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Identification of saline soils with multi-year remote sensing of crop yields

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ABSTRACT

Soil salinity is an important constraint to agricultural sustainability, but accurate information on its variation across agricultural regions or its impact on regional crop productivity remains sparse. We evaluated the relationships between remotely sensed wheat yields and salinity in an irrigation district in the Colorado River Delta Region. The goals of this study were to (1) document the relative importance of salinity as a constraint to regional wheat production and (2) develop techniques to accurately identify saline fields. Estimates of wheat yield from six years of Landsat data agreed well with ground-based records on individual fields (R^2 = 0.65). Salinity measurements on 122 randomly selected fields revealed that average 0-60 cm salinity levels > 4 dS m^{-1} reduced wheat yields, but the relative scarcity of such fields resulted in less than 1% regional yield loss attributable to salinity. Moreover, low yield was not a reliable indicator of high salinity, because many other factors contributed to yield variability in individual years. However, temporal analysis of yield images showed a significant fraction of fields exhibited consistently low yields over the six year period. A subsequent survey of 60 additional fields, half of which were consistently low yielding, revealed that this targeted subset had significantly higher salinity at 30-60 cm depth than the control group (p = 0.02). These results suggest that high subsurface salinity is associated with consistently low yields in this region, and that multi-year yield maps derived from remote sensing therefore provide an opportunity to map salinity across agricultural regions.

Abbreviations: ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; ECa, apparent soil electrical conductivity; ECe, electrical conductivity of a saturated soil extract; $EC_{e,0\text{-}60}$, average ECe for 0-60 cm ; $EC_{e,0\text{-}90}$, average ECe for 0-90 cm; ETM+, Enhanced Thematic Mapper Plus; fAPAR, the fraction of absorbed photosynthetically active radiation; GLASOD, Global Assessment of Human-induced Soil Degradation ; NDVI, normalized difference vegetation index; rmse, root mean squared error; SAGARPA, Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación; TM, Thematic Mapper;

INTRODUCTION

Accumulation of salts in irrigated soils has represented an important threat to agriculture throughout human history (e.g., Hillel, 1991). Presently, roughly 20% of irrigated agriculture worldwide is thought to be negatively affected by salinization (Ghassemi et al., 1995). However, large scale assessments such as GLASOD (Oldeman et al., 1990) typically rely on expert judgments from individual countries or regions, and are therefore "qualitative and (potentially) subjective" (description of GLASOD project available at http://www.isric.nl/). As Lal et al. (2004) point out, "Despite its significance, the available information on soil degradation is often based on reconnaissance surveys, public opinion, extrapolations based on sketchy data, and casual observations by interested travelers (p. 24)."

Improved inventories of the extent and impact of salinity in agricultural lands are needed to more accurately assess the threat of salinization and to guide management decisions and remediation efforts that can reduce productivity losses. The lack of objective, quantitative data reflects the difficulty of acquiring such information, in large part because of the high degree of spatial and temporal heterogeneity of soil salinity. Major advances have been made in the development and application of ground sensors that can rapidly measure ECa (an excellent review is provided by Corwin and Lesch, 2003). ECa measurements are often highly correlated with variations in ECe, in particular when soil moisture is near field capacity (Lesch and Corwin, 2003), thereby allowing one to map soil ECe with non-invasive techniques. ECa sensors are thus invaluable tools for mapping salinity within individual fields, but their ability to provide a comprehensive, regional view of salinity's extent and impact remains limited because of the time and expense required for each individual ECa survey.

Satellite-based remote sensing has been widely explored as an alternative to direct field sampling because of its potential to cover large areas repeatedly through time. However, these efforts have seen limited success due to a range of factors, as reviewed by Metternicht and Zinck (2003). Approaches to detecting salinity with remote sensing can be classified as either direct, in which the reflectance of bare soil itself is evaluated, or indirect, in which vegetation type or condition is used as an indicator of salinity (Metternicht and Zinck, 2003). Successful application of the direct approach using optical remote sensing data requires low soil moisture, a high percentage of exposed bare soil, and little variation in soil surface roughness due to factors other than salinity, such as cultivation. In agricultural regions, all of these conditions are difficult to obtain because of the predominance of crop and residue cover and the high spatial variability of management practices.

Alternatively, several studies have investigated the use of remotely sensed indicators of canopy condition, such as the NDVI, to map soil salinity (Madrigal et al., 2003; Wiegand et al., 1996; Wiegand et al., 1994). However, these approaches generally assume that salinity is the only factor affecting crop condition, and therefore will only be successful in situations where other factors are held constant (for instance by looking at variations within an individual field with fixed management) or where salinity has an extremely large impact on crop condition.

Given the shortcomings of traditional direct and indirect methodologies, we sought to develop and test a new indirect approach that is useful under a broader range of realistic agricultural settings. Rather than consider crop condition for any single date or growing season, we utilized maps of crop yields for multiple years derived from satellite data. Comparison of field measurements of salinity with remotely sensed yields was used to evaluate the degree to which salinity is predictable from single year and multi-year yield maps. The comparison of salinity with yields also provided insight into the overall impact of salinity on regional production.

METHODS

Site Description

The San Luis Rio Colorado Valley (SLRCV) in Sonora, Mexico, is situated at the mouth of the Colorado River just south of the United States border (32.4º N, 114.8º W; Figure 1). The Valley consists of roughly 27,000 irrigated Ha, sown predominantly to wheat (*Triticum aestivum*) and a mix of vegetable crops. This study focused on the most northern of three irrigation districts in SLRVC, which covers roughly 13,000 ha. The

SLRCV lies within a region classified in GLASOD as having strong (not reclaimable) degradation from salinization, but with infrequent extent (<5% of area; Oldeman et al., 1990). In contrast, local researchers often identify salinization as one of the most important constraints to crop production, with some reporting that up to 47% of land in this region is affected by salinity (López 2001).

Wheat in SLRCV is typically planted in late fall (Nov-Dec) and harvested in spring (Apr-May). Farmers normally apply one pre-plant and four auxiliary irrigations in a traditional basin irrigation system where wheat is planted as a flat, solid stand. The irrigation water for the entire SLRCV district is derived from a roughly equal fraction of surface and groundwater sources, although this fraction varies considerably throughout the region (López, 2001). Typical fertilizer rates are 250 kg N and 50 kg P ha^{-1}, and yields average 6.0 – 7.5 ton ha^{-1}, depending on year. Soils in this region are classified as Vertic Haplocalcids.

Remote Sensing Analysis

A combination of ASTER, Landsat TM, and ETM+ images was acquired for each of the six growing seasons of wheat from 2000 – 2005 (Table 1). These images were first converted to top of atmosphere reflectance using standard sensor calibration values (Irish, 1999) and georeferenced to within 30 m. The ratio of near-infrared to red reflectance (i.e., Landsat band 4 / band 3), which is positively correlated with vegetation abundance (Tucker, 1979), exhibited a bimodal distribution for most images. A simple threshold applied to each image therefore provided an indicator of pixels with active crops (Lobell et al., 2003). Pixels that contained active crops in all images acquired during the wheat growing season were identified as wheat. To validate this approach, the area of pixels identified as wheat was summed over the irrigation district and compared with official area reports from SAGARPA (Secretaría de Agricultura, 2005), revealing errors below 2% in all but one year and an rmse of just 2.4% (Table 2).

Yields were estimated for each wheat pixel using the technique of (Lobell et al., 2003), which is based on a simple light-use efficiency model. Briefly, fAPAR is estimated from reflectance values in each Landsat image using previously established relationships (e.g., Los et al., 2000). Values of fAPAR are then interpolated for each day during the growing season using a pre-defined, temperature-based phenology model, and the daily fAPAR values are multiplied by incident radiation measured at a local meteorological station to estimate total light absorption throughout the growing season. Values for light-use efficiency and harvest index (the ratio of grain to aboveground biomass), based on field data, are then used to translate light absorption into estimates of wheat yields. This approach has been successfully applied in the Yaqui Valley, another wheat region in Sonora, Mexico (Lobell et al., 2003; Lobell et al., 2005).

Despite the previous validation in a region with similar characteristics, we sought to independently evaluate the wheat yield estimates in SLRCV. Ground-based measurements of field-averaged yields across a commercial landscape inevitably requires the reliance on farmer records of grain harvests. This is especially true when attempting to validate yield estimates for prior years. As a result, substantial errors in “ground-truth” yields may exist because of inaccuracies in farmer reports. We obtained records from local credit unions that contained farmer reported yields for three years: 2000, 2002, and 2005. Any yields below 3 ton ha^{-1} or above 9 ton ha^{-1} were deemed unreliable and were omitted from comparison with remote sensing estimates. In addition, the locations of some fields were ambiguously identified, and these were therefore also omitted. A total of 43 farmer-reported yield values remained for validation.

Soil Sampling

This study consisted of two primary field campaigns. In January 2005, an exploratory survey was conducted where soil samples were taken from 122 randomly selected fields in the irrigation district. The main goal of this survey was to document the distribution of salinity values within SLRCV and compare salinity levels to remotely sensed yields. Soil cores were taken at random locations within each of four quadrants of each field, and then combined to produce a single field sample for 0-30cm and 30-60cm. The stratified random sample (with n = 4) was based on measurements of within field heterogeneity of salinity for ten fields (Lobell, unpublished data), which indicated that this approach would result in estimates of ECe with rmse < 0.5 dS m^{-1}.

A second, targeted field campaign was conducted in September 2005 and May-June 2006. Based on the observed relationships between ECe and wheat yields (see below), we hypothesized that fields with consistently low yields were more likely to contain high ECe. To test this hypothesis, a stratified random sample was collected. All pixels were first classified into two groups: (1) those that had wheat in at least five of the six years and whose yields were always below the 80th percentile of yields, and (2) all other pixels. Thirty fields were randomly selected from each group, forming a “target” and “control” sample. Due to logistical constraints, twenty fields (ten from each group) were visited prior to planting of the 2005-2006 wheat crop (in September) and another forty fields were sampled after harvest (May-June). Samples were collected for three depths: 0-30 cm, 30-60 cm, and 60-90 cm.

RESULTS AND DISCUSSION

Yield Estimation

The yield estimates from remote sensing agreed reasonably well with farmer-reported values, with 65% of the variance explained and most values falling near the 1:1 line (Figure 2). As discussed above, the farmer-reported values represent an independent estimate of yields but are not without error. Unfortunately, a reliable estimate of the rmse between farmer-reported values and actual yields is not available, as it would require an extensive effort to measure harvests in each field. The agreement with the remotely sensed estimates nonetheless gives confidence that remote sensing measurements provide a reliable indicator of wheat productivity in this region.

Salinity Survey

Measured values of ECe in the January survey are shown in Figure 3 and Table 3. Of the 122 surveyed fields, 10 had average 0-60 cm values above 3 dS m^{-1}, and only two were above 4 dS m^{-1}. Salinity values generally increased with depth (Table 3), suggesting that average salinity in the entire root zone, which extends to roughly 1 m, was likely higher than averages for the top 60 cm. Indeed, measurements from the second survey, when depths of 60-90 cm were sampled, showed that ECe for 0-60cm and 0-90 cm were highly correlated and could be related by the equation:

$$EC_{e,0\text{-}90} = 1.05 * EC_{e,0\text{-}60} - 0.08, \qquad R^2 = 0.96 \qquad [1]$$

Thus, values of 3.0 and 4.0 dS m^{-1} for 0-60 cm salinity correspond roughly to 3.1 and 4.1 dS m^{-1}, respectively, for 0-90 cm.

Using the standard threshold of 4 dS m^{-1} for defining a field as saline (Hillel, 1998), only one out of 122 fields was technically saline for 0-30 cm, although nine exceeded this threshold for 30-60 cm. Moreover, wheat is classified by the USDA Salinity Laboratory as a salt tolerant crop and is commonly believed to show negligible yield response up to 6 dS m^{-1} (Maas and Hoffman, 1977), a value exceeded by only one field for 30-60 cm and none for 0-30 cm. The field salinity measurements, combined with standard criteria for salinity classifications, thus suggest that salt-related yield losses in this region are currently rare.

Salinity-Yield Relationships

As soil samples were acquired during the 2005 season, we first compared soil ECe with yields from this season alone (Figure 4a). (Because fields were selected randomly without regard to crop type, only 72 of the 122 sampled fields had wheat in 2005.) Salinity at 0-30cm and 30-60cm both were weakly related to yields, although all fields near or above 4 dS m^{-1} in average 0-60cm salinity exhibited relatively low yields. Interestingly, average yields exhibited a slight decline with increased salinity even at fairly low ECe (Figure 4). This suggests that the threshold model of salinity response may be an over-simplification (Katerji et al., 2003), and/or that fields with an average ECe of, e.g., 2 dS m^{-1} are more likely to have parts of the field above critical salinity levels than fields with lower average ECe. In either case, the effect of salinity appears only minor until average ECe exceeding 4 dS m^{-1}. This, combined with the fact that few fields exceeded ECe of 4 dS m^{-1}, confirms the notion that salinity has an overall small impact on regional wheat productivity. For example, the average yield estimate for fields with ECe < 1 dS m^{-1} was 6.77 ton ha^{-1}, while the average for all surveyed fields was 6.72 ton ha^{-1}. If one assumes that salinity is uncorrelated with other factors that affect yields, than the regional yield loss due to salinity in this region was just 0.8% in 2005.

Figure 4 also clearly illustrates that low yields were not a reliable indicator of high salinity, since many low yielding fields had low values of EC_e. This is consistent with the notion that salinity is just one of many factors that can reduce yields. In this region, it appears that factors unrelated to ECe are the predominant cause of low yields in any single year. However, if these other factors were associated with management practices or weather conditions that varied from year to year, and salinity levels are assumed to be fairly stable over a five year period, then one would expect multi-year yield statistics to provide more reliable indicators of soil salinity.

Unfortunately, the low number of fields exceeding 4 dS m^{-1} in the January survey prohibited a reliable estimate of multi-year statistics for high salinity fields. As an alternative way to test the hypothesis that saline fields result in consistently low yields, we computed the proportion of fields that exhibited consistently low yields and compared it with the proportion expected by chance. If the former is significantly larger than the latter, then the presence of a factor that consistently suppresses yields is indicated.

For example, Figure 5 shows the proportion of image pixels (out of those that had wheat in all six years) that were above a specified yield threshold for 0, 1, 2, 3, 4, 5, and 6 years. Since the average yield varied between years, yield images for each year were converted to percentiles instead of yields, with 0% and 100% corresponding to the minimum and maximum estimated yield throughout the Valley for each year. The null distribution (i.e. the number of pixels, x, expected by chance) was calculated based on the binomial distribution:

$$p(X = x) = {}_{n}C_{x} \, (1-p)^{x} \, p^{(n-x)} \qquad [2]$$

where p is the threshold used. Figure 5 shows the observed and null distribution for p = 50% and p = 80%. In both cases, significantly more pixels were observed to exceed the threshold in 0 years than expected by chance, indicating the presence of a consistent, yield-suppressing factor. For example, roughly 39% of pixels never exceeded 80%, whereas only 26% of such pixels were expected by chance. While it is, of course, possible that factors other than salinity, such as poor management, contribute to consistently low yields, the high proportion of consistently low yielding fields suggests that this multi-year statistic provides useful information on some yield controlling factor(s), which may or may not include salinity.

Targeted Field Sample

To further test the hypothesis that multi-year yield statistics can be used to identify saline fields, measured ECe for the “target” and “control” groups in the second survey were compared (Table 4, Figure 6). The distribution of ECe within each group were generally not Gaussian (Figure 6), and therefore the non-parametric Mann-Whitney test was used to test differences in salinity distributions between groups. Average ECe in the targeted group were higher than the control at all depths, consistent with the hypothesis that consistently low yields indicate the presence of elevated salinity levels. These differences were not statistically significant at 0-30 cm depth ($p = 0.27$), but were highly significant at 30-60 cm ($p = 0.02$) and moderately significant for 0-60 cm and 30-90 cm average salinities ($p < 0.10$). Significance at 60-90 cm ($p = 0.13$) was lower than for 30-60 cm but higher than for 0-30 cm.

Two reasons likely explain the unique importance of salinity at 30-60 cm for wheat yields in this region. First, salinity values at 0-30 cm depth were generally lower than at 30-60 cm and almost always below 4 dS m^{-1} (Figure 6). Values at 30-60 cm, in contrast, were more frequently above 4 dS m^{-1}, and thus more likely to exert an influence on crop growth. Values at 60-90 cm also commonly exceeded this threshold; however the fraction of wheat roots reaching below 60cm is typically much smaller than the fraction found at 30-60 cm (Manske and Vlek, 2002). Thus, 30-60 cm represents an overlap between depths of relatively high salinity (below 30 cm) and depths of significant amounts of wheat roots (above 60 cm).

The importance of 30-60 cm salinity illustrates that measures of surface salinity, such as those made with the direct remote sensing techniques discussed in the Introduction, may be of limited relevance to crop production even if they are perfectly accurate. Indirect methods that rely on measures of crop stress, such as the approach presented here, may therefore provide more reliable indicators of crop-relevant salinity. This conclusion, though, may depend on region-specific cropping patterns, salinity levels, and correlations between 0-30 cm and 30-60 cm salinity values,

SUMMARY AND CONCLUSIONS

Given the difficulty of assessing soil salinity and its impact on productivity at the regional scale using traditional approaches, we evaluated the potential contribution of yield datasets derived from remote sensing. Remote sensing allows a fairly rapid and accurate assessment of wheat yields at hundreds of individual fields through time, a dataset that would be very difficult to obtain by other means. Comparison of yields with salinity measurements acquired randomly throughout the region revealed a very small impact of salinity on regional wheat production. The low frequency of EC_a values exceeding 4 dS m^{-1}, the relative tolerance of wheat to salinity, and the presence of other factors that reduce yields combine to explain the insubstantial effect of salinity on production in this region. It is possible that remotely sensed yield or biomass estimates for other crops, such as alfalfa or vegetables, which are more sensitive to salinity would present greater correlations with salinity. However, the area surveyed using these crops would be significantly smaller.

A previous study (Madrigal et al., 2003) reported much stronger relationships between wheat yields and salinity in a nearby region in Northwest Mexico than found here. The authors then used this correlation along with NDVI images to calculate that 58% of soils were salt-effected. However, their training sample was not obtained randomly, but rather by selecting areas with visible salinity problems. This led, for instance, to the inclusion of EC_a values as high as 20 dS m^{-1} in the training set. While this approach may be useful for investigating yield responses to high levels of salinity, their implicit assumption that the training set was representative of the entire region was unjustified. As shown in the current study, many factors other than salinity contribute to yield losses throughout an entire agricultural region, and yields in a single year therefore do not generally provide a reliable predictor of soil salinity.

Based on the hypothesis that yield-reducing factors other than soils will tend to vary between years, we evaluated the use of multi-year yield images to identify problem areas. Samples acquired on consistently low yielding fields exhibited significantly higher salinity levels at 30-60 cm depth, indicating that sub-soil salinity affects wheat yields in this region. The use of multi-year statistics therefore appears promising for identifying saline hotspots, although additional work is needed to test this approach, particularly in regions where salinity is a more common problem in crop productivity. Any increase in the efficiency and accuracy of salinity surveys would be a welcome advance, given the tremendous expense and difficult of regional salinity mapping with solely ground-based methodologies.

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FIGURE LEGENDS

1) The San Luis Rio Colorado Valley study region, as seen in band 3 of a Landsat TM+ image from Mar 31, 2002. Pixels with wheat appear dark in this image. Locations of field samples in surveys are also shown.

2) Comparison of image-based yield estimates with farmer reported yields for 43 fields.

3) Histograms of field average soil electrical conductivity (dS m^{-1}) at depths of 0-30 cm and 30-60 cm.

4) Comparison of soil electrical conductivity (dS m^{-1}) measured in January 2005 at (a) 0-30 cm (b) 30-60 cm and (c) 0-60 cm with image-based yield estimates for 2005.

5) Histograms of the number of years a pixel exceeded the 50^{th} (a) and 80^{th} (b) percentiles of yield in SLRCV (black lines). Only pixels with yields in all six years were included in histogram. Dashed gray lines shows null distribution expected for random yield variations. Significantly more fields than expected by chance were never above the given yield percentiles, suggesting the existence of factors that consistently suppress yields.

6) Histograms of field average soil electrical conductivity (dS m^{-1}) at depths of 0-30 cm, 30-60 cm, and 60-90 cm for 30 randomly chosen fields (left) and 30 “targeted” fields (right), which had remotely sensed yields always below the 80^{th} percentile.

Table 1. Images used for wheat area and yield estimation in each harvest year.

Harvest Year	TM Images	ETM+ Images	ASTER Images
2000		Feb 22, Apr 10	
2001		Jan 23, Mar 28	
2002		Feb 11, Mar 31	
2003		Jan 29	Apr 4
2004	Feb 9, Mar 28		
2005	Feb 27, Mar 31		

Table 2. Comparison of wheat area estimates from remote sensing with reported wheat area from SAGARPA.

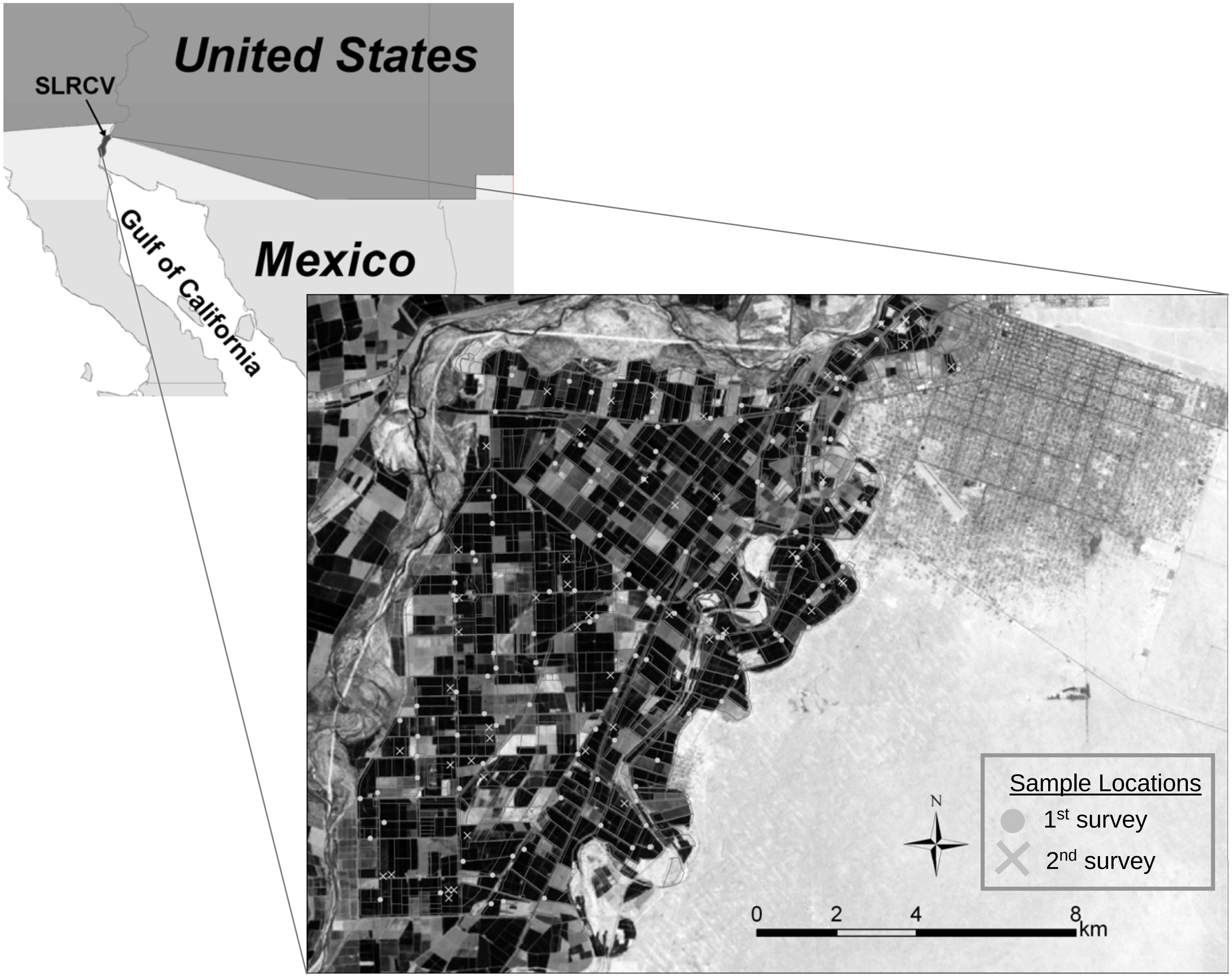
	Harvest Year					
	2000	2001	2002	2003	2004	2005
Reported Area (Ha)	16,250	17,000	16,224	16,809	16,159	14,155
Estimated Area (Ha)	16,549	17,063	16,073	15,895	16,288	14,306
% Difference	1.8	0.4	-0.9	-5.4	0.8	1.1

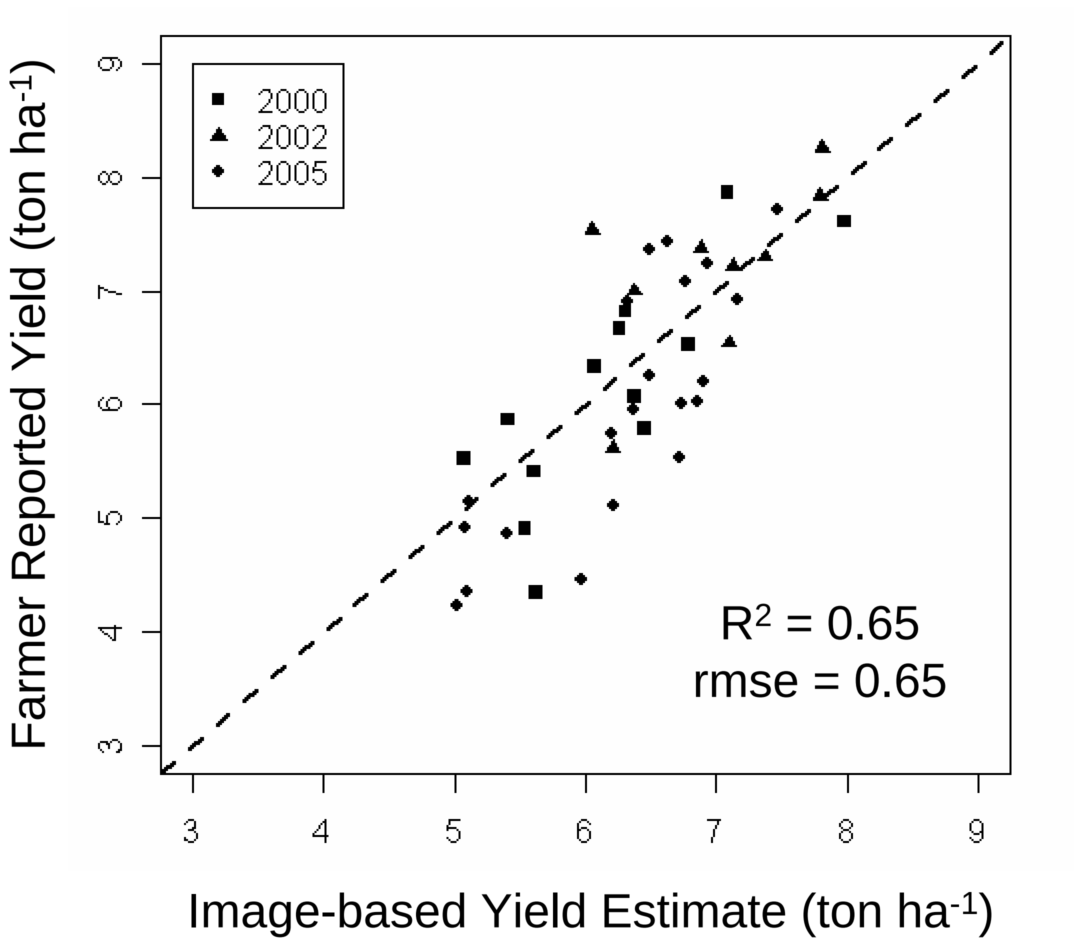
Table 3. Summary statistics for ECe (dS m^{-1}) and pH in January soil samples (n = 122).

	mean	Standard deviation	Percentiles				
			0	25	50	75	100
ECe, 0-30 cm	1.42	0.72	0.40	0.97	1.26	1.71	4.58
ECe, 30-60 cm	1.90	1.18	0.37	1.17	1.61	2.17	8.86
ECe, 0-60 cm	1.66	0.91	0.46	1.11	1.44	1.95	6.72
pH, 0-60 cm	7.63	0.22	7.05	7.49	7.61	7.78	8.19

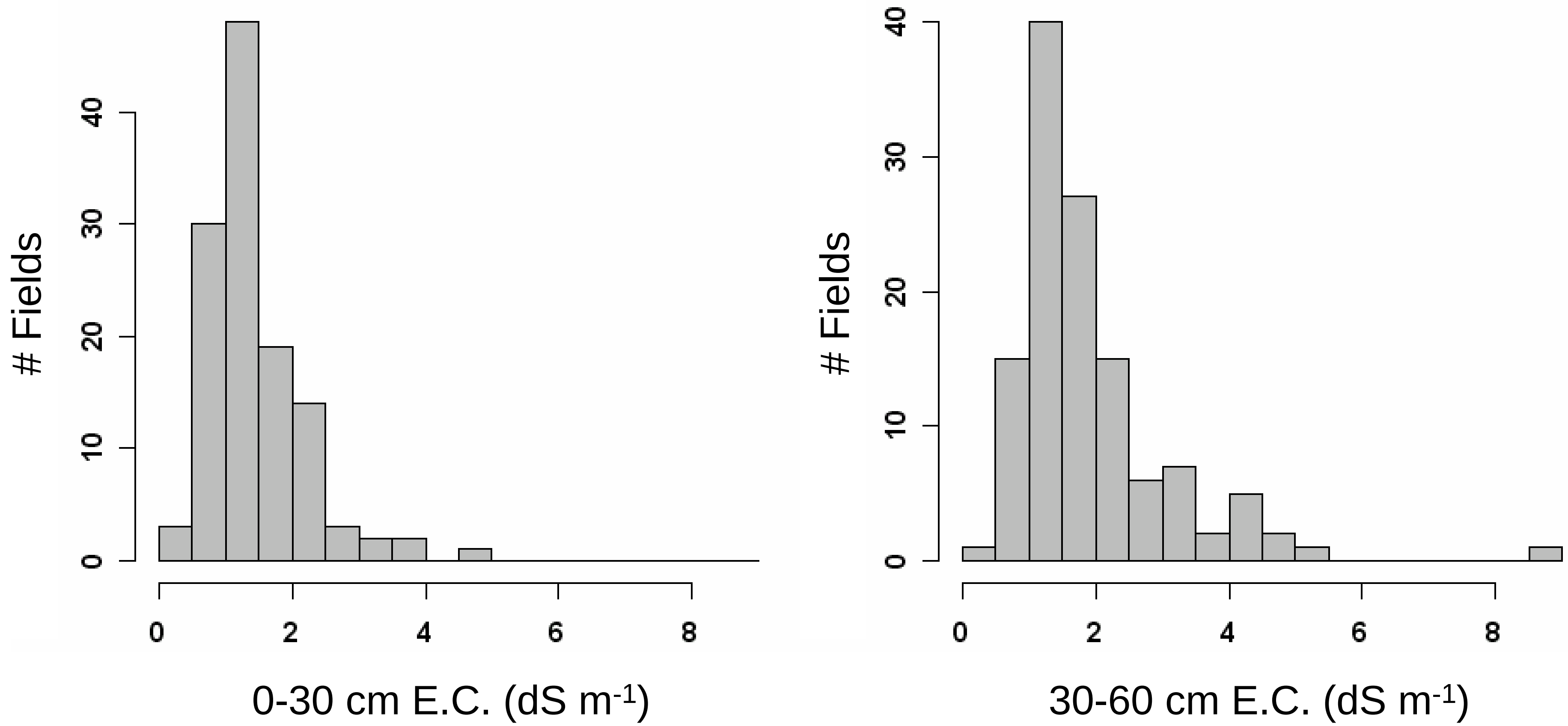
Table 4. Summary statistics for ECe (dS m^{-1}) in target and control groups in 2005-2006 soil survey. Each group contained 30 fields, whose histograms are shown in Figure 6.

Depth (cm)	Control mean	Target Mean	Mann-Whitney p-value
0-30	2.0	2.2	.27
30-60	2.1	2.8	.02
60-90	2.2	3.0	.13
0-90	2.1	2.5	.13
0-60	2.0	2.5	.09
30-90	2.2	2.9	.08

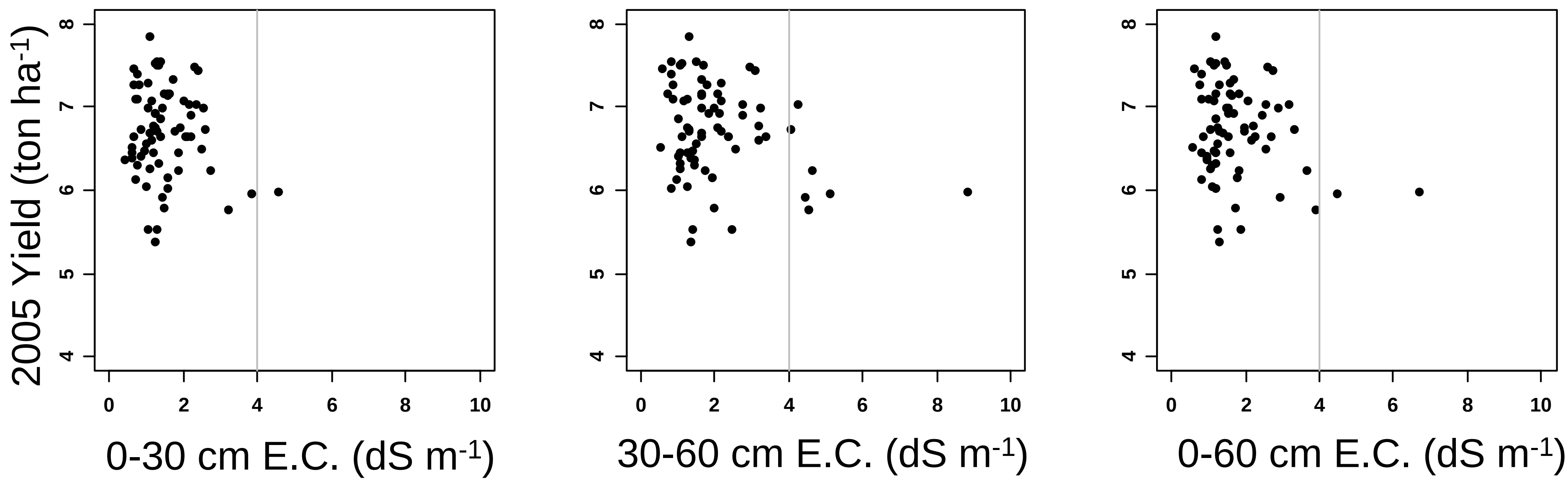

United States
SLRCV
Gulf of California
Mexico
N
Sample Locations
1st survey
2nd survey
0
2
4
8
km



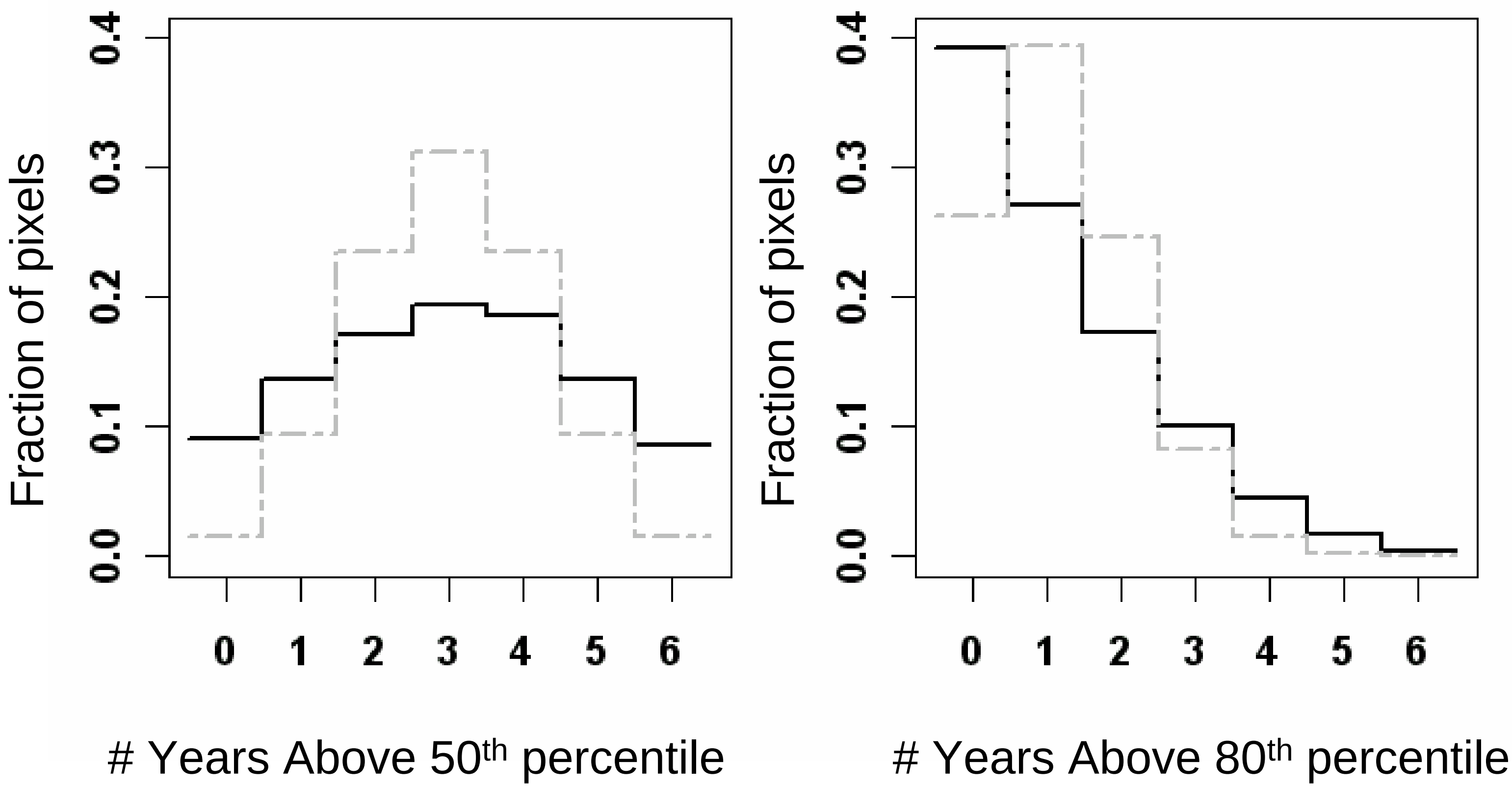
Farmer Reported Yield (ton ha-1)
Image-based Yield Estimate (ton ha-1)
2000
2002
2005
R2 = 0.65
rmse = 0.65
3
4
5
6
7
8
9

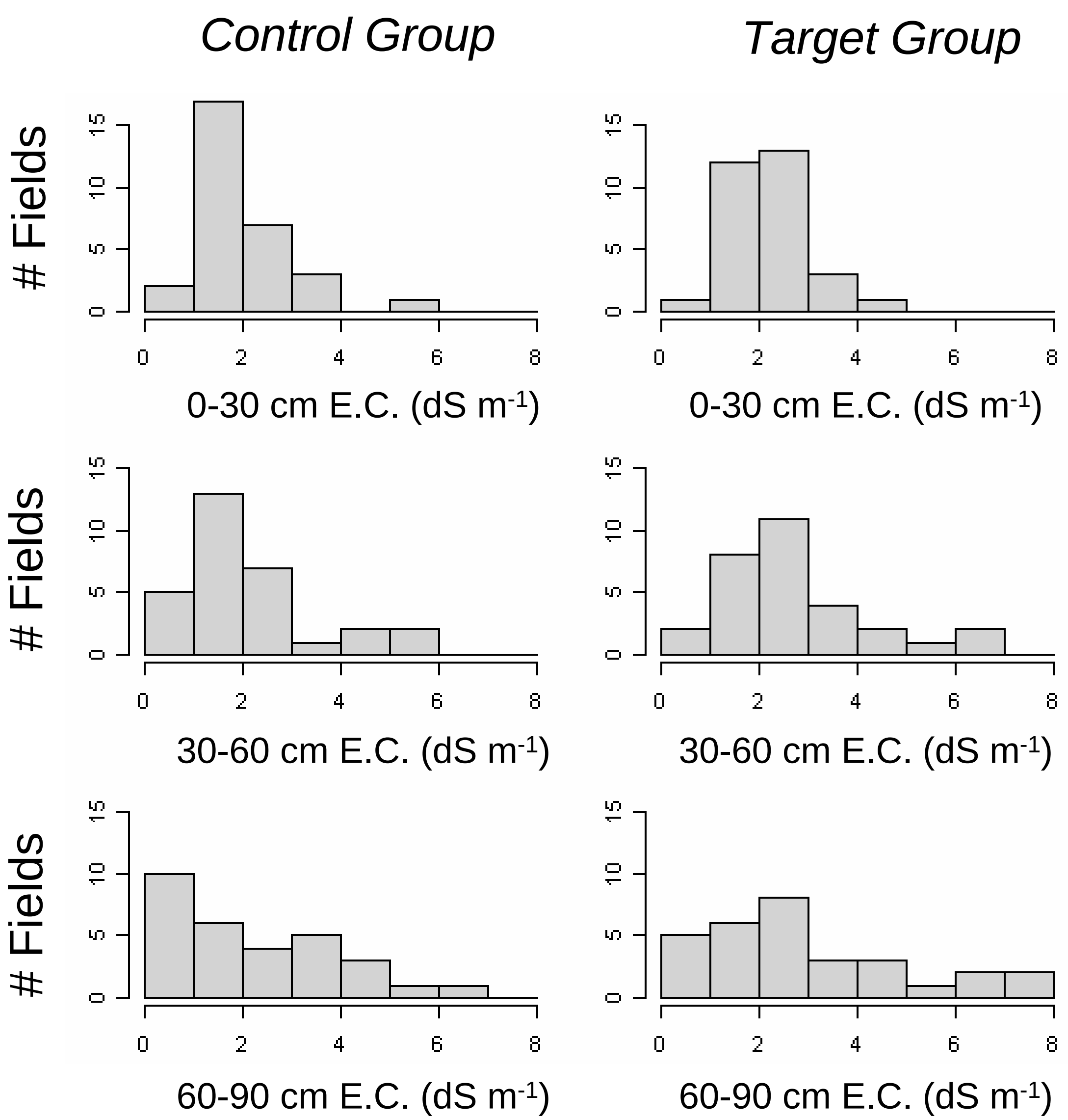


Fields
0
10
20
30
40
0
2
4
6
8
0-30 cm E.C. (dS m-1)
Fields
0
10
20
30
40
0
2
4
6
8
30-60 cm E.C. (dS m-1)



2005 Yield (ton ha-1)
0-30 cm E.C. (dS m-1)
30-60 cm E.C. (dS m-1)
0-60 cm E.C. (dS m-1)


Fraction of pixels
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6
Years Above 50th percentile
Fraction of pixels
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6
Years Above 80th percentile



Control Group
Target Group
Fields
Fields
Fields
0-30 cm E.C. (dS m-1)
0-30 cm E.C. (dS m-1)
30-60 cm E.C. (dS m-1)
30-60 cm E.C. (dS m-1)
60-90 cm E.C. (dS m-1)
60-90 cm E.C. (dS m-1)