Detecting Soil Salinity Levels in Agricultural Lands Using Satellite Imagery

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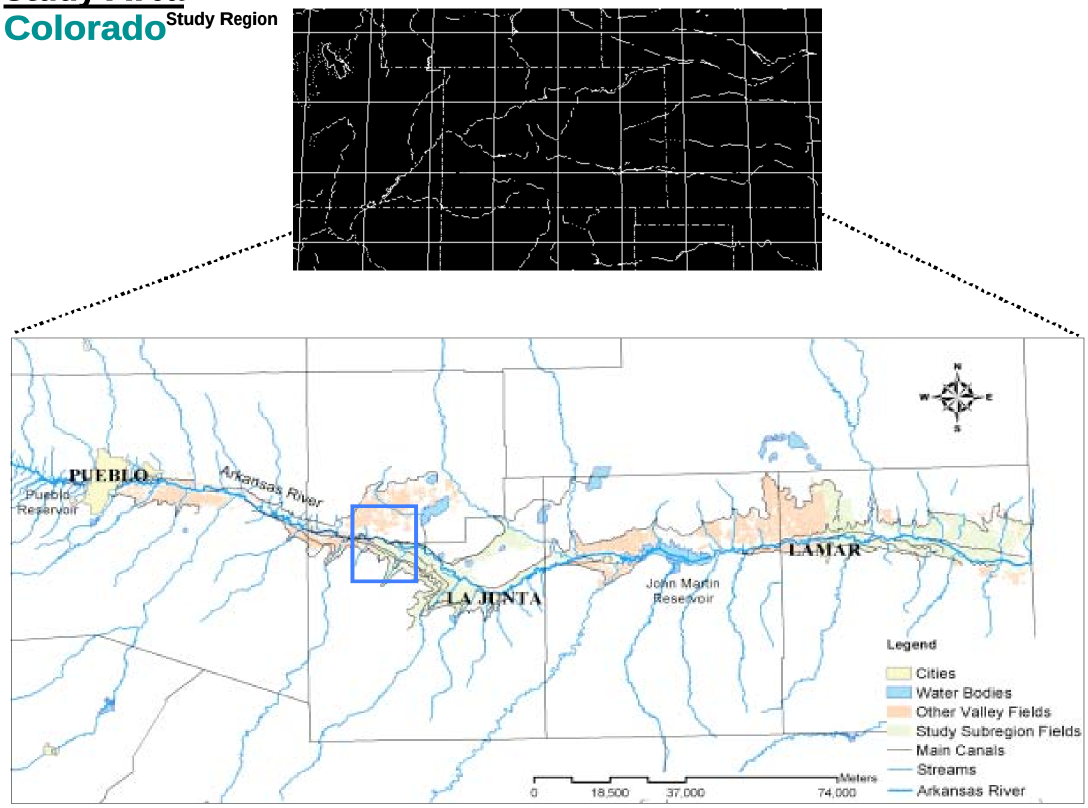
1 ABSTRACT

To assess a region's salinity problem, it is necessary to map the presence of saline soils. Such mapping can be accomplished in several ways. Soil samples can be collected or analyzed in the lab, or Electro Magnetic (EM) devices can estimate the amount of salt in the soil. Although both of these techniques can give good estimates of soil salinity, they are time consuming and might not be practical or economical when evaluating large areas. Two alternate approaches that are being investigated in the Arkansas River Basin in Colorado are described in this research. The first approach uses Ikonos 4 m satellite imagery and crop reflectance to determine the severity of soil salinity and its impact on crop yield. The reflectance of the crop in a multi-spectral satellite image is used as an indication of the severity of soil salinity. By comparing the satellite image with field-collected data, the multi-spectral data is trained to distinguish between different levels of soil salinity. The image can then be divided into several soil salinity classes and estimates can be made of how the different classes are likely to impact crop yield. The second approach uses lower resolution satellite imagery and the Energy Balance equation to relate crop reflectance and evapotranspiration to soil salinity.

2 INTRODUCTION

In recent years, methods for studying soil salinization have improved greatly. Techniques have evolved from using geographical analysis alone to using remote sensing analysis and visual interpretation of satellite images combined with computer processing of satellite images. Moreover, it is becoming increasingly popular to combine a remote sensing method with Geographic Information Systems (GIS) to solve complex problems (Peng, 1998). Our research attempts to use remote sensing techniques for the purpose of preparing a map of the extent and magnitude of salt-affected land in a study area around La Junta, Colorado. Although remote sensing techniques have been used to diagnose general salinity problems (Everitt et al., 1977; Ripple et al., 1986), only limited attempts have been made to evaluate their effectiveness in identifying soils where the primary inhibitor of plant growth is nutrient deficiency induced by either alkalinity or salinity (Weigand et al., 1993). Ghabour and Daels [1993] concluded that detection of soil degradation by means of a conventional soil survey requires a great deal of time, but remote sensing data and techniques offer the possibility for mapping and monitoring these processes more quickly and economically. However, to assess the accuracy of the ability of satellite images to map and monitor salinity, it is necessary to compare them with field measurements of salinity.

Study Area



3 BIOMASS METHODOLOGY

The proposed methodology uses crop condition as the main indicator of the presence and severity of saline soils. Elevated levels of soil salinity will affect the growth of most crops as well as their appearance. This can be detected remotely using satellite imagery. By enhancing the image, we can separate the crop condition into several classes that we can then extract from the satellite image. Using spatially referenced ground data collected at the study area, we can relate each class in the satellite image to a level of soil salinity. We can use these classes to create a signature file and classify (supervised classification) other areas planted with the same crop.

In order to test the proposed methodology a field was selected for calibration of the satellite image and the methodology was then applied to other fields covered by the image. Soil salinity data was collected in the calibration field using both an EM-38 probe and the SIW Kit. The calibration was conducted during the middle of the summer, in July or August, when the crop was fully developed. The multi-spectral image used for this project was a 4 band (red, green, blue and near infrared) image with 4 m resolution from the Ikonos satellite.

We have collected over 100 soil samples with each sample being comprised of 4 depths (1, 2, 3, and 4 feet). After multiple iterations it was decided that a linear regression between the EM-38 vertical reading and EC_e provided the best match (Figure 1). From these data we developed the following regression model that converts EM-38 vertical readings into dS/m values:

F = (SStemp-25)/10
where: SStemp = temperature of soil sample measured in deg C

$A = 1-0.203462\ F + 0.038223\ (F^2) - 0.005554\ (F^3)$
SSTc = A * SStemp (where: SSTc = temperature correction factor)
$EM_{Vc} = EM_V * SSTc$ (where: EM_{Vc} = Temperature corrected EM-38 vertical reading)

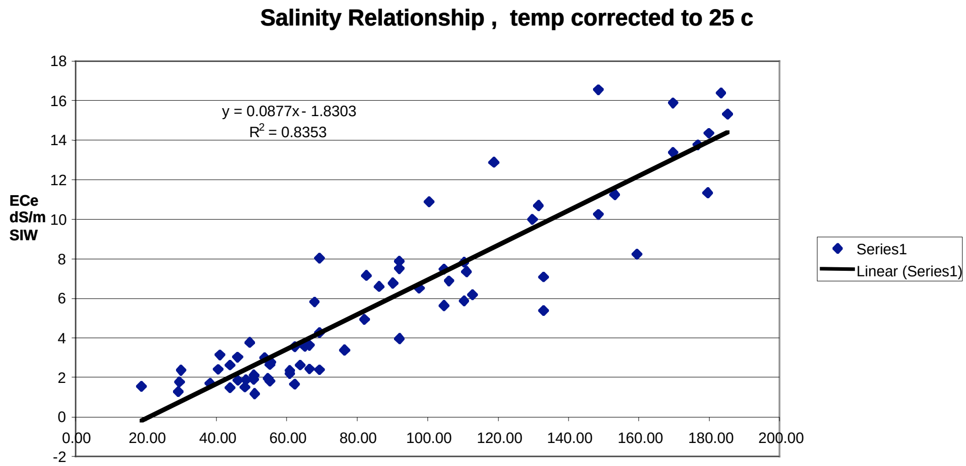


Figure 1. Regression equation relating EM_v and EC_e.

Study Field

Figure 2. Stu ... was taken

The field selected for cali ... il salinity values, ranging from less than 1 dS/m, which ... ch inflicts severe crop loss in corn. This variability was ... reflectance range for each salinity level within this fiel ... er fields in the study area. The selected field that fits thi ... fferent salinity levels were separated from this calibratio ... y linked the satellite image with the soil salinity data co ... M-38 and spatially located using a Global Positioning Sy ... ue, green and red bands in the satellite image, we selec ... onding to a different soil salinity level. Reflectance va ... ty points clustered around the 700 reflectance value, mo ... 400-500 reflectance value and the low salinity points mostly around the 200 reflectance value. The classified image was re-coded based on the soil salinity points obtained using the EM-38. This re-coding process was accomplished by spatially matching each image reflectance class with the soil salinity values. The sixteen reflectance classes are shown in Table 1.

Table 1: The sixteen reflectance/salinity classes obtained from the calibrated field

Class Num.	Num. Points	Min Value	Max Value	Mean (dS/m)	SD
1	7	0.0	1.3	0.8	0.40
2	24	1.8	6.0	3.3	1.24
3	35	1.0	6.6	3.1	1.24
4	59	1.3	9.7	3.8	1.50
5	61	1.7	6.7	4.5	0.94
6	36	1.4	7.0	5.2	0.97
7	32	3.5	7.7	5.5	1.12
8	19	3.1	7.3	5.7	1.15
9	27	3.2	7.4	6.0	0.97
10	25	3.8	9.2	6.2	1.22
11	15	2.3	8.0	6.2	1.46
12	15	4.3	10.4	6.6	1.31
13	25	1.3	10.1	6.7	1.98
14	48	4.7	10.6	7.4	1.19
15	56	4.3	11.0	8.1	1.37
16	18	7.2	11.4	8.8	1.24

To produce a model that can detect the above 16 classes, we used a subset from the data points collected with the EM-38. Using this subset we assigned each class a mean value of all the points associated with it, and then all classes were tested using another subset. The error between the measured and predicted soil salinity values for each class was calculated (Table 2), to cross validate within the field.

Table 2. Cross validation of the classes in the calibrated field

Training						Testing					
Class Num.	Points	Min	Max	Mean (dS/m)	SD	Class Num.	Points	Min	Max	Mean (dS/m)	Prediction Error (dS/m)
16	6	8	10	8.7	0.70	16	5	8	11	9.8	1.10
15	16	6	11	8.0	1.29	15	31	4	11	7.9	-0.07
14	21	6	10	7.5	1.10	14	16	6	11	7.6	0.06
13	6	6	9	7.7	1.24	13	13	5	10	6.8	-0.86
12	3	6	7	6.7	0.47	12	4	6	7	6.5	-0.16
11	5	5	8	6.0	1.00	11	7	6	10	7.0	1.00
10	15	4	8	6.0	1.20	10	8	5	7	6.0	0.00
9	8	4	6	6.0	0.70	9	10	5	8	6.0	0.00
8	10	4	8	5.7	1.25	8	15	5	10	6.0	0.30
7	10	4	7	5.7	1.10	7	8	4	7	5.7	0.00
6	20	4	10	5.4	1.60	6	16	3	9	5.5	0.10
5	29	3	6	4.3	0.89	5	28	2	9	4.8	0.50
4	26	1	6	3.4	1.30	4	26	1	6	3.5	0.10
3	22	1	7	3.1	1.40	3	13	2	5	3.1	0.00
2	16	2	4	2.8	0.60	2	11	3	4	3.0	0.20
1	4	1	1	1.0	0.00	1	2	1	1	1.0	0.00

The table shows that the maximum error was 1.1 dS/m and occurred in the extreme crop loss category. We since this area is mostly bare soil and lacks vegetation, our primary indicator. Other values of errors between the predicted soil salinity and the actual soil salinity were 10% or less.

Figure 3 shows the expected yield loss in corn due to soil salinity in relation to our sixteen classifications.

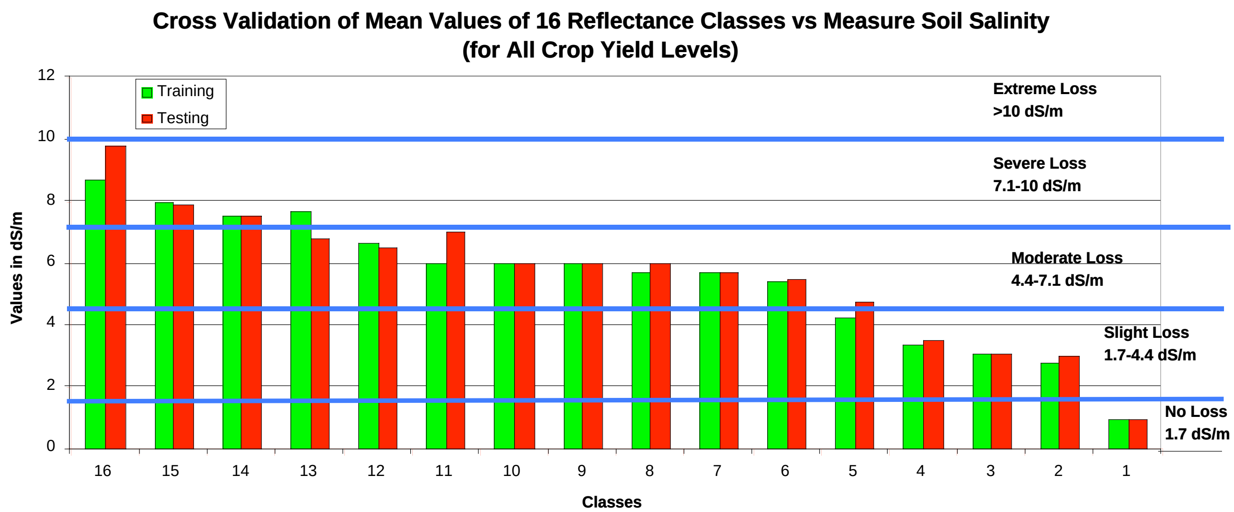


Figure 3: Graph of cross validation of mean values of 16 reflectance classes vs measure soil salinity in the calibration field (for all crop yield levels)

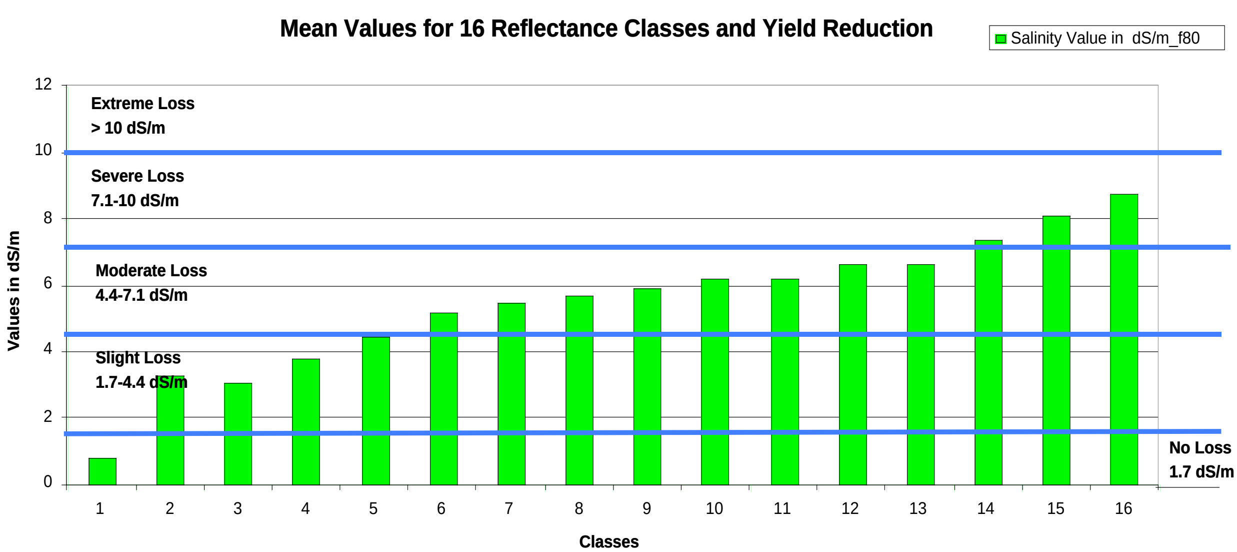


Figure 4. Mean values for the sixteen classes and their respective estimated yield losses in the calibration field

4 VALIDATING THE METHODOLOGY

To validate the methodology, an EM-38 was used to map soil salinity in another corn field, known as the RR field (Figure 5), that falls within the Ikonos calibrated image. In this validation field, EM-38 soil salinity measurements were taken using a differential GPS. The points were then overlaid on the classified image, and each class was compared to its mean to assess the prediction accuracy (Figure 6).

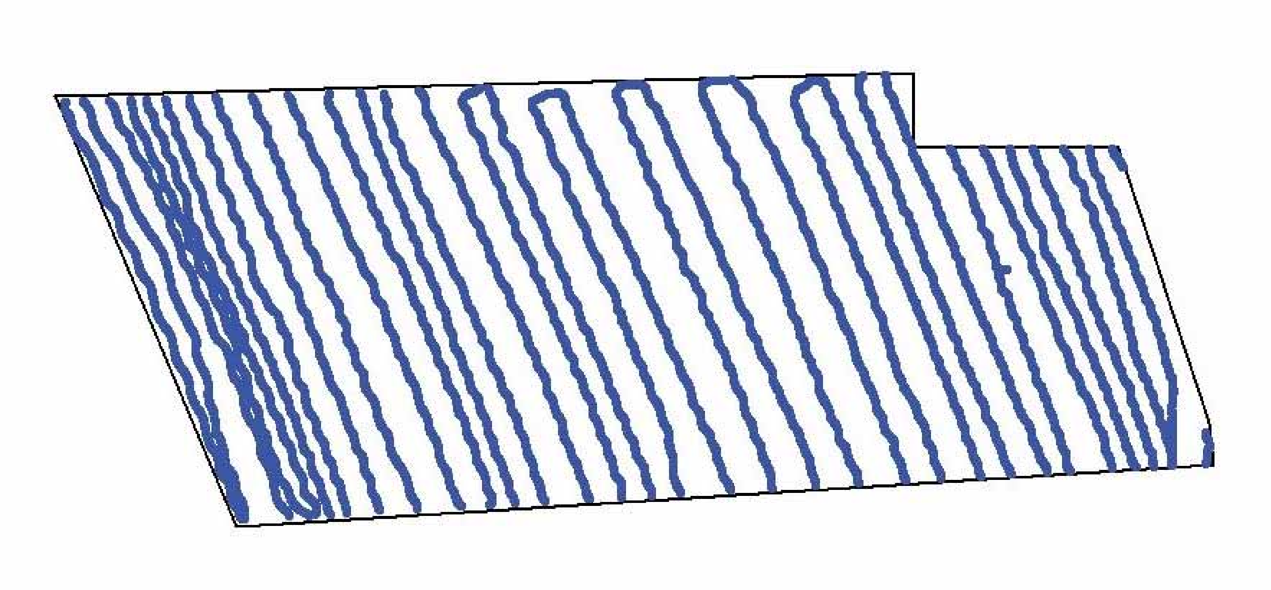


Figure 5. Soil salinity points in the RR field (validation field)

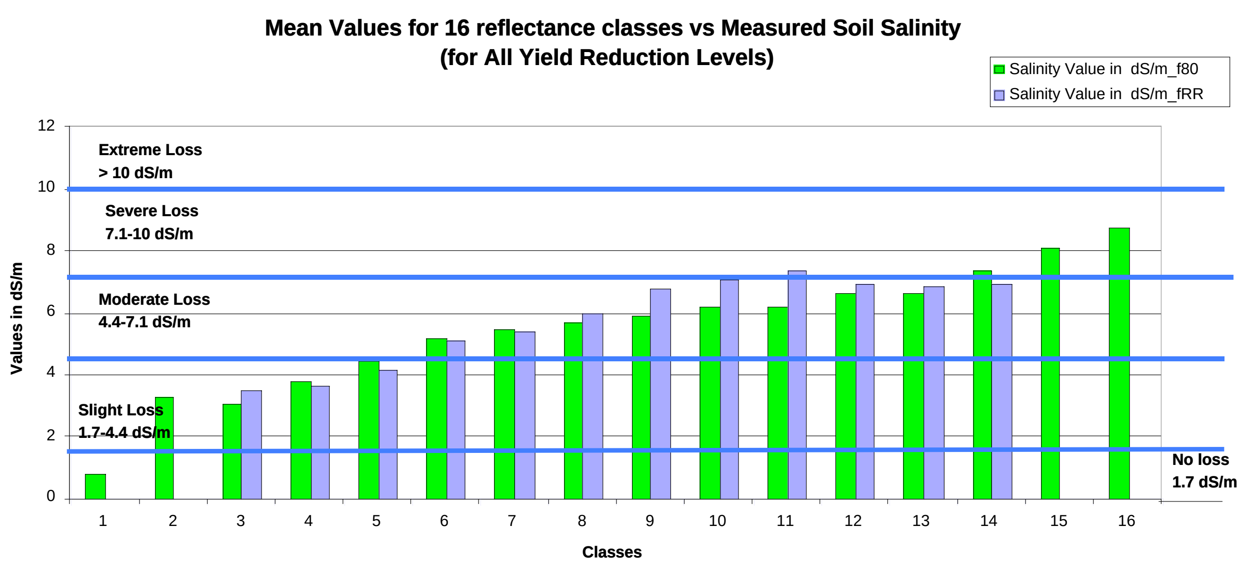


Figure 6. Measured soil salinity values versus predicted values in the validation field (RR)

Figure 6 shows that classes 1, 2, 15, and 16 were not represented in the RR field, so we were not able to evaluate the detection accuracy for these classes. Fortunately these four classes are in the no loss or severe loss categories. These categories are usually not as important during salinity evaluation since the categories 1 and 2 represent no salinity impact while categories 15 and 16 represent severe crop loss and very little crop might grow in these areas. Our model was able to separate and predict the other 12 classes with a range of errors from 1% to 12% and an average error of less than 5%.

Table 3. Predicted soil salinity values versus the measured values for the validation field RR*

Class Number	Predicted Value	Measured Value	Error
1	**0.8**	NA	NA
2	**3.3**	NA	NA
3	**3.07**	3.5	0.43
4	**3.8**	3.67	-0.13
5	**4.5**	4.2	-0.3
6	**5.2**	5.1	-0.1
7	**5.5**	5.4	-0.1
8	**5.73**	6	0.27
9	**5.95**	6.77	0.82
10	**6.24**	7.11	0.87
11	**6.2**	7.38	1.18
12	**6.64**	6.95	0.31
13	**6.65**	6.91	0.26
14	**7.35**	6.95	-0.4
15	**8.08**	NA	NA
16	**8.8**	NA	NA

*All values are in dS/m

5 ET BASED METHODOLOGY

In the previous approach we used image reflectance to evaluate the condition of the crop biomass and correlate it to soil salinity. The good performance of the model was partly due to the use of a high resolution image (4m). Using a different approach with lower resolution images (Landsat image (5 and 7) with 30 m pixels) we were also able to detect several levels of salinity. We compensated for the lower image resolution by taking into account another factor that is also sensitive to soil salinity: crop evapotranspiration (ET).

Crop ET can be estimated using satellite imagery by applying an Energy Balance approach. This approach uses the thermal information from the infrared band as well as the crop reflectance. Analyzing the image using the Energy Balance approach, yields a 30 m grid with each cell containing the crop ET information for a 24 hr period. We assumed that the plant's uptake of water would be affected by soil water salinity which is directly related to soil salinity. Geo-referenced soil salinity points were taken in five fields, and a preliminary linear correlation was made between the soil salinity measurements and the ET value at each point (Figure 7). The results are very promising: the root mean square error **(R)** was over **0.83.** This approach could be used to detect and evaluate soil salinity with acceptable accuracy for large areas at less cost than the first approach. We are continuing our research to determine the ET using remote sensing. Hence we expect to improve our ability to detect soil salinity using an ET based methodology.

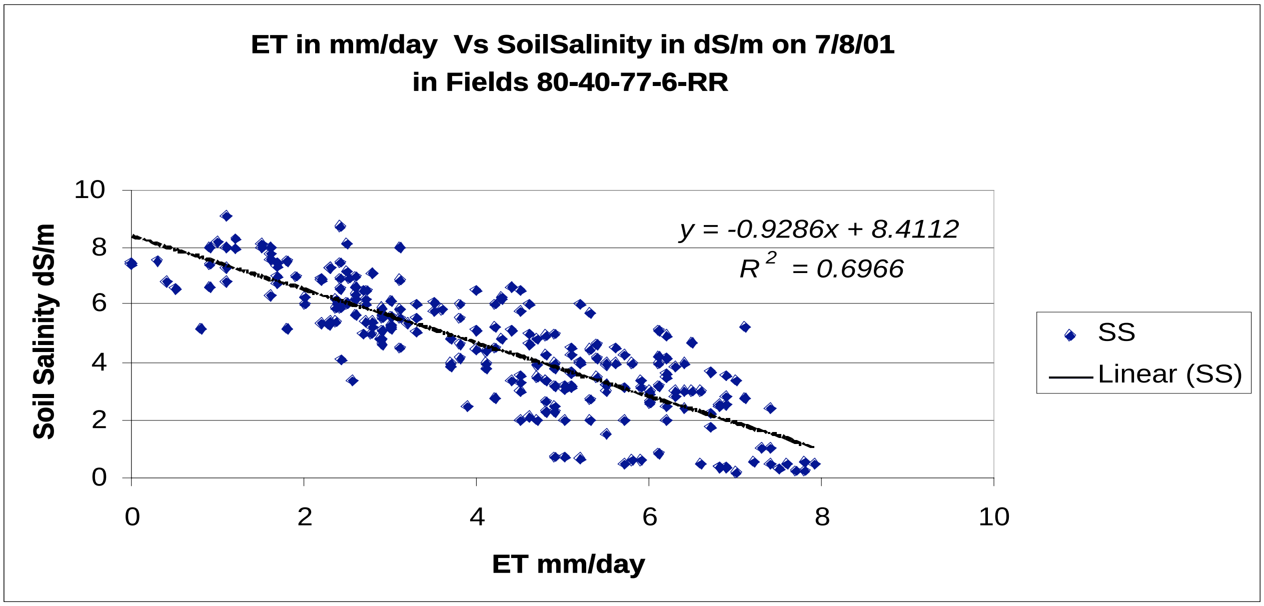


Figure 7. Corn ET in mm/day versus soil salinity (dS/m) for several fields on 7/8/01

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