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Evaluating the utility of dynamical downscaling in agricultural impacts projections

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Interest in estimating the potential socioeconomic costs of climate change has led to the increasing use of dynamical downscaling—nested modeling in which regional climate models (RCMs) are driven with general circulation model (GCM) output—to produce fine-spatial-scale climate projections for impacts assessments. We evaluate here whether this computationally intensive approach significantly alters projections of agricultural yield, one of the greatest concerns under climate change. Our results suggest that it does not. We simulate US maize yields under current and future CO_2 concentrations with the widely used Decision Support System for Agrotechnology Transfer crop model, driven by a variety of climate inputs including two GCMs, each in turn downscaled by two RCMs. We find that no climate model output can reproduce yields driven by observed climate unless a bias correction is first applied. Once a bias correction is applied, GCM- and RCM-driven US maize yields are essentially indistinguishable in all scenarios (<10% discrepancy, equivalent to error from observations). Although RCMs correct some GCM biases related to fine-scale geographic features, errors in yield are dominated by broad-scale (100s of kilometers) GCM systematic errors that RCMs cannot compensate for. These results support previous suggestions that the benefits for impacts assessments of dynamically downscaling raw GCM output may not be sufficient to justify its computational demands. Progress on fidelity of yield projections may benefit more from continuing efforts to understand and minimize systematic error in underlying climate projections.

agriculture | food security | NARCCAP | CORDEX

One of the greatest societal concerns related to anthropogenic climate change is its potential impact on food supply (1). A recent multimodel comparison projected 8–43% loss of caloric production from primary food crops by the end of the century (no-adaptation scenario with global mean temperature rise of ~5 °C) (2, 3). The spread in projections results in part because plants respond to highly local weather conditions in complex and nonlinear ways. Crop growth processes have ideal temperature ranges (4) and are sensitive to the timing of extreme temperature and/or precipitation events (5–9). Many agricultural models therefore attempt to represent crop physiology in detail and require inputs describing environmental conditions at high spatial and temporal resolution.

The importance of weather fluctuations to climate impacts has prompted interest in methods for downscaling general circulation model (GCM) output. Downscaling is necessary for agricultural impacts assessments because factors that affect crops (soil, surface, and farming practices) vary at finer scales than typical GCM spatial resolution (>100 km) (10, 11). Some of the earliest downscaling approaches used observed relationships between mesoscale and local climate variables to relate GCM output to local climate (12). These statistical downscaling methods have the benefit of relying on observations, but their central premise is uncertain: that observed statistical relationships would remain unchanged in a future climate (13, 14). An alternative approach uses nested modeling in which regional climate models (RCMs) are driven by boundary conditions derived from GCM outputs (15). This dynamical downscaling is computationally expensive but offers a self-consistent approach that captures fine-scale topographic features and coastal boundaries. It has been shown to improve weather and climate variability, especially over complex terrain (see ref. 16 for comparison with reanalysis and ref. 17 as example of comparison with statistical downscaling).

The use of dynamical downscaling in long-range climate projections has accelerated with the growth of computing resources. At present, many large collaborative projects are generating databases of downscaled climate output for model intercomparison and impacts assessment. The North American Regional Climate Change Assessment Program (NARCCAP), begun in 2006, has generated high-resolution (50 km) climate projections for the United States, Canada, and northern Mexico (18). In 2009, as a successor to the PRUDENCE (19) and ENSEMBLES (20) projects (2001–2009), the World Climate Research Program (WCRP) began the international Coordinated Regional Climate Downscaling Experiment (CORDEX) to produce similar output for all continents (21). Other examples of projects that use RCMs include JPI-Climate, SPECS, EUPORIAS, IMPACT2C, ECLISE, CLIM-RUN, CECILIA, and STARDEX (see *SI Text* for descriptions). The level of effort invested in dynamical downscaling warrants a proper evaluation of its benefits for impacts assessments.

For agricultural impacts, initial studies suggested that dynamical downscaling may improve projections, because the use of RCMs altered modeled crop yields by up to 20% (22–29). These studies were not definitive, however; they covered limited areas and times, which can increase GCM-RCM differences, and most used the delta method to remove climate model bias, which can reduce differences. The delta method takes only model

Significance

One of the largest concerns about future climate change is its potential effect on food supply. Crop yield projections require climate inputs at higher resolution than typical for global climate models, and the computationally expensive technique of dynamical downscaling is widely used for this translation. We simulate maize yield in the United States to test whether current dynamical downscaling methods add value over simpler downscaling approaches. Our results suggest that they do not. Addressing large-scale systematic biases in climate output may be a higher priority for understanding future climate change impacts.

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monthly mean changes and adds them to observations, so model cases share submonthly variations.

Bias correction is needed with or without dynamical downscaling, as systematic GCM errors have been shown to propagate into RCM output (30–33), and nonlinearities in crop responses mean that even constant biases can affect yield change projections. Hydrological studies support the importance of bias correction, as GCM and RCM output must be corrected to reproduce observed hydrology (34, 35). Impacts assessments appear dependent on observation-based adjustments even when dynamical downscaling is used (36). The alternative statistical approaches based purely on observations serve both purposes, downscaling GCM output from its native resolution and compensating for model systematic errors. (For this reason, statistical approaches are often termed simply bias correction, and we follow this convention.) The value added by dynamical downscaling to agricultural forecasts remains an active research question.

The recent completion of NARCCAP provides a tool for that evaluation. In this study, we compare US maize yields driven by both NARCCAP dynamically downscaled GCM output and by the original GCM output simply interpolated to 5 arcminutes (~10 km), near field scale, with and without a subsequently applied bias correction. We estimate historic and future yields with the widely used Decision Support System for Agrotechnology Transfer (DSSAT) crop model (37) driven with daily climate output from seven sources. We use 1980–1998 as the historical period (defined by overlap of available inputs), and for the future, consider 2041–2068 under the Special Report on Emissions Scenarios (SRES) A2 future emissions scenario, in which global mean temperature rises ~2.5 °C. For the historical period we use an observation set consisting of reanalysis temperatures, gridded precipitation from rain gauge measurements, and observation-based solar insolation. For both periods, we use climate output from two GCMs: the US Community Climate System Model (*ccsm*) at ~1.4° (~150-km) resolution and the Canada-based Coupled Global Climate Model (*cgcm*) at ~3.75° (~380 km), and corresponding dynamically downscaled output generated with two regional climate models: the Canadian Regional Climate Model (CRCM) and the Weather Research and Forecasting Model (WRFG). Each RCM is driven with boundary conditions from each GCM, producing model combinations denoted *crcm_ccsm*, *crcm_cgcm*, *wrfg_ccsm*, and *wrfg_cgcm*.

Because the purpose of this work is exploring the sensitivity of modeled yield to climate inputs and not validating the agricultural model, we use DSSAT-simulated yields driven by historical observed climate rather than the historical yields themselves, which are influenced by extraneous factors linked to management practices. [DSSAT does reproduce observed yields well when management practices are matched (Fig. S1).] We describe here only simulations of unirrigated agriculture, which is maximally sensitive to climate, but our qualitative results hold for irrigated agriculture as well (*SI Text*).

Results

Evaluating Downscaling Effects Using Historical Simulations. Simulations run over a historical period allow us to directly assess the effects of bias correction and dynamical downscaling on crop yields. These simulations also provide an estimate of the importance of climate model uncertainty to yields in a period when model confidence should be highest. First, we use the historical observation set to determine a bias correction at our 5-arcminute resolution for each of the climate model combinations described above. We use a simple monthly mean correction to preserve model submonthly weather variability. Corrections are of similar magnitude across model cases, with a 5th/95th percentile spread in local maximum temperatures of >6 °C across the eastern half of the United States where most maize is grown (Fig. S2). We then drive DSSAT with raw and bias-corrected versions of GCM and RCM climate products and, for the historic period, with the observation set itself. The resulting distributions of rainfed US maize yields for the historic period are shown in Fig. 1 (see Fig. S3 for irrigated and future scenarios). For all model cases, using nonbias-corrected input produces yield distributions skewed low relative to those driven by observations, and dynamical downscaling exacerbates the skew. Applying even our simple bias correction results in yield distributions largely consistent with those generated with historical observations. (Cases involving the WRFG RCM retain some low skew.)

The increased skew with uncorrected dynamical downscaling occurs because RCMs correct some but not all GCM biases. As expected given their imperfect representation of topography, both GCMs overestimate precipitation in the dry "rain shadow" east of the Rocky Mountains and therefore overpredict local yields (Fig. 2 and Figs. S4 and S5). This error is, however, more than compensated for by underestimating yields in the upper Midwest, which is too hot and dry in *ccsm* and too cold in *cgcm*. Dynamical downscaling corrects the errors related to topography but not the upper Midwest biases, deepening the net underestimation of US yields. Bias correction effectively eliminates both effects and produces yield distributions more consistent with those driven by historical observations. With bias correction,

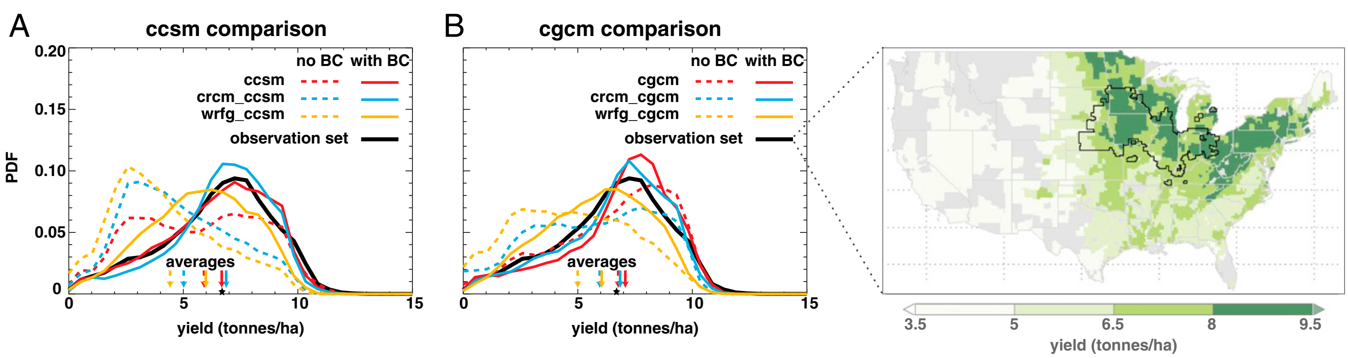

Fig. 1. DSSAT probability distributions of 1980–1998 rainfed maize yield driven by all climate products. *A* and *B* show yields driven by CCSM and CGCM output, respectively. Observation-driven yield distributions are duplicated in both panels (black line) and mapped on right (time-averages, with outline demarking the corn belt, counties with ≥1/4 land cultivated with maize). See ref. 38 to compare with data. Aggregation is by county and not normalized for size or total yield. Arrows and star in *A* and *B* show average county yield. Yields driven by nonbias-corrected inputs (dashed) are generally skewed low, with the skew worse for dynamical downscaling than for simply interpolated GCM inputs. Bias-correcting climate inputs (solid) largely eliminates distributional discrepancies against the observation set.

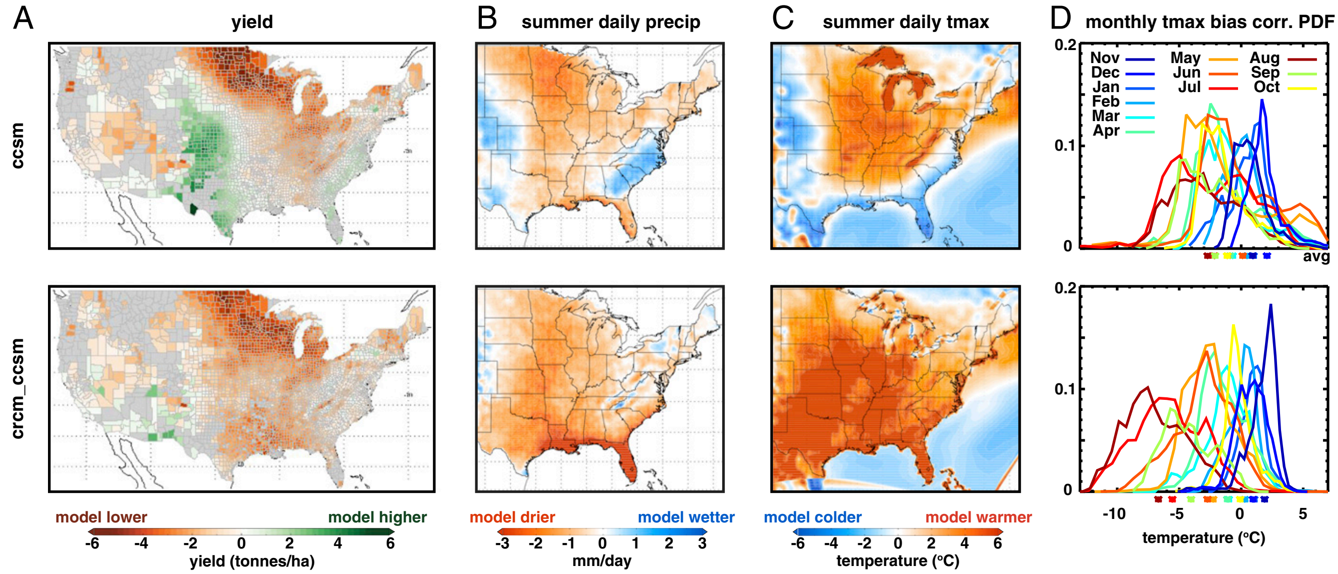

Fig. 2. Differences in 1980–1998 nonbias-corrected model- and observation-driven yields and corresponding climate inputs. Patterns in 1980–1998 average yield outputs (*A*) coincide with summer (JJA) average precipitation (*B*) and maximum temperature (*C*) inputs, which are too wet and cold near the Rockies and coasts in *ccsm* and too hot and dry across the United States for *crcm_ccsm*. Here, the addition of the RCM actually worsens maximum temperature inputs. Probability density functions (PDFs) of the applied bias correction over eastern US land (*D*) illustrate the magnitude of the errors in maximum temperature (reaching >5 °C in many locations), especially in the summer months of *crcm_ccsm*, which are particularly hot. Stars at the bottom indicate the average bias for each month.

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national time-averaged yield estimates for all model cases lie within 9% of the historical case (Table 1).

Downscaling Effects on Yield Projections. Successfully reproducing observation-driven yields is a necessary but not sufficient condition for accurate yield forecasts under changed climate. The fact that a simple monthly mean bias correction matches the historical case suggests that differences in short-term or interannual climate variability (climate extremes) are not large enough to distort aggregate crop yields. However, nonlinear crop responses mean that even constant climate biases could be important to projections of yield changes.

Our results show that climate model bias does propagate into yield change projections generated with GCM and RCM inputs (Table 1). In the absence of bias correction, all model cases estimate gains in maize productivity under climate change (6–31%), but with bias correction, the mean projection is neutral to negative (−11% to +2%). In the nonbias-corrected case, gains under climate change are driven by the initial underestimation of historical upper Midwest yields. For all model cases, yield depressions are ameliorated when climate change produces conditions more optimal for maize (Figs. S4–S7). In CCSM, lack of precipitation depresses historical period yields, but climate is wetter in the future. In CGCM, low temperatures hinder historical period growth, but future projections warm past critical maize thresholds.

Once a bias correction is applied, future yield changes in corn-growing areas are well explained by changes in summertime precipitation and daily temperature maxima (Fig. 3 and Figs. S6 and S7). Higher temperatures hasten phenological phase transitions and, where conditions are already near optimal, reduce yields (9). (Temperatures ∼35 °C can lead to crop failure.) Increased rainfall in the growing season tends to increase yields, as long as soil moisture remains below the threshold where waterlogging produces root death (39). DSSAT does include still-uncertain interactions related to elevated CO_2 concentration and altered nitrogen availability, but the general relationship between climate and yields here appears straightforward and is consistent with studies of historical yields (40).

A main goal of dynamical downscaling is to produce more faithful representation of spatial and temporal variations in climate and in climate change. We therefore examine the convergence of GCM- and RCM-driven yield forecasts as they are aggregated in space (at model grid, county, state, and national scales) and time (from 1 to 28 y). The spread of local climate and yield changes within a model case is generally smaller than the difference between model cases (Fig. 3) but may nonetheless be important to policy-relevant impacts assessments. Fig. 4 shows normalized RMS differences in future period yields between the *ccsm* and *crcm_ccsm* pair, which has the largest GCM-RCM yield differences of the model cases tested [26% of national time-averaged

Table 1. Summary of modeled US national average rainfed maize yields driven by different climate inputs

	ccsm	+crcm	+wrfg	cgcm	+crcm	+wrfg
Percentage difference from observation-driven yield*						
Bias correction	−2	2	−9	8	5	−9
No bias correction	−22	−34	−35	1	−14	−26
Projected future anomaly (% change)†						
Bias correction	2	−11	2	−2	−6	5
No bias correction	21	6	24	7	8	31

*Percentage difference in modeled historical US yield (1980–1998) driven by GCM or RCM input vs. observations. Addition of bias correction generally reduces discrepancies, and use of RCMs increases discrepancies. (The near-perfect cancellation of errors in *cgcm* as shown in Fig. S5 makes nonbias-corrected yield appear more accurate only for national averages.) Numbers would be slightly different if taken from the arrows of Fig. 1, which represent averages of county yields.

†Model percentage yield changes between historical and future (2041–2068) periods ($\Delta T \sim 2.5$ °C). (Values given as time-averaged national percentage difference of future from historical yields.) Raw climate input consistently produces forecast gains in US maize yields; adding a bias correction reduces those gains in all cases. Use of RCMs alters yield forecasts, but inconsistently between models.

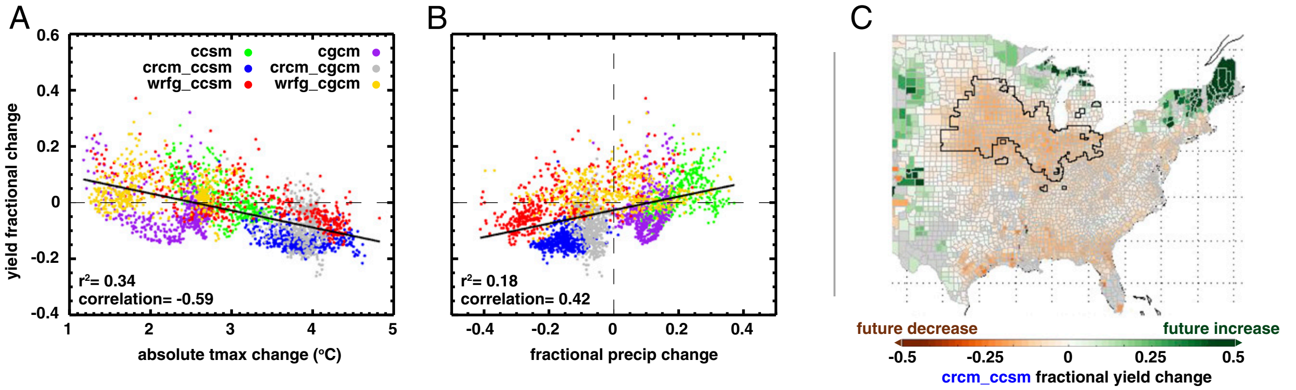

Fig. 3. Correlations between bias-corrected corn belt yield and climate changes. Dots represent differences between 2041–2068 and 1980–1998 for counties in the corn belt, as defined in Fig. 1 and outlined in *C*. Across model cases, yield changes are negatively correlated with absolute changes in summer (JJA) mean daily temperature maximum (*A*) and positively correlated with changes in summer precipitation (*B*). Solid black lines show best-fit line through all model yields, and dashed lines indicate no change. Yield changes are spatially homogeneous; *C* shows *crcm_ccsm* with large decreases across the corn belt.

mean GCM yield (~1.9 metric tons/ha) without bias correction and 10% (0.8 metric tons/ha) with bias correction; see Fig. S8 for other cases, which are similar, and Table S1 for normalization details].

As expected, yields generated with different downscaling techniques become increasingly similar with temporal and spatial averaging (Fig. 4 and Fig. S8). Temporally, a decade of averaging suffices for normalized RMS differences at all scales to converge to near-fixed values. Spatially, yield differences at the grid, county, and state scales become nearly identical with time averaging, implying that the dominant effects of dynamical downscaling are offsets in yield relatively constant over at least state scale. (These broad-scale effects are visible by eye in Fig. 3*C* and Fig. S7.) With bias correction, this homogeneity extends across maize-growing regions: time-averaged normalized RMS differences at all scales approach the national value (in turn lowering the national mean discrepancy). Dynamical downscaling appears to produce primarily broad-scale offsets in time-averaged yield rather than increased spatial variability at RCM resolution.

The significance of these offsets is not well understood. Nationally, offsets in mean yield introduced by RCMs (in the bias-corrected case) are smaller than the effect of bias correction itself and comparable in magnitude to the model variability error previously discussed (Table 1, row 1 vs. 3, and Fig. S9). For yield changes, the dynamical downscaling effect can differ in sign between RCMs. The GCM-RCM differences in climatic variables that govern yield changes (Fig. 3 and Figs. S6 and S7) are themselves not well understood (41). It is therefore not yet possible to evaluate whether any given RCM improves yield forecasts over GCM output.

Discussion

The comparison of modeled maize yields under different treatments of climate inputs suggests that dynamical downscaling as it is currently implemented may not add significant value to agricultural impacts assessments. Yield estimates made with both GCMs and RCMs require some form of bias correction to climate inputs. Once a simple bias correction is applied, time-averaged maize yields driven by GCM and RCM inputs show little significant difference in any simulations: historic or future. (That is, RCM-induced yield differences are comparable in size to the discrepancies produced by model output vs. observations.) The results suggest that the dominant climate-related factors that would compromise agricultural impacts assessments are large-scale (100s of kilometers) systematic errors in GCM output, which RCMs cannot fully compensate for.

This study is necessarily limited, because we consider only one crop in one country represented by a single agricultural model driven by a limited set of climate inputs, and GCM-RCM yield differences are shown to vary between crop, region, and modeled scenario (42). However, the conclusions are likely broadly applicable, as our scenario choices were made to maximize differences between GCM- and RCM-driven yields. We chose maize as our test crop, because it is among the most sensitive crops to climate (28). Further, our results are consistent across several factors: the many different crop environments in the large spatial domain of this study; rainfed and irrigated water management; and GCMs of different spatial resolution. Our results are also in agreement with previous studies on hydrological impacts (34, 35), which, like rainfed agriculture, should be highly sensitive to fine-scale precipitation inputs. Wood et al. (34) conducted an experiment similar to this one, driving a hydrological model of the Pacific Northwest region with ~14 km downscaled climate products and concluded that (*i*) nonbias-corrected RCM input are unable to reproduce observation-driven simulations and (*ii*) after correction for climate biases, coupling GCMs with RCMs has little to no benefit for hydrological impacts assessment.

Note that our results should not be taken as a broad judgment on the importance of spatial resolution in impacts assessment and only as a caution about dynamically downscaling systematically biased GCM output. We have not tested one plausible approach: driving an RCM with bias-corrected GCM output. The contribution of dynamical downscaling may be more apparent if applied to climate inputs stripped of their major systematic errors. Studies have suggested that dynamical downscaling of bias-corrected (as opposed to raw) GCM output does offer improvements in fidelity when reproducing historical climate (43, 44). Some authors have also suggested that using high-resolution GCMs could reduce some of the large-scale biases seen in coarser model output (45). To date, no studies have evaluated the consequences in an impacts model.

Continued efforts to improve climate inputs for agricultural impacts projections may be important. In this study, we show that given a bias correction, RCMs introduce only small fractional changes in US yield projections for rainfed maize (~7–10%) and still smaller changes for irrigated maize (~1–6%) (Table 1 and Figs. S3 and S9). These small differences are more important in counties with low yields because absolute GCM–RCM yield differences are roughly constant across the United States (Fig. S10). Uncertainty due to climate inputs may then be more important in the developing world, where yields are typically low, than in the United States, where yields are high due to intensive fertilizer use and sophisticated agricultural practices. [The 2011 average maize yields in Africa, for example, were one-fifth those in the United States (46).] A recent intercomparison

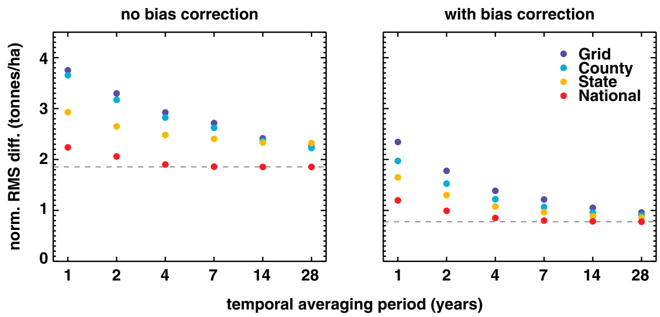

Fig. 4. Normalized RMS differences in projected future (2041–2068) rainfed maize yields from countrywide *ccsm* and *crcm_ccsm* inputs, with spatial and temporal aggregation. GCM-RCM RMS yield differences decrease with aggregation, as expected, for the nonbias-corrected (*Left*) and bias-corrected (*Right*) cases. Because maize areas are unevenly distributed in states and counties, yield averages differ by spatial scale, so RMS differences are normalized to national values (i.e., scaled by the ratio of their time-averaged mean absolute differences; Table S1). Bias correction reduces both spatial variance in RMS yield differences and the national mean value (dashed lines).

study of crop models concurred in finding that uncertainty in agricultural forecasts related to climate inputs was largest in the typically lower-yielding tropical regions (2). If our results prove globally applicable, they would suggest that meaningful agricultural impacts forecasts are more challenging in the developing world, where they may matter most.

Evaluating best practices for agriculture-relevant climate projections is a timely subject given the many ongoing international efforts at high-resolution modeling: for example, agricultural impacts in low-yield Africa are one of the major stated motivations for the CORDEX global project (21). The completion of NARCCAP provides a resource that can now inform future similar projects. Results of this study suggest it would be useful to consider alternatives to the standard methodology of dynamically downscaling raw GCM output.

Assessing agricultural impacts in developing countries is challenging, because observational climate data are most limited there, management practices are least characterized, and climate uncertainties are apparently most important. Making progress may require careful attention to the opportunity costs of efforts to improve the different components of an assessment: climate observations, emissions forecasts, agricultural models and their inputs (e.g., soil and management data), underlying GCMs, and the spatial resolution of climate inputs. The results here suggest that resolution alone is not a panacea and that caution is warranted when driving high-resolution computational models with systematically biased inputs.

Materials and Methods

pDSSAT. Crop yield calculations were made with a version of the DSSAT crop model (pDSSAT) (47) that uses the Swift parallel scripting language (48) to provide concurrent processing on several clusters. Maize in DSSAT is simulated with the crop environment resource synthesis model (CERES). Although this study is not intended as a model validation exercise, in the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP), pDSSAT typically produced yields near the median of the seven analyzed models, with maize yields exhibiting the least intermodel variation among the four analyzed crops (2). Because the purpose of the study is to isolate the effects of climate inputs, we fix cultivar choice, soil profiles [from the Harmonized World Soil Database (HWSD) (49)], management practices (rainfed or irrigated and fertilizer application), and planting date time periods. Results shown here assume 150 kg/ha of nitrogen fertilizer, consistent with most harvested maize in the United States. The DSSAT crop model produces yield estimates in potential kilograms per hectare per year at individual locations and was run on a 5-arcminute (∼10-km) grid as defined by the resolution of the HWSD soil dataset. We aggregate grid-level yields using harvested land-use metrics from Ramankutty et al. (50) to the Federal Information Processing Standard (FIPS) county, state, and national borders.

Climate Products. GCM data are taken from the WCRP's Coupled Model Intercomparison Project phase 3 (CMIP3) archive. We chose CCSM3 and CGCM3.1 because their spatial resolutions span the range of resolutions in the NARCCAP archive (51). Dynamically downscaled NARCCAP output was itself driven by GCM output from CMIP3. NARCCAP availability constrained the choice of simulations to a single realization of the future SRES A2 and historical "20c3m" emissions scenarios. The NARCCAP project drives its RCMs with a different 20c3m realization than the CCSM output used in this study (due to CMIP3 archive limitations), creating a potential source of disparity in historical comparisons. Our observational dataset uses temperature from the National Center for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) product (52). Because NCEP cloud coverage and precipitation are not reliable matches to observations, we use Climate Prediction Center (CPC) US Unified Precipitation compilation of 0.25° × 0.25° daily in situ precipitation measurements provided by the National Oceanic and Atmospheric Administration (NOAA)/Oceanic and Atmospheric Research/Earth System Research Laboratory Physical Sciences Division, and 1° × 1° resolution incoming shortwave radiation from the National Aeronautics and Space Administration (NASA) Langley Research Center Atmospheric Sciences Data Center NASA/Global Energy and Water Exchanges Surface Radiation Budget (SRB) Project, which uses satellite observations of outgoing radiation and is validated against US automatic weather station measurements (53).

Bias Correction. We chose a relatively simple and noninvasive bias correction method to preserve the spatial and temporal features of climate model output. We apply a monthly mean bias correction and spatial downscaling algorithm largely based on the Maurer et al. (54) method used for the bias-corrected and downscaled WCRP CMIP3 climate projections archive (Eqs. **1** and **2**). Corrections are made on the monthly level because seasonal cycle biases are important to yield estimates (55). For each model case, we first calculate the difference between 1983–1998 monthly averaged daily observed and modeled climate linearly interpolated to 5 arcminutes. These monthly differences are then linearly interpolated to the daily scale to prevent discontinuity in the applied bias correction. We separately bias correct the four climate variables used by DSSAT: daily precipitation, maximum temperature, minimum temperature, and downward incident solar radiation. Following standard practice, the bias correction is assumed constant in historical and future time periods, a necessary assumption given no prior knowledge of how model errors might change in time. Temperature adjustments are additive, but precipitation and solar radiation adjustments are multiplicative. For temperatures at location *i*, day *t*

$$T^{i,t}_{mod,BC} = T^{i,t}_{mod} + \Delta T^{i,t}, \qquad [1]$$

where $\Delta T^{i,t}$ is the daily corrections linearly interpolated from monthly biases $\Delta T^{i,m}$, with $\Delta T^{i,m} = \overline{T^{i,m}_{obs}} - \overline{T^{i,m}_{mod}}$, where the bar indicates mean over all years in the historical time period. Similarly, for precipitation at location *i*, day *t* (and for incident solar replace $P \rightarrow S$)

$$P^{i,t}_{mod,BC} = P^{i,t}_{mod} \cdot \Delta P^{i,t}, \qquad [2]$$

with $\Delta P^{i,t}$ again derived from monthly biases

$$\Delta P^{i,m} = \overline{P^{i,m}_{obs}} \Big/ \overline{P^{i,m}_{mod}}.$$

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