Global Change Biology (2008) **14,** 39–45, doi: 10.1111/j.1365-2486.2007.01476.x

Estimation of the carbon dioxide (CO_2) fertilization effect using growth rate anomalies of CO_2 and crop yields since 1961

DAVID B. LOBELL* and CHRISTOPHER B. FIELD†

Energy and Environment Directorate, Lawrence Livermore National Laboratory, Livermore, CA 94550, USA, †Department of Global Ecology, Carnegie Institution, Stanford, CA 94305, USA

Abstract

The effect of elevated carbon dioxide (CO_2) on crop yields is one of the most uncertain and influential parameters in models used to assess climate change impacts and adaptations. A primary reason for this uncertainty is the limited availability of experimental data on CO_2 responses for crops grown under typical field conditions. However, because of historical variations in CO_2, each year farmers throughout the world perform uncontrolled yield 'experiments' under different levels of CO_2. In this study, measurements of atmospheric CO_2 growth rates and crop yields for individual countries since 1961 were compared with empirically determine the average effect of a 1 ppm increase of CO_2 on yields of rice, wheat, and maize. Because the gradual increase in CO_2 is highly correlated with major changes in technology, management, and other yield controlling factors, we focused on first differences of CO_2 and yield time series. Estimates of CO_2 responses obtained from this approach were highly uncertain, reflecting the relatively small importance of year-to-year CO_2 changes for yield variability. Combining estimates from the top 20 countries for each crop resulted in estimates with substantially less uncertainty than from any individual country. The results indicate that while current datasets cannot reliably constrain estimates beyond previous experimental studies, an empirical approach supported by large amounts of data may provide a potentially valuable and independent assessment of this critical model parameter. For example, analysis of reliable yield records from hundreds of individual, independent locations (as opposed to national scale yield records with poorly defined errors) may result in empirical estimates with useful levels of uncertainty to complement estimates from experimental studies.

Keywords: carbon dioxide, climate change, CO_2 fertilization, crop yields, food security, global warming, maize, rice, wheat, yield models

Received 28 June 2006 and accepted 29 August 2006

Introduction

The response of crop yields to elevated carbon dioxide (CO_2) is one of the major sources of uncertainty when assessing the potential impacts of climate change on food security and the economy, as well as the effectiveness of different adaptation strategies (Long *et al.*, 2005, 2006; Parry *et al.*, 2005). For example, in a recent assessment of climate change impacts (Parry *et al.*, 2004), removal of the beneficial effect of elevated CO_2 in crop models was found to increase the projected number of malnourished people in 2080 by as much as 500 million.

Many experiments have attempted to estimate the CO_2 fertilization effect (CFE) by comparing yields in elevated CO_2 treatments to those under ambient ($\sim$375 ppm) conditions. The earliest studies were conducted in greenhouses and laboratory or field chambers (Kimball, 1983; Cure & Acock, 1986), while more recently free air (chamberless) CO_2 enrichment (FACE) trials have also been established (Ainsworth & Long, 2005; Long *et al.*, 2006). The relevance of results from chamber experiments has been widely questioned because of potential interactions of CO_2 with factors such

Correspondence: David Lobell, tel. +1 925 422 4148, fax +1 925 423 4908, e-mail: lobell2@llnl.gov

as nutrient and water availability, temperature, and pest damage. These factors are generally different within chambers than in farmers' fields. It has been suggested recently that yield responses to CO_2 in FACE experiments are systematically lower than in chamber studies (Ainsworth & Long, 2005; Long *et al.*, 2005, 2006), although comparisons are often difficult because of differences in CO_2 levels, cultivars, nutrient levels, and other factors between experiments (Amthor, 2001; Tubiello *et al.*, 2007).

The great variability of experimental results has resulted in 95% confidence intervals for the CFE of major crops (e.g. wheat) that often span a factor of two (Amthor, 2001). Responses for nonmajor crops are even more uncertain, with limited or no experimental data available for a majority of food crops. This uncertainty, of course, argues for more experiments that span a greater range of conditions and crops. However, it also emphasizes the potential value of independent measures of CO_2 effects on yields.

The main alternative to experiments is empirical analyses of historical observations of yields and CO_2. One major advantage of this approach would be that, by using data that reflect yields from actual farmers' fields, the results would not be prone to issues of representativeness, such as arise in the omission of pests in experimental trials. However, empirical studies require datasets that possess sufficient variability in CO_2 while having limited variability in other factors that control yields. The difficulty of finding such datasets, which likely explains the near complete absence of empirical studies in the published literature, is related to two factors.

First, historical changes in CO_2 have been relatively insignificant compared with technology-driven yield increases (Amthor, 1998). Thus, it is nearly impossible to empirically separate the small effect of increased CO_2 from the much larger effects of management and technology trends. Second, because CO_2 is a well-mixed gas, spatial variability of CO_2 concentrations is relatively small. For example, CO_2 typically varies by <3 ppm between locations within a hemisphere, with even smaller differences for the latitude range of most croplands (GlobalView-CO_2, 2005). Use of spatial CO_2 gradients would also be complicated by spatial variation in other factors affecting yields, such as climate, soils, and management practices.

CO_2 *growth rate anomalies*

Long-term trends or spatial variations in CO_2 thus appear to hold little promise for empirically determining the CFE. Short-term variations in CO_2 levels, specifically interannual variability of CO_2 growth rates, provide the only other natural gradient of CO_2 that might be exploited. Keeling *et al.* (1995) and Braswell *et al.* (1997) demonstrated that variations in CO_2 growth rates can provide useful insight into controls on oceanic and terrestrial ecosystem carbon uptake. In these studies, CO_2 growth rates were treated as the dependent (i.e. response) variable, with temperature and precipitation treated as independent (i.e. predictor) variables.

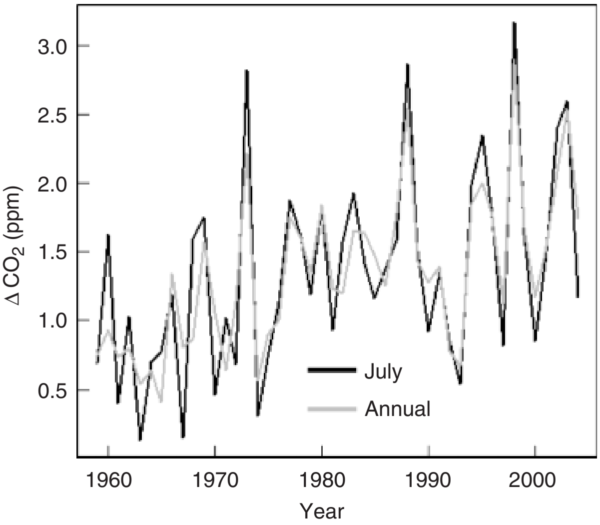

Fig. 1 Year to year changes (first differences) in July and Annual CO_2 (ppm), 1961–2002, at Mauna Loa station.

In contrast, evaluating the effects of CO_2 on yields requires using CO_2 growth rates as a predictor variable, and crop yield as the response variable. A major difficulty in this context is that other factors that are far more influential on yields, such as temperature and precipitation, exhibit substantial interannual variability as well. For example, CO_2 increases from July of one year to the next (Fig. 1) have averaged 1.35 ppm since 1960, with a standard deviation of 0.72 ppm. The CFE prescribed in commonly used crop models (Fig. 2) dictates a yield increase of roughly 0.1% for each 1 ppm CO_2 increase for C_3 crops. Thus, one would expect the average yield change due to CO_2 increase in 1 year to be on the order of 0.14%, with a standard deviation of 0.07%.

For comparison, year-to-year differences in global yields for the three major cereal crops are shown in Fig. 3. Even rice, which is widely irrigated, has a standard deviation of yield differences of 2.4%. Thus, the variance of CO_2-induced yield change is roughly one-tenth of the total yield variance in the best case, and smaller for crops with greater yield variability. Yield data at subglobal scales, for example individual country time series available from FAO, are generally more variable than global averages (FAO, 2006). CO_2 varia-

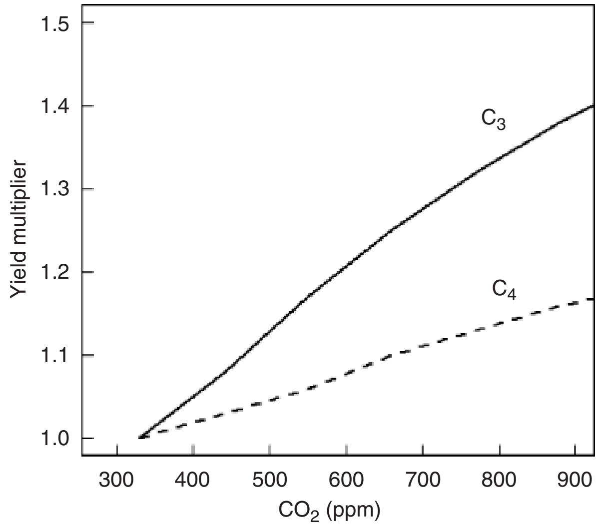

Fig. 2 Response of yield to CO_2 for C_3 and C_4 crops in the CERES crop model (source: CERES v3.5 source code).

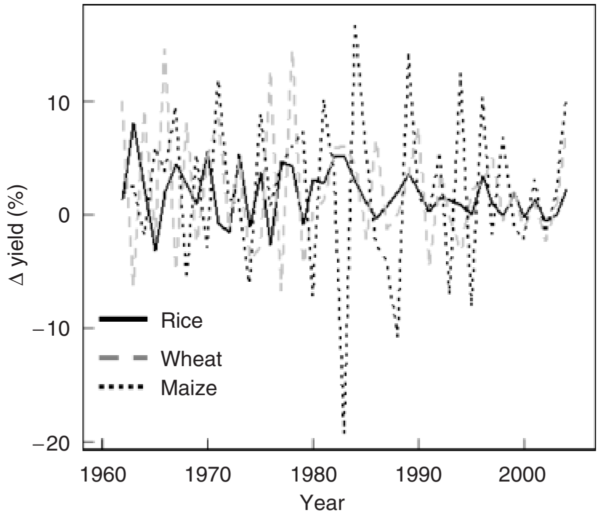

Fig. 3 Year to year changes in global cereal yields (%) for rice, wheat, and maize, 1961–2002 (source: FAO, 2006).

tions therefore represent a progressively smaller signal for smaller scale yield data.

A single time series, regardless of scale, would thus not provide a reliable indicator of the CFE. However, hundreds of individual yield time series are currently available, and many more could potentially be derived from subnational records. This study aims to introduce a new, empirical approach to estimation of the CFE by way of an example using country-level time series for three major crops (rice, wheat, and maize).

Materials and methods

Data sources

Monthly atmospheric CO_2 levels (ppm) for 1958–2002 recorded at the Mauna Loa Observatory in Hawaii, United States were obtained from http://cdiac.ornl.gov/ftp/trends/co2/maunaloa.co2. Growth rates for each month in 1959–2002 were calculated as the difference in CO_2 from the same month in the previous year. It was assumed that CO_2 growth rates at Mauna Loa were representative of the entire Northern Hemisphere, although the effect of this assumption is tested below.

Rice, wheat, and maize represent the three most widely grown and consumed crops in the world (FAO, 2006) and are the focus of most global assessments of future food security (Rosegrant *et al.*, 2001; Fischer *et al.*, 2005; Parry *et al.*, 2005). Yields for these crops for 1961–2002 were downloaded for all available countries in the online statistical databases of the United Nations' Food and Agriculture Organization (FAO, 2006), which reports all yields as $Mg\,ha^{-1}$. All countries within the Northern Hemisphere were ranked according to their 2002 production of each crop, and the top 20 countries for each crop were thereby identified. Countries in the Southern Hemisphere were omitted from the analysis.

As with CO_2 levels, growth rates of yields were computed as first differences from the 1961–2002 raw yield time series. To account for increased yield variance with increased average yields, which was apparent in several time series, the yield differences were converted to percent yield change by dividing the absolute yield change for each year by a 9-year moving average of yields centered around that year.

Estimation of CO_2 fertilization effect

For each country and crop, the CFE was estimated by ordinary least squares (OLS) linear regression of percent yield change on ppm CO_2 change in July (the middle of the growing season for most crops in the Northern Hemisphere). The variance of the OLS estimate for CFE is given by

$$Var(CFE) = \frac{\sigma^2}{S_{xx}}, \tag{1}$$

where σ^2 is the variance of model residuals and S_{xx} is the sum of square deviations of x (in this case, ppm CO_2) from its mean.

An estimate of CFE was made for each country, resulting in 20 separate estimates for each crop. An example for United States rice is shown in Fig. 4. An aggregrate estimate for CFE was then computed using

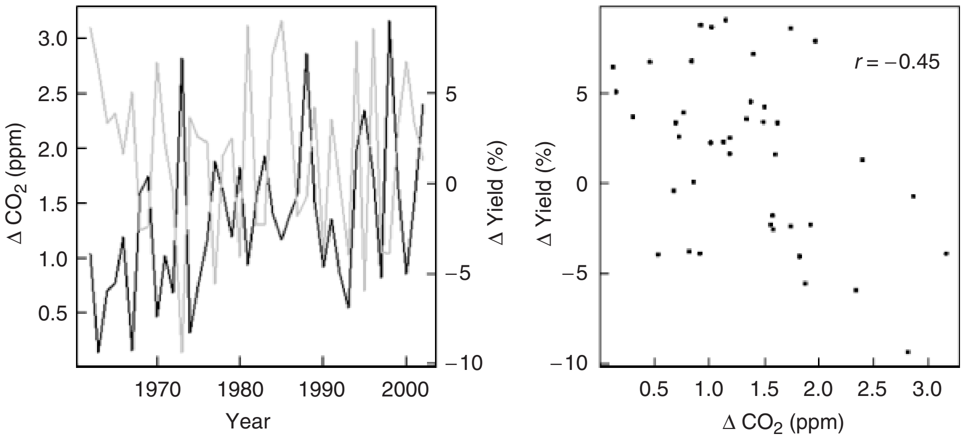

Fig. 4 (a) Year to year changes in US rice yield (gray line, %) and July CO_2 (black line, ppm), 1961–2002. (b) Percent yield change vs. ppm CO_2 change, 1961–2002.

a weighted average of the 20 estimates

$$CFE_{\text{agg}} = \sum_{i=1}^{20} \omega_i CFE_i, \tag{2}$$

with weights (ω_i for country i) proportional to the inverse of the variance for each estimate

$$\omega_i = \frac{1/Var(CFE_i)}{\sum_{k=1}^{20} 1/Var(CFE_k)}. \tag{3}$$

The aggregate estimate, assuming that errors for individual countries were uncorrelated with each other, has variance equal to

$$Var(CFE_{\text{agg}}) = \sum_{i=1}^{20} Var(\omega_i CFE_i) = \sum_{i=1}^{20} \frac{\omega_i^2 \sigma_i^2}{S_{xx}}. \tag{4}$$

The inverse variance weighting thus provides an aggregate estimate with lowest possible variance, which can be seen by setting the derivative of $Var(CFE_{\text{agg}})$ with respect to w_i equal to 0.

The aggregate estimate of CFE from Eqn (2) provides a measure of the global CFE if one assumes that (1) the effect of CO_2 on yields is the same in all regions and (2) the top 20 countries are representative of all growing regions in the world. Alternative weightings, for example based on the percent of global production in each country or considering correlation of errors between countries, could also be used.

Sensitivity tests

The above analysis rested on several assumptions that potentially influenced the results. First, it was assumed that first differences of yields were independent of technology trends, and thus that estimates of CFE were not biased by omission of a variable representing technology. In reality, first differences of yields in several countries exhibited a slight trend in time, indicating that yield time series were not stationary. Two approaches were used to test the sensitivity of results to these trends. First, the analysis was repeated after detrending the CO_2 and yield difference time series with a linear trend for each country. Second, the analysis was repeated after removing the first 10 years of the record, for which CO_2 changes appeared slightly lower than in the rest of the record (Fig. 4).

A second source of uncertainty was that actual CO_2 levels differ by region and crop, while the analysis always used changes in CO_2 levels at Mauna Loa in July. Unfortunately, measurements of CO_2 within the relevant region and season for each crop were not available. As a measure of sensitivity, we repeated the analysis using changes in annual average CO_2 at Mauna Loa rather than July.

Results and discussions

Estimates of CFE for individual countries varied considerably for rice (Fig. 5), wheat (Fig. 6), and maize (Fig. 7), although the 95% confidence intervals for most countries overlapped. Only one crop-country combination produced a 95% confidence interval that was entirely above zero (Thailand maize), with three cases entirely below zero (US rice, Nigeria rice, and China wheat). No consistent patterns were observed related to individual countries or regions across crops. For example, China was among the lower estimates for wheat, but higher estimates for maize. Nigeria possessed the lowest value for rice, but near average for maize.

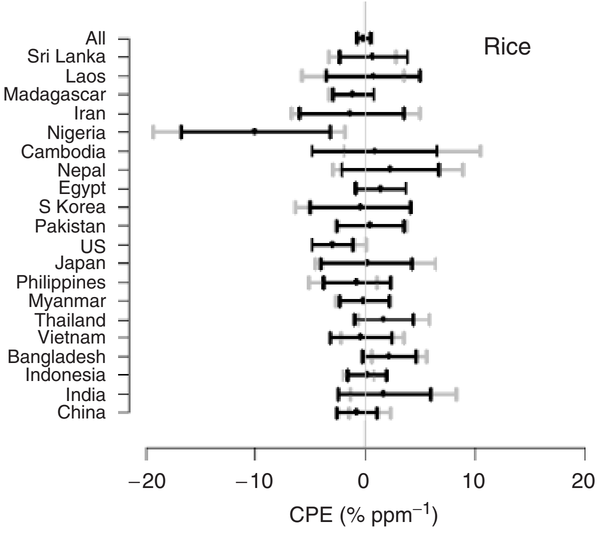

Fig. 5 Estimates of the CO_2 fertilization effect (% yield/ppm CO_2) for rice, for the top 20 producing countries in the Northern Hemisphere. Production rank decreases from bottom to top, based on 2004 production data from FAO. Also shown is the aggregate estimate (All) computed from Eqn (2). Black bars show 95% confidence interval using 1962–2002 data, while gray bars are based on 1972–2002 data.

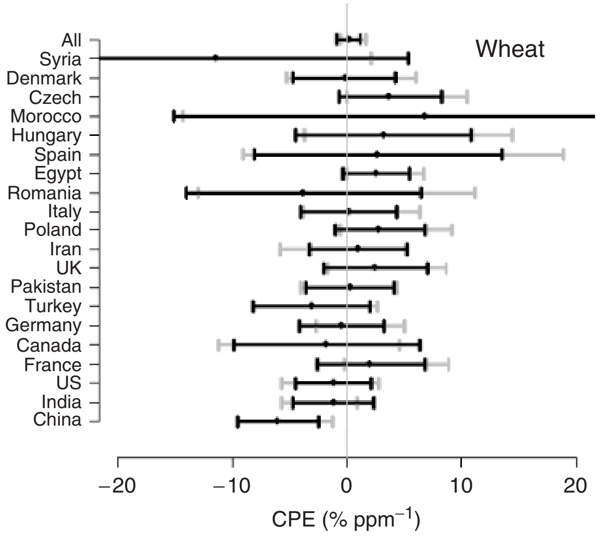

Fig. 6 Same as Fig. 5 but for wheat.

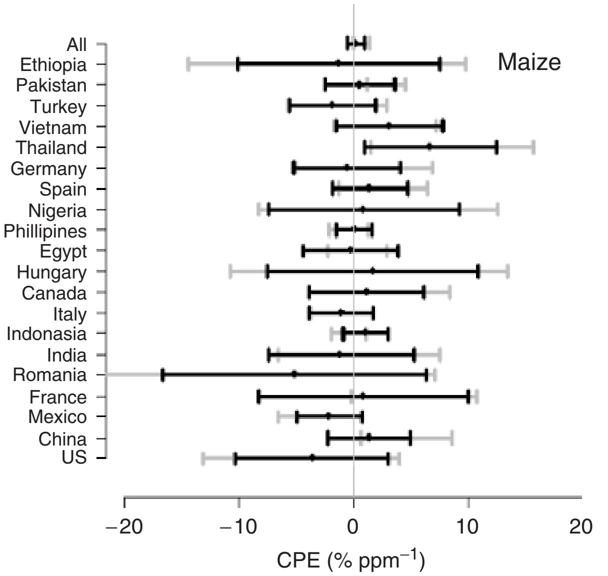

Fig. 7 Same as Fig. 5 but for maize.

The aggregate estimate for each crop included both 0% yield ppm^{-1} and 0.1% yield ppm^{-1} (Figs 5–7, Table 1). Thus, the uncertainties were sufficiently large that one cannot establish with these results the presence of a positive CFE, nor can one confidently refute the values currently used in impact assessment models (e.g. Fig. 2). Table 2 compares the value for wheat from this study with the meta-analysis of wheat experiments by Amthor (2001). The mean result from the empirical approach was surprisingly consistent with those from experimental studies, although the 95% confidence interval computed here was substantially larger.

The aggregate mean estimate for rice was negative, while wheat and maize were both positive. There was therefore no clear distinction made between C_3 (rice, wheat) and C_4 (maize) crops. Variances of the aggregate estimates were substantially lower for rice than the other two crops (Table 1), which reflect the lower yield variance for rice in most countries. As mentioned above, rice tends to be irrigated in most regions while maize and wheat are widely rainfed crops.

The aggregate estimates did not appear very sensitive to model assumptions for rice, with the mean estimate remaining below zero when detrended time series or annual CO_2 levels were used, and slightly positive when the first decade of records was omitted

Table 1 Aggregate estimates of CO_2 fertilization effect on crop yields (% yield ppm CO_2) derived from top 20 countries for each crop

Aggregate estimate of CFE	Rice		Wheat		Maize	
	Mean	SD	Mean	SD	Mean	SD
Base model	−0.19	0.31	0.13	0.51	0.17	0.39
Alternate models						
1971–2002 only	0.02	0.32	0.53	0.57	0.62	0.36
Detrended yields	−0.08	0.33	0.77	0.55	0.24	0.43
Annual CO_2	−0.14	0.39	−0.99	0.65	0.31	0.50

SD, standard deviation of estimate, from Eqn (1).
Alternate model formulations were used to test sensitivity of results to model assumptions.

(Table 1). In contrast, estimates for wheat and maize appeared quite sensitive to these changes. The effect of using annual CO_2 on wheat and maize estimates was considerably smaller when using only 1971–2002 data (not shown). As seen in Fig. 1, the greatest disparities between July and annual CO_2 are apparent before 1971. This suggests that uncertainties in CO_2 variations for specific growing seasons are less important when limiting analysis to recent decades. Overall, the sensitivity analysis indicates that model assumptions and choice of input datasets and time periods may be important and should be explicitly considered when deriving empirical estimates.

The uncertainties obtained here, for aggregate CFE estimates, were too large to constrain values beyond previous experimental work. A reasonable question is, therefore, what would be required to reduce uncertainties to useful levels. Using simulation to create artificial 40-year time series of CO_2 and yield differences, we evaluated the dependence of CFE uncertainty on the number of independent time series, as well as the level of yield variance in the yield difference time series (Fig. 8). In these simulations, it was assumed that the true CFE was 0.1% ppm^{-1}. The substantial reduction of uncertainty when progressing from a single time series to 20 was apparent regardless of yield variance. As expected, the standard deviation of CFE estimate decreased less rapidly as the number of time series increased, with minimal gains after ~200 time series.

Overall, it appears that comparisons of CO_2 and yield growth anomalies are unlikely to achieve standard deviations similar to experimental studies (~0.01–0.04% yield ppm^{-1}; Table 2) even with very large sample sizes and relatively low yield variances, such as for rice. However, three important points should be considered. First, it may be possible to reduce the 'noise' contained in yield variance by including explanatory variables other than CO_2, such as changes in growing season temperature and rainfall. In many cases, climatic variables may be able to explain 50% or more of the variance in yield changes (Nicholls, 1997; Lobell & Asner, 2003), which could improve detection of CO_2 effects.

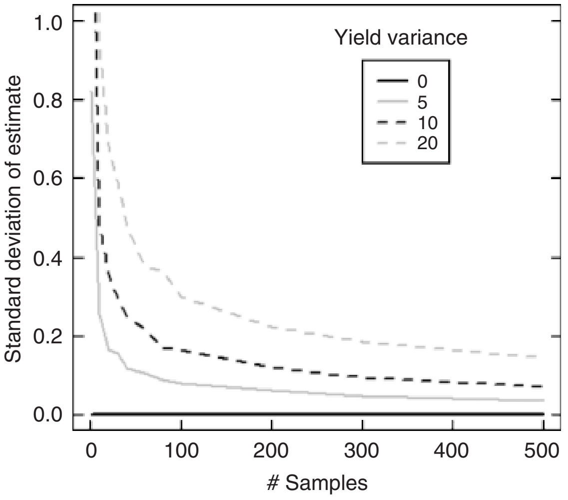

Fig. 8 The standard deviation for an estimate of the CO_2 fertilization effect using 40-year simulated artificial time series, as a function of the number of time series used to compute the estimate from Eqn (2). Simulations were performed assuming a true CO_2 effect of 0.1% yield ppm^{-1}, and yield variances of 0%, 5%, 10%, or 20%.

Table 2 Experiment-based estimates of CO_2 fertilization effect (% yield ppm CO_2) in wheat using different methods (from Amthor, 2001) vs. inferred value for wheat from historical CO_2 and yield growth rate anomalies (current study)

Method	Mean	95% Confidence interval
Laboratory	0.120	0.076–0.156
Glasshouses	0.140	0.071–0.210
Closed-top field chambers	0.080	0.048–0.112
Open-top field chambers	0.072	0.051–0.094
FACE	0.068	0.041–0.094
This study	0.13	−0.88–1.14

Experimental values are based on trials with ~200 ppm increases and assuming a linear response of yield to CO_2.

Second, even if accuracies of empirical approaches do not approach experimental values, estimates that are derived entirely independent of experiments provide a useful consistency check. For example, experimental approaches have some inherent limitations that empirical approaches do not, such as an inability to represent the diversity of conditions in farmers' fields, and a small spatial scale, which precludes investigation of potential local climate feedbacks from plant CO_2 response. Moreover, experiments are widely conducted only for a selected group of major crops, while empirical estimates could be applied to any crop with available data. Experimental approaches also have many distinct advantages, such as the ability to compare several cultivars and test the nonlinearity of CO_2 response by using a wide range of CO_2 levels. Empirical estimates based on historical CO_2 data would require assumptions about linearity in order to estimate effects of future CO_2 levels at which yield responses could saturate.

Finally, accuracies of any measurement technique must be compared with costs. Empirical approaches that utilize existing data and inexpensive computational resources have very limited requirements in terms of both expense and time. While significant effort may be required to compile accurate time series at subnational levels, the time required would likely be small compared to the several years needed to obtain robust experimental values. All of these points do not imply that experimental studies could or should be replaced in any way by empirical approaches, but rather that empirical studies could and should complement understanding of yield responses to CO_2 change.

Conclusions

This study evaluated whether historical data on CO_2 growth rates and national crop yields provide useful constraints on the CO_2 fertilization effect. For the three major cereal crops – rice, wheat, and maize – yields from each of the top 20 producing countries were regressed against year-to-year changes in CO_2 at Mauna Loa station. Mean estimates of CFE were consistent with values from experimental studies, but standard deviations were significantly larger than those from experiments and thus the retrieved values did not constrain estimates beyond previous studies.

The methodology presented here may be applied to larger datasets or adapted to include other predictor variables in order to reduce uncertainties to useful levels. The same approach can also be used for other crops for which experimental values are unavailable. Overall, the precision of empirical estimates are unlikely to equal those from experimental studies. However, empirical values provide a low-cost, independent measure of CO_2 response that implicitly includes interactions that occur in farmers' fields which may be neglected in current experiments.

Acknowledgement

This work was performed under the auspices of the US Department of Energy by University of California, Lawrence Livermore National Laboratory under Contract W-7405-Eng-48.

References

Ainsworth EA, Long SP (2005) What have we learned from 15 years of free-air CO_2 enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy. *New Phytologist*, **165**, 351–371.

Amthor JS (1998) Perspective on the relative insignificance of increasing atmospheric CO_2 concentration to crop yield. *Field Crops Research*, **58**, 109–127.

Amthor JS (2001) Effects of atmospheric CO_2 concentration on wheat yield: review of results from experiments using various approaches to control CO_2 concentration. *Field Crops Research*, **73**, 1–34.

Braswell RH, Schimel DS, Liner E, Moore B III (1997) The response of global terrestrial ecosystems to interannual temperature variability. *Science*, **278**, 870–872.

Cure JD, Acock B (1986) Crop responses to carbon-dioxide doubling – a literature survey. *Agricultural and Forest Meteorology*, **38**, 127–145.

FAO (2006) *World agriculture towards 2030/2050, Interim Report. Food and Agricultural Organization of the United Nations*. FAO, Rome, Italy.

Fischer G, Shah MN, Tubiello F, van Velhuizen H (2005) Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990–2080. *Philosophical Transactions: Biological Sciences*, **360**, 2067–2083.

GlobalView-CO_2 (2005) Cooperative Atmospheric Data Integration Project – Carbon Dioxide. Available at ftp.cmdl.noaa.gov

Keeling CD, Whorf TP, Wahlen M, van der Plichtt J (1995) Interannual extremes in the rate of rise of atmospheric carbon dioxide since 1980. *Nature*, **375**, 666–670.

Kimball BA (1983) Carbon-dioxide and agricultural yield – an assemblage and analysis of 430 prior observations. *Agronomy Journal*, **75**, 779–788.

Lobell D, Asner G (2003) Climate and management contributions to recent trends in US agricultural yields. *Science*, **299**, 1032.

Long SP, Ainsworth EA, Leakey ADB, Morgan PB (2005) Global food insecurity. Treatment of major food crops with elevated carbon dioxide or ozone under large-scale fully open-air conditions suggests recent models may have overestimated future yields. *Philosophical Transactions: Biological Sciences*, **360**, 2011–2020.

Long SP, Ainsworth EA, Leakey ADB, Nosberger J, Ort DR (2006) Food for thought: lower-than-expected crop yield stimulation with rising CO_2 concentrations. *Science*, **312**, 1918–1921.

Nicholls N (1997) Increased Australian wheat yield due to recent climate trends. *Nature*, **387**, 484–485.

Parry M, Rosenzweig C, Livermore M (2005) Climate change, global food supply and risk of hunger. *Philosophical Transactions: Biological Sciences*, **360**, 2125–2138.

Parry ML, Rosenzweig C, Iglesias A, Livermore M, Fischer G (2004) Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global Environmental Change*, **14**, 53–67.

Rosegrant M, Paisner M, Meijer S, Witcover J (2001) Global food projections to 2020: Emerging trends and alternative futures. International Food Policy Research Institute, Washington, DC.

Tubiello FN, Amthor JS, Boote KJ *et al*. (2007) Crop response to elevated CO_2 and world food supply: a comment on "Food for Thought ..." by Long et al., Science 312:1918–1921, 2006. *European Journal of Agronomy*, **26**, 215–223.