Department of Economics and Finance
Gordon S. Lang School of Business and Economics
University of Guelph

Discussion Paper 2024-04

Extended Crop Yield Meta-Analysis Data do not Support Upward SCC Revision

By:

Ross McKitrick
University of Guelph

Department of Economics and Finance
Gordon S. Lang School of Business and Economics | University of Guelph
50 Stone Road East | Guelph, Ontario, Canada | N1G 2W1
www.uoguelph.ca/economics

EXTENDED CROP YIELD META-ANALYSIS DATA DO NOT SUPPORT UPWARD SCC REVISION

Ross McKitrick
Department of Economics and Finance
University of Guelph
Ross.mckitrick@uoguelph.ca

June 24, 2024

Abstract: The Biden Administration has raised its Social Cost of Carbon (SCC) estimate about 5-fold based in part on global crop yield decline projections estimated on a meta-analysis data base first published in 2014. The data set contains 1,722 records but half were missing at least one variable (usually the change in CO_2) so only 862 were available for multivariate regression modeling. By re-examining the underlying sources I was able to recover 360 records and increase the sample size to 1,222. Reanalysis on the larger data set yields very different results. While the original smaller data set implies yield declines of all crop types even at low levels of warming, on the full data set global average yield changes are zero or positive even out to 5°C warming.

Key words: Climate Change, Agricultural yields, Social Cost of Carbon, Carbon dioxide fertilization

1 Introduction

Recent estimates of the Social Cost of Carbon (SCC) from the US Environmental Protection Agency (EPA) [1] are about 5 times higher than previously [2]. Part of the increase is due to an upward revision of the estimated agricultural damages from climate warming. The EPA used two damage modules, denoted DSCIM and GIVE, and in the latter, of the new 2030 SCC value ($220 under 2% discounting), $103, or nearly half, is attributed to projected agricultural damages ([1] pp. 78-81). The GIVE agricultural damage function is based on [3] which presents a reanalysis of a database first presented in [4] (herein denoted the "C14" dataset), which itself was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. The underlying models were parameterized based on results from field studies, and the authors selected them to be, as much as possible, globally representative.

In their multivariate model [4] reported results that would imply a moderate global net benefit from the warming associated with doubling the atmospheric CO_2 level. Despite using the same data, [3] reached much more pessimistic conclusions, projecting declining global crop yields due to the warming. Since both studies only provided limited reporting of regression results and the models are not nested it is difficult for readers to trace the sources of the differences. The first purpose of this study is to provide a transparent analysis of the C14 dataset, reproducing both sets of results as closely as possible, then to examine the effects of extending the underlying data set.

The C14 dataset consisted of 1,722 records but only half (*N*=862) had complete observations of all the variables necessary for regression analysis (changes in yield, CO_2 levels, temperature and precipitation matched to information about the climate zone, adaptation efforts and crop type). The variable most commonly missing was the change in ambient CO_2. But re-examination of the underlying sources showed that in many cases these could be recovered, for instance by consulting the original climate scenario tables. It was thus possible to increase the usable sample size by 40 percent to *N*=1,222. [3] critiqued the regression specification in [4] and estimated a model with many more interaction terms, though most were insignificant. The carbon dioxide fertilization benefit also differs between the two studies, with [4] treating it as linear and [3] imposing concavity (diminishing marginal gains).

Herein I replicate the results in [3] and [4] on the (incomplete) C14 dataset and I also obtain simulation results that qualitatively support the findings in [3] of negative yield effects across crop types especially soybeans. But after incorporating the newly-available data the conclusions change such that global average yield gains of all crop types under CO_2-induced warming are positive even out to 5°C warming. Overall I conclude that the climate change-related agricultural damage estimates in [3] are too pessimistic and the large implied revisions to the SCC are unsupported.

2 BACKGROUND

The main climatic influences on agricultural yields are increased ambient CO_2 levels (positive effect), higher temperatures (mix of positive and negative effects) and changed precipitation (mix of positive and negative effects). Based on laboratory and controlled field studies the literature has generated a profusion of yield change estimates that vary by region, plant type, adaptation efforts and other covariates [5]. For the purpose of computing the SCC we are only interested in the net effect of warming caused by increased CO_2, not of warming alone. Both [3] and [4] present bivariate graphs of partial yield effects from temperature change alone which can be misleading in the anthropogenic climate change context. For example [3] Figure 1 shows temperature effects on yields of four major crop types excluding the offsetting effect of CO_2 fertilization and adaptation. In all cases the effects are negative, but by construction such graphs only illustrate the effects of unanticipated natural warming trends not CO_2-induced warming.

Table 1 reports summary statistics of both the C14 dataset and the expanded version developed herein, columns denoted respectively as “C14” and “All”. When analyzing CO_2-induced warming any assumed temperature change (and induced precipitation change) must be based on an associated CO_2 change, the computation of which requires an assumption about climate sensitivity. For agricultural yield simulations in which CO_2 and temperature levels change gradually together a common metric is the Transient Climate Response (TCR) which estimates the temperature change at year 70 in a simulation in which CO_2 levels increase by 1% per year, which implies doubling at year 70. The most recent IPCC report [6] provides a best estimate of TCR based on observed temperature and ocean heat content records of 1.9°C. Since atmospheric CO_2 levels are growing at just under 0.6% per year since 1990 [7] doubling will take about 120 years. So a transient warming of 1.9°C is approximately the global average greenhouse gas-induced warming that can be expected over the next 120 years if the average annual rate of increase of CO_2 over the past 30 years continues throughout. An alternative metric is Equilibrium Climate Sensitivity (ECS) which is the eventual (multi-century) temperature response after all Earth systems including the oceans have adjusted to an instantaneous CO_2 doubling. It which has traditionally been estimated at about 3°C. While TCR is more relevant to the simulations herein, I will conservatively employ a 3°C sensitivity estimate which implies less CO_2 increase for a given temperature change.

The standard, stylized physics of warming [8] [9] is summarized as a logarithmic relationship between the change in temperature (ΔT) and the log CO_2 increase such that $\Delta T_\tau = \alpha\lambda^{-1}\ln\left(\frac{CO2_\tau}{CO2_0}\right)$ where τ denotes the interval in years since time 0, ΔT_τ denotes the amount of warming over that interval, $CO2_\tau$ denotes the ambient CO_2 concentration at time τ, $CO2_0$ denotes the ambient CO_2 concentration at time 0, α parameterizes the relationship between log CO_2 and radiative forcing and λ^{-1} parameterizes the relationship between radiative forcing and global average temperature. For the present purpose we do not need to separately identify α and λ instead we can compute them jointly using $\alpha\lambda^{-1} = \mathrm{ECS}/\ln(2)$. The change in CO_2 required for a given temperature increase ΔT is then given by

$$(1) \qquad \Delta C_\tau \equiv CO2_\tau - CO2_0 = CO2_0 \left(\exp\left\{ \frac{\Delta T_\tau}{\alpha\lambda^{-1}} \right\} - 1 \right).$$

The results shown below are not overly sensitive to the year selected as the baseline. I will conservatively assume time zero corresponds to preindustrial conditions hence $CO2_0 = 280\text{ ppm}$ [10]. Thus we have in mind an ongoing scenario with approximately 1°C of warming having taken place already. A key implication of the standard model is that a linear increase in temperature requires an exponential increase in CO_2: if for example 100 ppm yields 1°C warming, the next 1°C warming requires 200 ppm, then 400 ppm, etc.

On the C14 dataset [4] estimated the linear regression model

$$(2) \qquad dY_i = \alpha_0 + \alpha_1 AD_i + \alpha_2 TR_i + \alpha_3 C4_i + \alpha_4 dP_i + \alpha_5 dT_i + \alpha_6 dC_i + e_i$$

where dY_i is the % change in yield for region i, AD_i is a dummy variable denoting that the study incorporated adaptative behaviour, TR_i is a dummy variable denoting the region is in the tropics as opposed to a temperate zone, $C4_i$ is a dummy variable indicating that the crop type in the study is C4 (maize, millet or sorghum) rather than C3 (rice, wheat, soybeans and other crops)[1], dP_i denotes change in precipitation, dT_i denotes change in temperature, dC_i denotes the change in the CO_2 concentration and e_i is the regression residual. The coefficient estimates in [4] (see Table 2 below) imply a partial temperature effect on yield of -4.9% per °C and a partial CO_2 effect of +0.06% per part per million (ppm), both of which were reported to be highly significant (p<0.01). These coefficients imply that if the atmospheric concentration of CO_2 doubles from 280 ppm to 560 ppm and causes 3°C warming, the combined effect on yields would be, on average, -14.7% (due to warming) plus 16.8% (due to CO_2 fertilization) for a net effect of +2.1%.

[4] included dC_i as a linear term in their estimating equation, which implies that marginal benefits of CO_2 fertilization do not attenuate. By contrast [3] used a concave function

$$(3) \qquad fC(dC_i, C4_i) = \frac{dC_i}{A+(1-C4_i)B+dC_i}$$

with A and B chosen to equal 50. This dampens the marginal benefit of additional CO_2. [3] (Supplement) report a CO_2 fertilization benefit of only 8—12% from CO_2 doubling

[1] The labels C3 and C4 refer to the photosynthesis process, specifically the carbon compounds produced within the plant.

depending on crop type. Another methodological difference introduced by [3] was to argue that the regression specification should restrict yield changes to zero if no climate change takes place ($dT_i = dP_i = dC_i = 0$). In the specification in [4], adaptation without climate change would generate a gain of about 7% in the temperate zone and about 4% in the tropics, which indicates that the constant and dummy terms in equation (2) are not strictly measuring variables of interest for estimating the SCC. [3] included adaptation as an interaction with climate variables, however they also included the adaptation dummy on its own to measure yield gains due to non-climate-related adaptation activity, which they then subtracted back out from the predicted yield changes, an approach I also use herein.

3 RESULTS

Yield change predictions for each crop type were generated using the slope coefficient estimates from replication regressions (see Methods section) conditioned on sequential values of dT from 1.0 to 5.0 and the corresponding changes in CO_2 fertilization from equation (1) and precipitation. To project the warming-induced change in precipitation, dP_i was regressed on dT_i, dT_i^2 and dT_i interacted with national baseline temperatures with no intercept, separately by crop type. The coefficients were then used to generate $d\hat{P}_i$ conditioned on the assumed value of dT and the mean baseline temperatures for each region. 2σ error bars were computed using bootstrap resampling with 1,000 replications.

Table 2 compares the projected yield changes for 1—3°C warming as computed by [3] suppressing CO_2 fertilization and adaptation (F. Moore pers. comm.) and the same computed using the method herein on the C14 dataset. While the results are not identical the columns are sufficiently similar (correlation = 0.96) to establish the validity of the replication.

Yield change estimates for warming of 1°C to 5°C (in %) based on the C14 and “All” datasets taking account of CO_2 fertilization and adaptation are shown in Table 3 and Figure 1. Rice, wheat and soybean were simulated separately. Figure 1 shows the results with the lines labeled, respectively, “C14” (blue) and “All” (green).

[3] Supplementary figures 2—5 show regional yield changes are a mix of positive and negative globally at 1°C for maize, rice and wheat but go negative almost everywhere by 3°C. For soybeans yield changes are globally negative even at 1°C and rapidly worsen from there. The blue lines in Figure 1 match these expectations. But adding in the missing data noticeably changes the results. We now observe insignificant but positive average output gains for all crop types across the warming scenarios even up to 5 °C (at 5°C wheat drops slightly below zero). The negative temperature effects are fully offset by gains from CO_2 fertilization and adaptation. In the Supplement I show that virtually identical results are obtained using any configuration of the two key parameters, climate sensitivity (1.9°C or 3.0°C) and the CO_2 base case level (280 ppm or 370 ppm).

4 DISCUSSION

In a climate change scenario relevant to policymaking temperature changes in response to CO_2 increases, and precipitation changes in response to temperature changes. Consequently the analysis needs to be done using multivariate modeling, which unfortunately disqualified half the C14 dataset. On that version of the dataset I replicated the regression results of [4] and generated regression results and yield change simulations approximately matching those in [3]. But after rebuilding and extending the dataset I find different and much more optimistic results, namely that net crop yield changes are zero or positive even out to 5°C for all crop types, even soybean.

I focus herein on global average outcomes which are the relevant ones for computing the SCC. Dividing crops by zone shows that warming in tropical regions is more harmful to crops than warming in temperate regions (results shown in Supplement). But climate change simulations, including in [3], generally predict relatively greater warming in temperate regions compared to the tropics. Since relatively less warming happens where it is relatively more harmful and vice-versa, the global average yield change remains a suitable and informative metric for assessing global outcomes even considering regional variations in outcomes.

The welfare changes in [3] are not based solely on the yield equations, but on feeding the agricultural output changes into a global computable general equilibrium model called GTAP. When output of a crop increases it can generate welfare reductions in some regions based on terms of trade effects. An increase in global agricultural productivity means exporting regions might lose revenue if the price falls by enough, while importing regions benefit and the net effect will be positive. If over the next 100-200 years yields of all crop types increase it does not stand to reason that a global trade model could generate global welfare reductions. Consequently the large global welfare losses associated with agricultural damages under climate warming as presented in [3] are not supported by the analysis of a more complete version of the crop yield meta-analysis data base, and neither therefore is a large part of the recent upward SCC revision by the US EPA [1].

5 METHODS

I obtained the C14 dataset from A. Challinor (personal communication) the baseline ambient temperatures as used in [3] from Thomas Hertel (personal communication) and the [3] regression results and some simulation data from F. Moore (personal communication). [4] report $N = 882$ complete records but I found only 862 in the data set as supplied, so while I refer to it as the "C14" dataset the results are not identical to those they reported. In the Supplement I describe the process by which an additional 360 entries were obtained. In all cases where the change in ambient CO_2 was the only missing variable the underlying paper was re-examined. Often the name of the climate change scenario being used as an input into the crop model was given and the start and end dates of the model experiment were also given so the change in CO_2 could be recovered by consulting past IPCC reports where the scenarios were developed. Where many or most explanatory variables were missing in the C14 dataset these were not re-examined or the attempt to recover the missing data was unsuccessful. Data and code sufficient to reproduce all reported results are in the data archive listed below the references.

Table 4 lists the regression results reported in [4] (column 1), the results of estimating equation (2) on the C14 dataset as supplied (column 2) and the results on the extended data ("All", column 3). The estimations were done using R version 4.2.3 [11] and the *lm_robust* package [12] clustering errors on the Study variable. *P*-values are shown in parentheses below the coefficients. In columns 2 and 3 they are computed using *t*-statistics based on robust standard errors. Adaptation and CO_2 fertilization are clearly beneficial while temperature has a negative effect. Precipitation is significant only in the C14 reported results. The coefficient magnitudes are reasonably similar across the columns although significance levels are lower in the replication.

[3] estimated a panel regression model with crop-specific quadratic temperature terms:

(4) $$dY_i = a_1 MZ_i dT_i + a_2 MZ_i dT_i^2 + a_3 RC_i dT_i + a_4 RC_i dT_i^2 + a_5 WT_i dT_i + a_6 WT_i dT_i^2 + a_7 SB_i dT_i + a_8 SB_i dT_i^2 + a_9 MZ_i dT_i BT_i + a_{10} MZ_i dT_i^2 BT_i + a_{11} RC_i dT_i BT_i + a_{12} RC_i dT_i^2 BT_i + a_{13} WT_i dT_i BT_i + a_{14} WT_i dT_i^2 BT_i + a_{15} SB_i dT_i BT_i + a_{16} SB_i dT_i^2 BT_i + a_{17} C3_i \widehat{fC}_i + a_{18} C4_i \widehat{fC}_i + a_{19} dP_i + a_{20} AD_i dT_i + a_{21} AD_i + e_i$$

where MZ_i, RC_i, WT_i and SB_i are dummy variables for, respectively, maize, rice, wheat and soybean, BT_i is the average national baseline temperature (in °C) and $\widehat{fC}_i$ are the predicted values from equation (3) above with $A = B = 50$. [3] estimated equation (4) using ordinary least squares (OLS) and obtained standard errors using the block bootstrap with the blocks defined at the study level. The first column of Table 3 reports the coefficient point estimates obtained by [3] M17 (p-values were not supplied). Column 2 ("C14") reports the results of estimating equation (4) on the supplied version of the C14 dataset using OLS with cluster-robust errors. Column 3 ("All") reports the results using the extended data set. Maize was taken to include millet and sorghum though there were only 2 observations of each of these. Columns 1 and 2 exhibit considerable similarity. Column 2 shows very few coefficients are statistically significant, although the regression itself is highly significant. The coefficients associated with soybean ("sb") change considerably between the C14 and All datasets. The others remain more stable (correlation = 0.72).

6 References

1. US Environmental Protection Agency (2023) Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review", EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, November 2023, https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf accessed February 28, 2024.

2. US Interagency Working Group on Social Cost of Carbon (IWG) (2013) “Technical Support Document: Technical update of the social cost of carbon for regulatory impact analysis Under Executive Order 12866.” United States Government.

3. Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. https://doi. org/10. 1038/s41467-017-01792-x

4. Challinor, Andrew J., et al. A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change 4.4 (2014): 287.

5. Taylor, Charles and Wolfram Schlenker (2023) Environmental drivers of agricultural productivity growth: CO_2 fertilization of US field crops. National Bureau of Economic Research Working paper 29320, http://www.nber.org/paper/w29320

6. Forster, P., T. Storelvmo, K. Armour, W. Collins, J.-L. Dufresne, D. Frame, D.J. Lunt, T. Mauritsen, M.D. Palmer, M. Watanabe, M. Wild, and H. Zhang (2021): The Earth’s Energy Budget, Climate Feedbacks, and Climate Sensitivity. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 923–1054, doi: 10.1017/9781009157896.009.

7. https://gml.noaa.gov/webdata/ccgg/trends/co2/co2_annmean_mlo.txt

8. Table 6.2 in Intergovernmental Panel on Climate Change (IPCC 2001) Radiative Forcing of Climate Change. Chapter 6 in the Third Assessment Report (*Climate Change 2001: The Scientific Basis* Chapter 6, [Houghton, J.T.,Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA).

9. Meinshausen, M., Raper, S. C. B., and Wigley, T. M. L. (2011) Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. *Atmos. Chem. Phys.*, 11, 1417–1456, https://doi.org/10.5194/acp-11-1417-2011, 2011.

10. IPCC, 2021: *Summary for Policymakers*. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)] Table 2.1

11. R Core Team (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

12. Blair, Graeme, Jasper Cooper, Alexander Coppock, Macartan Humphreys, Luke Sonnet, Neal Fultz, Lily Medina and Russell Length (2022) Package 'estimatr'. Available at https://cran.r-project.org/package=estimatr accessed June 2, 2013

DATA AVAILABILITY:

Data and Code archive for this paper:

https://www.dropbox.com/scl/fi/2fibwte1vqh97g9t7sqko/R.archive.zip?rlkey=xjma2frds

2hekk6ot5x4lsqwv&dl=0

7 TABLES

	Mean	Med	Std Dev	Min	Max
C14 (*N* = 862)					
Chg in Yield (%)	-4.82	-4.00	20.30	-81.80	62.30
Chg in Temperature (°C)	2.72	2.42	1.37	0.00	8.67
Chg in Precip (mm)	6.50	6.00	16.76	-46.00	194.00
Chg in CO_2 (ppm)	161.23	192.50	137.66	0.00	504.50
Tropics	0.52	1.00	0.50	0.00	1.00
Adaptation	0.40	0.00	0.49	0.00	1.00
C4	0.34	0.00	0.47	0.00	1.00
Baseline Temp (°C)	20.95	21.25	5.17	10.10	27.69
ALL (*N* = 1,222)					
Chg in Yield (%)	-3.81	-4.00	23.11	-90.50	135.00
Chg in Temperature (°C)	2.67	2.43	1.39	-1.21	8.67
Chg in Precip (mm)	5.50	5.00	16.16	-46.00	194.00
Chg in CO_2 (ppm)	176.18	202.00	132.94	0.00	504.50
Tropics	0.46	0.00	0.50	0.00	1.00
Adaptation	0.38	0.00	0.49	0.00	1.00
C4	0.32	0.00	0.46	0.00	1.00
Baseline Temp (°C)	20.83	21.25	5.55	7.85	27.69

Table 1: Summary statistics of C14 dataset and extended ("All") data set.

		M17 result	Replication on C14 Data
Maize, Millet and Sorghum			
	dY = 1C	-6.1	-7.9
	2C	-14.0	-14.9
	3C	-23.7	-21.0
Rice			
	dY = 1C	-5.6	-9.4
	2C	-10.3	-16.1
	3C	-14.1	-20.1
Wheat			
	dY = 1C	-4.0	-6.1
	2C	-10.5	-12.8
	3C	-19.3	-19.9
Soybean			
	dY = 1C	-14.2	-16.1
	2C	-26.4	-31.0
	3C	-36.7	-44.9

Table 2: Comparison of Temperature- and Precipitation-only yield changes computed by [3] (column 1) with the same computed on the C14 dataset as supplied using the method described in the text (column 2).

		C14	All
Maize, Millet and Sorghum			
	dY = 1C	-0.9	6.8
	2C	-3.7	5.7
	3C	-7.4	3.7
	4C	-10.7	1.8
	5C	-13.5	0.5
Rice			
	dY = 1C	-4.0	5.9
	2C	-5.1	7.0
	3C	-5.5	7.5
	4C	-4.2	8.6
	5C	-0.7	10.6
Wheat			
	dY = 1C	-0.8	7.3
	2C	-1.8	8.0
	3C	-5.3	6.4
	4C	-10.4	3.4
	5C	-16.5	-0.3
Soybean			
	dY = 1C	-10.7	3.2
	2C	-20.0	2.2
	3C	-30.4	1.3
	4C	-40.6	1.6
	5C	-50.3	3.6

Table 3: Point estimates of yield changes (%) estimated on C14 dataset and expanded data set ("All").

	C14 Reported Results	C14 Data	All Data
Intercept	-5.40	-5.67	-3.60
	(0.44)	(0.63)	(0.71)
Adaptation	7.16**	7.42*	7.17**
	(0.02)	(0.06)	(0.04)
Tropics	-2.83	-4.09	-3.36
	(0.47)	(0.43)	(0.48)
C4	0.00	-0.02	-2.27
	(0.99)	(0.99)	(0.59)
dPrecip	0.53***	0.25	0.26
	(0.00)	(0.35)	(0.14)
dTemp	-4.90***	-4.20**	-4.69***
	(0.00)	(0.02)	(0.01)
dCO2	0.06***	0.06*	0.06*
	(0.00)	(0.10)	(0.07)
R-sq	NA	0.21	0.172
Adj R-sq	NA	0.21	0.168
F-stat	NA	2.44**	2.920**
N	882	862	1,222

Table 4: Coefficients from estimation of equation [1] on C14 dataset and expanded data set ("All") compared to results reported in [4] (column 1). *p*-values of robust *t*-statistics in parentheses. Significance: < * 10%, ** 5%, *** 1%.

	M17 Coefs	C14 Data	All Data
mz.dT	3.714	2.635	5.490
		(0.882)	(0.662)
mz.dT2	-0.887	0.165	-1.613
		(0.967)	(0.596)
rc.dT	50.374	45.240*	23.450
		(0.093)	(0.523)
rc.dT2	-12.778	-11.819*	-6.397
		(0.071)	(0.479)
wt.dT	-5.595	-6.672	-3.068
		(0.618)	(0.751)
wt.dT2	1.871	2.676	0.665
		(0.335)	(0.815)
sb.dT	-144.926	-107.181	42.830
		(0.278)	(0.664)
sb.dT2	61.710	41.417	0.735
		(0.364)	(0.975)
mz.dT.bt	-0.403	-0.532	-0.625
		(0.404)	(0.183)
mz.dT2.bt	0.038	0.013	0.089
		(0.942)	(0.539)
rc.dT.bt	-2.223	-2.140*	-1.247
		(0.057)	(0.372)
rc.dT2.bt	0.521	0.499*	0.272
		(0.058)	(0.438)
wt.dT.bt	0.161	0.064	-0.219
		(0.902)	(0.647)
wt.dT2.bt	-0.180	-0.199	-0.062
		(0.166)	(0.693)
sb.dT.bt	5.818	4.075	-2.570
		(0.332)	(0.550)
sb.dT2.bt	-2.723	-1.839	0.008
		(0.371)	(0.993)
c3.fC	17.20	23.929*	25.254**
		(0.061)	(0.027)
c4.fC	10.82	19.708	18.900

		(0.153)	(0.082)
dP	0.21	0.211	0.210*
		(0.243)	(0.087)
ad.dT	0.17	0.799	2.655
		(0.683)	(0.178)
ad	NA	5.487	-0.901
		(0.263)	(0.850)
R-sq		0.418	0.399
Adj-R-sq		0.404	0.388
F		6749.509	568.225
N		862	1222

Table 5: Column 1: estimated coefficients from F. Moore (pers. comm.) and [3] Supplement. Columns 2 and 3: coefficients from estimation of equation [3] on C14 dataset and expanded data set ("All"). *p*-values of robust *t*-statistics in parentheses. Significance: < * 10%, ** 5%, *** 1%.

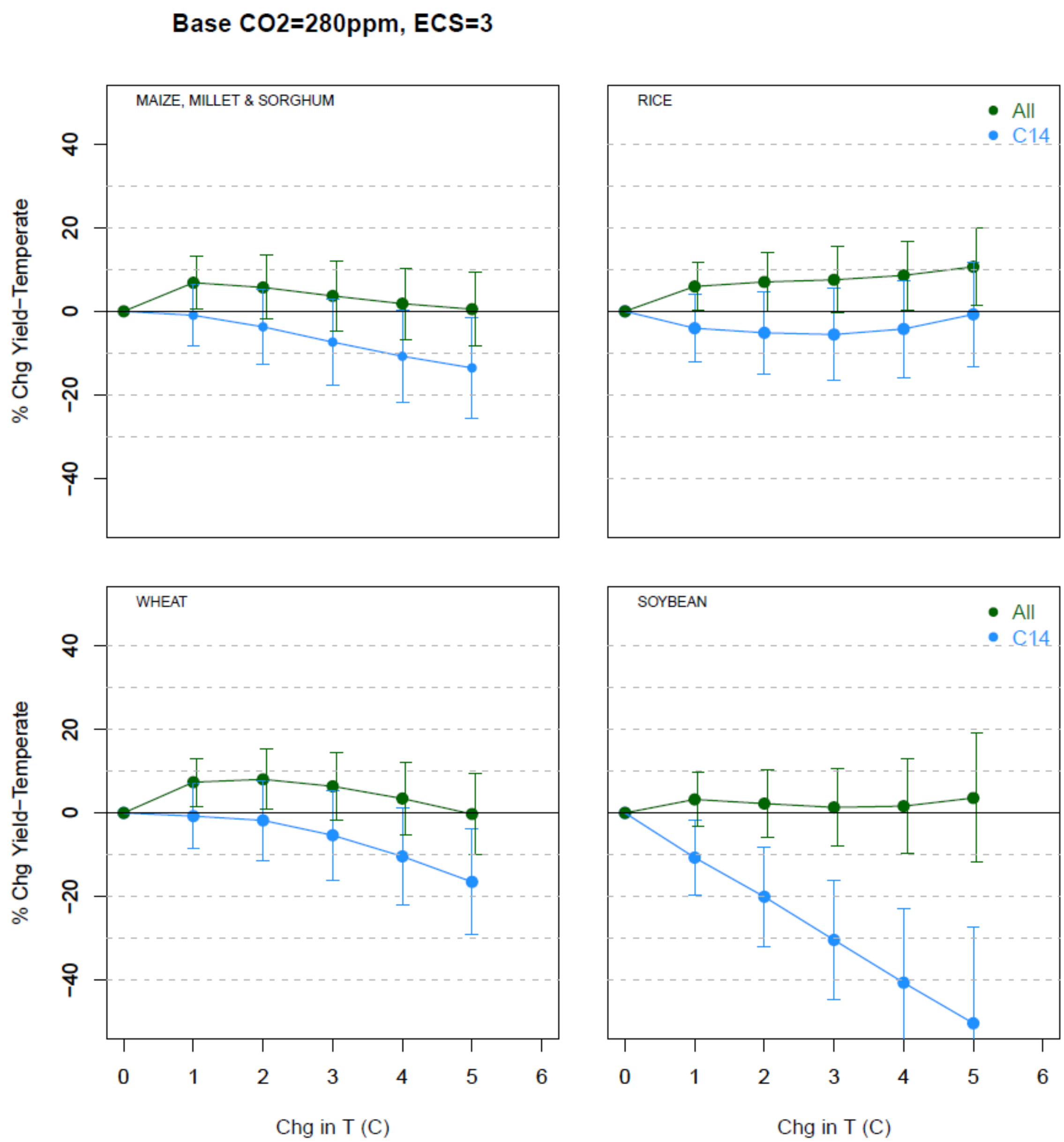

Figure 1. Yield change simulations based on indicated data sets. Blue: C14 data. Green: All data.