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Relative importance of soil and climate variability for nitrogen management in irrigated wheat

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Abstract

Increased efficiency of nitrogen (N) fertilizer use may be achieved with management practices that account for spatial variability in soil properties and temporal variability in climate. In this study, we develop a N management decision model for an irrigated wheat system that incorporates hypothetical diagnostics of soil N and growing season climate. The model is then used to quantify the potential value of these forecasts with respect to wheat yields, farmer profits, and excess N application. Under the current scenario (i.e. no diagnostics), uncertainty in soil and climate conditions is shown to account for an average over-application of N by roughly 35%. Both soil diagnostics and climate forecasts are shown to increase profits significantly and decrease over-application of N, with minimal changes in yield. Soil variability is roughly three times as important as climate variations in terms of potential impact on profits in this region. The model was also used to simulate the effect of increases in fertilizer price, which have similar positive effects on excess N application but negative impacts on profits. Finally, the role of forecast uncertainty was evaluated, indicating that even limited information on soil or climate can be a useful input to management decisions. Future work is needed to improve operational diagnostics of soil N and growing season climate, whose cost can then be compared to benefits calculated in this study to determine their net value to N management decisions.

Keywords: Climate variability; Management decisions; Nitrogen; Soil variability; Uncertainty; Wheat

1. Introduction

The worldwide application of fertilizer nitrogen (N) in agriculture has increased more than six-fold since 1960 (FAO, 2003), and at roughly 80 Mt N per year is currently second only to biological N fixation as a source of N to terrestrial ecosystems (Galloway et al., 1995). While increased fertilizer use has played an important role in keeping food production in pace with population growth, off-site consequences such as eutrophication and N-oxide gas production have raised concerns about environmental impacts of current practices (Matson et al., 1997; Gregory et al., 2002).

Improvements in the efficiency of nitrogen use in major cropping systems will be a central component of efforts to produce more food while reducing environmental impacts (Conway, 1997; Cassman, 1999). Several opportunities have been identified

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for improving nitrogen use efficiency (NUE) through crop management, all of which attempt to improve the congruence between the dynamics of crop N demand and supply from soil, fertilizer, and other sources, and thereby reduce the amount of N lost from the system. These include (1) improved timing and/or placement of fertilizer application to match crop needs, (2) improved sources of N, such as slow-release fertilizers, and (3) adjustment of application rates based on yield goals and available soil N (Ortiz-Monasterio, 2002).

The latter approach recognizes that traditional blanket fertilizer recommendations fail to address spatial and temporal variations in N supply and demand, resulting in potentially significant N wastes. For example, Dobermann et al. (2002) showed that the indigenous N supply in rice systems in Asia can vary two to three-fold between individual fields, and that site-specific recommendations based on on-farm measurements of indigenous N improved NUE by 30–40%. A major appeal of these approaches is that, because N losses negatively impact both environmental quality and farmer income, improvements in NUE represent a win–win situation for the farmer and the environment.

The appropriate N rate for a given field can be expressed as (Ortiz-Monasterio, 2002):

$$N_{rate} = \frac{N_{req} - N_{con}}{N_{eff}} \quad (1)$$

where N_{req} is the amount of N required to meet the yield goal (i.e. crop N uptake requirement), N_{con} the contribution of N from the soil (derived from residual mineral N), and N_{eff} is the expected efficiency of fertilizer recovery. While much effort is currently focused on measuring N_{con} in order to adjust N rate, significant potential may also exist to address variations in N_{req} that arise from climate variability (Dobermann and Cassman, 2002; Sadras, 2002). Observed N fertilizer uptake efficiency in rice–wheat systems of India, for instance, varied from 18% in 1 year to 49% in the next, attributed to better weather and therefore higher yields in the latter year (Cassman et al., 2002). With some forecast of growing season weather, it should be possible to adjust yield goals, and hence fertilizer rates based on projected yield potential, e.g. N rates could be reduced in particularly bad years when low yields are anticipated.

To direct research and management efforts, it is important to quantify the potential gains from site-specific and season-specific N management. While the relevant measure of gain may differ for various farmers and policy makers, three important aspects of N management are its effect on crop yields, farmer income, and environmental quality. Integrated studies of fertilizer management should consider at least these three factors.

In this study, we investigate and compare the potential agronomic, economic, and environmental value of growing season climate forecasts and soil N diagnostics as they relate to N management in the Yaqui Valley, an intensive wheat system in Sonora, Mexico. Using data from experimental trials and on-farm measurements, we first quantify the temporal variation in climatic yield potential and the spatial variation in N_{con} within the Valley. A Monte Carlo simulation is then used to estimate wheat yields, farmer profits, and the amount of excess fertilizer N under scenarios where farmers attempt to maximize expected profits using climate forecasts and N_{con} diagnostics with a prescribed level of uncertainty. Finally, we evaluate the sensitivity of forecast value to its level of uncertainty and the costs of N fertilizer. While this study is focused on a particular region, the modeling approach developed here provides a framework that can be used to evaluate the value of N management strategies in any location.

2. Methods

2.1. Site description

The Yaqui Valley is situated between the Gulf of California and the Sierra Madre mountains on the west coast of Sonora, Mexico (Fig. 1A). It comprises roughly 225,000 ha of irrigated cropland, with 50–75% of this area typically planted to spring wheat in November–December, which is then harvested in April–May. N fertilizer applications, which average over 250 kg N ha^{-1} per year for wheat, represent the largest single cost of production to farmers, accounting for roughly 20% of total production expenses (Matson et al., 1998). In addition to entailing sizeable costs to farmers, high N rates result in significant losses to the environment, including leaching (Riley

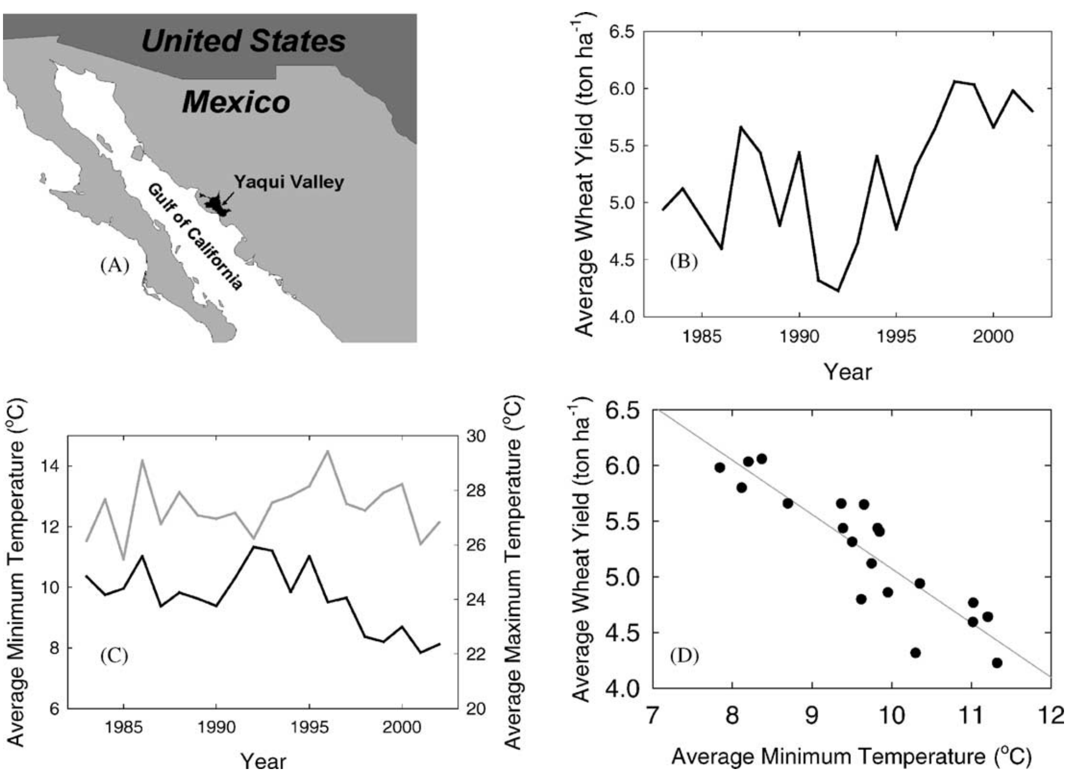

Fig. 1. (A) Location of Yaqui Valley, Sonora, Mexico, (B) average wheat yields, (C) average January–April minimum (black line) and maximum (gray line) temperatures in the Yaqui Valley for 1983–2002, and (D) relationship between minimum temperatures (T_{ja}) and wheat yields for the 20-year period.

et al., 2001) and some of the largest rates of N_2O production ever recorded (Matson et al., 1998).

Average wheat yields in the Yaqui Valley are among the highest in the world, varying between roughly 4.0 and 6.0 Mg ha^{-1} over the last two decades (Fig. 1B). While water availability is becoming an increasingly important issue in the Valley, irrigation has historically been sufficient (>400 mm ha^{-1} per cycle) to prevent significant water stress. In addition, the availability of new germplasm generated by the collaboration between the Instituto Nacional de Investigaciones Forestales Agricolas y Pecuarias (INIFAP) and the Centro Internacional de Mejoramiento de Maiz y Trigo (CIMMYT) has limited the extent of yield loss due to pests and disease. As a result, variations in temperature and solar radiation have been the primary control on average yields (Fischer, 1985; Reynolds et al., 2002).

In particular, we have found that average nighttime temperature in the January–April period is highly correlated with wheat yields over the last two decades ($R^2 = 0.80$; Fig. 1D), with increased temperatures associated with lower yields. Interestingly, average daytime temperature exhibit non-significant correlation with both nighttime temperature and yields ($P > 0.1$). This finding suggests that the primary mechanism of yield loss associated with higher temperature is increased rates of plant respiration, which can be offset by increased rates of photosynthesis during the day, but not at night.

The strong relationship between average wheat yields and January–April nighttime temperature, hereafter called T_{ja}, suggests that a forecast of growing season minimum (i.e. nighttime) temperature would be useful for N management decisions by enabling an adjustment for a more realistic yield goal. However, the degree to which a forecast is useful depends on several factors (Jones et al., 2000; Hansen, 2002), including, but not limited to (a) the uncertainty of the forecast, (b) the relationship between N rates and yield, and (c) the cost of fertilizer relative to wheat prices. The following sections attempt to quantify the potential value of forecasts with consideration of these factors.

2.2. Simulation of N management scenarios

Fig. 2 provides a schematic representation of the model used in the study. In a given year, yield potential is computed as the minimum of two potentials: Y_C, the yield potential for the given climate conditions, and Y_N, the yield potential for the amount of N applied.

2.2.1. The yield goal

The value of Y_C in a given year is randomly selected from a distribution $f(Y_C \mid x_c)$, which is the distribution of Y_C conditioned on some predictor variable, x_c. At one extreme, x_c could be a variable that provides no information on yield, in which case $f(Y_C \mid x_c)$ is equal to the marginal distribution of yield, $f(Y_C)$. At the other extreme, we can consider x_c to represent a perfect forecast of T_{ja}, in which case there is significant information regarding the expected yield ($f(Y_C \mid x_c) \neq f(Y_C)$). Here we consider Y_C to be a linear function of x_c:

$$Y_C = \beta_0 + \beta_1 x_c + \varepsilon \tag{2}$$

where β_0 and β_1 are the intercept and slope, respectively, of a regression between x_c and Y_C, and ε is an error term representing uncertainty. For simplicity, we consider x_c to be drawn from a standard normal distribution

$$x \sim N(0, 1)$$

(In practice, any normally distributed variable, such as T_{ja}, can be transformed to a standard normal variable by subtracting the mean and dividing by the standard deviation.) In this case, the best estimate of β_0 and β_1, in a least squares sense, can be expressed as

$$\beta_0 = \mu_{Y_C} \tag{3}$$

$$\beta_1 = \mathrm{corr}(x_c, Y_C) \times \sigma_{Y_C} \tag{4}$$

where μ_{Y_C} is the mean of Y_C, corr(x_c, Y_C) the correlation between x_c and Y_C, and σ_{Y_C} the standard deviation of Y_C. The distribution of the error, ε, is normal with mean zero and variance, σ^2, which can be expressed as

$$\sigma^2 = (\sigma_{Y_C})^2 - (\beta_1)^2 \tag{5}$$

Therefore, with the given values of x_c, μ_{Y_C}, σ_{Y_C}, and corr(x_c, Y_C) we can compute a distribution of values for Y_C based on Eqs. (1)–(4). Values of μ_{Y_C} and σ_{Y_C} were computed from 13 years of yield trials on experimental plots where wheat was grown using common varieties but controlling for non-climatic constraints such as nutrient and water stress, diseases, insects and weeds (Table 1; K. Sayre, personal communication). Yields in these trials averaged 7.49 Mg ha^{-1}, with a standard deviation (σ_{Y_C}) of 0.69 Mg ha^{-1}.

2.2.2. N requirement

The value of Y_N was determined from the amount of N applied (N_{rate}) based on the equation:

$$Y_N = 3.55 \log_e(N_{rate} N_{eff} + N_{con}) - 11.41 \tag{6}$$

which defines the maximum yield associated with a given amount of N uptake. The logarithmic form of

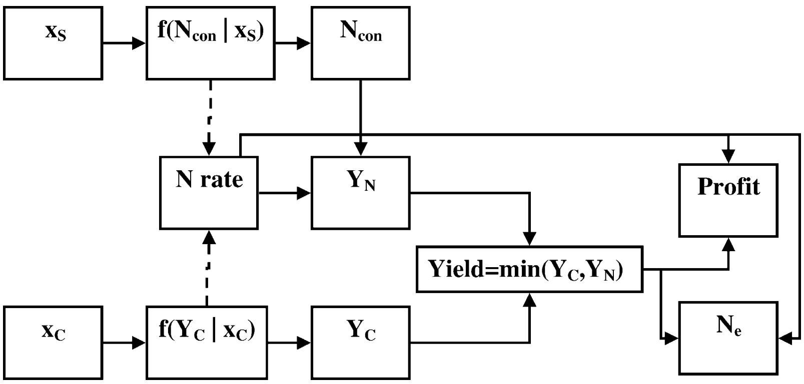

Fig. 2. N management decision model used in this study, where N rate is determined by maximizing expected profit.

Table 1
Climatic yield potential as measured in experimental trials in the Yaqui Valley (from K. Sayre)

Year	Yield (Mg ha^{-1})
1986	7.17
1987	7.90
1988	8.60
1989	7.11
1990	8.17
1991	7.70
1992	6.09
1993	7.51
1994	7.31
1995	6.53
1996	7.26
1997	7.74
1998	8.26
Mean	7.49
S.D.	0.67

Eq. (6), as well as the value of the coefficients, has been determined from prior field studies in the Yaqui Valley conducted under average farmer conditions (Ortiz-Monasterio, unpublished data; $n = 502$, $R^2 = 0.81$). N_{eff} was prescribed a value of 50% based on field experiments, which largely reflects the inevitable losses of fertilizer N to ammonia volatilization, denitrification, nitrous and nitric oxide emissions, nitrate leaching, and soil immobilization (the latter of which may contribute to N_{con} in the following year).

In an analogous manner to the computation of Y_{C}, N_{con} is a linear function of a hypothetical diagnostic of soil N availability, named x_{s}, where the uncertainty of the relationship between N_{con} and x_{s} is quantified by corr(x_{s}, N_{con}). Thus, as before, given values for the mean and standard deviation of $N_{\mathrm{con}}(\mu_{N_{\mathrm{con}}}, \sigma_{N_{\mathrm{con}}})$ and values for x_{s} and corr(x_{s}, N_{con}), we can compute a distribution of values for N_{con}. Values for $\mu_{N_{\mathrm{con}}}$ and $\sigma_{N_{\mathrm{con}}}$ were parameterized as 108 and 47 kg N ha^{-1}, respectively, based on measurements of residual soil N in 28 farmer fields. N_{con} was estimated in each field by collecting wheat grain and straw samples at maturity to measure total N uptake in wheat plots where no N fertilizer was applied.

2.2.3. Model outputs

In addition to yield, which provides a measure of agronomic output, we consider two additional variables, farmer profit and excess N, which measure the economic and environmental output, respectively. Farmer profit (N\$ ha^{-1}) is expressed as

$$\mathrm{profit} = (P \times \mathrm{yield}) - (C_{\mathrm{N}} N_{\mathrm{rate}} - C_{\mathrm{O}}) \tag{7}$$

where P is the price of wheat (N\$ t^{-1}), C_{N} the cost of N fertilizer (N\$ kg^{-1}), and C_{O} the cost (N\$ ha^{-1}) associated with all aspects of production other than fertilizer, including land preparation, seed purchase, irrigation, pest control, etc. Values for P (N\$ 1660 t^{-1}), C_{N} (N\$ 4.0 kg^{-1}), and C_{O} (N\$ 6928 ha^{-1}) were defined based on the 2001–2002 wheat cycle (SAGARPA, 2002). (Note: current exchange rate is N\$ 11.2/US\$.)

Excess N (N_{e}) represents the amount of N applied in fertilizer that exceeds the requirements for crop growth, and is therefore prone to leaching or gaseous losses. N_{e} is calculated as

$$N_{\mathrm{e}} = N_{\mathrm{rate}} - N^{*}_{\mathrm{rate}} \tag{8}$$

where N^{*}_{rate} is the minimum N rate needed to reach the actual yield, and is determined using Eq. (6).

2.2.4. Monte Carlo simulation

The model in Fig. 2 was applied repeatedly to evaluate yields, profits, and N excesses under different scenarios. This procedure is referred to as a Monte Carlo simulation, because each run of the model involves "rolling the dice" to add random perturbations representing uncertainty in model parameters or inputs. Specifically, the entire simulation of N management using uncertain forecasts was executed as follows:

(1) Values of corr(x_{c}, Y_{C}) and corr(x_{s}, N_{con}) are defined to represent the uncertainty of the climate forecast and soil N diagnostic, respectively.
(2) Values of x_{c} and x_{s} are randomly generated from independent standard normal distributions.
(3) A distribution of 1000 potential values of Y_{C} is computed using Eqs. (2)–(5).
(4) A distribution of 1000 potential values of N_{con} is computed in an identical manner, using x_{s}, $\mu_{N_{\mathrm{con}}}$, $\sigma_{N_{\mathrm{con}}}$, corr($x_{\mathrm{s}}$, N_{con}) in place of x_{c}, $\mu_{Y_{\mathrm{C}}}$, $\sigma_{Y_{\mathrm{C}}}$, and corr(x_{c}, Y_{C}).
(5) N rate is determined by iterating the model until the average profit for the given distribution of Y_{C} and N_{con} is maximized. In essence, the farmer must decide how much N to apply given some

uncertainty in the soil N supply and growing season conditions, and therefore chooses a rate that maximizes the expected profit.

(6) Given this optimal N rate, the model is then run a single time to simulate the actual outcome of the current year.
(7) Steps 2–6 are repeated for a large number of years (1000) to compute the average outcome under the values prescribed in step 1.
(8) Steps 1–6 are repeated for different values of corr(x_c, Y_C) and corr(x_s, N_{con}), to test the sensitivity of the value of a climate forecast or soil diagnostic to its uncertainty.

This procedure thus identifies the optimal N fertilizer rates and the resulting yields, profits, and excess fertilizer amounts for a field where yields are constrained only by climate or N. The effect of other yield constraints, such as water stress or disease, are not explicitly modeled but are discussed below.

Finally, we note that because the management decision is based on optimizing profit, it is apparent from Eq. (7) that this depends on the ratio of N cost to wheat price. To test the sensitivity of model results to the cost of N relative to wheat, steps 1–7 were repeated using $N_{cost} = \text{N\$}\,5.0\,\text{kg}^{-1}$. This represents a 25% increase in N costs and provides a means to evaluate the potential effect of price changes relative to climate forecasts on yields, profits, and N_e.

3. Results and discussion

3.1. Baseline scenario

The main simulation results are presented in Table 2 and Fig. 3, which show the model outputs for different combinations of soil and climate forecast certainties (corr(x_c, Y_C) and corr(x_s, N_{con}), respectively). In the figure, the value of each output at the origin represents the modeled value under a scenario with no accounting for soil or climate variability, similar to the current situation, whereas the value at $(\text{corr}(x_c, Y_C)^2 = 1,\ \text{corr}(x_s, N_{con})^2 = 1)$ corresponds to a best-case scenario where N_{con} and Y_C are known perfectly. In the former case, which we refer to as the baseline, the rate of N application that maximizes expected profit is 274 kg N ha^{-1}. This agrees remarkably well with the average observed N rate in the Valley, which was 263 ± 5 kg N ha^{-1} in a survey of 75 farmers in 2001 (R. Naylor, personal communication). The similarity of these two values supports the assumption in the model that farmer behavior can be explained in terms of maximizing expected profits under uncertain conditions.

The optimal N rate of 274 kg N ha^{-1} is sufficient to meet N demand up to 8.15 Mg ha^{-1} of yield with an average soil N contribution. Clearly, this optimal N rate in the baseline scenario results in large excess of N in years where climate limits yield, resulting in average over-application of N of nearly 100 kg N ha^{-1} (Fig. 3C). This is illustrated in Fig. 4A, which shows

Table 2
Average simulated N rate, yield, profit, and excess N for different combinations of soil and climate forecast accuracies (i.e. management scenarios)[a]

Scenario		Optimal N rate (kg N ha^{-1})	Average yield (Mg ha^{-1})	Average profit (N\$ ha^{-1})	Excess N (kg N ha^{-1})
(corr(x_c, Y_C))^2	(corr(x_s, Y_N))^2				
0	0	274	7.30	4082	97
0	0.5	244	7.31	4220	71
0	1	221	7.29	4286	47
0.5	0	262	7.33	4186	84
0.5	0.5	236	7.32	4272	62
0.5	1	208	7.29	4335	35
1	0	255	7.35	4250	70
1	0.5	226	7.33	4335	46
1	1	188	7.38	4559	3

[a] N costs equal N\$ 4.0 kg^{-1}.

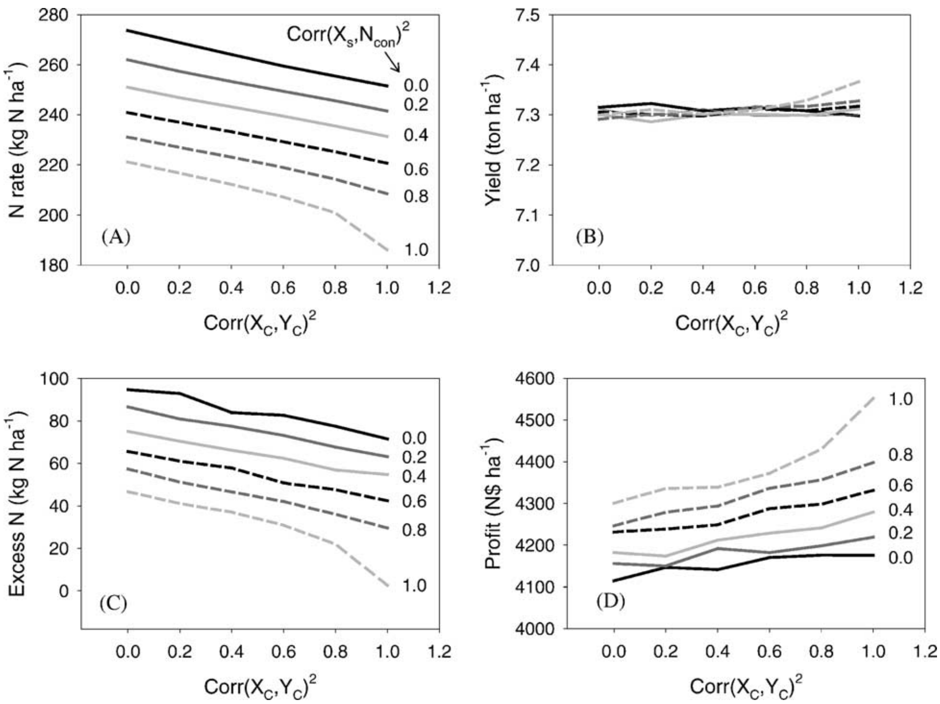

Fig. 3. Average simulated (A) N rate, (B) wheat yield, (C) profit, and (D) N excess using forecasts of Y_C and N_{con} at various prescribed levels of accuracy. Each line represents a different level of soil diagnostic accuracy, corr(x_s, N_{con})^2.

the simulated yields and N_e for 50 years of the baseline simulation. The current prices of fertilizer and wheat are such that farmers are more willing to waste large amounts of N on average than to risk N limitation of yields in years with favorable weather. Uncertainty in N supply and demand thus results in a simulated average over-application of more than 35%.

The average yields and profits in the baseline scenario are 7.3 Mg ha^{-1} and N$ 4115 ha^{-1}, respectively. Again, these figures assume that farmers' yields are not limited by factors other than climate and N. In most cases, yields and profits will be lower due to other constraints, as discussed in Section 3.4.

3.2. Forecast value

N rates decrease from the baseline scenario as both soil N diagnostics and climate forecasts improve from 100% uncertainty (i.e. no forecast) to 100% certainty (Fig. 3A). Under perfect knowledge of soil N contributions, average rates are only 221 kg N ha^{-1}, a decrease from the baseline of 19%. Associated with the drop in N rate is a decrease in average N excess of 48 kg N ha^{-1} (51%) and an increase in profit of N$ 186 ha^{-1} (4.5%). Yields change very little (<1%; Fig. 3B) as either soil or climate forecasts improve because, as discussed above, farmers respond to uncertainty by applying enough N to meet demand of the all but the highest potential yields.

As forecasts of climatic yield potential improve from the baseline scenario (i.e. corr(x_c, Y_C) approaches 1), average profits increase, yields remain fairly stable, and both N rates and N excess decline. The increase in profits for a perfect forecast of Y_C is N$ 61 ha^{-1} (1.5%), or roughly one-third the increase that is simulated for soil N diagnostics. This indicates that spatial variations in N_{con} are roughly three times as important as temporal variations in N_{req} for N management decisions in an economic sense. Similarly, N rates and N excess decrease by 8 and 24%, respectively, under perfect Y_C forecasts compared to the 19 and 51% decrease under perfect N_{con} diagnostic. Thus, climate-induced variations in N demand are less important than soil variations in N supply, but still represent a significant opportunity for improved N management.

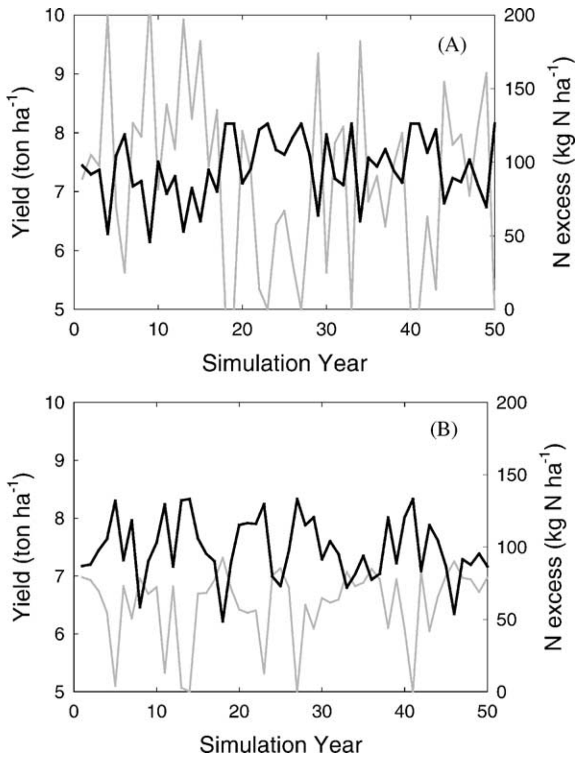

Fig. 4. A 50-year simulated time series of yield (black line) and N excess (gray line) for a field with fixed soil N (108 kg N ha^{-1}) and (A) no climate forecast or (B) a forecast that explains 50% of climate variability. In (A), N excess rises sharply as yields decrease due to unchanging N rates. In (B), increases in N excess are much smaller because rates are decreased in years with low yields.

An important aspect of the model results in Fig. 3 is the synergy between soil and climate information. For example, average profits increase by 10.6% with perfect knowledge of both N_{con} and Y_C, which is nearly twice the sum of the gains with knowledge of either factor alone. In other words, even with perfect knowledge of climate, farmers are still likely to apply a lot of fertilizer if soil N contributions are uncertain. Similarly, soil N diagnostics will be most valuable when climate uncertainty is reduced.

3.3. Effect of N costs

Fig. 5 illustrates the model simulation results when N cost is increased by 25% over its current value. In the baseline scenario, average N rates are 253 kg N ha^{-1}, or 7.7% lower than under current N cost. This is roughly equal to the effect of a perfect forecast of Y_C (Fig. 3A). However, two important differences are observed between these two scenarios. With increased N cost, profits are decreased by 6% and excess N drops by only 15% relative to current cost. In contrast, a forecast of Y_C would slightly increase profit and would decrease excess N by 24%. Unlike cost incentives, such as increased fertilizer taxes, climate forecasts would have a beneficial effect on both farmer profits and environmental pollution in the Yaqui Valley. In addition, reduction of average N rates through the use of forecasts is more effective at limiting excess N, since farmers are able to decrease N rates more in years that have lower yield potential and thus higher levels of wasted N.

The impacts of climate and soil diagnostics are slightly larger at higher N cost. For example, profits increase by 13.9% with perfect knowledge of both N_{con} and Y_C over the baseline scenario, compared to 10.6% under current cost. This indicates that improved knowledge of soil and climate variability becomes more valuable as the cost of fertilizer rises relative to wheat. Simulations were also performed at various other levels of fertilizer and wheat prices, with decreases in wheat prices exhibiting the same effect as increases in fertilizer price, and with the effect of both roughly proportional to the magnitude of price change.

3.4. Other yield constraints

The above discussion of profits and N excess assumed that yields are constrained only by climate or N. In reality, many factors including water, weeds, insects, and disease suppress yields below the potential dictated by climate and fertilizer, and actual yields attained in farmers' fields are often well below this potential. As a result, the yields and profits realized by farmers are often much lower than the values discussed above, and the amount of excess N is correspondingly much higher because less N is taken up by the crop. For example, a farmer with an average yield of 5.5 Mg ha^{-1}, as opposed to 7.4 Mg ha^{-1}, will realize an average profit of roughly N\$ 1100 ha^{-1}, with average excess N equal to 158 kg N ha^{-1} in the baseline scenario. Thus, farmers operating below the yield potential will

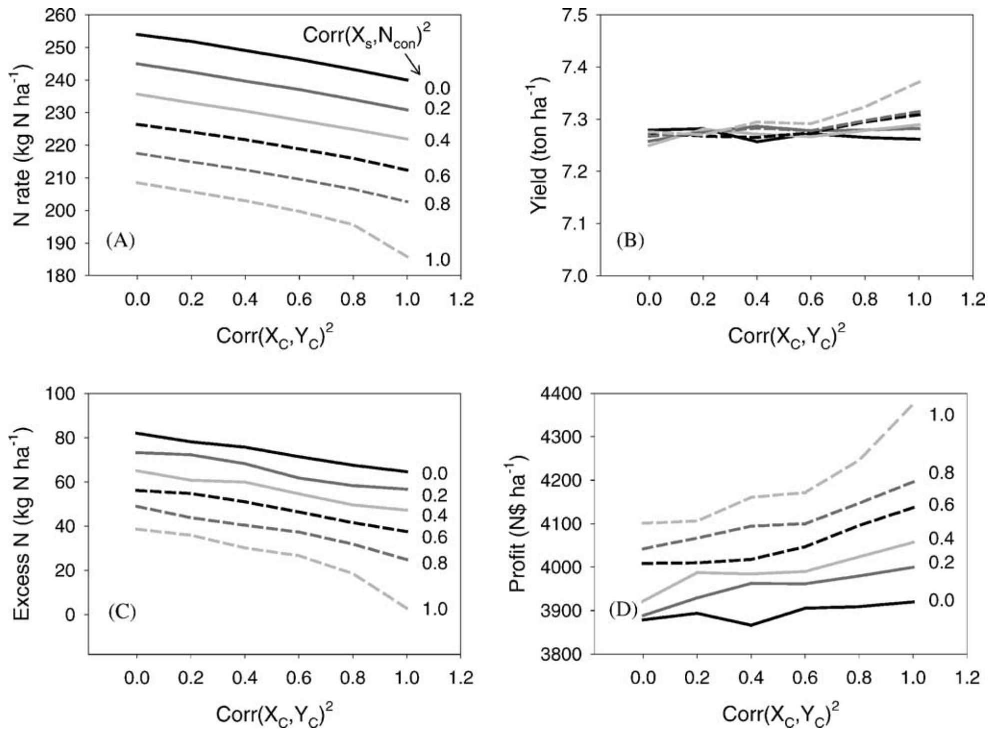

Fig. 5. As in Fig. 3 but with N cost equal to N$ 5.0 kg^{-1}.

experience a greater proportional impact on profits and a smaller proportional impact on N excess resulting from changes in N rates than farmers with higher yields. Forecasts that enable reductions in N rates would therefore be of particular importance to farmers who currently experience marginal profits, and whose N costs represent a more substantial fraction of net income.

3.5. Forecast feasibility

While this study explored the potential benefits of soil N and climate diagnostics, it did not address their feasibility. Currently we are testing several approaches to diagnose soil N, including comparison of fertilized and unfertilized strips with ground-based and airborne sensors. For growing season climate forecasts, statistical analyses of ocean surface temperatures indicate that T_{ja} can be predicted with an R^2 of 40% up to 6 months before the growing season (D. Lobell, unpublished data). Future work is needed to better understand the ocean–atmosphere interactions that affect winter climate in Sonora, and thereby improve growing season forecasts. The incorporation of more mechanistic crop growth models may also improve the prediction of Y_C, and should be explored in the future.

4. Conclusions

Both soil N diagnostics and growing season climate forecasts have significant potential to reduce excess N fertilizer application in the Yaqui Valley, with subsequent benefits to farmer income and environmental quality. In relative terms, soil variability of N supply is roughly 2–3 times as important to quantify as climate variability in this region, but the latter still represents a significant opportunity to raise income and reduce over-application of N. Moreover, there is a synergy between reducing uncertainty in soil N supply and crop N demand, such that soil N diagnostics are more valuable when climate uncertainty is low, and vice versa.

The greatest gains are achievable when both sources of uncertainty are simultaneously reduced.

Price incentives, such as increased fertilizer taxes, were also shown to result in decreased average N rates, but with corresponding decreases in farmer profit. In addition, because N rates are decreased uniformly in all years under a price change scenario, the average amount of excess N is not reduced as efficiently as under a soil or climate forecast scenario. For these reasons, price incentives appear less attractive for improving N use efficiency.

The analysis presented here used field measurements of climatic yield potential and soil N contributions to define the magnitude of variability within the Yaqui Valley. The results concerning the relative importance of soil and climate variability are therefore specific to the current study region, and would likely differ for other regions, such as in rainfed environments with large rainfall variations from year to year. Nonetheless, the modeling approach used here provides a means of evaluating the value of soil and climate information in any system. In regions without experimental values of Y_C, crop simulation models could be used to simulate variations in climatic yield potential.

Matching N supply to variations in crop demand both spatially (within and between fields) and temporally (within and between seasons) will be an important component for simultaneously achieving greater crop yields and improving agricultural sustainability. Simulation models such as the one presented in this study can provide important quantitative insight for prioritizing future research and management efforts. Based on the results of this study, efforts to quantify and predict soil and climate variability can substantially reduce N over-application and simultaneously improve farmer income.

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