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Soil, climate, and management impacts on regional wheat productivity in Mexico from remote sensing

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Abstract

Understanding sources of variability in net primary productivity is critical for projecting ecosystem responses to global change, as well as for improving management in agricultural systems. However, the processes controlling productivity cannot be fully addressed with field- or global-scale observations. In this study, we performed a regional observational experiment using remote sensing to analyze sources of yield variability in an irrigated wheat system in Northwest Mexico. Four different soil types and 3 years with contrasting weather served as the two main experimental factors, while remotely sensed yields provided thousands of observations within each treatment. Analysis of variance revealed that 6.6 and 4.6% of the variability in yields could be explained by soil type and climate, respectively, with a negligible fraction explained by soil-type–climate interactions. The majority of the variability in yields (88.6%) was observed within treatments and was attributed mainly to variations in management. The impacts of management were observed to depend significantly on both soil type and climate, as revealed by distributions of yields within each treatment. The results indicate that changes in management will have the greatest impact on regional production, and will also play a large role in determining the impact of any changes in climate or soil. This work also demonstrates the use of consistent remote sensing estimates to perform regional studies unfeasible with field-based approaches.

Keywords: Carbon cycle; Climate impacts; Remote sensing; Wheat; Yield; Yield loss

1. Introduction

Spatial and temporal variations in the productivity of terrestrial vegetation can have profound impacts on humans and their environment, with effects ranging from atmospheric chemistry and climate to global food production (Pielke et al., 1998; Schimel et al., 2001). This variability arises from changes in numerous factors, including soil physical and chemical properties, temperature, precipitation, solar radiation, and human management. In an effort to project the impact of future changes in these controlling factors, it is critical to understand the relationship between productivity and each factor, along with their interactions.

Interactions between human activity and environmental controls are particularly relevant in managed ecosystems such as agriculture. For example,

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agronomists have long noted the significant difference between yields achieved on experimental plots and average yields in farmers' fields. This "yield gap" is commonly attributed to superior soils or management at the experimental station, but the exact reasons are often unknown due to a paucity of measurements across the entire region of interest (Cassman and Pingali, 1995). As global food demand continues to grow, understanding and minimizing the differences between maximum and regional average yields will be increasingly important (Cassman, 1999; Penning de Vries et al., 1997).

Sources of variation in productivity have traditionally been investigated with controlled field experiments, which provide useful insight into the role of specific factors. However, these studies are limited in their ability to address spatial and temporal variability for two main reasons. First, the strength of a control in a field experiment does not necessarily correspond to its importance at the regional scale. For example, the soil properties and management practices in an experimental plot may not be representative of nearby locations. Second, important interactions between factors are difficult to assess with limited sample sizes. In order to better understand controls on productivity and the relevance of these controls at the regional scale, studies that span larger spatial and temporal scales than are typically feasible with field-based experimental approaches are needed.

As an alternative to field experimentation, several studies have analyzed continental to global-scale patterns in net primary productivity (NPP) using remote sensing from satellite sensors, such as the Advanced Very High Resolution Radiometer. These sensors collect data at daily to weekly intervals which, when used with models of NPP, provide estimates of productivity with spatial resolutions greater than 1 km (Field et al., 1995). However, these satellite approaches suffer serious limitations at the smaller spatial scales relevant to management. First, the generality required by global-scale applications results in limited accuracies for any single region (Lobell et al., 2002b; Malmström et al., 1997). Second, the low repeat frequencies of satellite sensors with sufficient spatial resolutions for regional applications (<100 m) preclude using the NPP models employed at the global scale. Images from a single date, for instance, do not provide very tight constraints on plant development throughout the entire growing season. This is especially true in agricultural systems where crop type and planting dates can vary from field to field.

Bridging the gap between field and global-scale studies requires methods to accurately and consistently quantify plant productivity at high spatial resolutions. Recent work has focused on remote sensing of crop productivity (i.e., yields) in agricultural systems, where spatial and temporal variability affects farmer income and food production (Lobell et al., 2002a). Combining this information with knowledge of soil, climate, and management conditions, it becomes possible to observe thousands of realizations of field "experiments" to analyze sources of variability.

In this study, we employed a remote sensing approach to investigate sources of wheat yield variability in the Yaqui Valley, an intensive agricultural region in Northwest Mexico. Yields derived from 3 years of Landsat satellite imagery were combined with soil type and climate data to determine the importance of these factors for wheat production. In addition, comparisons of yield variations within each treatment (i.e., soil–year combination) were used to investigate soil and climate interactions with management. The results were then used to assess the effects of potential soil, climate, and management changes in the future on regional crop productivity.

2. Methods

2.1. Site description

The Yaqui Valley is an agricultural region in Northwest Mexico (27°N, 110°W) with agro-climatic conditions similar to that of 40% of developing world wheat production (Pingali and Rajaram, 1999). The Valley covers 225,000 ha between the Sierra Madre Mountains to the east and the Gulf of California to the west (Fig. 1). Commonly referred to as the home of the Green Revolution, the region produces some of the highest wheat yields in the world resulting from a combination of irrigation, high fertilizer rates, and modern cultivars (Matson et al., 1998). Nonetheless, regional yields have averaged only 69% of yields achieved at the local research station over the past 10 years (K. Sayre, personal communication), leaving significant potential to reduce the yield gap.

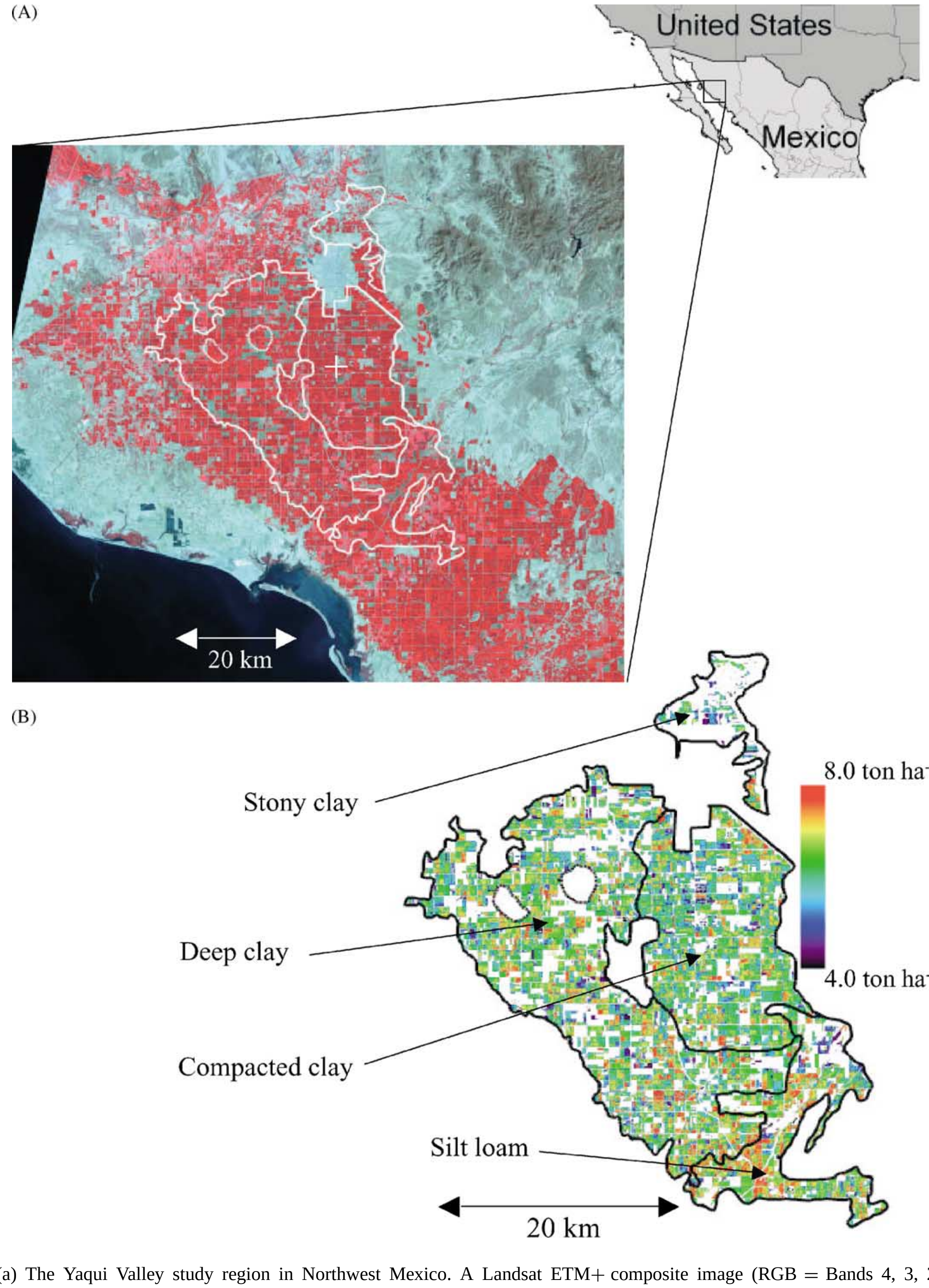

Fig. 1. (a) The Yaqui Valley study region in Northwest Mexico. A Landsat ETM+ composite image (RGB = Bands 4, 3, 2) from 16 March, 2001 shows the dominant presence of wheat fields, which appear red at this time of year. The four soil zones used in this study are outlined in white and the meteorological station is marked by crosshairs. (b) Yield estimates for the 2000–2001 growing season for the four soil zones, derived using ETM+ scenes from 11 January and 16 March, 2001.

The climate in the Yaqui Valley is semi-arid, with an average annual precipitation of 317 mm falling mainly between June and September. The wheat growing season (November–April) is characteristically dry, and farmers typically apply 4–5 irrigations throughout the crop cycle. Most of the soils in the region are vertisols with organic matter (OM) content below 1%, while coastal and river areas are characterized by aridisols with slightly higher OM. In this study, we focused on four predominant soil types within the Valley: montmorillonitic Petrocalcic Calcitorrert, montmorillonitic Chromic Calcitorrert, montmorillonitic Typic Calcitorrert, and mixed Vertic Haplocalcid. These soils are referred to hereafter as stony clay, compacted clay, deep clay, and silt loam, respectively.

2.2. Remote sensing of yields

Fig. 2 outlines the approach used to estimate yields, which is described in detail by Lobell et al. (2002a). Briefly, pixels containing wheat fields are first identified using temporal composites of vegetation indices. Yield for each pixel in which wheat is growing is then modeled using the equation (Monteith, 1972, 1977):

$$\text{Yield} = \left(\sum \text{PAR} \times \text{fAPAR} \times \Delta t\right) \varepsilon \text{HI} \quad (1)$$

where PAR is incident photosynthetically active radiation (MJ from 400 to 700 nm), fAPAR is the fraction of PAR absorbed by the canopy, ε is the light-use efficiency in units of gram biomass MJ PAR^{-1}, and HI is the harvest index, or ratio of grain mass to aboveground biomass. Satellite estimates of fAPAR, in this case from the Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) sensors, are used to constrain the temporal evolution of fAPAR, which is based on growing-degree days and has been established by previous field trials in the region. Combining satellite and ground data in this manner provides estimates of daily fAPAR for each pixel. These values are then combined with daily solar radiation measurements to estimate total growing season light absorption, while values for ε (2.16 g MJ PAR^{-1}) and HI (0.37) are based on field studies. Uncertainties in each model input are propagated through the model to derive spatial estimates of both mean yields and standard deviations.

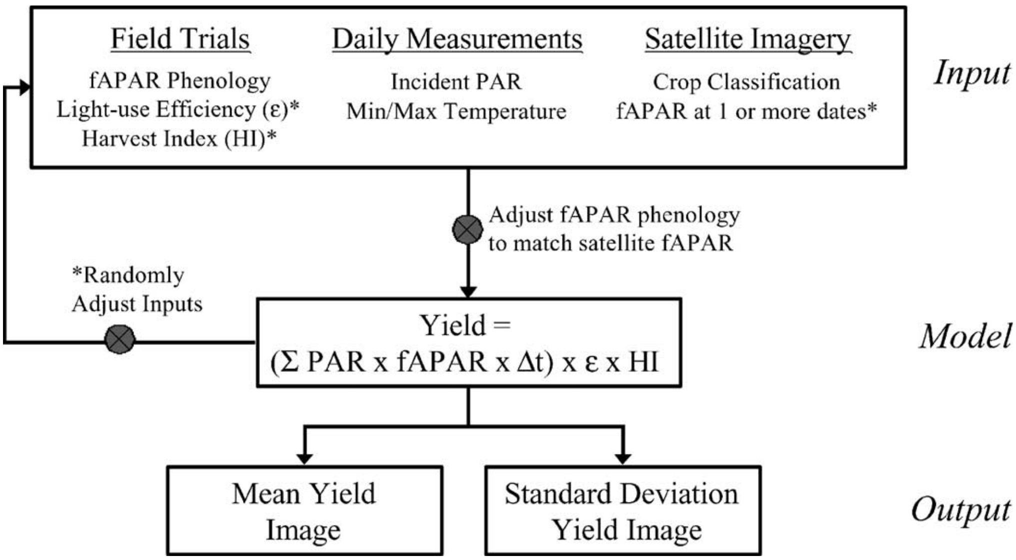

Fig. 2. A schematic representation of the method used to remotely sense wheat yields. The model is run several times on each pixel classified as wheat, with inputs marked by an asterisk randomly adjusted in each iteration to estimate uncertainty in modeled yields. fAPAR phenology, which is based on growing-degree days, is adjusted to match satellite observations at each pixel by varying the planting date and maximum fAPAR.

Lobell et al. (2002a) demonstrated that this approach provides robust estimates of regional wheat production in the Yaqui Valley, with errors under 5% for quantifying total regional harvests. However, the authors did not validate yield estimates on individual fields, a critical step when attempting to understand inter-field yield variations. Therefore, in this study we interviewed farmers who kept records of production for individual fields for the 2000–2001 growing season. Yields were calculated by dividing the total weight of grain sold by the total area harvested. A total of 80 fields scattered throughout the Valley were used in this study, with an average field size of 20 ha.

To acquire observations across a range of climatic conditions, Landsat images were collected for three growing seasons with contrasting climatic regimes: 1993–1994, 1999–2000, and 2000–2001. Table 1 displays the Landsat sensor, image dates, and growing season characteristics for each year. The growing season minimum temperature in 1993–1994 was among the highest on record, while for 2000–2001 it was the lowest since 1971. This provided the necessary contrast to analyze temperature effects on productivity.

2.3. Analysis of variance

For this study, we selected four areas within the Valley that (1) possessed contrasting soil types, (2) contained a large number of wheat fields, and (3) were close to the meteorological station where daily temperature, precipitation, and solar radiation were recorded. The latter constraint was imposed to minimize the degree of spatial variability in climate, due to a lack of additional stations. Fig. 1 displays each of these areas within the study region. For simplicity, we refer to each combination of soil and climate as a treatment, with a total of 12 treatments (four soils × 3 years).

Two-way analysis of variance (ANOVA) was used to quantify the contribution of soil type, climate, and their interaction to yields. Traditional ANOVA assumes that observations within each treatment are normally distributed, with equal variance among treatments. However, for balanced designs (equal number of observations in each treatment) with a large number of observations, violations of these assumptions result in only small errors (Sahai and Ageel, 2000). Therefore, while yield distributions were slightly skewed and varied between treatments, the results of the ANOVA are considered robust.

The number of pixels classified as wheat varied between soil types and years, ranging from 12,810 to 390,982. In order to obtain a balanced experimental design, we randomly selected 10,000 pixels from each treatment as input to ANOVA. Repeated tests indicated that changing the sequence of random numbers had a negligible effect on the results.

Variability within each treatment was, by definition, due to factors other than soil type and climate. We attribute the majority of this residual variability to management, including factors such as date of sowing, amount and timing of fertilizer applications, number and timing of irrigations, tillage and cultivation practices, and pest control. Another possible source of variability was differences in soil physical and chemical properties within soil types. However, spatial distributions of yields indicated that most of the variability occurred between individual fields, which is commensurate with management (see below). This suggests that variations in soil properties affecting yield were relatively minor within soil types, or that any major soil properties contributing to yields vary from field to field, and are therefore likely themselves to be the result of different management histories (e.g., tillage practices, burning of crop residues, groundwater pumping).

To investigate interactions between management and soil type or climate, we compared yield distributions between the 12 treatments. The median value within each treatment was used to quantify yield on an average field, while the difference between the first and third quartiles, referred to as the interquartile range (IQR), provided a measure of the gap between well-managed and poorly managed fields. This comparison assumed that the distribution of management was identical in different soil types and years. Since management appears to be randomly distributed within the study region, this assumption should hold for different soil types. Between years, management can systematically change as, for instance, water availability changes or farmers apply more fertilizer. However, changes within the 7-year period of this study are believed to be small. For example, nitrogen application rates changed from an average of 242 kg ha^{-1} in 1993–1994 to 268 kg ha^{-1} in 2000–2001. This represents only a 10% change,

Table 1
Image and growing season characteristics for each year of the study

Growing season[a]	Image dates	Satellite sensor	Ground resolution (m)	Average minimum temperature (°C)	Average maximum temperature (°C)	Average solar radiation (MJ m^{-2} per day)	Average relative humidity (%)	Total precipitation (mm)
1993–1994	1 February, 6 April	Landsat TM	30.0	10.7	27.3	18.5	74.3	42.9[b]
1999–2000	26 February, 16 April	Landsat ETM+	28.5	9.3	28.4	19.7	68.4	3.1
2000–2001	11 January, 16 March	Landsat ETM+	28.5	8.0	26.3	18.6	67.2	6.1

[a] Growing season is 1 November–30 April.
[b] 40.1 mm (93%) of this amount fell by 6 November, before most of the wheat is planted.

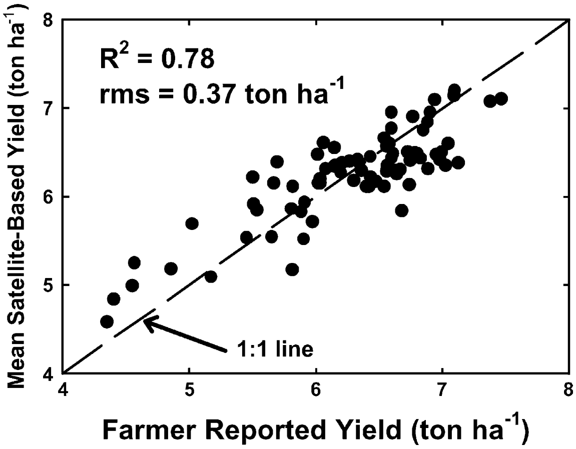

Fig. 3. A comparison of mean yield estimates on 80 fields with farmer reported yields for the 2000–2001 growing season.

and field experiments suggest that increasing fertilizer rates at such high levels has minimal impacts on yields (Ortiz-Monasterio, unpublished data).

3. Results and discussion

3.1. Yield estimation

The mean yield estimates using Landsat ETM+ for 2000–2001 are compared with farmer reported values in Fig. 3. For these 80 fields, the average estimation error was 0.37 t ha^{-1}, or 5.9%, providing confidence in the subsequent analysis of variability. The yield image in Fig. 1 demonstrates the large spatial variability in productivity. While some variations exist within fields, the greatest differences are evident between fields. This supports the assumption that management, and not natural soil variability, is the major source of yield variations within each soil type.

3.2. Analysis of variance

The results of ANOVA are presented in Table 2. Soil type and climate explained 6.6 and 4.6% of yield variability, respectively, representing significant yet minor controls. The interaction between soil and climate was statistically significant, but explained less than 0.25% of variability and was, therefore, deemed negligible. The remaining 88.6% of variability was due to within treatment effects, attributed mainly to management.

In addition to ANOVA, we considered the spatial distribution of yields as an alternative measure of the relative importance of soils and management. Fig. 4 shows a semi-variogram computed for the 2000–2001 yield image. Semi-variograms summarize the variance between samples as a function of separation distance, or lag (Curran and Atkinson, 1998). Conceptually, if management is randomly distributed we expect no additional variance due to management at lags greater than the maximum field length, which in this case is approximately 1 km. Any additional variance beyond this lag must arise from non-management sources, such as spatial variations in soil properties or climate. As seen in Fig. 4, the variance at a lag of 1 km is 9264, which is roughly 93% of the total variance (≈10,000). This agrees well with the results of the ANOVA, which indicated that management explained 92.8% of the variability within a single year (i.e. the variability not explained by climate). The ability to relate a semi-variogram to the relative importance of environmental and management factors may be especially useful in regions where information on soil boundaries or spatial heterogeneity of climate is not readily available.

Table 2
ANOVA table for wheat yields

Source of variation	Degrees of freedom	Sum of squares	% Total	Mean square	*F*-value	*P*-value
Soil type	3	9573.6	6.6	3191.2	54.9	<0.001
Year	2	6638.1	4.6	3319.0	57.1	<0.001
Interaction (soil × year)	6	348.9	0.2	58.1	54.1	<0.001
Error	119,988	128916.0	88.6	1.1		
Total	119,999	145476.6	100			

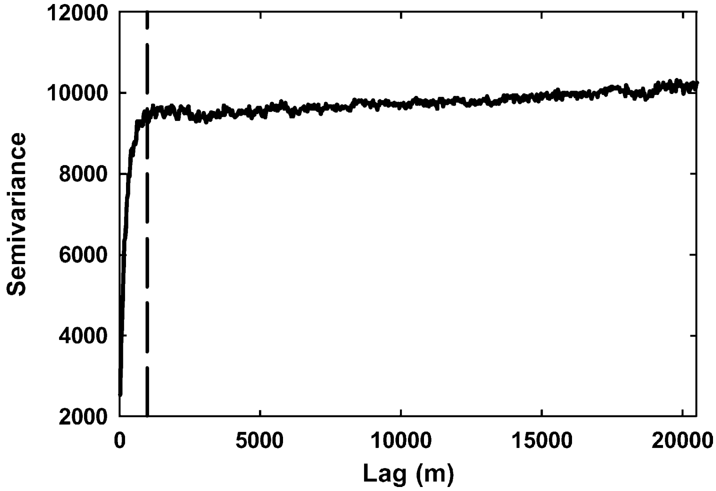

Fig. 4. Semi-variogram of 2000–2001 yield image. Dotted line indicates a lag of 1 km, roughly equal to the maximum size of fields in this region.

3.3. Soil–climate–management interactions

Fig. 5 shows the frequency distributions of yield estimates within the four soil types for each of 3 years. In all cases, yields were distributed between roughly 300 and 800 $g\,m^{-2}$ (3–8 $t\,ha^{-1}$). However, differences in other aspects of the distributions revealed important aspects of soil and climate effects on yields, as well as their interactions with management (see Fig. 5 and Table 3). In better soils, the yield distributions were skewed more toward high values than in the poorer soils. For example, in 1994 the silt loam exhibited a distribution skewed heavily toward high yields, while yields on the stony clay were skewed toward relatively low yields. The difference in median yields in this case, which represent productivity on a field with average management, was 1.21 $t\,ha^{-1}$. These patterns demonstrate that poorer soils demand a higher level of management to achieve the same yields. While yields of 6.0 $t\,ha^{-1}$ were possible on the stony clay, this occurred only above the 70th percentile, while the same yields were realized at the 40th percentile on the silt loam.

Similar patterns were observed for changes in climate. Within each soil, yields became more skewed toward higher values in years with favorable climate (lower minimum temperatures). This resulted in higher median yields as well as smaller differences between the first and third quartiles. Fig. 6 shows the median and IQR as a function of growing season minimum temperature for each soil type. While median yields decreased linearly in most cases with growing season temperature, the IQR exhibited a non-linear increase with temperature. This indicates that climate has a

Table 3
Median and IQR of wheat yields within each treatment

Year	Stony clay		Compacted clay		Deep clay		Silt loam		Average	
	Median	IQR	Median	IQR	Median	IQR	Median	IQR	Median	IQR
1993–1994	5.13	2.13	5.49	2.08	5.97	1.81	6.34	1.61	5.73	1.91
1999–2000	5.32	1.70	5.88	1.36	6.04	1.40	6.56	1.27	5.95	1.43
2000–2001	5.77	1.67	6.28	1.22	6.39	1.32	6.61	1.33	6.26	1.39
Average	5.41	1.83	5.88	1.55	6.13	1.51	6.50	1.40	5.98	1.58

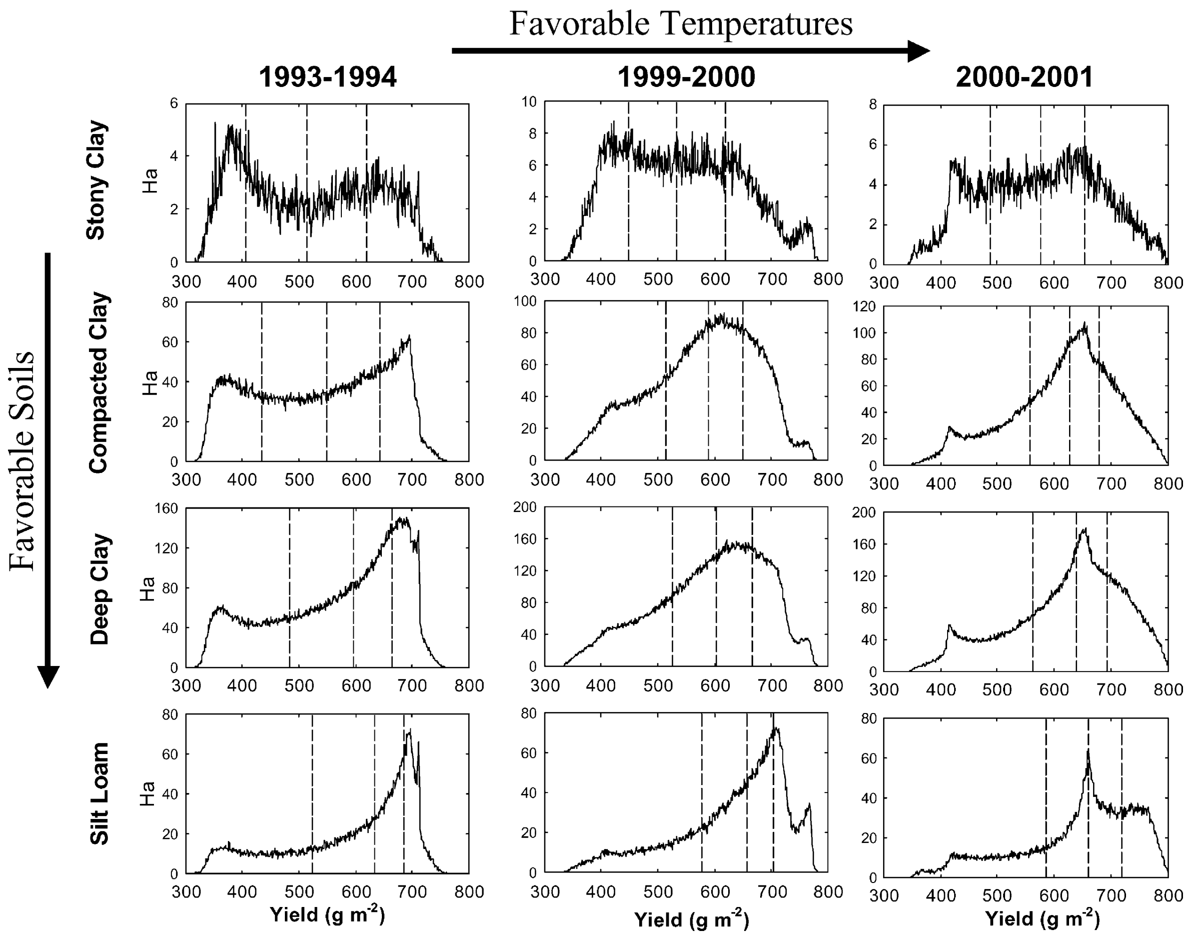

Fig. 5. Histograms of yields in each soil type for each year. Dotted lines show first, second (median), and third quartiles. Climate conditions improve from left to right, while soil improves from top to bottom.

different effect at different levels of management, with a greater yield response to temperature for poor management (first quartile) compared to good management (third quartile).

These interactions between climate and management are further illustrated in Fig. 7A, which presents the empirical distribution function for yields in each year, averaged over all soil types. The empirical distribution function depicts the cumulative proportion of pixels that are less than or equal to each yield value. In this figure, a given level of management coincides with a value on the *y*-axis, while the yield difference between years is the horizontal distance between curves at this *y*-value.

At relatively low levels of management, the difference between the hottest and coolest growing seasons was significantly larger than at higher levels of management. This indicates that poorly managed fields are more susceptible to losses in warmer years, and similarly are able to increase their production more in cool years. However, differences between years were still evident even at the 100th percentile, demonstrating the fundamental limitations imposed by light and temperature, even in the best managed fields.

Fig. 7B shows the empirical distribution function for yields on different soil types, averaged over all years. Comparing Fig. 7A and B reveals two significant distinctions between soil and climate interactions

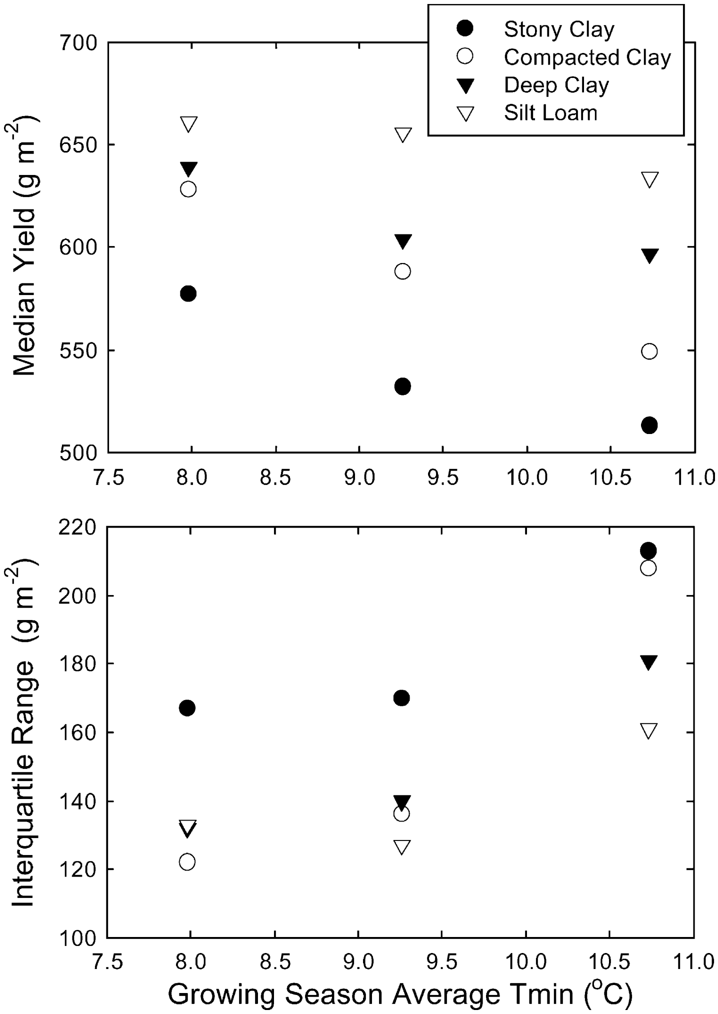

Fig. 6. (a) Median and (b) IQR of yields as a function of growing season minimum temperature for each soil type.

with management. First, all soil types possessed the same minimum and maximum yields, indicating that it is possible to overcome soil limitations with sufficiently good management. This contrasts with the effects of climate, which changed the maximum attainable yield from year to year. Second, unlike with climate, the impacts of soils on yields were maximized at medium levels of management. Evidently at low levels of management, soil quality becomes less relevant to productivity.

To illustrate the observed interactions between soil, climate, and management, consider an example where management differences are due solely to different timing of irrigations, with the poorest management representing the worst-case (e.g., no irrigation) and the best management representing optimal application. In soils that retain more moisture, water stress to crops will occur at a slower rate, placing less demand on the exact timing of irrigation. Therefore, at average levels of management, better soils will reduce water stress and thereby increase yields. However, with perfect timing of irrigation, the extent to which soils provide room for error is less important, and differences between yields at high levels of management will

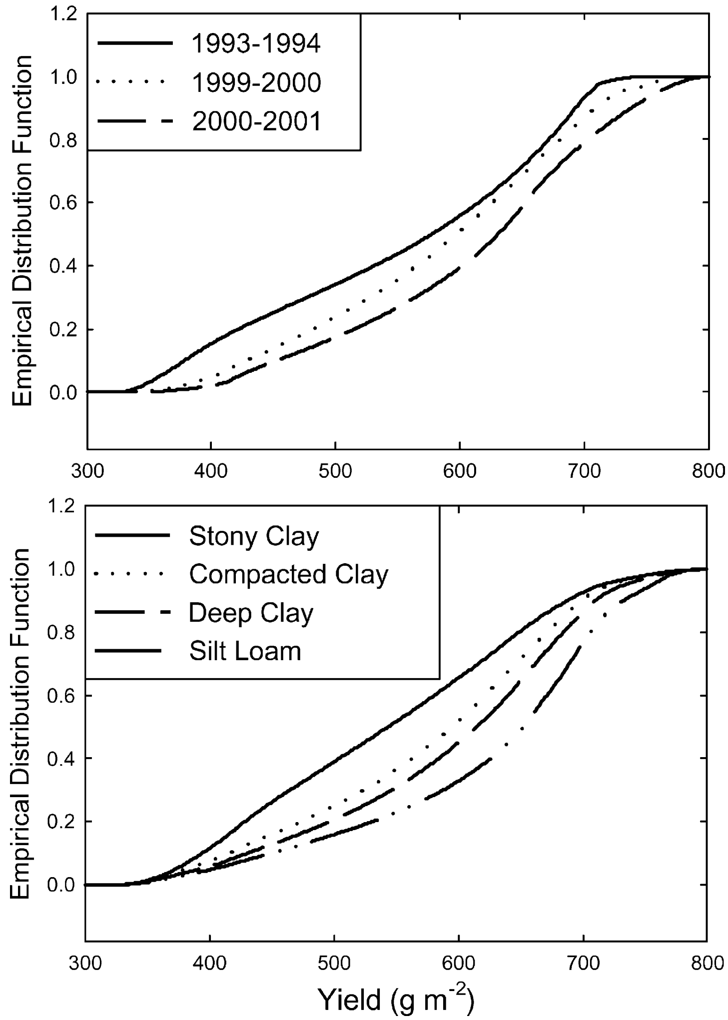

Fig. 7. Empirical distribution function of yields for (A) all soil types within each year and (B) all years within each soil type.

consequently be smaller. Similarly, fields without irrigation will experience significant water stress regardless of soil properties, reducing the yield difference between soils. On the other hand, cooler climate will reduce water stress at all levels of management, by lowering crop evapotranspiration rates.

The observed relationships between soil, climate, management, and productivity have several implications for potential future changes. The first of these regards the potential for reducing spatial variability in yields. While soils and climate were found to have a significant impact on yields, these differences were small when compared to the effect of management. For example, the average yield difference between low and high management (25th and 75th percentile, respectively) was twice the average difference between poor and high quality soils (Table 3). Therefore, significant yield increases appear possible provided that the necessary changes in management can be identified and implemented. However, it should be stressed that variations due to soil and climate are still fairly significant. In this case, the average difference between the best and worst soils (1.09 t ha^{-1}) or years (0.53 t ha^{-1}) corresponded to 18.3 and 8.9% of the average median yield of 5.98 t ha^{-1}, respectively. Future changes in climate and soil quality could therefore have significant impacts on productivity.

The results presented here also emphasize that the effects of future climate and soil changes will largely depend upon management practices. At high levels of management (third quartile), for instance, the average yield in the best year was 0.29 t ha^{-1} (4.4%) higher than the worst year (Fig. 7A). The corresponding difference in poorly managed fields (first quartile) was 0.93 t ha^{-1} (20.7%). The difference between these responses to climate represents a "range of vulnerability" to climate variation that is important when considering future scenarios. A region managed uniformly at the level of the third quartile, e.g., would be nearly five times less affected by climate variations than at the level of the first quartile. Improving management is therefore critical not only for increasing yields, but also for reducing future vulnerability to climate changes and soil degradation.

4. Conclusions

Using remotely sensed yields in combination with soil and climate data, we analyzed the effects of soil, climate, and management on wheat productivity. In the Yaqui Valley region, management differences were more important than soil type and climate variations for determining wheat yields, although the latter two represented significant sources of variability. Management interactions with soil type and climate were also important for understanding yields, as the impacts of both soil and climate changes depended on management. Future work will focus on identifying the specific management factors that are most important to wheat production.

The results presented here provide insight into the processes governing yields, as well as the response of regional production to future changes. For example, increases in temperature resulting from global warming could cause decreased yields, but these losses would depend largely on the level of management. Several modeling studies have resulted in similar conclusions, showing that the impact of climate changes on agriculture is sensitive to adaptation responses (IPCC, 2001). The importance of management to food production was also highlighted by Döös and Shaw (1999), who considered various controls on global food production and concluded that greatest changes in future production will be due to "direct human factors such as improved management and the increased use of fertilizers, rather than natural and/or indirect human factors such as climate change, irrigation, salinization, waterlogging, or pests."

Extending this approach to other regions should enable a comparative study of controlling factors in agricultural production. In some regions, such as rain-fed systems, it is possible that soils or climate play a more important role than management in determining yields. Identifying the relevant constraints and interactions in each case could provide important information to direct management and research efforts. The methodology demonstrated here is also applicable to other ecosystems, provided that productivity estimates can be properly validated. In general, the capability of remote sensing to provide thousands of observations should greatly aid studies of spatially and temporally dynamic processes at the regional scale.

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