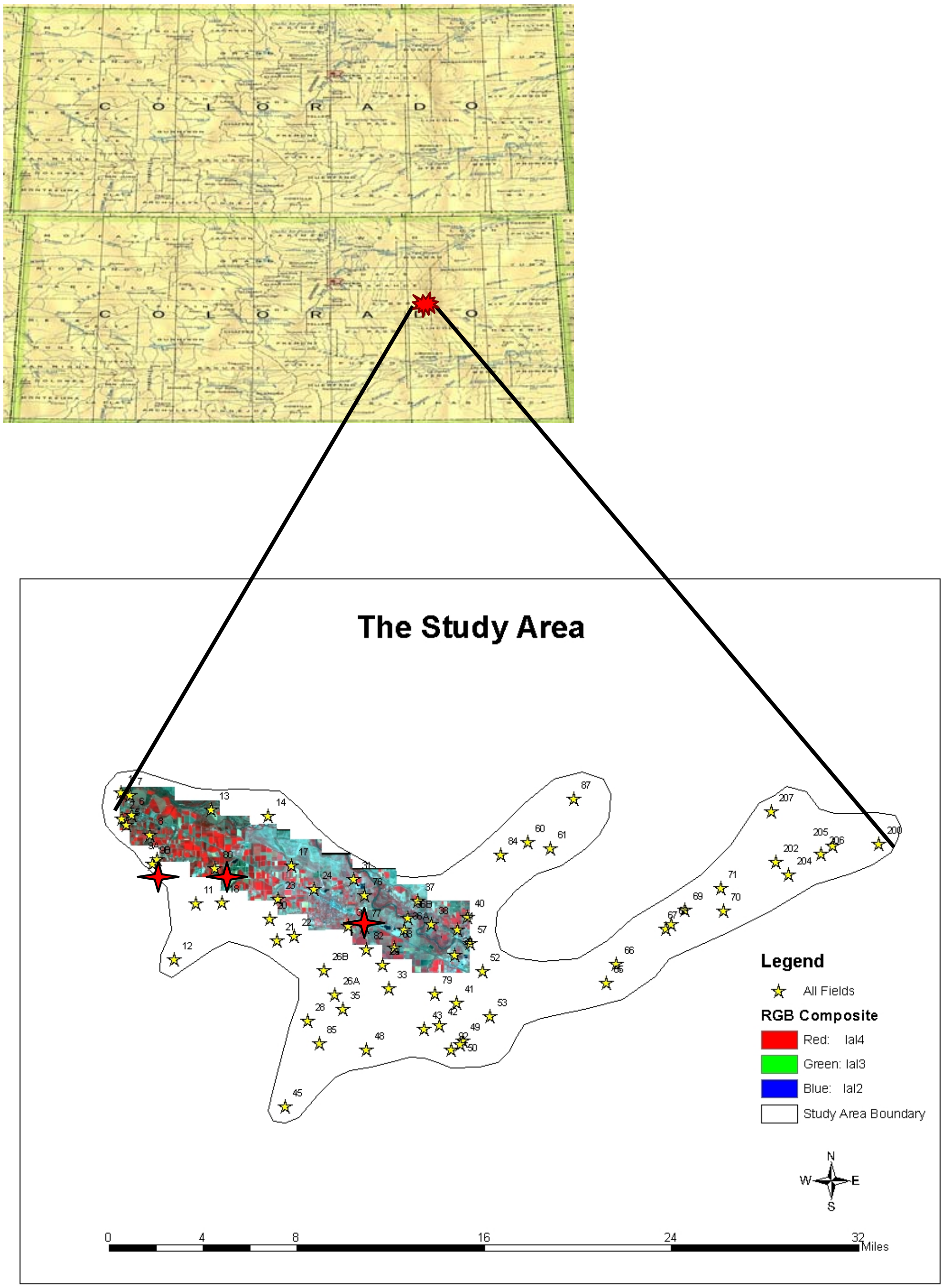

Figure 1. Map of the Lower Arkansas Valley study area.

3. Methodology and Procedure

A satellite image from Ikonos was taken in 2001 which covers a part of the study area where the field scale monitoring is taking place. The irrigated fields in this region are mainly alfalfa, corn, wheat, cantaloupe, and onion. The reflection of the satellite image is affected mainly by the ground cover type, and each crop has a different reflection. For, the study described in this paper, only fields planted with corn (17, 40, and 80) were used.

Soil salinity data collected using the EM-38 salinity probe are tied by location to the corresponding values from the different bands of the Ikonos satellite image. The stepwise regression technique is used to decide the combination of variables from the Ikonos image bands that relate to soil salinity. The relationships between soil salinity data and the four bands of the Ikonos satellite image (blue, green, red, and near infrared), the normalized difference vegetation index (NDVI), the near infrared band divided by red band (NIR/R), and principal component analysis (PCA) are evaluated with the regression models. The residuals from the regression models were tested for spatial autocorrelation using Moran's I and the Lagrange multiplier test. In analyzing the residuals inverse distance weighting was used to define the spatial proximity of the sample data. If the residuals showed signs of spatial autocorrelation, the model was refit using a spatial autoregressive model (SAR). A likelihood ratio test was used to test the improvement of the SAR model to that of the ordinary least squares (OLS). Competing models were evaluated using Akaike Information Corrected Criteria (AICC).

4. Results and Analysis

Table 1 summarizes the results of the analysis. The OLS model included the green band, the near infrared band, and near infrared band divided by red band (NIR/R). The green band and NIR/R band ratio had a positive relationship with soil salinity while the near infrared band had a negative relationship. Analysis of residuals suggested that there might be some spatial dependency based on the Lagrange multiplier test. To account for the spatial dependency, the same variables were also presented to the SAR model, however their level of significant was lower. The likelihood ratio test indicated that the SAR model was a significant improvement over the OLS model. Also, the AICC for the SAR was smaller than that for the OLS model. There was a significant amount of spatial autocorrelation in the residuals ($\hat{\lambda}$ = 0.93). This explains the decrease in the R^2 value for the SAR model when compared to the OLS model (0.24 vs. 0.52). The presence of spatial autocorrelation makes the relationship between the satellite imagery and soil salinity more important than it actually is, thus inflating the R^2 value as well as deceasing the standard errors associated with the parameter estimates.

Table 1. Summary of statistics for the OLS and SAR models for predicting soil salinity as a function of remote sensing imagery.

Variable		OLS	SAR
	R^2	0.5206	0.2365
	Residual Standard error	1.5623	1.3387
Intercept	Coefficient	6.238	4.6293
	Standard Error	1.462	2.1523
	p-value	0	0.0324
Green Band	Coefficient	0.0136	0.0128
	Standard Error	0.0029	0.0028
	p-value	0	0
Near infrared Band	Coefficient	-0.0112	-0.0101
	Standard Error	0.0019	0.0024
	p-value	0	0
NIR/R	Coefficient	0.9405	1.0577
	Standard Error	0.3588	0.3639
	p-value	0.0093	0.004
$\hat{\lambda}$	Coefficient		0.9353
	Standard Error		0.0349
	p-value		0
AICC		962.7875	897.1561
p-value (Lagrange)		0	
Likelihood ratio *p*-value			0
Sample Size		257	257

Analysis of the residuals from the SAR model are displayed in figures 2,3 and 4. The residuals are approximately normally distributed as is clear from Figure 2. The errors associated with the predicted soil salinity increased with increasing value of soil salinity values as seen in Figure 3. Finally, in the plot of residuals versus a weighted average of nearest neighbors (Figure 4), no pattern exists, suggesting that the SAR was able to account for the spatial dependency in the residuals.

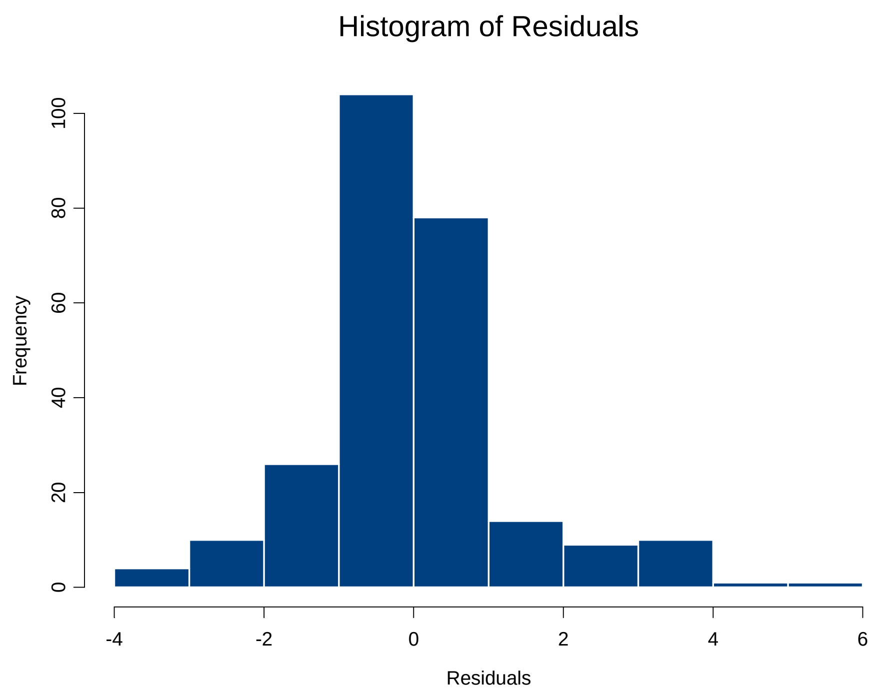

Figure 2. Histogram of residuals.

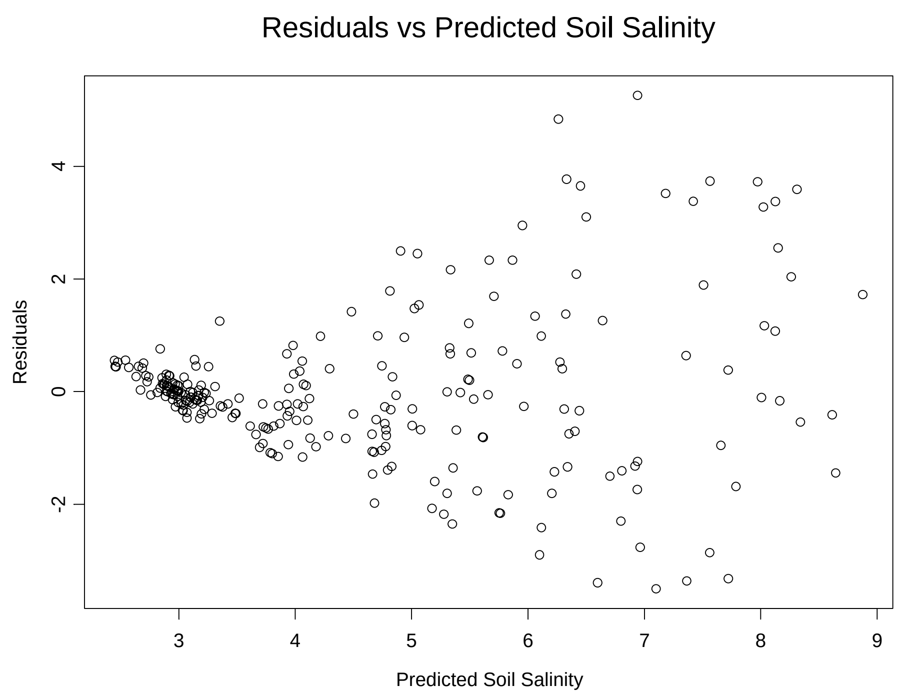

Figure 3. Residuals versus predicted values of soil salinity.

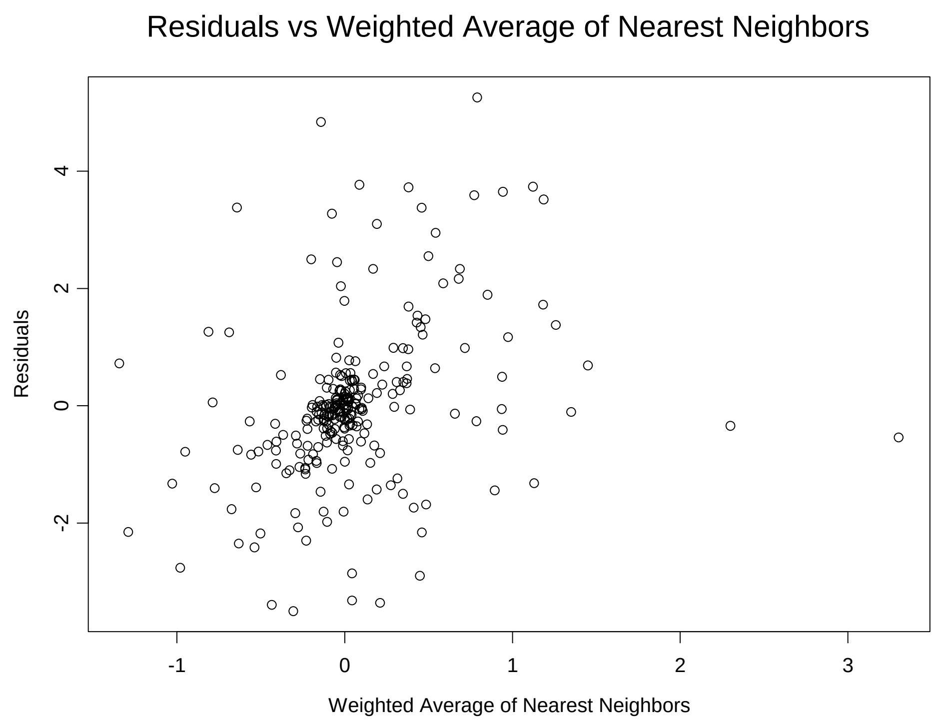

Figure 4. Residuals versus the weighted average of nearest neighbors.

The following figures (5, 6, 7, and 8) show the predicted soil salinity maps for the area covered by the image and another three corn fields. These maps are derived using the equation for the SAR model shown in Table 1. Figure 5 represents the whole area covered by the image. In addition to the irrigated fields, this area contains many other non-irrigated areas (rivers, lakes, urban areas, etc). The soil salinity values for these non-irrigated areas are not realistic since there were no data collected for these areas. But when looking at the fields where data were collected, especially for the images of the individual fields, the non-irrigated areas help in interpreting the results. Field 17 represents one of the homogeneous fields, except for a small area at the left north part of the field, the field's salinity level is almost the same throughout. This homogeneity is reflected in the predicted soil salinity map shown in Figure 6. Field 40 and field 80 represent heterogeneous fields. The predicted maps for these two fields (Figures 7 and 8) show most of the highly affected areas by soil salinity.

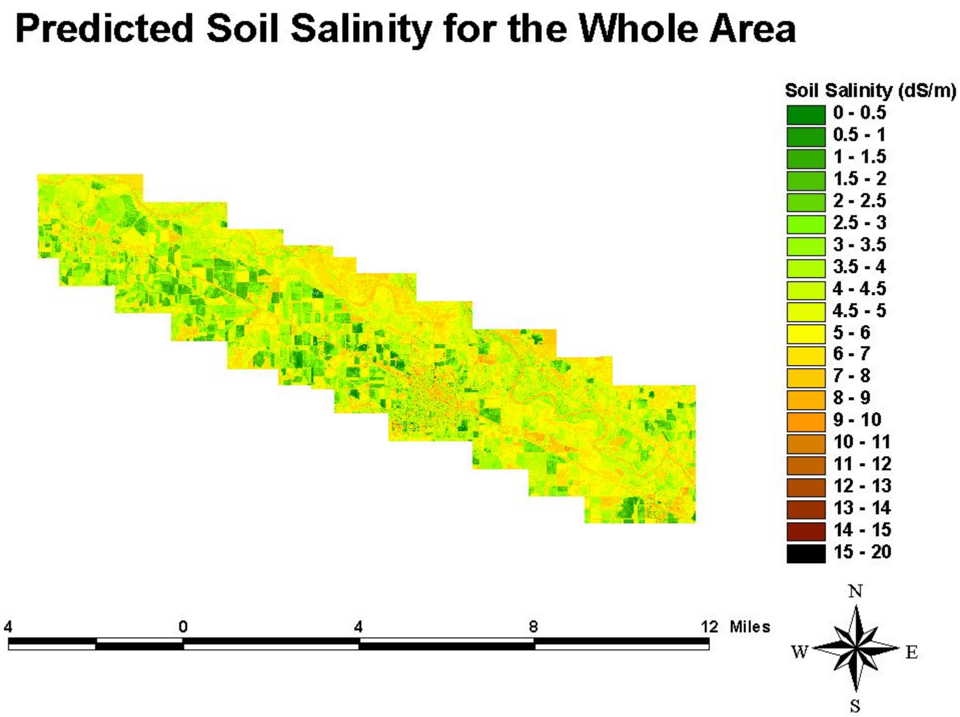

Figure 5. Predicted soil salinity for the area covered by the image.

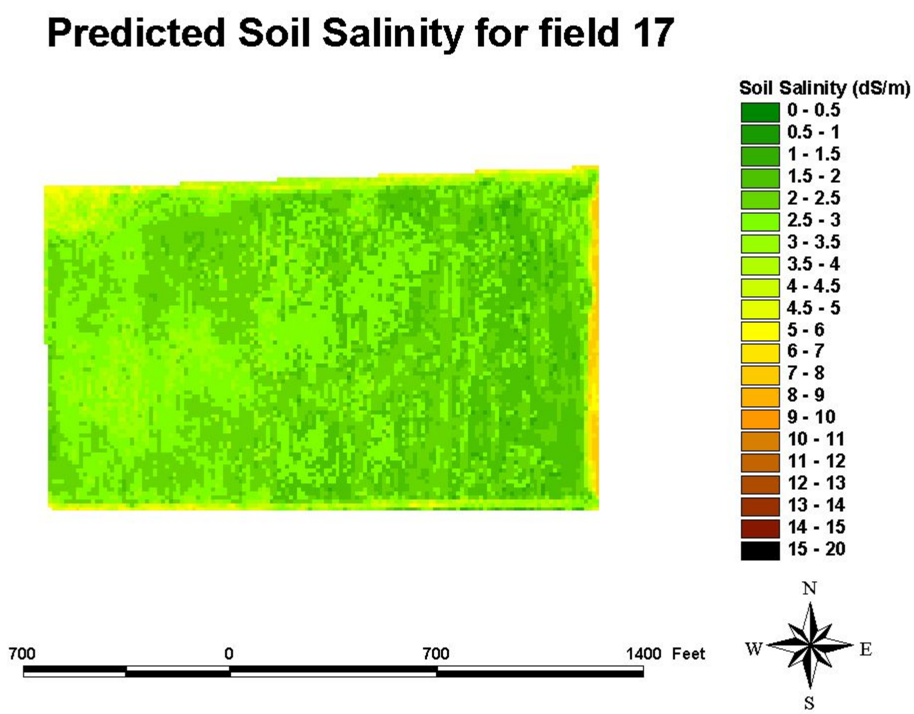

Figure 6. Predicted soil salinity for field 17.

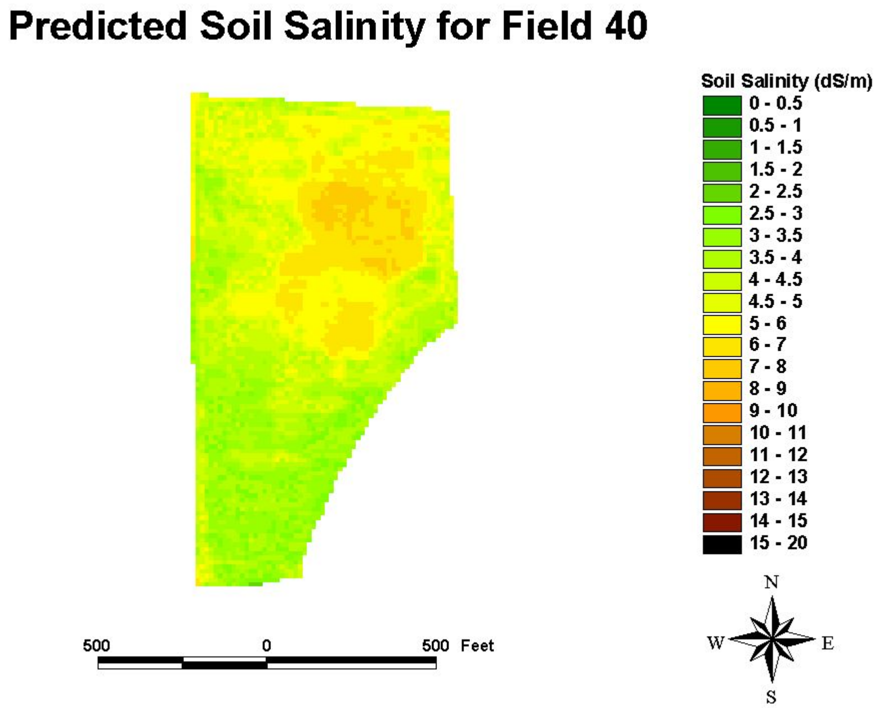

Figure 7. Predicted soil salinity for field 40.

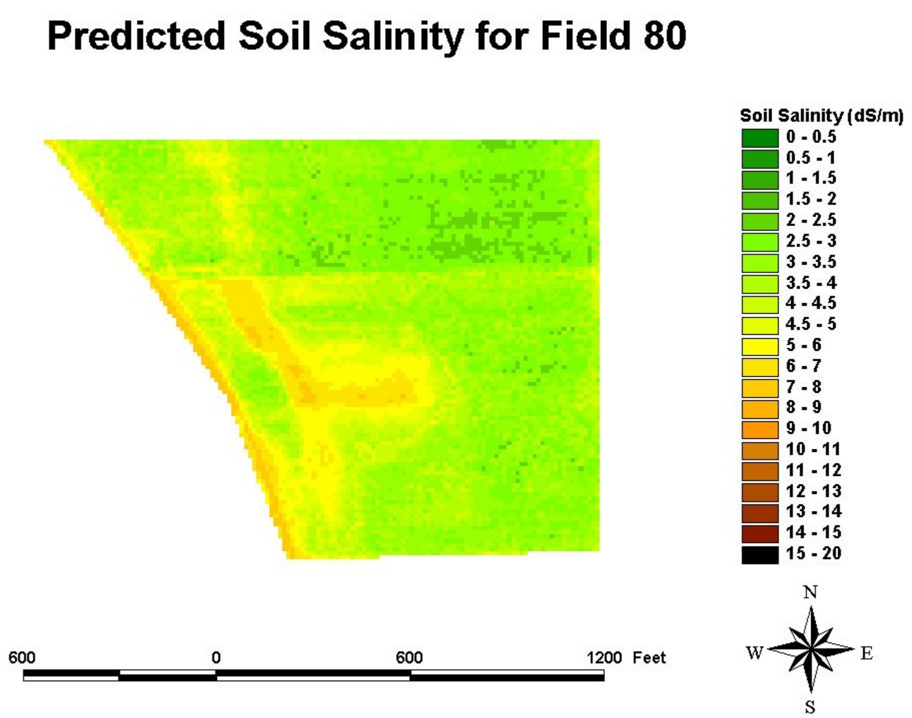

Figure 8. Predicted soil salinity for field 80.

5. Summary and Conclusion

The results presented in this paper show the feasibility of using remote sensing data to predict soil salinity. Compared to the labor, time, and money invested in field work devoted to collecting soil salinity data, the availability and ease of acquiring satellite imagery is very attractive. Numerous combinations of bands have been evaluated using OLS and SAR models. It is clear from the results presented in this paper that selecting the regression model is very important in determining the quality of the map of predicted soil salinity. The results also show the importance of the residuals and how they can affect the quality of the maps generated. The presence of spatial autocorrelation makes the relationship between the satellite imagery and soil salinity more important than it actually is. In evaluating the regression techniques for soil salinity, attention should be paid to the issue of selecting the most suitable regression model. It is very important for future research to consider most of the regression variables that control the accuracy of the regression. This paper shows that depending only on R^2 and standard errors will not produce salinity maps of high quality and high accuracy when using remote sensing. Likelihood ratio test, Lagrange multiplier, and AICC must be considered to improve the quality of the interpolated maps.

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