Regional-scale Assessment of Soil Salinity in the Red River Valley Using Multi-year MODIS EVI and NDVI

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The ability to inventory and map soil salinity at regional scales remains a significant challenge to scientists concerned with the salinization of agricultural soils throughout the world. Previous attempts to use satellite or aerial imagery to assess soil salinity have found limited success in part because of the inability of methods to isolate the effects of soil salinity on vegetative growth from other factors. This study evaluated the use of Moderate Resolution Imaging Spectroradiometer (MODIS) imagery in conjunction with directed soil sampling to assess and map soil salinity at a regional scale (i.e., 10–10^5 km^2) in a parsimonious manner. Correlations with three soil salinity ground truth datasets differing in scale were made in Kittson County within the Red River Valley (RRV) of North Dakota and Minnesota, an area where soil salinity assessment is a top priority for the Natural Resource Conservation Service (NRCS). Multi-year MODIS imagery was used to mitigate the influence of temporally dynamic factors such as weather, pests, disease, and management influences. The average of the MODIS enhanced vegetation index (EVI) for a 7-yr period exhibited a strong relationship with soil salinity in all three datasets, and outperformed the normalized difference vegetation index (NDVI). One-third to one-half of the spatial variability in soil salinity could be captured by measuring average MODIS EVI and whether the land qualified for the Conservation Reserve Program (a USDA program that sets aside marginally productive land based on conservation principles). The approach has the practical simplicity to allow broad application in areas where limited resources are available for salinity assessment.

The mapping of soil salinity hazards across broad regional scales (10–10^5 km^2) remains a significant challenge to soil monitoring despite decades of research. The limited success achieved by past efforts can be traced to a combination of two factors. First is the high spatial and (in some cases) temporal variability of soil salinity, which limits the ability to interpolate between ground measurements taken at individual points in space and time. Second is the relative lack of skill of noninvasive, rapid measurement approaches that could provide more continuous spatial and temporal monitoring, such as those offered by satellite-based remote sensing instruments. There has been considerable success in using noninvasive, ground-based measures of apparent soil electrical conductivity (EC_a) to map salinity across individual fields, such as through electrical resistivity (ER), electromagnetic induction (EM), or time domain reflectometry (TDR) surveys (Corwin and Lesch, 2003), yet these methods are currently too time consuming to be applied cost-effectively at regional scales.

The challenges facing remote sensing of soil salinity are many, as discussed in several relevant review papers (e.g., Mougenot et al., 1993; Ben-Dor, 2002; Metternicht and Zinck, 2003). Most notably, although many surface salts can be readily detected in satellite data if the soils are sufficiently dry, there are few times of the year when these salts are present and not obstructed by overlying vegetation, particularly in cultivated soils that maintain active crops for much of the year and are commonly plowed in the off-season. Moreover, subsurface salinity is not always associated with visible surface salts. Monitoring of vegetation condition provides a potential alternative, as poor vegetation growth can be a proxy for high levels of subsurface salinity. This approach has indeed proved successful in some

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Abbreviations: EC, electrical conductivity (dS m^{-1}); EC_e, electrical conductivity of the saturation extract (dS m^{-1}); EC_a, apparent soil electrical conductivity (dS m^{-1}); EVI, enhanced vegetation index; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, normalized difference vegetation index; NRCS, USDA Natural Resource Conservation Service; RRV, Red River Valley.

cases (Wiegand et al., 1994, 1996; Madrigal et al., 2003), particularly when salinity values are so excessive that they cause a complete absence of vegetation. However, monitoring of salinity at more moderate values has proven much more difficult, even within small areas in which management is fairly uniform. Across the multitude of fields that comprise large regions, variations in management, pests, disease, climate, and other soil properties can have a far greater influence on vegetation than salinity, thus limiting the utility of vegetation mapping for salinity assessment.

Yet some promise is offered by two recent developments. First is the observation that using multiple dates of remote sensing data can reduce some of the error introduced by dynamic factors other than soil salinity, because these tend to fluctuate more through time than salinity. At any single point in time, one can consider crop biomass to be influenced by both salinity and nonsalinity factors:

$$Y_t = \alpha S_t + O_t \quad [1]$$

where Y_t represents crop biomass at time t, S_t represents soil salinity at time t, α is the effect of salinity on crop biomass, and O_t represents the net effect of all other factors at time t, such as management, climate, and soil properties other than salinity. As mentioned, these other factors will vary spatially and in most settings their effect will overwhelm the first term related to salinity. As a result, crop biomass at any single time will exhibit a relatively low correlation with salinity. As the other factors change each year, however, the "noise" from nonsaline factors (O_t) will diminish as one averages biomass across longer time periods, and the correlation between Y_t and S_t should strengthen. For example, Lobell et al. (2007) found very weak relationships between salinity and yields in individual years in the Colorado River Delta Region of Mexico, but much stronger correspondence between salinity and maximum yield over a 6-yr period. In Australia, Furby et al. (1995) reported large errors for a classification of saline soils when using a single year of Landsat imagery, because many areas of poor crop condition were incorrectly labeled as saline, but these errors were reduced from 20% to 2% by the addition of a second year of Landsat data.

A second encouraging trend is the increasing availability of long-term remote sensing records. Landsat archives date back to the late 1970s and as of 2008 are being distributed at no cost. For regional scales, the MODIS sensor has acquired coarser resolution (250 m compared to 30 m for Landsat) but more frequent (daily compared to every 16 d for Landsat) measurements of vegetation condition since late 1999, and is also freely available. MODIS data are also radiometrically and geometrically corrected before dissemination, which facilitates their use in both research and operational monitoring. However, to our knowledge MODIS has not yet been used for regional salinity assessment.

The promise offered by trends in remote sensing analysis and data availability justifies the continued evaluation of multi-year remote sensing for salinity assessments. One substantial challenge, however, in evaluating any remote sensing approach is the potentially large mismatch between scales of ground and satellite measurements. For example, soil cores are typically taken at the scale of a few square centimeters, while the resolution of a MODIS pixel is 62,500 m^2 (250 by 250 m). Direct comparison of ground measurements with values for a pixel surrounding the sample site can thus easily be misleading. Even if the remote sensing is perfectly measuring pixel average salinity it may poorly reproduce local values. Thus, one requires some information on the spatial heterogeneity of salinity within the scale of individual pixels for a proper evaluation of remote sensing capabilities. Furthermore, the number of ground measurements can be too labor and cost intensive to make a comparison between imagery and soil salinity practical even at a research level, particularly if a grid sampling design is used.

Contemporary soil salinity problems in the United States have been primarily associated with the irrigated lands of the arid southwestern United States, such as California's San Joaquin Valley and the lower Colorado River Basin, but the areas of dryland farming in the northern Great Plains such as the RRV are also a concern. Salinity in the northern Great Plains is primarily associated with saline seeps where shallow water tables and undulating topography create areas of recharge and associated down-slope areas of saline discharge (Brown et al., 1983). Concern over spatial and temporal change in soil salinity levels and extent in the RRV has increased over the past 15 yr due to a change in weather patterns, which has increased precipitation concomitantly raising water tables and salinity in the soil profile. The inventorying of soil salinity in the RRV is the responsibility of the National Cooperative Soil Survey, whose lead agency is the USDA-Natural Resource Conservation Service (NRCS). Soil salinity mapping of the RRV is a high priority concern of NRCS because information on salinity levels are used to determine eligibility for certain conservation programs, help implement appropriate management practices, and assess the value of agricultural land. The ability of NRCS to map soil salinity at the field scale is thus essential to meet their responsibility. Although many local NRCS staff suspect salinity is increasing in the RRV, understanding trends and quantifying the problem is difficult.

The goal of the current study is to test the utility of MODIS for mapping soil salinity in the RRV. A series of ground surveys were conducted in central and western Kittson County, Minnesota, to assess salinity at scales commensurate with MODIS data. Single and multi-year measures of vegetation condition from MODIS were then tested for their ability to map soil salinity. Although greater accuracy could potentially be obtained with higher resolution data, for instance using Landsat data as in Australia's "Land Monitor" program (Furby et al., 2010), we restrict the current analysis to MODIS measurements, in part because it represents an approach that could be easily scaled to larger regions without significant labor or cost requirements.

Materials and Methods

Site Description

The RRV, designated as Major Land Resource Area (MLRA) 56, stretches over about 17,000 km^2 from northeastern South Dakota through northwestern Minnesota and eastern North Dakota into southern Manitoba, ending at the southern end of Lake Winnipeg (Fig. 1). The area in the United States is principally located in Minnesota (57%) and North Dakota (43%), but a small portion (0.3%) extends into South Dakota. This MLRA mostly consists of a nearly level glacial lake plain that is bordered

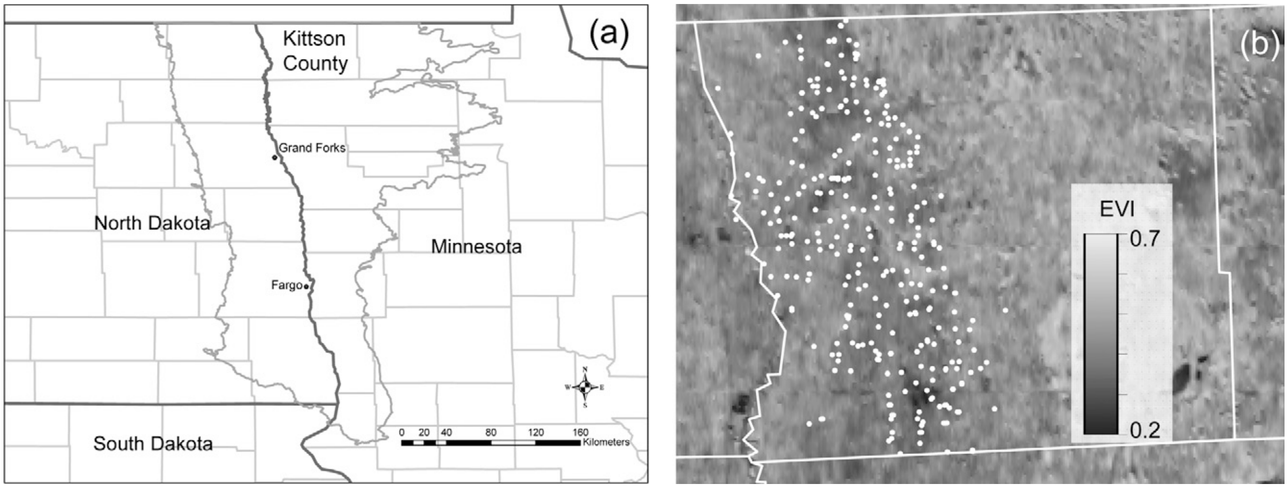

Fig. 1. (a) The Red River Valley study region. (b) Average MODIS EVI in summer (10 June–13 September) for 2000 to 2006 in Kittson County (outlined by white line). White dots show location of 313 sites that comprise the $EC_{pred,1:1}$ dataset. MODIS EVI refers to Moderate Resolution Imaging Spectroradiometer enhanced vegetation index.

by outwash plains, beach areas, and deltas. The elevation of the Red River falls about 70 m from its headwaters at the southern end (943 msl) to its mouth in the northern end, for an average slope of about one-half foot per mile. The Red River drains the valley, but has a poorly defined floodplain due to the flatness of the terrain. Streams entering the RRV are slow flowing and meandering, except where they have been channelized.

The original vegetation of the RRV was primarily tall bluestem prairie (*Andropogon gerardii* Vitm.), with cottonwood (*Populus deltoides*), willow (*Salix* spp.) and elm (*Ulmus* spp.) trees along streams and a savannah prairie forest mix on the eastern fringe. Nearly all this area is now in dryland farms, with spring wheat (*Triticum aestivum* L.), soybean [*Glycine max* (L.) Merr.], potato (*Solanum turberosum* L.), sugar beet (*Beta vulgaris* L.), and corn among the important crops. In Kittson County, Minnesota, the focus of the current study, harvested area for 2000 to 2006 averaged roughly 58,000 ha for spring wheat, 23,000 ha for soybean, 12,000 ha for sugar beet, and 7000 ha for alfalfa (*Medicago sativa* L.) (National Agriculture Statistics Service, 2008). The soil resources for Kittson County are described by Barron (1979)

The soils in the RRV represent some of the more saline soils in the United States, with the negative economic impact of salinity conservatively estimated at $50 million annually. An extensive evaluation of the salinity in the northern RRV (primarily Grand Forks County, North Dakota) was conducted by the USDA-ARS in 1960s (Benz et al., 1976). However, due to the cost and time associated with traditional ground surveys, soil salinity has not been consistently mapped within this area and an inventory of salinity for this MLRA is considered incomplete and out of date. Since 1993, in response to wetter weather patterns, areas of salt-affected soils are believed to have grown considerably in the region. Seasonal high water table, capillary rise, and geomorphic position are responsible for salinity increases in the rooting zone in many areas (Skarie et al., 1986).

MODIS Measurements

We used two common measures of vegetation condition routinely computed with MODIS data, the NDVI and EVI (Huete et al., 1999):

$$\mathrm{NDVI} = (\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}})/(\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}) \qquad [2]$$

$$\mathrm{EVI} = G\,(\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}})/\,(\rho_{\mathrm{NIR}} + C_1\rho_{\mathrm{RED}} - C_2\rho_{\mathrm{BLUE}} + L) \qquad [3]$$

where ρ_{NIR}, ρ_{RED}, and ρ_{BLUE} are MODIS measured reflectance in near-infrared, red, and blue wavelengths, respectively, and $G = 2.5$, $C_1 = 6$, $C_2 = 7.5$, and $L = 1$. The NDVI is a well-established and widely used measure of vegetation but is prone to contamination by variations in soil or aerosol reflectance and saturation at high levels of plant biomass. The EVI was recently designed to overcome some of these shortcomings, and thus provides a potentially more robust measure of vegetation activity (Huete et al., 2002).

Both NDVI and EVI were extracted from the MODIS product MOD13Q1 (Version 4), which provides 16-d composite values for both at 250 m resolution. The compositing procedure depends on the number of cloud-free days in the 16-d period, but generally seeks the maximum value for a nadir view angle over the period (MODIS, 2003). The algorithm also flags any values considered contaminated with clouds, and these were omitted for all subsequent analysis.

To measure vegetation condition during the main growing season, we averaged the vegetation indices for the six 16-d composites beginning on 10 June for 2000 to 2006. That is, for each of seven summers we computed the average NDVI and EVI for all values spanning the period 10 June–13 September. In rare pixels with one or two missing values during a summer, the average was computed for the four or five remaining values.

Field Measurements

To evaluate the value of MODIS for EC mapping, three different field datasets were used, each representing a different sampling design and thus a different tradeoff between the accuracy of individual samples and the total sample size. The first dataset was acquired during a field campaign in May 2006 aimed at mapping salinity distributions in fine and very fine textured soils (i.e., across approximately 85% of the county area) specifically using EVI readings. In this first study, the 7-yr averaged EVI data for the Kittson County area was used as a stratification variable during the field selection process. More specifically, all of the NRCS classified fine textured fields across the county were stratified into 20 ordered EVI classes and then one field from each class was randomly selected for EM surveying and soil sampling. The selected fields were intensively surveyed using a mobilized Geonics EM38 sensor (mounted on a nonmetallic sled and pulled through each field using an all terrain vehicle). The EM38 signal information was then analyzed using the ESAP software package (Lesch et al., 2000; Lesch, 2005) and six locations were selected in each field for soil sampling using a spatial response surface site selection algorithm (Lesch, 2005). In 19 of the 20 fields, six soil cores were then extracted from these sampling locations and electrical conductivity of the saturation extract (EC_e) was measured in the laboratory for 0 to 1.5 m (0–5 ft) depth at 0.3-m (1-ft) intervals. (In one field, only four locations were sampled.) Thus, these readings represent the most accurate measures of EC_a but cover a total of only 118 individual points from 20 fields.

The second and third datasets were derived from a multi-year NRCS soil salinity survey (spanning the spring seasons of 2004–2006) that measured EM for 410 transects throughout fine textured soils (% clay > 50%) of Kittson County. Most transects typically consisted of five survey positions, spaced approximately 15 m apart. Soil samples were collected at either one or two survey positions in each transect from three to four sampling depths; for example from 0 to 15, 15 to 30, 30 to 60, and 60 to 90 cm depths. Four depths were acquired in 2004, but beginning in 2005 the 0 to 15 and 15 to 30 cm intervals were combined into a single 0 to 30 cm depth sample (and samples were generally collected at only one survey position in 2005 and 2006). A total of 313 soil samples and 1474 individual EM readings were collected in this analysis across fine textured fields.

Due to both time and financial constraints, the soil samples were not analyzed directly for the traditional measure of salinity (EC_e) or the closely related EC of a saturated soil paste (EC_p). Instead, the temperature normalized EC of 1:1 soil/water extract ($EC_{(1:1)}$) were measured. Laboratory tests of 47 soil cores taken from 15 fields surveyed during this study revealed that nearly all of the analyzed soil samples exhibited saturation percentages (SP) within the range of 85 to 115%, and most fell within the range of 90 to 110%. $EC_{(1:1)}$ were therefore treated as equivalent to EC_p, and were then converted to EC_e using the equations of Rhoades et al. (1999). Predictions of EC_e were then compared to measured values of EC_e for the subset of 47 soils using a simple linear regression analysis. The fitted model produced intercept and slope estimates that were not statistically different from 0 and 1, respectively (F = 1.19, p = 0.341) and the predictions agreed very well with the measured values (**R^2 = 0.989, Root MSE = 0.13 dS/m**). Based on these results, the full set of depth specific $EC_{(1:1)}$ measurements were subsequently converted into EC_e readings using the Rhoades equation and then 0 to 0.9 m bulk average EC_e values were calculated at each of the 313 sampling locations. These 313 calculated EC_e values represent our second salinity data set.

Finally, predicted EC_e values were also estimated at all of the 1474 EM transect locations using a regression model fit to the 118 sites from the first data set. This regression model converted the temperature corrected EM38 transect survey readings into predicted salinity values via the following equation:

$$\ln(EC_e)_{0\text{–}1.5\text{m}} = -8.471 + 2.968[\ln(EM_V)] - 1.225[\ln(EM_H)] \quad [4]$$

The vertical (EMV) and horizontal (EMH) signal readings used in Eq. [4] were first temperature corrected to 25°C using the cubic polynomial temperature correction equation given in Rhoades et al. (1999). The natural log salinity predictions ($\ln(EC_e)_{0\text{–}1.5\text{m}}$) represent the 0 to 1.5 m bulk average values. As stated above, Eq. [4] was derived from a statistical analysis of the first data set (R^2 = 0.67); hence these soil salinity estimates (predictions) in our third data set are subject to a greater degree of uncertainty.

In short, the three datasets consisted of measured EC from saturated extracts, predicted EC from 1:1 solution extracts, and predicted EC from EM readings. We refer to these three datasets throughout the remainder of this paper as EC_{meas}, $EC_{pred,1:1}$, and $EC_{pred,EM,}$ with corresponding sample sizes of 118, 313, and 1474, respectively. As discussed above, the EC_{meas} and $EC_{pred,EM}$ data represent 0 to 1.5 m bulk average values, while the $EC_{pred,1:1}$ represent data acquired from the 0 to 0.9 m sampling depth.

Recall that MODIS measurements reflect the average characteristics of a 250 by 250 m pixel, and thus comparison with field measurements at individual points requires some assumption about how the two scales relate. One common approach is to simply assume homogeneity within each pixel, and thereby directly compare the field and satellite data. Here we compare that approach with one that uses spatial interpolation to estimate recalculated field data on a 250 by 250 m block support. Specifically, for $EC_{pred,1:1}$ and $EC_{pred,EM,}$ an ordinary kriging model was used with an isotopic exponential spatial variogram fit to the data. The resulting variograms were then used to generate 16 point kriging estimates of log salinity values on a 4 by 4 grid (spanning 250 by 250 m) at every MODIS location associated with a soil sample site. These 16 point estimates were then averaged at each site to produce the MODIS co-located 250 by 250 m block-kriging log salinity predictions.

For EC_{meas}, an ordinary kriging approach could not be used due to the clustered nature of the sampling design and substantial between-field variation present in the data. A spatial analysis of variance (spatial ANOVA) model was instead used to adjust for these field-specific log-salinity effects. A no-nugget, isotopic exponential covariance model was found to adequately describe the empirical spatial covariance structure of the ANOVA model residuals (from the 118 sampling locations associated with the 20 fields), and this fitted model was then used to generate log salinity predictions on a 4 by 4 grid at every MODIS location. These 16 point estimates were again averaged at each site to produce the MODIS co-located 250 by 250 m block-kriging predictions.

The final parameter estimates for the both the kriging and spatial ANOVA models were then estimated using restricted maximum likelihood (REML). All of the modeling analy-

Table 1. Summary statistics of salinity for three field-based datasets used in this study.

Dataset	Support	Mean EC_e†	Standard deviation	Median	Minimum	Maximum	Correlation between Point and Block Support (ln data)
		dS m^{-1}					
EC_{meas}	Point	4.4	4.3	2.3	0.5	19.9	0.92
	Block	4.0	3.8	2.3	0.6	12.5	
$EC_{pred,1:1}$	Point	3.6	3.5	2.3	0.1	17.4	0.95
	Block	3.1	2.5	2.2	0.3	10.8	
$EC_{pred,EM}$	Point	4.3	3.7	2.9	0.4	22.3	0.90
	Block	3.9	2.7	2.8	0.7	14.7	

† EC_e = electrical conductivity of the saturation extract (dS m^{-1}); EC_{meas} = dataset of size 118; $EC_{pred,1:1}$ = dataset of size 313; $EC_{pred,EM}$ = dataset of size 1474.

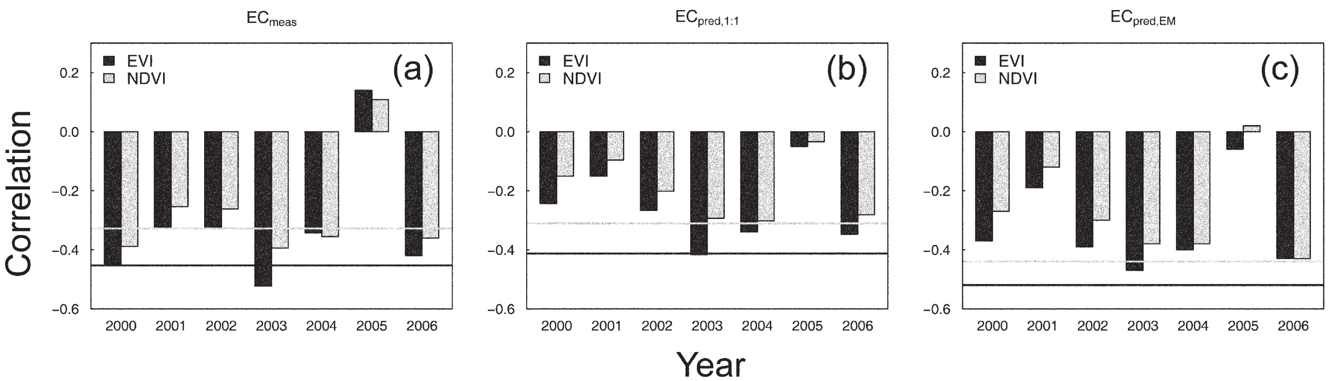

Fig. 2. Correlation between point estimates of ln(EC_e) and MODIS measurements of EVI and NDVI for (a) EC_{meas}, (b) $EC_{pred,1:1}$, and (c) $EC_{pred,EM}$ datasets. Horizontal line indicates the correlation of EC_e with EVI (dark) or NDVI (light) averaged over all years. EC_e = electrical conductivity of the saturation extract (dS m^{-1}); EC_{meas} = dataset of size 118; $EC_{pred,1:1}$ = dataset of size 313; $EC_{pred,EM}$ = dataset of size 1474; MODIS = Moderate Resolution Imaging Spectroradiometer; EVI = enhanced vegetation index; and NDVI = normalized difference vegetation index.

ses discussed above were performed using SAS (MIXED and KRIGE2D procedures).

Correlation and Regression Analyses

Values of NDVI and EVI were extracted for each pixel containing a field estimate of EC. Given the skewed distribution of raw EC values (see Results and Discussion), we follow the common approach of focusing correlation and regression analyses on the natural logarithm of EC, ln(EC), which exhibits a more Gaussian distribution. Pearson correlation coefficients were computed between ln(EC) and summer averages of each EVI in each year, as well as the average summer EVI over the 7-yr period.

In addition to the simple correlation analysis, we considered multiple regression models that contained an additional predictor variable ancillary to EVI. In particular, although we hypothesized that salinity would be an important factor influencing average vegetation condition over multiple years, and thus that the latter represents a useful proxy for the former, we recognized that average EVI's were also likely to be affected by the type of vegetation cover. Most notably, although most of the study region is planted with spring wheat or other annual crops, a significant fraction is enrolled in the Conservation Reserve Program (CRP). Lands enrolled in CRP are typically covered in a mix of perennial grasses and/or natural brush vegetation that may exhibit much different biomass and/or sensitivity to soil salinity than the commonly sown crops. Fortunately, data on the locations of CRP fields were available from the NRCS state GIS database. We therefore tested regression models that included both EVI and an indicator variable (IN_CRP) that had a value of 1 if the site was enrolled in CRP and a value of 0 otherwise (i.e., a "dummy" variable).

Results and Discussion

The ground-based estimates of EC are summarized for the three datasets in Table 1. All datasets contained a substantial fraction of points above 4 dS m^{-1}, reflecting the ubiquity of salinity problems in this region. The salinity distributions were all positively skewed, with a few high salinity values causing the mean value to be greater than the median. The EC estimates for a 250 by 250 m block support exhibited similar means but smaller variance than the point support, as expected since spatial averaging will tend to smooth extreme values. The correlations between point and block support exceeded 0.9 in all three datasets.

Comparison of the point ln(EC) estimates with co-located MODIS EVI and NDVI measurements revealed several interesting features (Fig. 2). First, EVI nearly always provided a larger absolute correlation than NDVI. This finding supports the notion that EVI represents a more robust measure of vegetation condition than NDVI, the latter being more sensitive to variations in soil and atmospheric conditions (Huete et al., 2002). Second, the correlations exhibit substantial variation depending on the year under consideration. Years such as 2003 exhibited relatively strong correlations while almost no relationship was evident in 2005. Thus, any effort to map salinity using remote measurements in a single year faces a significant risk of producing poor results. Third, and most importantly, the average of EVI over the 7 yr exhibited a relatively strong re-

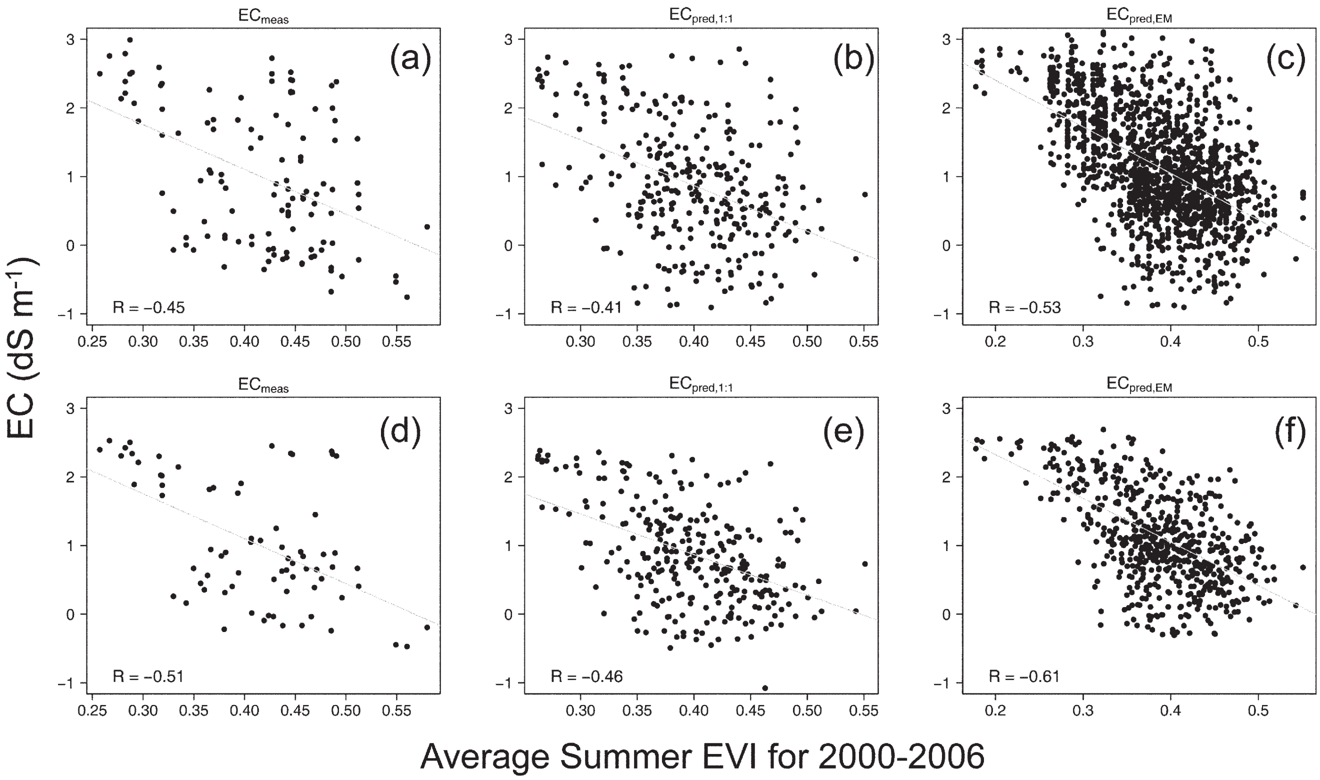

Fig. 3. Scatter plots of 2000 to 2006 average summer EVI from MODIS vs. ground estimates of EC_e at point (top) and block (bottom) support for EC_{meas}, (a,d), $EC_{pred,1:1}$ (b,e), and $EC_{pred,EM}$ (c,f) datasets. Numbers in lower left of panel give linear correlation coefficient. EC_e = electrical conductivity of the saturation extract (dS m^{-1}); EC_{meas} = dataset of size 118; $EC_{pred,1:1}$ = dataset of size 313; $EC_{pred,EM}$ = dataset of size 1474; MODIS = Moderate Resolution Imaging Spectroradiometer; and EVI = enhanced vegetation index.

Table 2. Summary of regression models using different predictor variables for three different datasets. In all cases, the response variable was $\ln(EC_e)$ at block (250 by 250 m) support. Enhanced vegetation index (EVI) corresponds to average summer EVI for 2000 to 2006, and IN_CRP indicates whether or not the site was enrolled in the Conservation Reserve Program.†

	Dataset					
	EC_{meas} (n = 118)		$EC_{pred,1:1}$ (n = 313)		$EC_{pred,EM}$ (n = 1474)	
Predictor variables	**Model R^2**	**RMSE**	**Model R^2**	**RMSE**	**Model R^2**	**RMSE**
Constant	0.00	0.90	0.00	0.72	0.00	0.65
Constant + EVI	0.26	0.77	0.21	0.64	0.37	0.52
Constant + IN_CRP	0.40	0.70	0.21	0.64	0.16	0.60
Constant + EVI + IN_CRP	0.53	0.61	0.34	0.58	0.41	0.50

† EC_e = electrical conductivity of the saturation extract (dS m^{-1}); EC_{meas} = dataset of size 118; $EC_{pred,1:1}$ = dataset of size 313; $EC_{pred,EM}$ = dataset of size 1474. RMSE = root mean square error.

lationship with ln(EC) in all three datasets. The absolute value of the correlation was close to or, in the case of $EC_{pred,EM}$, greater than that observed in the best single year. The hypothesis that averaging across years will tend to emphasize landscape features that are relatively stable in time (such as soil salinity), while averaging across more variable conditions that influence vegetation growth such as management and climate, thus appears supported by the data. If this hypothesis were not true, then one would expect to see the correlation between ln(EC) and average EVI to be roughly the average of the correlations found in each individual year, which was clearly not the case.

Thus, it appears that EVI is a more reliable indicator of salinity than NDVI, and that averaging over multiple years provides a more robust measure than most individual years. Even average EVI, however, was able to explain only roughly 25% of the variance in point estimates of $\ln(EC_e)$. Comparison of results using point and block estimates of $\ln(EC_e)$ (Fig. 3) suggest that part of the unexplained variance in point measurements arises from the scale differences between MODIS pixels and individual soil samples. That is, the correlations for all three datasets improved when using estimates of pixel average $\ln(EC_e)$ rather than the original point support field data. We therefore focus the discussion of regression results using $\ln(EC_e)$ at block support.

Predictions of $\ln(EC_e)$ using only average EVI resulted in R^2 of 0.21 to 0.37, depending on the dataset (Table 2). Adding a second predictor variable that identified whether or not the field was in CRP, significantly improved the model performance in all cases, raising the R^2 to 0.34 to 0.53. An interaction term for EVI × CRP was also evaluated but did not significantly improve any of the models. Thus, roughly one-third to one-half of the spatial variation in $\ln(EC_e)$ can be captured by measuring average MODIS EVI and whether the field is in CRP.

Conclusions

The results indicate that average summer vegetation condition, as measured by MODIS vegetation indices, provides a useful indicator of soil salinity levels in part of the RRV. When combined with information on whether lands are in CRP, multi-year averages of EVI were able to explain one-third to one-half of field-measured variations in salinity across Kittson County. We find that multi-year averages of EVI performed significantly better than most individual years, supporting the hypothesis that factors affecting vegetation other than salinity tend to exhibit more variable spatial patterns from year to year. The evidence also suggests that in comparison with NDVI, EVI is a more reliable measure of vegetation condition, and thus salinity, in this region.

This is the first study to our knowledge to use MODIS for assessment of soil salinity. Future work is needed to test whether this approach works well in parts of the RRV outside of Kittson County, as well as in other regions. Additional variables will also likely be considered in future work to improve the yield predictions, with information on surface hydrology and depth to groundwater two potentially useful variables. Cropping history patterns, derived either from remote sensing or ground surveys, fine scale elevation data, and soil type classifications may also prove useful. Finally, incorporation of finer resolution measures of vegetation, such as the 30 × 30 m resolution Landsat data employed by Furby et al. (2010), could improve results, although the improvement would have to be weighed against the substantially greater processing times and operational costs associated with finer resolution data.

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