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Yield uncertainty at the field scale evaluated with multi-year satellite data

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Abstract

The level of yield risk faced by a farmer is an important factor in the design of appropriate management and insurance strategies. The difference between field scale and regional scale yield risk, which can be significant, also represents an important measure of the factors that cause the yield gap – the difference between average and maximum yields. While field scale yield risk is difficult to assess with traditional data sources, yield maps derived from remote sensing offer promise for obtaining the necessary data in any region. We analyzed remotely sensed yield datasets for two regions in Northwest Mexico, the Yaqui and San Luis Rio Colorado Valleys, in conjunction with time series of aggregated regional yields for 1976–2002. Regional scale yield risk was roughly 8% of average yields in both regions. Field scale yield risk was determined to be 58% higher than regional scale risk in both regions. The difference between field and regional scale risk accounted for 50% of the spatial variance in yields in the Yaqui Valley, and 70% in the San Luis Rio Colorado Valley, indicating that

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climatic uncertainty represents an important source of the spatial yield variability. This implies that accurate seasonal climate forecasts could substantially reduce yield losses in farmers' fields. The results were shown to be fairly sensitive to assumptions about the magnitude and nature of errors in yield estimation, suggesting that improved understanding of estimation errors are needed to realize the full potential of remote sensing for yield risk analysis.

Keywords: Climate variability; Remote sensing; Risk; Wheat; Yield; Yield gap

1. Introduction

Average crop yields in agricultural regions vary from year to year as weather conditions and other factors influencing crop growth change. The associated variations in regional crop production can have important implications for crop prices and food security risks, and therefore regional yield variability has been widely studied (e.g., Naylor et al., 1997; Calderini and Slafer, 1998; Harwood et al., 1999). Such studies typically utilize available data on regional crop yields obtained, for instance, from government surveys (e.g. FAO, 2004; NASS, 2004).

At the scale of individual farmers, crop yield variability represents an important source of income uncertainty and, in the case of subsistence farming, food security risk (risk is defined here as uncertainty that affects an individual's welfare; Harwood et al., 1999; Hardaker et al., 2004). Studies that attempt to assess farmer-level risk with regional crop yield data, however, tend to under-estimate risk (Debrah and Hall, 1989; Marra and Schurle, 1994; Rudstrom et al., 2002; Gorski and Gorska, 2003). This is because temporal yield variations for different fields within a region are not perfectly correlated, owing to differences in management, soil, and local climatic conditions. As a result, regional crop yield variability is often lower than average field variability.

The yield risk at the field scale ideally could be estimated from time series of yields from individual fields. However, obtaining field scale yield records is difficult and expensive, and the sources that do exist may be subject to substantial bias (Rudstrom et al., 2002). In contrast, objective measurements of individual crop fields are routinely made by Earth orbiting satellites, and these measurements of surface reflectance properties have been successfully used to estimate crop yields in many regions (e.g., Moulin et al., 1998; Shanahan et al., 2001; Lobell et al., 2003; Baez-Gonzalez et al., 2005).

This paper describes an attempt to use remotely sensed yields to quantify field scale yield variability. Section 2 outlines the conceptual basis for this approach, as well as the relationship between temporal and spatial yield variability. Section 3 discusses some of the limitations of using remote sensing and describes the remote sensing techniques used in this study. Section 4 describes the study areas and methods, while Sections 5–7 discuss the main results and conclusions.

2. Conceptual framework

To elucidate the difference between regional and field scale variability, the yield at field i in year t can be expressed as

$$Y_{it} = Y_{\mathrm{R}t} + (Y_{it} - Y_{\mathrm{R}t}) \tag{1}$$

where $Y_{\mathrm{R}t}$, the regional yield at time t, is the weighed average of yields for all fields in the region, with the weights corresponding to the relative area of each field. The temporal variance (uncertainty) of yield at the field scale can be written as:

$$\mathrm{Var}(Y_{it}) = \mathrm{Var}(Y_{\mathrm{R}t}) + \mathrm{Var}(Y_{it} - Y_{\mathrm{R}t}) + \mathrm{Cov}(Y_{\mathrm{R}t}, Y_{it} - Y_{\mathrm{R}t}) \tag{2}$$

The last term represents the covariance between regional yields and field-region differences, which has expectation equal to zero (Harwood et al., 1999):

$$E[\mathrm{Cov}(Y_{\mathrm{R}t}, Y_{it} - Y_{\mathrm{R}t})] = \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{\mathrm{R}t} - \overline{Y_{\mathrm{R}t}})((Y_{it} - \overline{Y_{it}}) - (Y_{\mathrm{R}t} - \overline{Y_{\mathrm{R}t}}))/NT = 0 \tag{3}$$

since $\overline{Y_{\mathrm{R}t}}$, which represents the regional average over all years, and $\overline{Y_{it}}$, which represents the field average over all fields and years, are equal (ignoring variations in field size, which in extreme situations may cause the weighted average to differ significantly from the simple arithmetic average). Eq. (2) can thus be simplified to:

$$\mathrm{Var}(Y_{it}) = \mathrm{Var}(Y_{\mathrm{R}t}) + \mathrm{Var}(Y_{it} - Y_{\mathrm{R}t}) \tag{4}$$

which signifies field scale variance is the sum of regional scale variance and the variance of field-region differences.

As seen from Eq. (4), estimation of yield uncertainty at the field scale requires either (1) long-term datasets on yields in actual farmers' fields, to directly estimate $\mathrm{Var}(Y_{it})$; or (2) long-term datasets on average regional yields to estimate $\mathrm{Var}(Y_{\mathrm{R}t})$, combined with an estimate of the variance of field-region differences, $\mathrm{Var}(Y_{it} - Y_{\mathrm{R}t})$. A lack of time-series data on field scale yields has precluded the former approach in most regions, with some exceptions (e.g., Marra and Schurle, 1994). Estimation of the variance of field-region differences thus represents a key bottleneck to improved understanding of field scale yield uncertainties.

An interpretation of Eq. (4) is that uncertainty at the field scale has a component that is shared among neighbors, due to common factors such as regional climatic conditions, and a component that varies from field to field. The latter component arises from interactions between spatial and temporal variations. For example, weather conditions will not only impact average yields, but will affect the difference in yield between a farmer who plants early and one who plants late.

A somewhat separate line of inquiry in agricultural research concerns the source of spatial variability in yields, often measured by the difference between the highest yielding fields and the regional average. We refer to this difference as the "yield gap", although this term is reserved by some authors to signify the difference between the genetic yield potential and average yields (Evans, 1993; Cassman, 1999). In intensively irrigated and fertilized systems, such as those studied here, the highest yielding fields are often very close to genetic yield potential. Nonetheless, the distinction may be important in some systems and we emphasize that any gap between yield potential and the highest yielding fields is not addressed here.

A common issue is whether the yield gap can be reduced by improved management, and if so what specific actions should be taken (Cassman et al., 2003; Rosegrant et al., 2003). In general, many soil, climatic, and management factors contribute to yield losses in farmers' fields, and we wish to identify the few factors that are most responsible for these losses. One can classify these factors into two classes: those that are consistent (or fixed) in time and those that are not. Examples of each are given in Table 1. An understanding of how much each class of factors contributes to yield variability is an important step toward understanding causes of the yield gap and identifying appropriate strategies to improve regional productivity.

From the discussion above, it is clear that the issue of field scale temporal variability is closely related to that of spatial variability. That is, some fraction of spatial variance may arise from temporally constant, site-related factors, but a significant portion may also result from space–time interactions. Seen in this context, the variance of field-region differences, in addition to its importance for measuring field scale yield uncertainty, provides a measure for how important space–time interactions are in driving spatial differences in yield.

Mathematically, the average spatial variance of yield over time, which we denote as V_{YS}, can be defined as:

$$
\begin{aligned}
V_{\mathrm{YS}} &= \sum_{t=1}^{T} \mathrm{Var}(Y_{it} - Y_{\mathrm{R}t})/T \\
&= \sum_{t=1}^{T} \sum_{i=1}^{N} \left[Y_{it} - Y_{\mathrm{R}t} - (\overline{Y_{it} - Y_{\mathrm{R}t}})\right]^2 / [T(N-1)] \\
&= \sum_{t=1}^{T} \sum_{i=1}^{N} (Y_{it} - Y_{\mathrm{R}t})^2 / [T(N-1)] \qquad (5)
\end{aligned}
$$

Table 1
Examples of temporally consistent (i.e., site-related) and inconsistent factors affecting field-region yield differences

Consistent factors	Inconsistent factors
Soil properties (e.g., texture, mineralogy)	Climatic conditions
Topography and drainage characteristics	Farmer (if rented)
Distance to canals, wells, cities, and other landscape features	Variable annual management decisions (e.g., planting, fertilizer and irrigation dates)
Farmer (unless rented)	Management–climate interactions
Long-term management decisions (e.g., irrigation system, soil management)	Soil–climate interactions
Consistent annual management decisions (e.g., planting, fertilizer and irrigation dates)	

where $\overline{Y_{it} - Y_{Rt}}$, the average across all fields of the difference between field yield and regional yield, is zero. In comparison, the average temporal variance of field-region differences, which we denote hereafter as V_{YT}, can be expressed as

$$V_{YT} = \sum_{i=1}^{N} \mathrm{Var}(Y_i - Y_R)/N = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[Y_{it} - Y_{Rt} - (\overline{Y_i - Y_R})\right]^2 / N(T-1) \quad (6)$$

where $\overline{Y_i - Y_R}$, the average field-region yield difference for field i, can be thought of as the systematic difference in yield at field i due to factors such as soil quality or farmer skill.

Expansion of the quadratic term in Eq. (6) gives

$$\begin{aligned} V_{YT} &= \sum_{i=1}^{N} \sum_{t=1}^{T} \left[(Y_{it} - Y_{Rt})^2 - 2(Y_{it} - Y_{Rt})(\overline{Y_i - Y_R}) + (\overline{Y_i - Y_R})^2\right] / [N(T-1)] \\ &= \sum_{i=1}^{N} \sum_{t=1}^{T} \left[(Y_{it} - Y_{Rt})^2 - (\overline{Y_i - Y_R})^2\right] / [N(T-1)] \end{aligned} \quad (7)$$

Therefore, the main difference between Eqs. (5) and (7) is the additional term in Eq. (7) representing the time average squared field-region difference for each field. The ratio

$$I = V_{YT}/V_{YS} \quad (8)$$

represents the variance of field-region differences as a fraction of total spatial yield variance. In cases where spatial variability is largely due to consistent variations in soil properties, farmer skill, topographic position, weather conditions, etc., the observed spatial patterns of yields will be fairly consistent and the fraction, I, is expected to be fairly close to zero. Conversely, values of I near one would indicate that a large fraction of total spatial variability is attributable to factors that are not consistent in time. An ability to distinguish between these two sets of factors based on observed values of I would offer useful insights into constraints on regional crop production.

It should be noted that Eqs. (5)–(7) are analogous to an ANOVA decomposition, where the total sum of squares of yields are separated into effects of fields and years, with one observation for each field–year combination. However, the representation of variability in terms of variances rather than sum of squares is more useful in situations where V_{YS} and V_{YT} are estimated from different data sources. For example, V_{YS} may be estimated from exhaustive datasets from one or two years, while V_{YT} may be estimated from a few fields with longer time series.

To summarize, an accurate estimate of V_{YT} can help to quantify both field scale yield uncertainty and the importance of consistent, site-related factors in driving spatial yield variations. The former is of great importance when evaluating the potential value of risk management strategies to farmers, while the latter provides insight into the causes of spatial yield variability (i.e., the yield gap) and therefore the potential value of approaches to raise regional yields. However, estimation of V_{YT} remains problematic due to a paucity of long-term, field scale yield datasets.

3. Remote sensing of crop yields

In this paper, we present an approach to estimate V_{YT} using multi-year yield maps, generated from remote sensing data acquired by the Landsat thematic mapper (TM) and enhanced thematic mapper plus (ETM+) sensors. The datasets and methods used to generate the yield maps used here are described in detail by Lobell et al. (2003). Briefly, each 30×30 m Landsat pixel containing wheat is identified based on the ratio of near-infrared (NIR) to red reflectance values at different dates. Yields for wheat pixels are then estimated by fitting a curve of daily canopy light absorption (derived from a crop model) to Landsat estimates of light absorption at each image date. The estimate of total growing season light absorption is then multiplied by the ratios of biomass to light absorption and grain yield to biomass, which are relatively well conserved properties and are prescribed constant values based on field trials (Lobell et al., 2003).

This light-use efficiency model thus provides a yield estimate for each 30×30 m pixel with wheat. When images are available from multiple years, careful geo-registration of images allows successive years to be overlain on each other and compared. The yield time series for individual fields can then be extracted from the multi-year yield images.

However, two issues arise when using remote sensing datasets to estimate V_{YT}. First, only relatively short-term records are obtainable for individual fields in most situations, owing to limited availability of satellite records. An estimate of V_{YT} based on yields for a single field will therefore be prone to large errors associated with the small sample size. To avoid such errors, one may perform similar estimates for a large number of fields and compute the average value of V_{YT}. This is demonstrated in Fig. 1, which plots the average sample variance for a

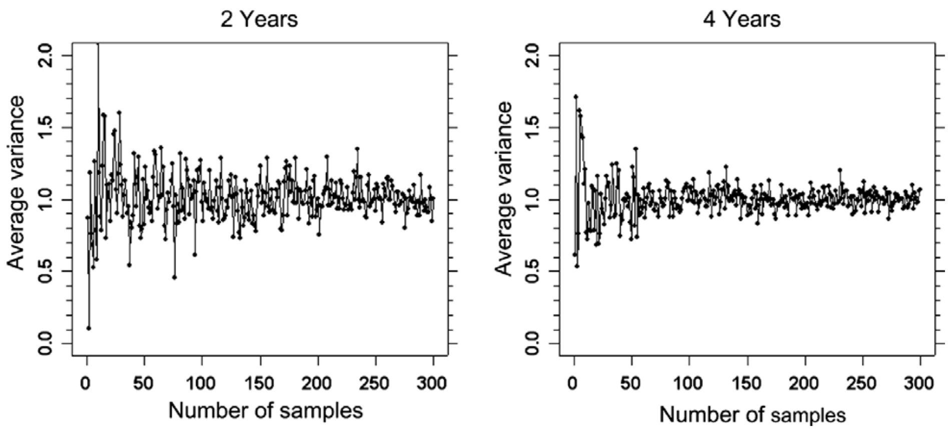

Fig. 1. Average temporal variance of simulated random variables with length two years (left) and four years (right). True variance is equal to 1. These simulations demonstrate the expected accuracy of V_{YT} estimates based on the number of fields and number of years of yield data.

simulated random variable with true variance equal to 1.0. The average sample variance is determined by two factors: (1) the number of years used to compute the variance for each sample and (2) the total number of samples (i.e., fields). With only two years of data (Fig. 1a), the average sample variance often deviates from the true value by more than 20%, even for sample sizes above 200. With four years of data (Fig. 1b), however, the estimate becomes more reliable and is generally confined to within 10% of the true value for sample sizes above 100. Thus, using the spatial coverage of remote sensing to observe a large number of fields, sampling errors related to the relatively sparse temporal coverage can be substantially reduced.

A second problem related to the use of remote sensing is that yield estimates may be prone to substantial uncertainties, resulting from the various modeling assumptions necessary to translate satellite measured radiance to yield estimates (Lobell et al., 2003). In fact, the problem of measurement error is not unique to remote sensing, but is often ignored when using data from more traditional sources, such as field surveys. For any measurement of yield at field i in year t (Z_{it}) that has some error (ε_{it}) associated with it, we cannot estimate $\mathrm{Var}(Y_{it} - Y_{\mathrm{R}t})$ directly, but rather $\mathrm{Var}(Z_{it} - Z_{\mathrm{R}t})$. This value can be expressed as:

$$\begin{aligned}\mathrm{Var}(Z_{it} - Z_{\mathrm{R}t}) &= \mathrm{Var}(Y_{it} - Y_{\mathrm{R}t} + \varepsilon_{it} - \varepsilon_{\mathrm{R}t}) \\ &= \mathrm{Var}(Y_{it} - Y_{\mathrm{R}t}) + \mathrm{Var}(\varepsilon_{it} - \varepsilon_{\mathrm{R}t}) + \mathrm{Cov}(Y_{it} - Y_{\mathrm{R}t}, \varepsilon_{it} - \varepsilon_{\mathrm{R}t}) \end{aligned} \quad (9)$$

where $\varepsilon_{\mathrm{R}t}$ is the average error across all fields (i.e., bias). Hereafter, we assume that any bias has been accounted for in the model, and thus $\varepsilon_{\mathrm{R}t} = 0$. If we further assume that measurement errors are random and therefore independent of yield, then the last term in Eq. (9) is zero and we are left with

$$\mathrm{Var}(Y_{it} - Y_{\mathrm{R}t}) = \mathrm{Var}(Z_{it} - Y_{\mathrm{R}t}) - \mathrm{Var}(\varepsilon_{it}) \quad (10)$$

Thus, an estimate of the variance of measurement error, $\mathrm{Var}(\varepsilon_{it})$, must be subtracted from the observable $\mathrm{Var}(Z_{it} - Y_{\mathrm{R}t})$ to derive $\mathrm{Var}(Y_{it} - Y_{\mathrm{R}t})$. Similarly, $\mathrm{Var}(\varepsilon_{it})$ should be subtracted from the computed spatial variance of yield measurements to estimate V_{YS}. To estimate $\mathrm{Var}(\varepsilon_{it})$, one can employ error propagation techniques, such as Monte Carlo simulation, within the yield estimation model or directly compare estimates with field measured values. For the data used in this study, both approaches have previously been applied (Lobell et al., 2003, 2005) and indicate a value of approximately 0.1 $\mathrm{Mg}^2\ \mathrm{ha}^{-2}$ for $\mathrm{Var}(\varepsilon_{it})$. Since these estimates of error are themselves subject to uncertainty, we analyze below the sensitivity of results to the assumed value of $\mathrm{Var}(\varepsilon_{it})$.

4. Methods

Here we apply the remote sensing approach outlined above to two irrigated agricultural regions in Northwest Mexico: the Yaqui Valley (YV) and San Luis Rio Colorado Valley (SLRCV) (Fig. 2). The total area of irrigated cropland is 225,000 Ha in YV and 27,000 in SLRCV. Both regions grow predominantly irrigated spring wheat

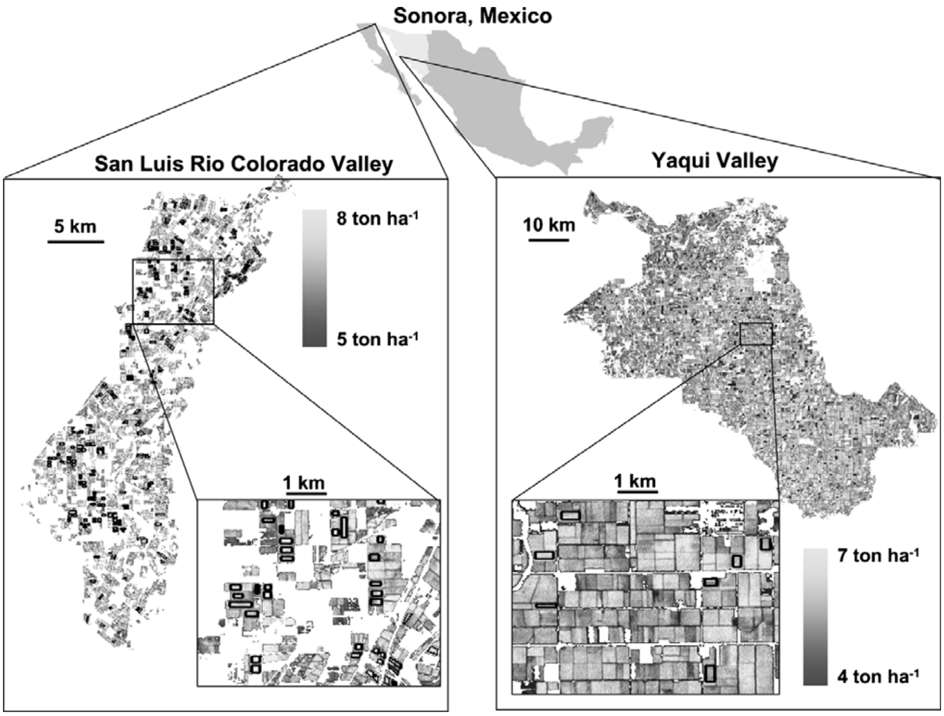

Fig. 2. The study regions of the Yaqui Valley (right) and San Luis Rio Colorado Valley (left). Images display estimated wheat yields for 2002 in both regions. Black boxes outline locations of fields randomly selected for multi-temporal analysis.

(roughly 60% of total cropland is typically sown to wheat in each region) and therefore the analysis focused on this crop. In both regions, wheat is sown in late fall (November–December) and harvested in late spring (April–May). Throughout this paper, the year of yield refers to the year in which the crop was harvested.

Records of average wheat yields (Y_{Rt}) for 1976–2002 were obtained for each region from Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación (Secretaría de Agricultura, 2003). The variance of regional yields, Var(Y_{Rt}), was computed by first fitting a linear trend to the yield time series to remove long-term trends (Fig. 3), and then computing the variance of yield anomalies from this trend (Marra and Schurle, 1994; Harwood et al., 1999).

Field scale yields of wheat were obtained from remote sensing derived yield maps for four years (2000–2003) in YV and five years (2000–2004) in SLRCV. Very few fields were planted with wheat in 2004 in YV because of limited water availability, and therefore this year was omitted from the analysis. Within each region, the raw yield images were first converted to images of field-region differences, ($Z_{it} - Y_{Rt}$), by subtracting the average image yield for each year. The sequence of yield difference images was then used to mask out pixels that did not contain wheat in all image

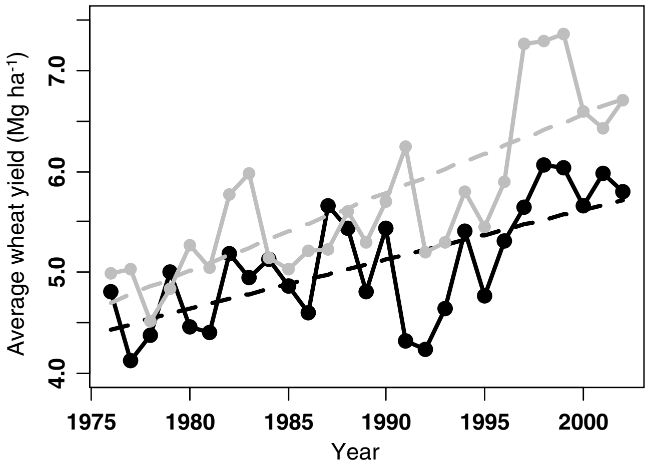

Fig. 3. Wheat yields for 1976–2002 for the Yaqui Valley (black line) and San Luis Rio Colorado Valley (gray line). Dashed lines show best-fit linear regression.

years. Pixels with values of ($Z_{it} - Y_{Rt}$) greater than three standard deviations from the mean, deemed to indicate mis-specification of crop type, were considered outliers and thus also removed from subsequent analysis. Among the remaining pixels, 200 fields were randomly selected in each region for further analysis. This number was deemed sufficient to obtain a reliable estimate of V_{YT} based on the number of years and simulations presented above (Fig. 1).

Each field was manually outlined in a geographic information system (GIS) to identify those pixels within the field. To avoid errors incurred at field boundaries, where pixels may include mixtures of roads and other fields, pixels near the edge of the field were excluded from the so-called region of interest (ROI). The average image value for pixels in each ROI ($i = 1, 2, \ldots, 200$) and year ($t = 1, 2, \ldots$, NYR) was then extracted, resulting in a $200 \times \mathrm{NYR}$ array (D) of field-region differences ($d_{i,t}$), where NYR equaled four in YV and five in SLRCV.

$$D = \begin{pmatrix} d_{1,1} & d_{1,2} & \cdots & d_{1,\mathrm{NYR}} \\ d_{2,1} & d_{2,2} & \cdots & d_{2,\mathrm{NYR}} \\ \vdots & \vdots & \ddots & \vdots \\ d_{200,1} & d_{200,2} & \cdots & d_{200,\mathrm{NYR}} \end{pmatrix} \tag{11}$$

The variance of each row of D was calculated to estimate $\mathrm{Var}(Z_{it} - Y_{Rt})$ for each field, with the average over all fields minus $\mathrm{Var}(\varepsilon_{it})$ used to estimate a characteristic V_{YT} for the region. Similarly, the variance of each column of D was used to compute the spatial variance within each year, with the average over all columns, minus $\mathrm{Var}(\varepsilon_{it})$, used to estimate V_{YS}. As discussed above, different values of $\mathrm{Var}(\varepsilon_{it})$ were evaluated to track the sensitivity of the results to assumptions about image noise.

5. Results

5.1. Regional scale yield variability

The variance of yield residuals from the 1976 to 2002 trend is given for each region in Table 2. V_{RT} was slightly higher in SLRCV than in YV, with the standard deviation of yield residuals in both regions equal to roughly 7.5% of average yields. This magnitude of variability is low relative to most major wheat growing nations, which typically exhibit absolute values of yield deviations between 10% and 20% of average yields (Calderini and Slafer, 1998). The greater stability in Northwest Mexico likely reflects a combination of greater irrigation rates and less variable climate relative to other major wheat producing regions.

5.2. Field scale yield variability

Fig. 4a–c displays the histograms for field sizes, field-region yield differences, and yield variances computed from the remotely sensed data in YV. The average field size was 12.5 ha for the ROI's in this region. The distribution of field-region differences ($Z_{it} - Y_{\mathrm{R}t}$) for all fields and years, shown in Fig. 4b, was skewed toward negative values (skewness = −0.50). This indicates that large negative field-region differences were more common than large positive differences, which is consistent with previous studies documenting the non-normality and negative skewness of yield anomaly distributions (e.g., Atwood et al., 2002).

The observed values of $\mathrm{Var}(Z_{it} - Y_{\mathrm{R}t})$, whose distribution is shown in Fig. 4c, averaged 0.21 $\mathrm{Mg}^2\ \mathrm{ha}^{-2}$. The average observed spatial variance, equal to the average variance of columns in D, was 0.32 $\mathrm{Mg}^2\ \mathrm{ha}^{-2}$ for YV. As discussed above, relating these values to V_{YT} and V_{YS} requires an estimate of the error in yield estimation $\mathrm{Var}(\varepsilon_{it})$. Fig. 4d displays values of V_{YT}, V_{YS}, and their ratio (I) as a function of the magnitude of error. For a value of $\mathrm{Var}(\varepsilon_{\mathrm{it}}) = 0.1$, for instance, the inferred values are $V_{\mathrm{YT}} = 0.11$, $V_{\mathrm{YS}} = 0.22$, and $I = 0.5$. To test whether temporal variance was significantly lower than spatial variance, a null distribution for I was derived using Monte Carlo simulation to compute I 100 times for normally distributed random noise across 200 fields over four years. The 99% confidence interval was 0.93–1.05, thus the values of I reported here are statistically significant at $p < 0.01$.

Table 2
Regional statistics for 1976–2002 wheat yields

Region	Trend (kg $\mathrm{ha}^{-1}\ \mathrm{yr}^{-1}$)	Variance of yield residuals (V_{RT}) ($\mathrm{Mg}^2\ \mathrm{ha}^{-2}$)	Standard deviation of residuals (σ) (Mg ha^{-1})	2000–2002 average yield (μ) (Mg ha^{-1})	Coefficient of variation (σ/μ) (%)
YV	49.3	.19	.44	5.81	7.5
SLRCV	77.8	.24	.49	6.57	7.4

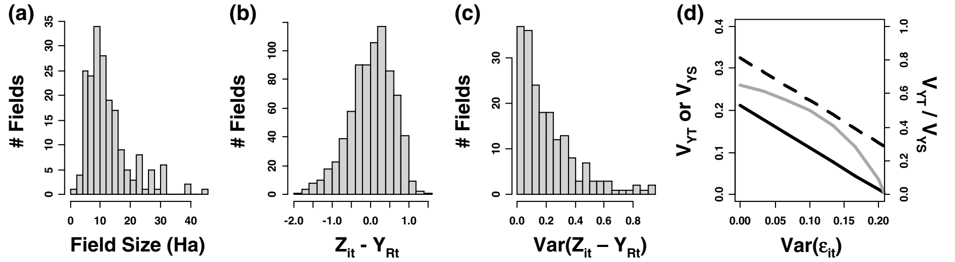

Fig. 4. Summary of multi-temporal yield analysis for the Yaqui Valley. (a) Histogram of field size (ha) for selected fields; (b) histogram of measured field-region differences, $Z_{it} - \mathrm{Y}_{\mathrm{R}t}$, for all years ($\mathrm{Mg\,ha^{-1}}$); (c) histogram of temporal variance computed from $Z_{it} - Y_{\mathrm{R}t}$ time series at each field ($\mathrm{Mg^2\,ha^{-2}}$); (d) estimated values of V_{YT} (solid black line; $\mathrm{Mg^2\,ha^{-2}}$), V_{YS} (dashed black line; $\mathrm{Mg^2\,ha^{-2}}$), and $I = V_{\mathrm{YT}}/V_{\mathrm{YS}}$ (gray line; unitless) for different assumed values of measurement noise, $\mathrm{Var}(\varepsilon_{it})$ ($\mathrm{Mg^2\,ha^{-2}}$).

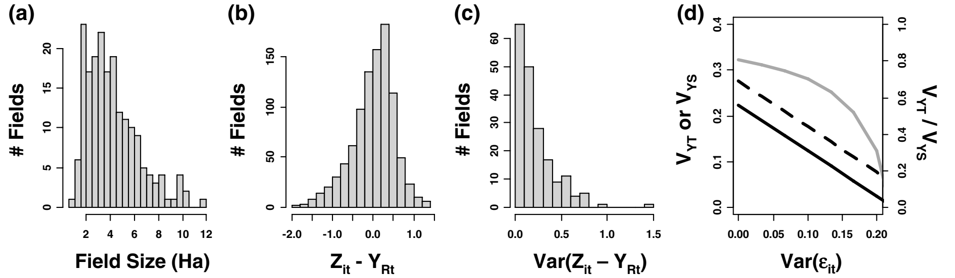

Fig. 5. Same as Fig. 4 but for the San Luis Rio Colorado Valley.

Fig. 5 displays the corresponding results for SLRCV. The average size of ROI's in this region was 4.3 ha, or roughly one-third the size of ROI's in YV. Again, the distribution of field-region yield differences exhibited negative skewness (−0.85) and was significantly non-normal (kolmogorov test, $p < 0.01$). The average variance of the rows and columns of D was 0.24 and 0.30, respectively. Assuming $\mathrm{Var}(\varepsilon_{it}) = 0.1$, this translates to $V_{\mathrm{YT}} = 0.14$, $V_{\mathrm{YS}} = 0.20$, and $I = 0.7$. Thus, temporal variability in SLRCV was similar to YV but spatial variability was substantially lower (F test, $p < 0.05$).

6. Discussion

We highlight two important aspects of the results presented above: (1) the relative values of V_{YT} and V_{YR} and (2) the relative values of V_{YT} and V_{YS}. We do not focus on the evidence for or against normality of yield anomalies, which can be an important issue when setting insurance premiums (Just and Weninger, 1999; Atwood et al., 2002; Sherrick et al., 2004).

The following discussion assumes that $\mathrm{Var}(\varepsilon_{it}) = 0.1$, which is deemed appropriate based on previous uncertainty analysis and comparison with field data. However, as seen in Fig. 4d and Fig. 5d, the interpretation of multi-year yield estimates is quite sensitive to the assumed value for $\mathrm{Var}(\varepsilon_{it})$ (i.e., noise level). It is also important to note that errors are assumed to be entirely random, i.e., they contribute equally to spatial and temporal yield variance. However, the yield estimates rely on remotely sensed estimates of canopy condition, which in turn are subject to errors associated with differences in soil reflectance or crop cultivar (which influences canopy architecture and leaf color) that are likely to exhibit consistent spatial patterns (Myneni and Williams, 1994). Unfortunately, testing the spatial and temporal randomness of errors requires validation data for several fields in multiple years, a dataset which is not currently available.

Therefore, we suspect that the contribution of error to spatial variance is likely higher than the contribution to temporal variance. The ratio of temporal to spatial variance, I, is thus deemed a conservative (i.e., minimum) estimate for the proportion of spatial variability owing to inconsistent factors. Finally, an assumption made throughout this analysis is that fields that contain wheat in all image years are representative of all fields with wheat in a single year; that is, selecting only those fields with wheat every year does not bias our results. This assumption would not hold if, for instance, less productive fields are less likely to be planted when prices are unfavorable, or if more productive fields are more likely to be planted with higher value crops in some years.

6.1. Regional vs. field scale yield uncertainty

The inferred values of V_{YT} in YV (0.11) and SLRCV (0.14) are, in both regions, 58% of the inferred value for V_{YR}. This indicates that field scale variability is roughly 50% greater than regional-scale variability in both regions. Interestingly, while these two regions differed in average field size (YV roughly three times bigger), region size (YV roughly 10 times bigger), and the ratio of field to region size, there was either no effect on the V_{YT}:V_{YR} ratio or any effects canceled each other out.

The increase of risk by 58% when moving from the regional to field scale is not only consistent between the two sites studied here, but agrees well with previous studies from other regions. In a study of wheat yields in Kansas, Marra and Schurle (1994) computed average yield standard deviations of roughly 0.46 Mg ha^{-1} at the county scale and 0.56 Mg ha^{-1} at the field scale, which translates to a ratio of field to county variance of 1.49. In a study of wheat yields in Canada, Rudstrom et al. (2002) report an average ratio of field:municipality yield variance of 1.6. While several factors contribute to the effect of aggregation on yield risk (Marra and Schurle, 1994; Rudstrom et al., 2002; Gorski and Gorska, 2003), it thus appears that a roughly 50% increase in risk in terms of yield variance is common when moving from regional to field scales.

6.2. Temporal vs. spatial yield variability

In YV, the temporal variance of field-region differences was one-half the magnitude of average spatial yield variance ($I = 0.5$). We interpret this to mean that spatial variability of wheat yields in YV can be explained roughly equally well by the factors in left and right hand side of Table 1. As shown in Table 1, annual management decisions such as planting date and fertilizer rates can either be consistent or inconsistent, depending on the actions of the farmer. For instance, some farmers tend to always apply high fertilizer rates, and therefore this factor would tend to be consistently different between fields. On the other hand, a factor such as planting date may vary based on the farmer's schedule from year to year. Thus, it is impossible to entirely classify annual management decision as consistent or inconsistent. However, based on our experience, farmers tend to manage their land similarly from year to year. Thus, the 50% explained by inconsistent factors is likely due not to variation in management practices, but by interactions of climate with spatially variable factors, such as soil and management properties.

A simple interpretation of $I = 0.5$ is that no more than half of yield variability can be explained by factors associated with location (i.e., soil properties, landscape position, farmer identity, etc.). This, in turn, implies that efforts to address these factors will, at best, reduce the yield gap by 50%. The higher value of $I = 0.7$ in SLRCV indicates that a maximum of just 30% of yield variability in this region can be explained by location. It therefore appears that non-site related factors drive the majority of spatial variations in yield performance. If we assume that management is fairly consistent through time at each field, this implies that the relative yield performance of farmers is largely the result of uncertain factors, namely climatic conditions via their interaction with management and soil properties. This, in turn, implies that forecasts of growing season weather conditions, which could be used to adjust management based on known climate–management interactions, has the greatest potential to contribute to yield gap reductions in these agricultural regions. These conclusions are somewhat at odds with traditional views of many farmers and researchers, which is that while climate is important for determining average performance, the difference between farmers is strongly related to skill, access to capital, and biophysical resources.

7. Conclusions

Remote sensing provides access to unparalleled datasets on the temporal variability of crop yields at the field scale. The extensive spatial coverage of Landsat-like instruments can overcome problems associated with the relatively short records attainable from satellite. The yield datasets used in this study relied on methods that utilize minimal ground information and therefore can be readily applied to different agricultural regions, including those in developing regions where reliable ground data can be sparse. Thus, overall remote sensing can greatly contribute to understanding of yield variability at the field scale. However, improved understanding of the errors associated with remote sensing yield estimates is needed to fully realize this potential, since the interpretation of yield patterns are sensitive to assumptions about measurement errors.

In the case studies presented here, field scale yield variability was determined to be roughly 58% greater than regional-scale variability in both regions, illustrating that individual farmers face substantially greater risk than suggested by aggregated yield time series. This finding agrees with several previous studies from other regions and emphasizes the need to be mindful of scale when assessing farmer risk and decision making. Further work is needed to test whether this magnitude of risk increase is indeed very common, with potential implications for insurance rating and other risk management efforts.

The results of this study also indicate that a significant fraction of spatial yield variability can be attributed to the same factors that give rise to field scale yield risk, namely climate variability. Forecasts of growing season weather therefore appear critical to significantly reducing spatial yield variability and the associated yield gap. Reductions in the yield gap may be increasingly important if crop demand rises at a faster rate than genetic yield potential (Cassman et al., 2003).

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