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Changes in diurnal temperature range and national cereal yields

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Abstract

Models of yield responses to temperature change have often considered only changes in average temperature (T_{avg}) with the implicit assumption that changes in the diurnal temperature range (DTR; the difference between daily maximum and minimum temperature) can safely be ignored. The goal of this study was to evaluate this assumption using a combination of historical datasets and climate model projections. Data on national crop yields for 1961–2002 in the ten leading producers of wheat (*Triticum* spp.), rice (*Oryza* spp.) and maize (*Zea mays*) were combined with datasets on climate and crop locations to evaluate the empirical relationships between T_{avg}, DTR and crop yields. In several rice and maize growing regions, including the two major nations for each crop, there was a clear negative response of yields to increased DTR. This finding reflects a nonlinear response of yields to temperature, which likely results from greater water and heat stress during hot days. In many other cases, the effects of DTR were not statistically significant, in part because correlations of DTR with other climate variables, and the relatively short length of the time series resulted in wide confidence intervals for the estimates.

To evaluate whether future changes in DTR are relevant to crop impact assessments, yield responses to projected changes in T_{avg} and DTR by 2046–2065 from 11 climate models were estimated. The mean of climate model projections indicated an increase in DTR in most seasons and locations where wheat is grown, mixed projections for maize, and a general decrease in DTR for rice. These mean projections were associated with wide ranges that included zero in nearly all cases. The estimated impacts of DTR changes on yields were generally small (<5% change in yields) relative to the consistently negative impact of projected warming of T_{avg}. However, DTR changes did significantly affect yield responses in several cases, such as in reducing US maize yields and increasing India rice yields. Because DTR projections tend to be positively correlated with T_{avg}, estimates of yield changes for extreme warming were particularly affected by including DTR (up to 10%). Finally, based on the relatively poor performance of climate models in reproducing the magnitude of past DTR trends, it is possible that future DTR changes and associated yield responses will exceed the ranges considered here.

Keywords: DTR; Climate change impacts; Maize; Wheat; Rice

1. Introduction

The impacts of climate change on food production have been extensively studied over the past few decades in order to evaluate the benefits of climate change mitigation or agricultural adaptation activities (e.g., Adams et al., 1990; Rosenzweig and Parry, 1994; Parry et al., 2005). Nearly all of these studies have utilized climate model projections of average temperatures and rainfall on a monthly or annual average basis. A smaller number of studies have also considered other aspects of climate change, such as changes in daily and inter-annual variability of climate (Mearns et al., 1997), increased frequency of heat spells or other extreme events (Rosenzweig et al., 2002; White et al., 2006), and changes in humidity and solar radiation (Brown and Rosenberg, 1997).

One aspect of climate change that has received limited attention is the potential difference between changes for

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daily maximum (T_{max}) and minimum (T_{min}) temperatures, and resulting changes in the diurnal temperature range ($DTR = T_{max} - T_{min}$). Historical observations have revealed a substantial decreasing trend in globally averaged DTR for 1950–1990, as T_{min} has risen faster than T_{max} (Easterling et al., 1997; Vose et al., 2005), and many climate models project further significant changes in DTR (Stone and Weaver, 2003; Lobell et al., 2007). Moreover, projected changes in DTR are often positively correlated with projections of average temperature (T_{avg}) changes, because increased cloud cover and soil moisture is negatively correlated with both quantities (Lobell et al., 2007). As a result, effects of DTR on crops may be important to consider in impact and adaptation studies, as they may affect both estimates of mean impacts as well as associated estimates of uncertainty.

A response of crop yields to DTR changes can be expected because some plant processes (e.g., photosynthesis) occur exclusively during the day, while others (e.g., crop development) are nonlinearly related to temperature, so that increased temperature during the day may have different effects than increases during (a typically cooler) night. For example, increased DTR for a given T_{avg} may reduce yields because the associated increase in T_{max} results in increased water stress or reductions in photosynthesis rates (Dhakhwa and Campbell, 1998). Reductions in T_{min} associated with increased DTR may also be harmful in cases where freezing temperatures can result in crop injury or death (Rosenzweig and Tubiello, 1996; Tubiello et al., 2002).

Alternatively, increased DTR may benefit yields in cases where development or grain filling rates are more sensitive to T_{min} than T_{max} (Wilkens and Singh, 2001) with crops able to grow longer, and produce more grain with lower nighttime temperatures. Crops that benefit from increased chilling hour accumulation, such as fruit and nut trees, would also be favored by increases in DTR (Lobell et al., 2006). Perhaps most importantly, increased DTR is often associated with higher solar radiation (Bristow and Campbell, 1984), which can benefit crop yields, especially in the case of well-fertilized and irrigated fields (Monteith, 1972; Fischer, 1985).

While there are thus several mechanisms by which DTR can influence yield, a quantitative understanding of the net effects of DTR is limited to a few studies in selected regions, such as rice in the Philippines (Peng et al., 2004; Sheehy et al., 2006), wheat in Mexico and California (Lobell et al., 2005; Lobell and Ortiz-Monasterio, 2007), and maize and wheat in the USA (Rosenzweig and Tubiello, 1996; Dhakhwa and Campbell, 1998). The goal of the current study is to provide a broader assessment of DTR effects on the three major cereal crops—wheat (*Triticum* spp.), rice (*Oryza* spp.) and maize (*Zea mays*)—throughout their major growing regions. First, data on past variations in growing season climate and national yields are used to deduce the impacts of changes in T_{avg} and DTR. Projections of future T_{avg} and DTR for the relevant months and nations are then used to evaluate the potential role of DTR in determining future impacts of climate change.

2. Methods

2.1. National yield models

Wheat, rice and maize are the three most widely grown crops in the world, and comprise the bulk of consumed calories throughout the world (FAO, 2006). Yields of these crops for 1961–2002 were obtained from the Food and Agriculture Organization of the United Nations statistical databases (FAO, 2006) for all countries with complete records for the entire time period. Countries such as Russia, which were included in Soviet Union estimates prior to 1991, were excluded from analysis.

For comparison with the yield data, estimates of T_{avg}, DTR and precipitation (P) were derived for each crop and country as follows. First, the growing season months were prescribed based on crop calendars for each country and crop (USDA, 1994) (Table 1). Second, the spatial distribution of crops within the country were defined based on the $0.5^\circ \times 0.5^\circ$ maps of crop area by Leff et al. (2004), which are based on a combination of satellite and census data (0.5° is roughly equal to 55 km at the equator). Finally, $0.5^\circ \times 0.5^\circ$ gridded monthly climate datasets from the Climate Research Unit (Mitchell and Jones, 2005) were averaged for the growing season months, and weighted by the spatial distribution to produce a single value of T_{avg}, DTR and P for each year for each country-crop combination.

To remove the influence of technology trends on crop yields, a first difference time series was computed for both the yields and climate variables by subtracting the prior year's value from each year (Nicholls, 1997). These first differences (Δyield, ΔT_{avg}, ΔDTR, and ΔP) were then used to compute a multiple linear regression model for each country-crop combination:

$$\Delta\text{yield} = \beta_0 + \beta_{T_{avg}}\Delta T_{avg} + \beta_{DTR}\Delta\text{DTR} + \beta_P\Delta P + \varepsilon \quad (1)$$

where β_0 represents the model intercept, other β's are the coefficients for each climate variable and ε is the model error. A precipitation term was included since both T_{avg} and DTR are correlated with P (see Section 3),

Table 1
Definition of main growing season months for crops and countries used in this study (source: USDA, 1994)

Wheat	Global production (%)	Yield (Mg ha^{-1})	Months	Rice	Global Production (%)	Yield (Mg ha^{-1})	Months	Maize	Global production (%)	Yield (Mg ha^{-1})	Months
China	14.7	4.2	March–June	China	29.3	6.3	June–September	US	41.6	10.1	June–August
India	11.6	2.7	January–March	India	21.3	3.0	July–November	China	18.3	5.2	June–August
United States (US)	9.4	2.9	March–June	Indonesia	8.9	4.5	January–February	Brazil	5.8	3.4	January–March
France	6.4	7.6	April–July	Bangladesh	6.3	3.4	May-October	Mexico	2.8	2.5	June–August
Canada	4.2	2.6	June–August	Viet Nam	6.0	4.9	February–November	France	2.3	9.0	June–August
Germany	4.1	8.2	April–July	Thailand	4.5	2.7	July–September	Argentina	2.1	6.4	January–March
Turkey	3.4	2.2	January–May	Myanmar	3.6	3.7	July–October	Romania	2.0	4.7	June–August
Australia	3.3	1.7	August–November	Philippines	2.4	3.5	June–October	India	1.9	2.0	August–November
Pakistan	3.2	2.4	January–March	Brazil	2.2	3.6	January–March	Indonesia	1.6	3.4	January–March
United Kingdom (UK)	2.5	7.9	April–July	Japan	1.8	6.4	July–September	Italy	1.5	9.2	June–August

Also shown is the average yield and percentage contribution to global crop production for 2004 (source: FAO, 2006).

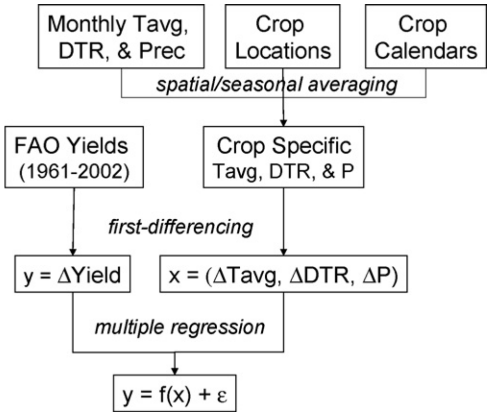

Fig. 1. Overview of steps to estimate yield–temperature relationships. See text for details.

and omission of this variable could therefore bias results. To estimate the sampling uncertainty associated with the derived values of β's (i.e., due to the limited historical sample size), a bootstrap resampling approach was used. Specifically, the original data was resampled with replacement, a new regression model was computed, and this was repeated 1000×.

Fig. 1 illustrates the above steps for deriving the national yield models. Methods of detrending other than first differences, such as removing a polynomial or cubic spline trend, were also considered, and produced qualitatively similar results although often with weaker relationships between climate and yields. Finally, the analysis was repeated using either absolute yields or the natural logarithm of yields in Equation (1), the latter accounting for a potential increase of yield variance with rising average yields. For brevity, only the results based on log-transformed yields are presented, although the results were similar for both approaches.

2.2. Estimates of future impacts

To evaluate the potential importance of future DTR changes, output of daily T_{min} and T_{max} were obtained for 11 climate models for the 1961–2000 and 2046–2065 periods (Table 2) from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) at Lawrence Livermore National Laboratory (http://www-pcmdi.llnl.gov). Projections for several IPCC emission scenarios are available for 2046–2065 temperatures. Here, we use results for the A2 scenario, which is representative of most emissions scenarios out to mid-century, with differences becoming more important after 2065 (Cubasch et al., 2001). Changes in T_{min} and T_{max} were computed for each month by subtracting the model average for 1961–2000 from the corresponding

Table 2
Climate models whose output was used in this study

Model designation	Originating group(s)	Runs[a]
GFDL-CM2.0	Geophysical Fluid Dynamics Laboratory, USA	1, 1
GFDL-CM2.1	Geophysical Fluid Dynamics Laboratory, USA	1, 1
GISS-ER	NASA/Goddard Institute for Space Studies, USA	1, 1
MIROC3.2 (medres)	Center for Climate System Research, National Institute for Environmental Studies, and Frontier Research Center for Global Change, Japan	3, 3
MIUB/ECHO-G	Meteorological Institute of the University of Bonn, Germany and Meteorological Research Institute of KMA, Korea	3, 3
BCCR-BCM2.0	Bjerknes Centre for Climate Research, Norway	1, 1
CCCma-CGCM3.1(T47)	Canadian Centre for Climate Modelling and Analysis, Canada	5, 3
CNRM-CM3	Centre National de Recherches Météorologiques, France	1, 1
CSIRO-Mk3.0	CSIRO Atmospheric Research, Australia	3, 1
ECHAM5/MPI-OM	Max Planck Institute for Meteorology, Germany	2, 1
IPSL-CM4	Institut Pierre Simon Laplace, France	1, 1

Details on individual models are available at http://www-pcmdi.llnl.gov.
[a] Runs = number of realizations averaged for 20th century (before comma) and SRES A2 (after comma) simulations.

average for 2046–2065. For models with more than one available realization (Table 2), an average of the ensemble of realizations was used.

Changes in T_{avg} and DTR were computed for each crop and country in a similar manner as described above. Namely, gridded climate projections were averaged for the growing season months and spatially averaged using the crop maps of Leff et al. (2004) as weights. The multiple regression yield models derived above were then used to estimate the impact of the projected temperature changes. To separate the contributions of T_{avg} and DTR changes, yield changes were estimated first using only T_{avg} projections from each climate model (setting ΔDTR to zero), then for DTR projections ($\Delta T_{avg} = 0$), and finally for both T_{avg} and DTR projections.

While temperature changes are a major factor in crop response to climate change, other factors such as precipitation, CO_2 concentration, new cultivars and new management practices by farmers can also play a substantial role. The estimates of temperature impacts in this study should therefore not be interpreted as representing the correct magnitude or even sign of net climate change impacts. Rather, the results are intended to provide a measure of the sensitivity of temperature impacts to changes in DTR. This knowledge can help determine the crops and/or regions where assessments of climate change impacts should consider changes in DTR.

3. Results and discussion

3.1. National yield models

3.1.1. Responses to T_{avg}

The regression model coefficients revealed a consistently negative response of yields to warmer growing season T_{avg} (Fig. 2). This result agrees with many studies using process-based models that project a negative response of regional or global yields to warming in the absence of rainfall changes, CO_2 fertilization, or adaptation (e.g., Rosenzweig and Parry, 1994). More rapid crop development and greater water stress are among the most likely mechanisms that explain the reduction of yields with warming.

Japanese rice was the only case where a clear positive effect of warming was observed. A beneficial effect of warming for Japan has been noted previously and attributed to the fact that the current climate in Japan is cool during flowering stages compared to most rice growing areas (Furuya and Koyama, 2005). For example, average growing season temperatures for 1961–2002 in Japan computed in the current study (21.2 °C) were more than 3 °C lower than any other country for rice.

3.1.2. Responses to DTR

Estimates of yield response to DTR (β_{DTR}) were characterized by large uncertainties relative to those for T_{avg} in most cases, with the 90% confidence interval (defined by the 5th and 95th percentiles of the coefficients obtained from the bootstrap resampling procedure) often spanning zero (Fig. 2). Several factors likely contributed to the relatively large uncertainty for β_{DTR}. First, inter-annual variations of DTR were small in many regions, as changes in T_{min} and T_{max} tend to be highly correlated from year to year (Fig. 3). Variability of DTR appeared particularly low in tropical countries, such as Brazil and Philippines.

Another important factor was that DTR changes were often strongly correlated with changes in precipitation (Fig. 3), with higher rainfall associated

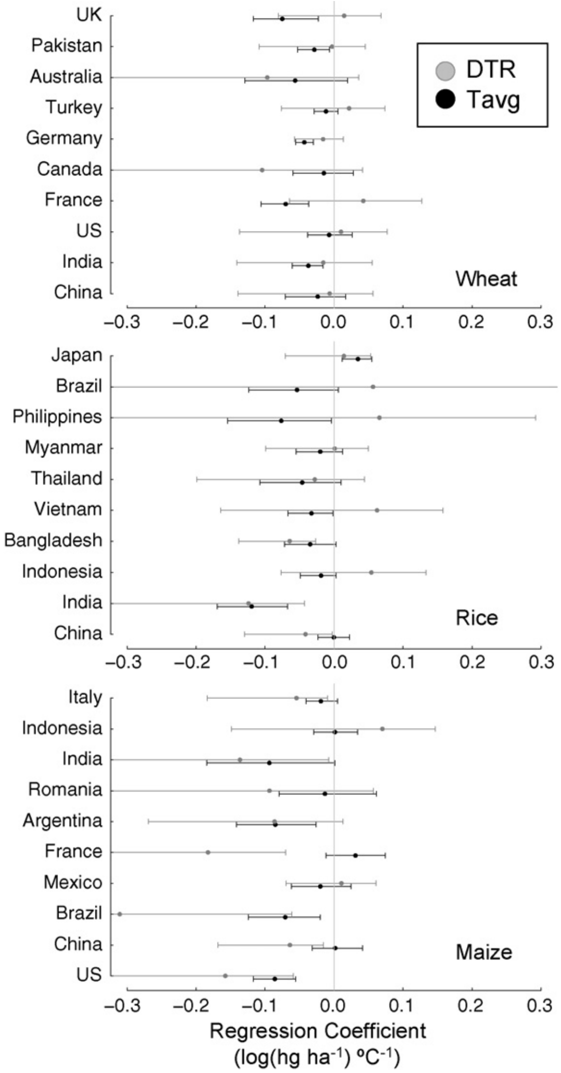

Fig. 2. Estimated coefficient for response of Δyield to ΔT_{avg} and ΔDTR in a multiple linear regression model. Error bars show 90% confidence interval (5th–95th percentile) based on bootstrap resampling of historical data with 1000 samples.

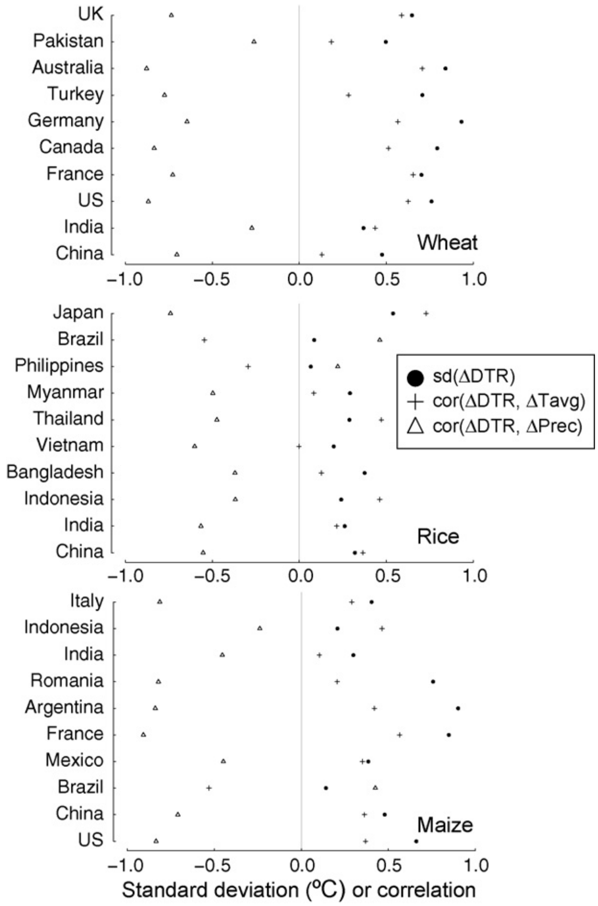

Fig. 3. Historical standard deviation of ΔDTR (°C) and correlation of ΔDTR with ΔT_{avg} and ΔP (unitless). Estimation of yield responses to DTR is made difficult by relatively low inter-annual variability of ΔDTR and high correlation with other climate variables.

with greater cloud cover that tends to reduce DTR (Dai et al., 1999). This co-linearity makes it difficult in an empirical model to separate the effects of DTR from rainfall. To a lesser extent, DTR changes were often correlated with T_{avg} changes (Fig. 3), leading to a similar problem of co-linearity.

Despite these problems and the fairly wide confidence intervals for β_{DTR}, there were several locations where DTR had a strong, and sometimes statistically significant effect on yields. For wheat, DTR was estimated to have a relatively strong negative effect in Australia and Canada, while a positive effect was estimated in France. Examples of the data on which these regressions are based are provided for Australia and France in Fig. 4.

A negative response of Australian wheat yields to DTR was also reported by Nicholls (1997), who showed that a trend of decreasing DTR from 1952 to 1992 had contributed up to half of the observed yield increase over that period. Decreases of DTR are believed to benefit yields in this region because of the associated reduction in frost occurrence (Nicholls, 1997). The mechanisms behind the positive effect in France are less clear. As mentioned in the Section 1, increased DTR is often associated with greater solar radiation, and in wheat can also result in longer growth duration (Lobell and Ortiz-Monasterio, 2007). The positive relationship may also be partly or entirely due to chance, since more than 10% of the distribution for β_{DTR} in France lies below zero.

For rice, China, India and Bangladesh exhibited significant response to DTR, and in all cases yields were

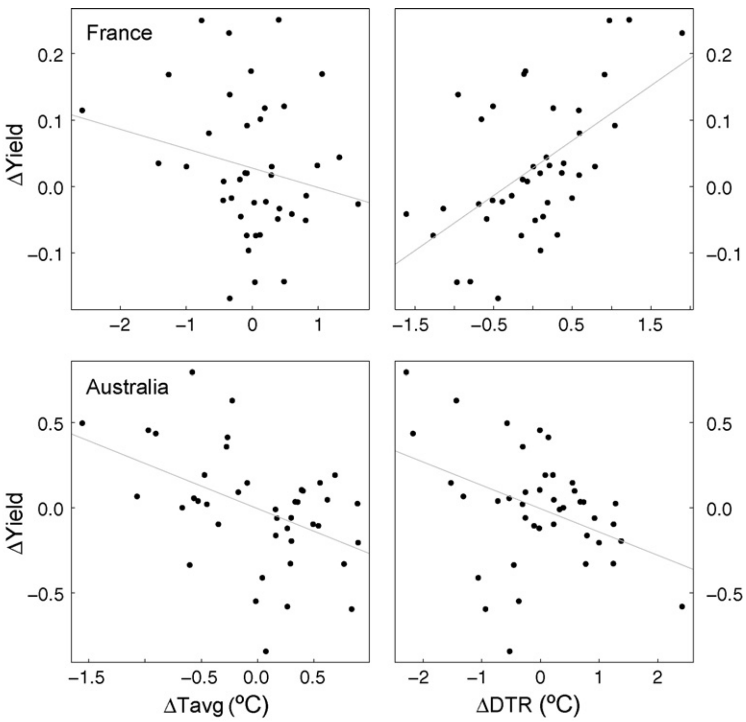

Fig. 4. Values of Δyield for 1962–2002 plotted against corresponding ΔT_{avg} and ΔDTR for France (top) and Australia (bottom). Gray line indicates best-fit linear regression.

diminished with increased DTR (Fig. 2). All significant cases for maize were also characterized by negative responses to DTR, with six of the countries showing a significant response: US, China, Brazil, France, India and Italy. Thus, for the 30 cases considered in this study (ten locations for each crop), all nine cases with a highly significant effect of DTR ($p < 0.05$) exhibited a negative impact of DTR on yields. Moreover, these cases included the two biggest producers of rice (China and India) and maize (US and China).

A negative yield response to DTR, coupled with a negative yield response to T_{avg} in most regions, indicates that temperature increases are more harmful during day than at night. In studies with the EPIC crop simulation model, Dhakhwa and Campbell (1998) concluded that DTR increases resulted in lower maize yields in the US because of greater evapotranspiration losses, and consequent water stress. A recent study of US maize yields that utilized daily T_{min} and T_{max} data provided strong empirical evidence that yields decrease nonlinearly with temperatures above 25 °C, with even short periods above 30 °C resulting in significant yield losses (Schlenker and Roberts, 2006). However, the relative importance of water stress and direct heat effects on photosynthesis and development rates could not be determined from the empirical dataset.

For rice, a recent analysis of temperature and yield variations at several stations throughout China found that spikelet sterility for rice was positively correlated with average T_{max} during the 20 days before and after anthesis (Tao et al., 2006). This finding is consistent with the negative effects of increased DTR inferred in the current study for rice yields, and suggests that the response may be more closely related to direct heat effects than in the case of maize, which is less commonly irrigated than rice and thus, more prone to water stress.

However, Peng et al. (2004) inferred a strong positive effect of DTR in experimental yield trials at the International Rice Research Institute in the Philippines (increased T_{min} reduced yields by 10% per degree celsius, while T_{max} effects were insignificant), which contradicts the general pattern of negative DTR effects observed in Fig. 2 for rice. A possible explanation for this discrepancy is that low T_{min} is often associated with enhanced dew formation, which can promote the incidence and severity of foliar and stem diseases (Ken Cassman, personal communication.) These diseases are avoided in yield potential trials such as those analyzed by Peng et al. (2004) through the use fungicides, but can cause substantial yield losses in farmers' fields. Further study is therefore needed to better understand the role of diseases in yield-temperature relationships, and thus the applicability of experimental trials (and crop models based on these trials) to projections of climate change impacts on broad-scale food production.

The lack of significant DTR effects for wheat in any of the top ten producing countries is intriguing, given that several cases for rice and maize were significant. One possible explanation is that the negative effects associated with water and/or heat stress are balanced by a positive effect of DTR on crop development. The optimal temperature for wheat development, at which growth rates are maximized, is believed to be lower for wheat than rice or maize (Ritchie and NeSmith, 1991; Wilkens and Singh, 2001). In many regions, day temperatures can often exceed this optimum, so that temperatures changes during the day have a small effect on development relative to night. Since faster development results in shorter growing seasons and shorter periods of grain formation and filling, yields may be helped by increases in DTR. As discussed above, DTR increases also often correspond to increases in solar radiation, although this effect would be expected to influence the three crops equally.

3.2. Estimates of future impacts

3.2.1. Climate model projections of T_{avg} and DTR

Whether yield sensitivities to DTR will play a role in climate change impacts depends on future changes of DTR in the locations and seasons in which these crops are grown. In contrast to past trends and future projections for many regions (e.g., Vose et al., 2005), the average projected change by mid-century in DTR across models was positive for most major wheat regions and many maize areas (Fig. 5). Many of the leading wheat and maize countries are in North America and Europe, where models project drying of soils in summertime (Wang, 2005) that contributes to higher DTR (Dai et al., 1999). Projected changes in DTR tended to be negative for rice growing areas that are concentrated in more humid Asian locations.

In nearly all cases, the range of DTR projections included zero change, indicating that climate models do not give a strong consensus on the direction of DTR change by 2050. This contrasts with projections of T_{avg}, for which models unanimously predict warming of at least 1 °C for all crops and countries. Another feature of the climate projections illustrated in Fig. 5 is the tendency for model projections of T_{avg} and DTR to be positively correlated. That is, the models that simulate the greatest warming also tend to simulate the largest increases (or smallest decreases) in DTR.

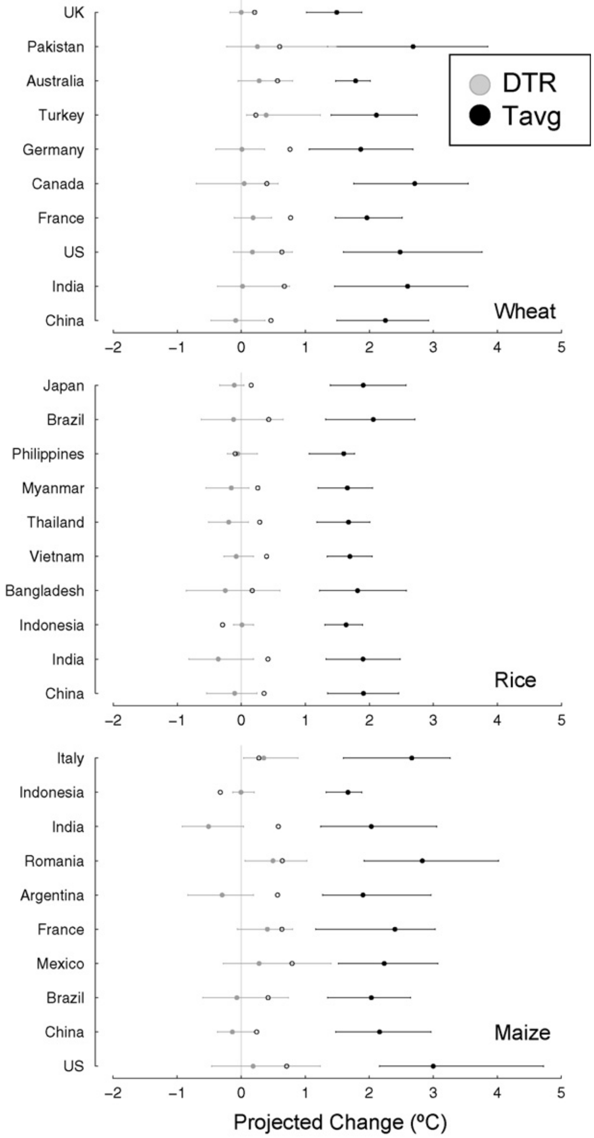

Fig. 5. Average (dot) and range (bars) of projected changes (2046–2065 minus 1961–2000 averages) in T_{avg} and DTR for 11 climate models by crop and country. Open circles indicate the inter-model correlation between T_{avg} and DTR projections.

3.2.2. Yield responses

As expected from the negative values of $\beta_{T_{\mathrm{avg}}}$ in most regions (Fig. 2) and the projected warming in all regions (Fig. 5), the anticipated effects of changes in T_{avg} was to decrease yields for most cases (Fig. 6). The impacts of DTR changes varied by country and crop, depending on the estimated values of β_{DTR} and the mixed projections of DTR. In all cases, a wide range of DTR projections

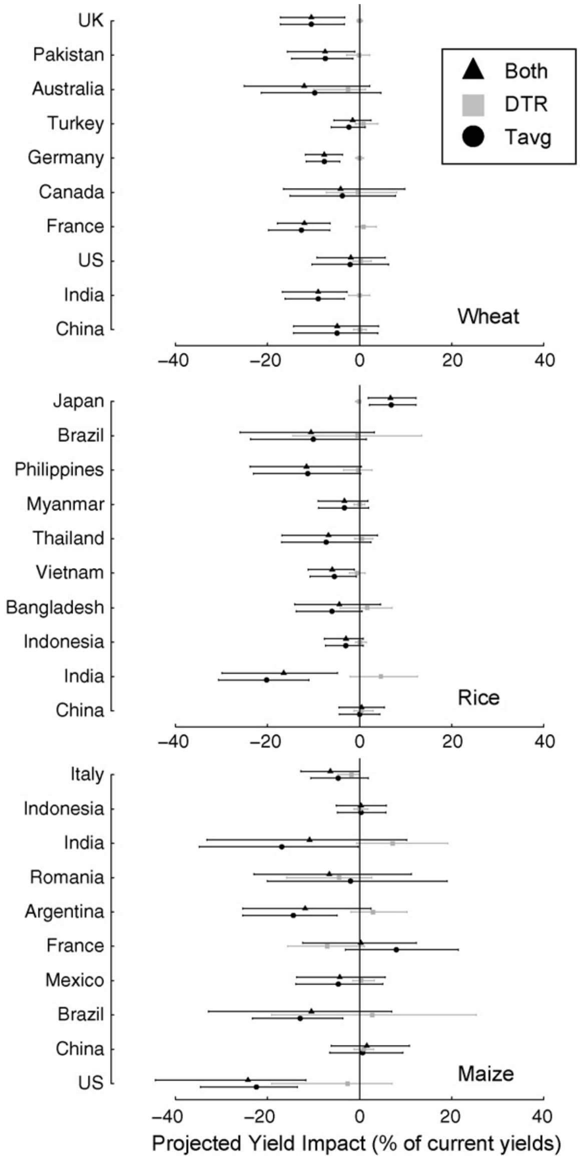

Fig. 6. Modeled yield impacts of projected changes by 2046–2065 in T_{avg} only, DTR only, and both T_{avg} and DTR. Error bars indicate 90% confidence interval (5th–95th percentile) based on uncertainties in climate projections (estimated by using output from 11 climate models) and yield responses (estimated by bootstrap resampling of historical data with 1000 samples).

resulted in modeled yield responses to DTR that included zero.

A comparison of projected yield changes when using only T_{avg} to those using both T_{avg} and DTR was used as an indicator of DTR's potential role in climate change impacts. With a few important exceptions, the differences were relatively small, and consideration of DTR changes therefore does not appear to be a priority for impact assessments in most regions. However, DTR did significantly affect the projected maize yield responses in the US. The mean estimated yield change decreased from −23 to −25% when including DTR, while the 5th percentile exhibited a more substantial change from −35 to −45%. Thus, DTR appears particularly important for defining the low-probability, high consequence tails of the distributions, in the case of maize for the US and some other countries (e.g., Brazil and France). This finding emphasizes the significance of the positive correlation between T_{avg} and DTR projections. The most extreme scenarios of T_{avg} changes corresponded to the largest increases of DTR, which exacerbated the yield losses.

Rice in India provides another example where DTR had a noticeable effect on yield response estimates. In this case, climate models tended to simulate a reduction in DTR, which favors higher rice yields in India (Fig. 2). As a result, simulated yield losses were slightly reduced when including DTR changes.

4. Conclusions

This study evaluated (1) whether inter-annual variations in DTR have measurable effects on average national cereal yields and (2) whether DTR is therefore an important variable to consider in climate change impact assessments. Despite uncertainties associated with limited sample sizes and correlation of DTR with other climatic variables, a clearly negative impact of DTR on yields was observed for several rice and maize producing countries. These results indicate that the historical reduction of DTR in many locations in the latter half of the 20th century may have aided yield progress of rice and maize. Effects of DTR on wheat were less clear, which may reflect competing effects of DTR on water stress and crop development rates. However, further study is needed to better understand the mechanisms of DTR influence.

The effect of future DTR changes was estimated using projections of T_{avg} and DTR from 11 climate models for the middle of the 21st century. The projected changes in DTR were generally too small to result in significant yield effects relative to the negative impact of increased T_{avg}. However, the notable exceptions of maize in the US and rice in India indicate that DTR can be important in certain situations, particularly for estimating the probability of extreme impacts.

An important remaining question is whether the range of DTR projections in the current ensemble of climate models includes the actual future changes in DTR. Simulations of DTR changes over the 20th century with an earlier version of one of the models used here (CCCMA-CGCM) produced a reduction of DTR that was only one-fourth the magnitude of observed trends (Stone and Weaver, 2002). Therefore, confidence in projections of future DTR changes, even when considering multi-model averages, may be considered low at present time. If actual DTR changes over the next 50 years exceed those considered in this study, then the relative role of DTR in crop yield responses could be larger.

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