

Impact of Climate Change on Crop Yield: A Case Study of Rainfed Corn in Central Illinois

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ABSTRACT

This paper assesses the effect of climate change on crop yield from a soil water balance perspective. The uncertainties of regional-scale climate models, local-scale climate variability, emissions scenarios, and crop growth models are combined to explore the possible range of climate change effects on rainfed corn yield in central Illinois in 2055. The results show that a drier and warmer summer during the corn growth season and wetter and warmer precrop and postcrop seasons will likely occur. Greater temperature and precipitation variability may lead to more variable soil moisture and crop yield, and larger soil moisture deficit and crop yield reduction are likely to occur more frequently. The increased water stress is likely to be most pronounced during the flowering and yield formation stages. The expected rainfed corn yield in 2055 is likely to decline by 23%–34%, and the probability that the yield may not reach 50% of the potential yield ranges from 32% to 70% if no adaptation measures are instituted. Among the multiple uncertainty sources, the greenhouse gas emissions projection may have the strongest effect on the risk estimate of crop yield reduction. The effects from the various uncertainties can be offset to some degree when the uncertainties are considered jointly. An ensemble of GCMs with an equal weight may overestimate the risk of soil moisture deficits and crop yield reduction in comparison with an ensemble of GCMs with different weight determined by the root-mean-square error minimization method. The risk estimate presented in this paper implies that climate change adaptation is needed to avoid reduced corn yields and the resulting profit losses in central Illinois.

1. Introduction

Potential effects of climate change on crop yield have attracted great attention from farmers, government officials, and scientists. Numerous studies have employed a water balance approach to evaluate the effects of climate variability on crop production (e.g., Semenov and Porter 1995; Thomas 2000; Eitzinger et al. 2001, 2003; Brumbelow and Georgakakos 2001; Williams et al. 2001; Alexandrov et al. 2002; Tubiello et al. 2002; Richter and Semenov 2005). Those studies provided appropriate sensitivity analyses and helped to define a plausible range of outcomes. However, today the climate risk factors for agriculture at the local level still remain highly speculative. Among various reasons, the following two are most notable: 1) although there is general

scientific agreement that global temperature increases will likely occur in the next century, mesoscale changes in temperature and precipitation remain uncertain (Jones 2000; Reilly et al. 2003), and 2) the details of climate change—in particular, the effect on the frequency of extreme weather and intraseasonal variability at the local scale—are not clear (Hu and Buyanovsky 2003; Changnon and Hollinger 2003; Schlenker and Roberts 2006).

Presently, the general circulation models (GCMs) used to predict climate changes are mixed in their forecasts of climate parameters, such as temperature and precipitation, that affect crop water requirement and availability. The major uncertainties with GCM predictions arise from the following: 1) emissions scenarios derived from projections of economic activity, population growth, and technological development; 2) global climate sensitivity (CS) to greenhouse gas forcing; and 3) regional variability, which occurs between models of different regional responses (RRs) and within models of chaotic behaviors and modes of climate variability

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(Jones 2000; Huntingford et al. 2005). Because of such uncertainties, GCMs can generate numerous climate change scenarios, and they are subject to different assumptions of climate sensitivity and greenhouse gas (GHG) emissions containing a level of probability. For example, Brumbelow and Georgakakos (2001) compared the effect of climate change projections from two GCMs (one developed by the Canadian Centre for Climate Modelling and Analysis and the other by Hadley Centre for Climate Prediction and Research) on crop yield in the entire conterminous United States. They found the two GCMs were not consistent in soil moisture and crop yield prediction. Huntingford et al. (2005) analyzed a range of climate model projections of change in temperature and rainfall for the northern Africa region corresponding to enriched GHG concentrations in the future. They also found that the changes expected by the end of the twenty-first century varied considerably among the models tested. At best, GCM applications provide a range of projected climate change bounded by high and low extremes to produce a range of effects with no probability specification, but the results are often too broad to be of practical use (Jones 2000; Reilly et al. 2003).

Moreover, meaningful uncertainty quantifications for agriculture also need to address how global-scale climate change affects day-to-day weather variability at a local scale and not just predictions of average temperature and precipitation over the entire growing season (Changnon and Hollinger 2003; Hu and Buyanovsky 2003; Schlenker and Roberts 2006). The neglect of intraseasonal weather variability may end with biased crop yield estimates. For example, Changnon and Hollinger (2003) demonstrated that weather-crop yield regression models can generate biased predictions because they ignore this day-to-day weather variability. Thus local weather simulations and GCM climate change projections should be combined to specify the possible alterations to both interannual and intraseasonal variations in rainfall and temperature. This requires methods of downscaling large-scale outputs from GCMs to small-scale biophysical models that are appropriate for assessing the effects on agriculture. This paper will present a systematic downscaling approach for assessing the effects of uncertainties in climate change projections and intraseasonal weather variability. The approach is facilitated by data and models from atmospheric science, hydrology, and agronomy. The outputs will allow the development of a probability distribution of crop yield and crop yield loss risk.

The downscaling approach will be applied to assess the climate change effect on the rainfed corn yield in central Illinois. The case study area is located in the

Corn Belt. Many studies have examined climate variability and projected climate change in this area, and their subsequent effects on soil moisture and crop yield. Most climate models predict that both annual rainfall and summer temperatures will increase in the Corn Belt. However, these projections are subject to a large degree of uncertainty, and they do not address the intraseasonal variability that is critical for assessing the effects of climate change on agriculture. These weaknesses cause inconsistent and even contradictory estimates of crop yield changes. With the projections of increasing precipitation, there is a widespread hypothesis that corn yields will increase during coming decades. For example, the National Assessment Synthesis Team (NAST 2000) projected a 15% increase in corn yields by 2030. However, Adams (1989) reported a 12%–19% decline of corn yield in the region. The EPA (1997) speculated that yields of rainfed corn could be reduced by as much as 32% in Illinois. Meanwhile, Williams et al. (2001) estimated that corn yields might drop by only 3% under a climate change scenario that evaluates the effects of greenhouse gases alone, whereas the yields could decrease by 20% if sulfate effects were also included in the model.

Some recent studies related the projected declining trend in crop yields in the Corn Belt to prediction uncertainty and weather variability. Kunkel (1997, unpublished manuscript) argued that future changes in summer and fall precipitation in central Illinois were highly uncertain (see also Williams et al. 2001; Changnon and Hollinger 2003). Changnon and Hollinger (2003) found that a 40% summer rain increase had little influence on the crop yield if these rains did not occur during the midsummer period when crops are particularly prone to water stress. Furthermore, they found that only small average increases in corn yields would occur if the growing season rainfall exceeded the long-term average by 10%–40%.

These inconsistent estimates of climate change effects on agriculture in central Illinois call for a more rigorous approach for evaluating the role of uncertainties from climate change projections. By using a downscaling approach integrating the various inputs and outputs, this paper will examine the role of individual uncertainty sources and the combined sources in the agricultural impact assessment of climate change.

2. Methodology

A probability-based approach is developed to take into account the uncertainties of climate change. This framework, displayed in Fig. 1, involves GCM outputs and uncertainty sources, local climate data, the weather generator, and the impact assessment model, a hydroagronomic

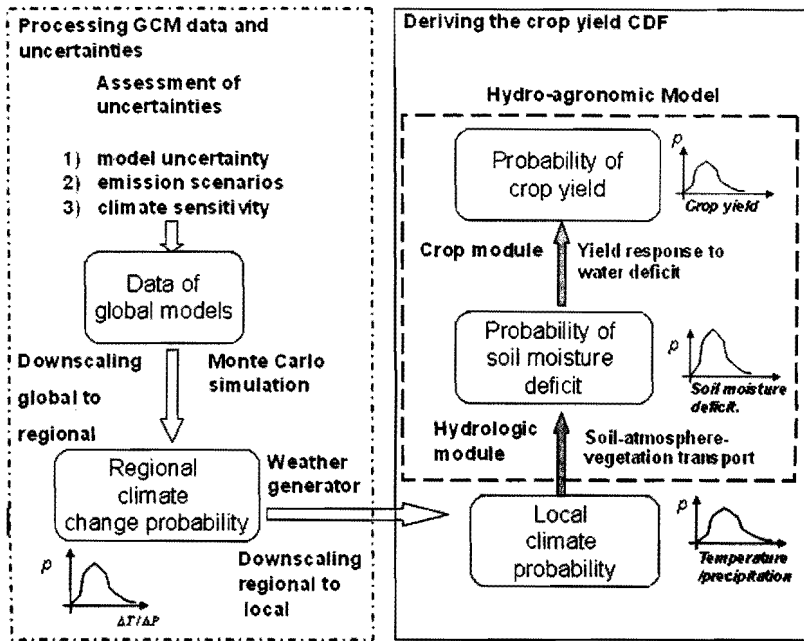


FIG. 1. Procedures for deriving the probability distribution of crop yield from GCM uncertainties and local climate variability.

model that assesses the effect of climate change on soil moisture and crop yields at the local level. The overall procedure can be understood to convert the probability distribution of regional climate change that is subject to the various uncertainties into the probability distribution of local weather, soil moisture level, and finally crop yield, considering the factors of global warming, regional climate change, and local climate pattern.

a. Procedures for processing climate change projection uncertainty

The procedures for evaluating the uncertainty of GCMs and downscaling that uncertainty to regional and local levels are shown in the left part of Fig. 1. First, the different sources of uncertainty in regional climate change projections for the central region of the United States (roughly contiguous with the Corn Belt region) are quantified. Then, following the procedures from Jones (2000), the probability density functions (PDFs) of GCM outputs (i.e., the changes in temperature, precipitation, and solar radiation), emissions scenarios, and climate sensitivity are used to determine a range of possible regional climate changes through Monte Carlo simulations.

1) GHG EMISSIONS SCENARIOS

In the Special Report on Emissions Scenarios (SRES; Nakicenovic and Swart 2000), the Intergovernmental

Panel on Climate Change (IPCC) developed 40 scenarios, known as SRES scenarios, which, in turn, represent combinations of various scenarios of economic development, global population, technological advances, and other factors believed to contribute to climate change. These scenarios are then divided into six groups (A1B, A1FI, A1T, A2, B1, and B2). Within each group, the scenario that best represents the group is selected, which are denoted as the illustrative scenarios (Nakicenovic and Swart 2000). These six illustrative scenarios are most widely used for impact assessment studies. For the sake of simplicity without losing significance, only these six scenarios will be considered in this study.

The developers of the SRES scenarios assume that the same likelihood of occurrence should be assigned to all scenarios when making any attempt to quantify this uncertainty (Nakicenovic and Swart 2000). Although a few studies doubted this point of view (e.g., Webster et al. 2003), the uniform distribution is still selected to describe the likelihood of emissions scenarios occurring in this study by the majority of the scientific community, as discussed in the recently published U.S. Climate Change Science Program Synthesis and Assessment Product (CCSP SAP) report (DOE 2007). However, the modeling framework presented in this study allows for the inclusion of nonuniform probability distributions, if necessary.

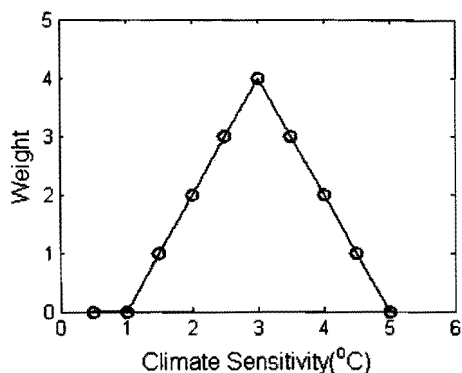


FIG. 2. PDF of the climate sensitivity (based on New and Hulme 2000).

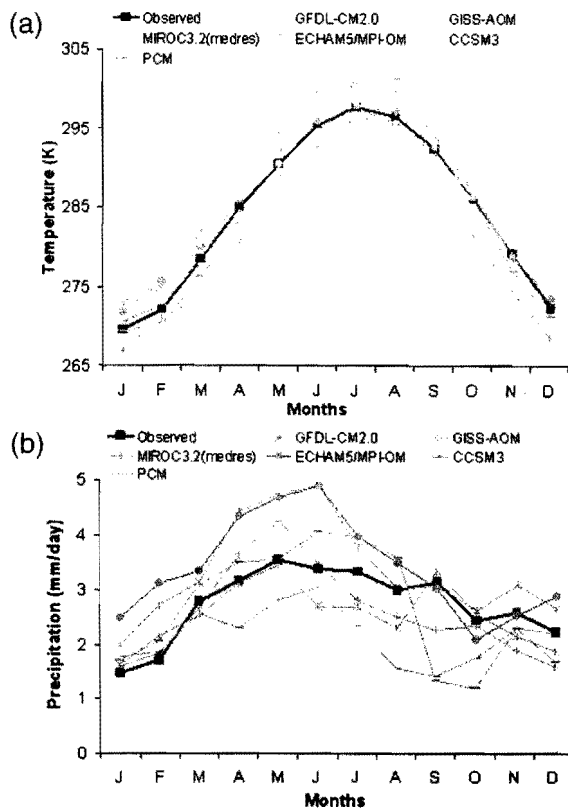


FIG. 3. Observed and projected (a) monthly temperature and (b) precipitation from six selected GCMs, from 1961 to 1990 in the central United States.

2) CLIMATE SENSITIVITY

Climate sensitivity measures the increase in the equilibrium global-mean surface air temperature that would occur if the atmospheric CO₂ concentration doubles. Our study follows recent publications (e.g., Andronova and Schlesinger 2001; Forest et al. 2002; Gregory et al. 2002) that have represented climate sensitivity with PDF. We chose one typical PDF—a symmetrical triangular distribution that covers the range from ±1.5° to ±4.5°C (Fig. 2)—that New and Hulme (2000) suggested because its range is close to the one determined in the third IPCC assessment report (Watson et al. 2001).

3) GCM SUITABILITY IN TERMS OF REGIONAL CLIMATE VARIABILITY

Although GCM projections converge at the global scale, they may differ widely at the regional scale. Figure 3 illustrates the discrepancy among average monthly temperature and precipitation estimates for the central region of the United States during a 1961–90 base period generated from the various GCMs and compares them to observed values. These results are then used to quantify the suitability of the GCMs for estimating average monthly temperature and precipitation in central Illinois following the methods that Laurent and Cai (2007) developed. This method, based on maximum entropy, uses information such as the climate observations in historical periods to assign a probability (i.e., skill score) to each GCM.

Two methods, the simple multimodel ensemble average method (SMMEM) and the root-mean-square error minimization method (RMSEM), are used in the present study because they are representative of two different types of GCM users' priorities. The SMMEM assumes that all GCMs are equally good at predicting the future climate in a particular region and assigns

a uniform probability distribution to the set of GCMs. The RMSEM is based on the capability of GCMs in verifying historical observations with consideration of month-to-month weather variability, which assumes that the better a GCM is at retrieving the climate in historical periods, the more suitable the GCM will be for predicting the future climate. The RMSEM assigns a nonuniform probability to the set of GCMs. Figure 4 presents the probabilities of the GCMs from the RMSEM for temperature and precipitation projections, respectively, in the Corn Belt region (Laurent and Cai 2007).

Laurent and Cai (2007) demonstrated that RMSEM and SMMEM corresponded to the smallest and largest RMSE, respectively, in terms of model prediction and observation. Within the range of RMSEM and SMMEM, one can choose a series of methods, depending upon whether it is desired to weigh the results from each model equally or whether it is better to assign weights to the results based upon their ability to generate historical observations. In this study, both methods are used to determine if there is any difference in their

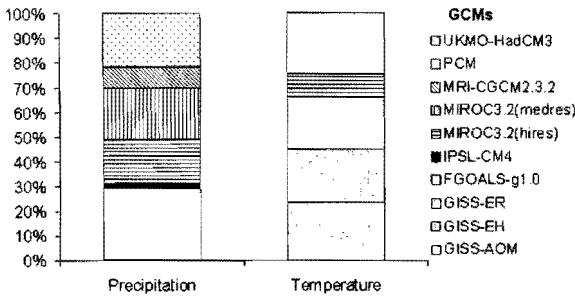


FIG. 4. Probability distribution of GCM suitability (skill scores or "weights" for selected GCMs) for precipitation and temperature, respectively, from RMSEM in the central United States.

suitability for predicting climate change effects on corn yields in central Illinois.

The GCM data were downloaded from the IPCC Fourth Assessment Model Output database (available online at http://gcmd.nasa.gov/records/GCMD_IPCC_AR4_MODEL_OUTPUT.html). Monthly precipitation and temperature data from the Climate of the 20th Century Experiment (20C3M) were extracted from 18 GCMs. For each of these models, several scenarios under different initial conditions are available from the climate experiment (20C3M). Without compromising significance, a single scenario (scenario 1) is used for this study. Future studies could address the effect of scenario selection on climate change.

b. Climate change downscaling from global level to regional level

The *pattern-scaling method*, developed by Santer et al. (1990) for projections of regional climate change under diverse conditions, is used in this study. This approach stems from the assumption that "while the magnitude of climate change alters over time in proportion to the global warming, the pattern of change from the Global Climate Model remains constant" (Carter et al. 1999). This statement is illustrated by

$$\Delta V(A, Y) = R(V, A) \times \Delta T(G, Y), \quad (1)$$

where V is the variable of interest [precipitation (P), temperature (T), or solar radiation (Rad)], $\Delta V(A, Y)$ is the projected change of V , by year Y , over the area of study A . Here $\Delta T(G, Y)$ is the projected change in temperature by year Y at the global level G . Both changes are computed using the same control period representative of present conditions (e.g., 1961–90). Following the assumption stated above, the coefficient $R(V, A)$, which denotes a response coefficient regarding a particular variable V to global warming, is independent of the year Y and represents the pattern of change

for variable V for the area of study A . To convey information specific to one GCM, $R(V, A)$ can be identified as the regional response for GCM(i), which is denoted as $RR(i, V, A)$. Therefore, the GCM model's uncertainty is reflected by the variation of $RR(i, V, A)$, which is computed for each GCM(i) in terms of each variable (V) for area (A) using a formula that stems from Eq. (1):

$$RR(i, V, A) = \Delta V(I, A) / \Delta T(G, Y), \quad (2)$$

where $\Delta T(G, Y)$ represents the global warming and conveys information about the global behavior of the system, such as the concentration of GHGs and the sensitivity to changes in their concentration. It can be computed *independently* from GCM outputs under various global forcing conditions with inputs from the Model for the Assessment of Greenhouse-Gas Induced Climate Change (MAGICC; Wigley and Raper 1987, 1992; and updated by Raper et al. 1996). MAGICC uses a combined set of gas-cycle, climate, and ice-melt models to determine changes in global-mean temperatures based on various user-specified emissions scenarios (ESs) and different climate sensitivities. The joint distribution of $\Delta T_{CS,ES}(G, Y)$ with six emissions scenarios and seven climate sensitivity scenarios (chosen from the PDF shown in Fig. 2) is shown in Table 1.

The pattern-scaling method allows for the computation of regional changes for any combination of CS, ES, and RR factor represented by GCM uncertainty, as illustrated by

$$\Delta V_{CS,ES,RR}(A, Y) = RR(i, V, A) \times \Delta T_{CS,ES}(G, Y). \quad (3)$$

MONTE CARLO SIMULATIONS

With Eq. (3), the distribution of $\Delta V_{CS,ES,RR}(A, Y)$ is computed with a Monte Carlo simulation method. Here $\Delta T_{CS,ES}(G, Y)$ is sampled from the *joint distribution* under the conditions of emissions scenarios and climate sensitivity presented in Table 1. The GCM regional response $RR(i, V, A)$ is calculated based on Eq. (2), where $\Delta V(I, A)$ is the projected change by GCM(i). Thus the probability of $RR(i, V, A)$ is determined by the GCM probability assessed by SMMEM or RMSEM. Given these probability distribution functions represent the different sources of uncertainty, the Monte Carlo simulation creates a set of triplets using the probability distributions of the three uncertainty sources as inputs. First, the Monte Carlo simulation generates N samples of $\Delta V_{CS,ES,RR}$ composed of randomly chosen combinations of the three sources of uncertainty. Next, the K -means data clustering procedure (MacQueen 1967) is used to categorize the N samples into K clusters ($K = 10$ is used in this study) to simplify the following impact assessment models without losing too

TABLE 1. The values of $\Delta T_{CS,ES}(G, Y)$ under the joint distribution of ES and CS scenarios.

$\Delta T_{CS,ES}(G, Y)$		ES probabilities					
		1/6	1/6	1/6	1/6	1/6	1/6
CS probabilities	1/16	0.7979	0.9639	0.8237	0.7197	0.5873	0.6757
	2/16	1.1125	1.3305	1.1561	1.0003	0.8272	0.9519
	3/16	1.3831	1.6414	1.4445	1.2410	1.0368	1.1932
	4/16	1.6169	1.9074	1.6954	1.4490	1.2203	1.4044
	3/16	1.8207	2.1375	1.9152	1.6303	1.3818	1.5904
	2/16	1.9997	2.3382	2.1090	1.7896	1.5249	1.7549
	1/16	2.1579	2.5148	2.2809	1.9305	1.6523	1.9014

much generality. The samples within each cluster are as close as possible from each other and as far as possible from samples in other clusters. The associated probability for each cluster is calculated by the ratio of the number of samples ($n_k, k = 1, 2, \dots, 10$) within that cluster to the total number of samples in all clusters (N). Thus the probability for cluster k is n_k/N . These 10 probability-based clusters of regional climate change are subsequently used as inputs in the weather generator (WG), as described below.

c. Climate change downscaling from regional level to local level

Daily precipitation, temperature, and solar radiation data for a specific location are often required to estimate the water availability for a particular crop. Given the monthly projections of climate changes derived at the regional scale from the procedures described above, both temporal downscaling (from monthly to daily) and spatial downscaling from the regional (e.g., Midwest) to the local scale (e.g., central Illinois) will be needed to generate daily weather data at a local scale. For this purpose, WGs are usually used when there are inadequate or incomplete series of daily climate data (Wilks and Wilby 1999). Among the many types of WGs that have been developed, this study uses a stochastic WG, called the Long Ashton Research Station WG (LARS-WG), which generates a synthetic daily weather time series that is statistically identical to observations (Semenov and Barrow 1997; Semenov et al. 1998). One advantage of the LARS-WG is that it is a computationally inexpensive tool capable of producing climate change scenarios incorporating local climate variability.

Three steps are taken to downscale the GCMs from a regional scale to a local scale. First, the historical daily time series are used to calibrate the WG. The historical data for the study area are obtained from a weather station in the study area maintained by Midwestern Regional Climate Center, with an observation record from 1948 to 2007. The statistical parameters such as the long-term mean, standard derivation, and higher-

moment statistics extracted from the analysis of historical data characterize the distribution of daily and monthly precipitation, temperatures, and solar radiation, as well as the distribution of the lengths of wet and dry spells. Second, the WG modifies the statistical parameters derived from the reference historical period using the projected ensemble average monthly changes of temperature, precipitation, and solar radiation under each of the 10 clusters as described above. The monthly changes in temperature and solar radiation are additive changes, as the values of a change are added to the statistical temperature and solar radiation values, respectively. Meanwhile, the monthly changes in precipitation are multiplicative, as the statistical precipitation values are multiplied by the percentages representing the monthly changes in precipitations.

Third, to predict the weather in a future year, such as 2055, an ensemble of realizations of annual samples of daily weather data in the study area is generated. Daily meteorological data include solar radiation, minimum and maximum temperature, humidity, wind speed, and rainfall. To reflect the probability distribution of climate change represented by the 10 clusters, the number of the annual samples ($m_k, k = 1, 2, \dots, 10$) under each cluster is proportional to the probability associated with the cluster (n_k/N). Altogether, the number of samples the WG generates corresponds to $M (= \sum_{k=1,10} m_k)$. Therefore, more samples will be generated from the clusters with higher probabilities. Following that, each of these annual samples of daily weather data is applied to an impact assessment model to calculate the soil water moisture and crop yield, whereas the probability distributions of soil moisture and crop yields are derived through a frequency analysis over the M samples.

d. Procedures for impact assessment

The right part of Fig. 1 illustrates the procedures for converting the climate change PDFs into soil moisture PDFs and, subsequently, deriving ones for crop yield. A soil-vegetation-atmosphere transfer (SVAT) model is calibrated to the case study area to simulate soil moisture,

crop evapotranspiration, and groundwater percolation from the crop root zone. A crop module coupled with the SVAT calculates the crop yield. The PDFs of soil moisture and crop yield are generated using the model outputs under the various climate change scenarios.

THE IMPACT ASSESSMENT MODEL

The Soil–Water–Atmosphere–Plant model (SWAP; Van Dam et al. 1997), a hydrologic–agronomic simulation model is used to assess the effects of various climate change scenarios to corn yields in central Illinois. SWAP is a one-dimensional, physically based model that can estimate water (based on Richard's equation) availability, heat, and solute transport in both the saturated and unsaturated zones of soil and includes modules for simulating crop water requirements and crop growth. In this study, a soil profile of a depth of 180 cm, which is the average soil depth in the study area, is divided into 28 compartments with variable depths. The upper-boundary conditions include the sink term—that is, crop actual evapotranspiration (ETA)—and the source term: rainfall. The lower boundary condition is a given groundwater level that fluctuates seasonally within the study area.

In this study, we discuss the effect of climate change on rainfed crops. ETA is equal to the precipitation that infiltrates to the crop root zone and can be used for crop growth. The relative yield (i.e., the ratio of actual yield over potential yield) is calculated by a linear relationship between ETA and potential evapotranspiration (ETP) (Doorenbos and Kassam 1979):

$$\frac{YA}{YP} = 1 - Ky \left(1 - \frac{\sum_{k=1}^K ETA_k}{\sum_{k=1}^K ETP_k} \right), \quad (4)$$

where k is the index of crop growth stages; YA and YP are the actual and potential yield (kg ha^{-1}), respectively; ETA_k and ETP_k are the actual and potential crop evapotranspiration in stage k (cm), respectively; and Ky is the average yield response factor over the entire growing season.

To address the uncertainty with crop yield, we consider the uncertainty with Ky as another source together with the three sources in climate change projection (CS, RR, and ES). A symmetrical triangular distribution is employed to represent the probability distribution of Ky in the range of 0.7–1.3 and with a mean value of 1.0 (Fig. 5; Doorenbos and Kassam 1979).

The SWAP model is calibrated to the study area by adjusting various parameters, including soil hydraulic properties, following the method used by Wang and Cai (2007). The case study for this paper uses the data from

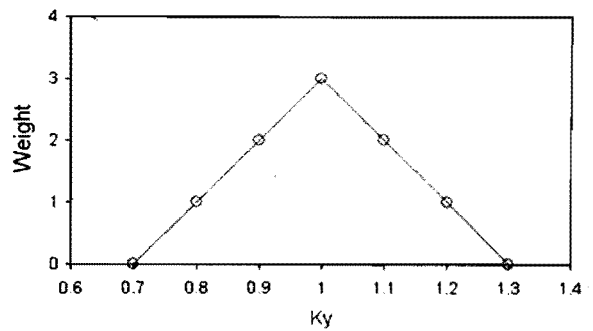


FIG. 5. PDF of crop response coefficient (Ky) in the range of 0.7–1.3 and with a mean value of 1.0.

2002. Soil moisture measurements taken in the grasslands of Champaign County (Illinois Climate Network 2005), which has the same soil texture as the cornfields in the study area, are used as observation to calibrate the SWAP model. The soil moisture was measured with a neutron probe tube twice a month from April to October up to a depth of 2 m. The daily climate data—which include total solar radiation (kJ m^{-2}), minimum and maximum air temperature ($^{\circ}\text{C}$), average humidity (kPa), average wind speed (m s^{-1}), and total daily precipitation (mm)—are taken from the same data source (Illinois Climate Network 2005). The groundwater depth used for all climate scenarios is 165 cm, a value typical for central Illinois (Illinois Climate Network 2005). Here we assume climate change does not affect the groundwater level. In addition, the crop growth season is set to start on 1 May and end on 1 October. The initial condition is prepared by running the SWAP model starting on 1 April, and it assumes that the pressure head of each soil compartment is in hydrostatic equilibrium with the initial groundwater level.

The outputs from the SWAP model are used to calculate a soil moisture deficit index (SWDI) for each of the five distinct crop growth stages—land establishing, vegetative, flowering, yielding, and ripening—using the following equation:

$$SWDI_k = 1 - \frac{ETA_k}{ETP_k}. \quad (5)$$

The SWDI represents the gap between actual and potential seasonal crop ET in stage k and has a value between 0 and 1. The average SWDI for the entire crop season is expressed as

$$SWDI = 1 - \frac{\sum_{k=1}^K ETA_k}{\sum_{k=1}^K ETP_k}. \quad (6)$$

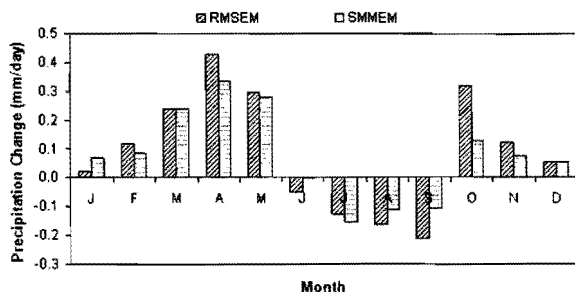


FIG. 6. Expected monthly precipitation change in central Illinois for year 2055 from RMSEM and SMMEM.

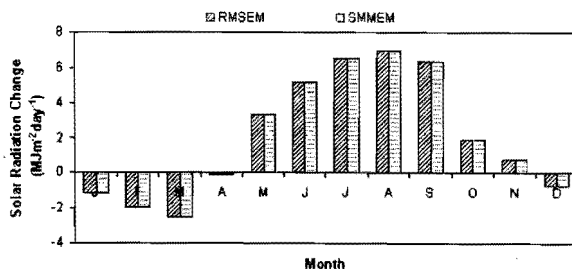


FIG. 8. As in Fig. 6, but for solar radiation.

In summary, the climate impact assessment method adopted in this paper features the following components: 1) a comprehensive assessment of uncertainties in climate change projections; 2) incorporation of intra-seasonal variability of weather and soil moisture and different yield responses in crop growth stages; and 3) procedures for deriving probability distributions from the PDF of regional climate variables to the complementary cumulative density function (CCDF) of crop yield (i.e., exceedance probability), which allows us to identify the risk of crop yield loss. These components are integrated with expertise from multiple disciplinary areas such as atmospheric science, hydrology, and agronomy.

3. Results

The expected monthly precipitation, temperature, and solar radiation values resulting from the pattern-scaling method are shown in Figs. 6–8, respectively. Notable variations of monthly values are projected for all of the parameters. The results suggest that the temperature during the growing season is expected to increase, whereas the precipitation during this period is expected to decline. Furthermore, Fig. 9 compares the probability distributions of average temperatures from 15 July to 15 October at present and in 2055, and Fig. 10 provides the comparison of the total precipitation dur-

ing the corn growth season in central Illinois. These PDFs show a major increase of temperature and a slight change of precipitation during the period 15 July–15 October. Also, the greater width of the 2055 PDF curves indicates that temperature in 2055 is expected to have a larger variance than it currently does.

The increase in temperature and solar radiation during a typical corn growth season in the region will lead to an increase in potential crop evapotranspiration and, subsequently, an increased crop water requirement. This may occur contemporaneously with a decrease in rainfall during the major months (June–September) of the growing season, which will impose additional water stress on rainfed crops in the region. Figure 11 plots the CCDF [i.e., “1” refers to the cumulative distribution function (CDF), representing the exceedance probability of different values of SWDI] of the average SWDI over the whole crop season at present and in 2055. The right shift of the CCDF curves in 2055 from present conditions shows that the same level of SWDI will have higher exceedance probability in 2055 than at present, particularly when the SWDI is greater than 0.2. For

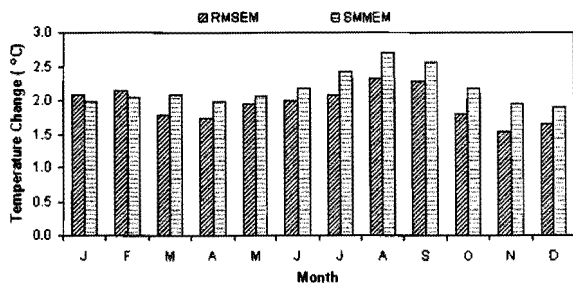


FIG. 7. As in Fig. 6, but for temperature.

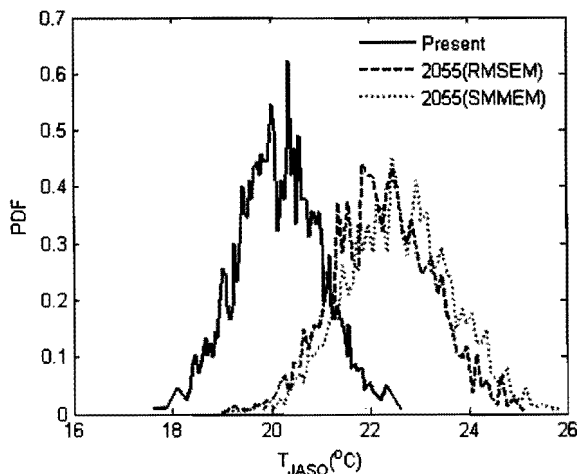


FIG. 9. The PDF of average temperature during the period 15 Jul–15 Oct, at present and in 2055 (SMMEM and RMSEM).

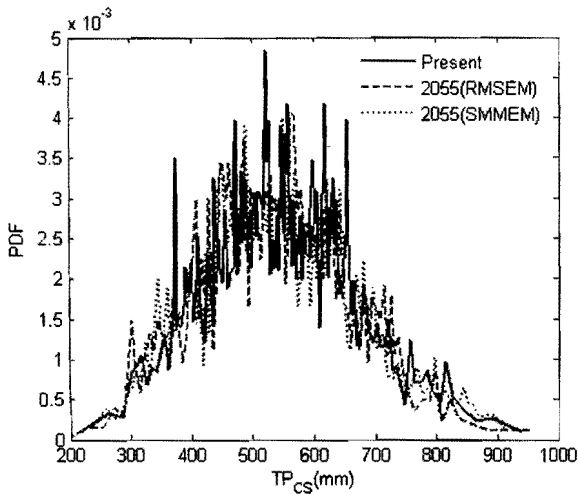


FIG. 10. The PDF of the total precipitation during the period 15 Apr–14 Oct in central Illinois.

example, the exceedance probability of $SWDI = 0.4$ is 0.10 at present and 0.66 in 2055. The maximum SWDI in 2055 can be as high as 0.80 compared to the present maximum of 0.60. Moreover, soil moisture is likely to be affected more by larger weather variability in 2055, because the portion of the 2055 CCDF curve describing the likelihood of achieving relatively higher values of SWDI is steeper than the current one. For instance, the occurrence probability for SWDI within the range from 0.4 to 0.6 is only 0.10 at present but could increase to 0.56 by 2055, as shown in Fig. 11.

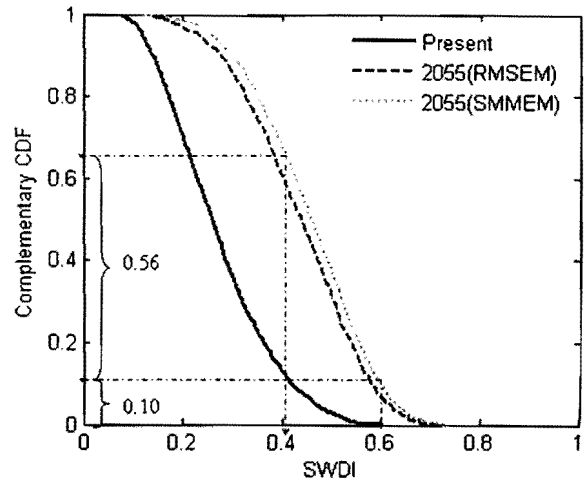


FIG. 11. Complementary CDFs of average SWDI over the crop season.

Table 2 compares details of the statistics of SWDI in each crop growth stage—including the mean, median, and standard deviation—and the exceedance probability (i.e., CCDF) of SWDI = 0.3, 0.5, and 0.7 for present and 2055 conditions, with both RMSEM and SMMEM values listed for the latter year. The mean value, standard deviation, and exceedance probabilities in Table 2 suggest that the soil moisture deficit during the establishing stage will be lower and less variable in 2055 than at present, which can be attributed to an increase in precipitation during the January–April period that precedes the growing season (Fig. 6). During the vegetation

TABLE 2. Statistics of SWDI at present, 2055 (RMSEM), and 2055 (SMMEM).

Growth stage		Mean	Median	Std dev	Exceedance probability (or CCDF) (%) of SWDI		
					0.3	0.5	0.7
Whole season	Present	0.276	0.265	0.106	39.2	2.0	0.0
	2055 (RMSEM)	0.440	0.445	0.112	89.0	30.1	0.4
	2055 (SMMEM)	0.455	0.460	0.112	91.4	36.0	0.8
Establishment	Present	0.220	0.168	0.212	30.3	12.6	3.2
	2055 (RMSEM)	0.168	0.122	0.173	19.2	7.5	0.2
	2055 (SMMEM)	0.176	0.128	0.175	30.9	7.7	0.7
Vegetative	Present	0.120	0.096	0.093	5.5	0.2	0.0
	2055 (RMSEM)	0.122	0.111	0.068	1.5	0.0	0.0
	2055 (SMMEM)	0.126	0.116	0.069	2.2	0.0	0.0
Flowering	Present	0.203	0.170	0.134	21.8	3.4	0.0
	2055 (RMSEM)	0.337	0.332	0.180	56.1	20.2	2.0
	2055 (SMMEM)	0.353	0.346	0.180	58.4	23.9	2.5
Yield formation	Present	0.313	0.283	0.168	46.5	15.0	1.8
	2055 (RMSEM)	0.511	0.528	0.177	85.4	55.7	15.5
	2055 (SMMEM)	0.538	0.558	0.174	88.8	59.8	20.1
Ripening	Present	0.304	0.252	0.219	43.3	22.1	6.2
	2055 (RMSEM)	0.497	0.515	0.233	76.0	52.6	22.7
	2055 (SMMEM)	0.517	0.536	0.226	79.6	56.0	24.4

TABLE 3. Statistics of relative yields at present, 2055 (RMSEM), and 2055 (SMMEM).

		Mean	Median	Std dev	Exceedance probability (%) of relative yield		
					0.3	0.5	0.7
Ky = 1.00	Present	0.724	0.735	0.106	99.9	97.9	60.7
	2055 (RMSEM)	0.560	0.555	0.112	99.5	69.8	10.9
	2055 (SMMEM)	0.546	0.540	0.112	99.1	64.0	8.5
Ky = 1.25	Present	0.655	0.669	0.132	99.6	86.8	39.9
	2055 (RMSEM)	0.450	0.444	0.140	85.8	35.7	4.3
	2055 (SMMEM)	0.432	0.425	0.140	82.5	31.6	3.1

stage, the difference between precipitation conditions in the present and in 2055 (Fig. 6) is small. As a result, crop growth during this stage should not be affected significantly.

However, reduced summer precipitation combined with increases in summer temperatures is expected to increase the soil moisture deficit during the subsequent three crop growth stages. The probability of larger soil moisture deficits during these stages is considerably greater in 2055 than that at present, and the range of deficits is also expected to increase. For example, in the flowering stage, the probability that the SWDI will exceed 0.5 may range from 0.20 to 0.23 in 2055 as compared to 0.03 at present. The median SWDI over the entire season ranges from 0.30 to 0.36 in 2055 as compared to 0.02 at present. In addition, the mean, median, and standard deviation of SWDI are only slightly different between RMSEM and SMMEM, but the exceedance probabilities with a particular SWDI under SMMEM are much higher than those under RMSEM, which implies the SMMEM with an equal weight on all the GCMs may overestimate the risk of soil moisture deficits.

The resulting SWDI values are used to compute corn yields. The effect of these changes in soil moisture to crop yields depends on the values of K_y , the response coefficient to water stress as shown in Eq. (4). The statistics of relative yields at present and in 2055 (RMSEM and SMMEM) are displayed in Table 3. Assuming the potential yield remains the same, when $K_y = 1.0$, the mean yield will decline by 23% with RMSEM and 25% with SMMEM, whereas when $K_y = 1.25$, the mean yield will decline by 31% with RMSEM and 34% with SMMEM. Therefore, the rough range of yield decline is 23%–34%. The exceedance probability for attaining at least 50% of the potential yield markedly declines from the current 98% to 64%–70% in 2055 when $K_y = 1.0$ and from 87% to 32%–36% when $K_y = 1.25$. This suggests that corn yields in central Illinois might become vulnerable to climate variability in the future. We also notice that when $K_y = 1.25$, the variance of the yield (represented by the standard deviation) is higher and

the exceedance probability of attaining a given level of yield is lower than it is when $K_y = 1.00$.

The crop yield distribution under the effect of climate change is comparable to some econometric studies that establish a relationship between weather and the degree of skewness in the distribution of crop yields, with respect to weather variability and a constraining maximum yield. For example, using the assessed corn yields during 1965–88 in Urbana in central Illinois, Park and Sinclair (1993) predicted that a 3°C rise and a 10% reduction in precipitation without a change in ambient CO₂ would cause the mean of corn yields in Urbana to decrease by about 20%. Our results show that a 2.5°C rise and a 4% reduction in precipitation during the crop growth season without a change in ambient CO₂ would cause the mean of corn yields in central Illinois to decrease by about 24%, from the present mean relative yield (0.72) to that in 2055 (0.55) (Table 3). Moreover, Park and Sinclair (1993) found that the moments of the distribution of corn yields in Illinois were sensitive to changes in temperature and precipitation—a warmer, drier climate is associated with lower yields and a flatter distribution. Figure 12, which compares the PDF of the relative yield at present and in 2055, demonstrates that our results corroborate the yield distribution assessment from Park and Sinclair (1993).

4. Discussion

In this section, we further discuss the effect of uncertainty of particular input data sources—such as CS, ES, and RR factor—and the yield response coefficient to water stress (K_y), as well as the limitations of the methods employed in this study.

a. Dominating uncertainty and compensating effect among the various sources

The procedures illustrated in Fig. 1 determine the effect of a particular source of uncertainty while taking the expected value of the other three sources. As can be seen in Fig. 13, the CCDF curve with the emissions

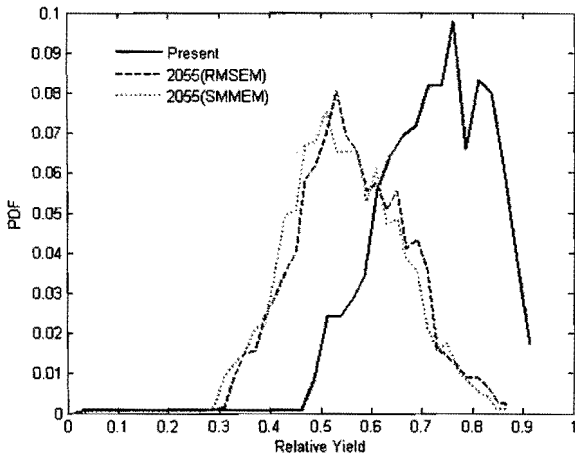


FIG. 12. PDFs of relative corn yield in central Illinois at present and in 2055 (RMSEM and 2055 SMMEM).

uncertainty is closest to the CCDF that considers the joint uncertainty of the four sources. This implies that among the multiple uncertainty sources, the emissions uncertainty may be the dominating source in estimating climate change effects on crop yields in central Illinois. This can be partially explained by the fact that the emissions scenarios, which are assumed to have a *uniform distribution*, have the largest uncertainty among the four sources because there is not much empirical knowledge available to estimate their range of potential values as there is for characterizing RR and CS.

Furthermore, if ES uncertainty is not considered—as the three cases shown in Fig. 13 (RR, CS and Ky), where the expected value of $\Delta T_{CS,ES}(G, Y)$ over the six emissions scenarios is used—the effect on yield prediction is larger than the case with joint uncertainties or ES solely. Thus the effect of these three cases on yield prediction may be biased, or more specifically, overestimated, whereas when the uncertainties are considered simultaneously, the effects from different sources can be offset.

However, for lower relative yields (less than 0.55 in Fig. 13) under larger water stress, the effect of ES uncertainty on crop yield is not dominating and the effect of other sources becomes important. The CCDF curve is located in a range bounded by the ES curve and the Ky curve and the compensating effect of the various sources still exists.

b. Limitations of the method and implications for future study

The systematic method developed to address multiple sources of uncertainty in the prediction of climate change effects to corn yield does not fully address the correlations among the uncertainties of the input data

(ES, CS, and RR): the joint distribution between ES and CS is considered, whereas it assumes RR is independent to the other two sources. In addition, changes in temperature and precipitation at the local scale are correlated as well (Dettinger 2005), a relationship that is not analyzed explicitly though the correlation simulated in the GCMs is inherited with the GCM outputs, which are inputs to the analysis presented in this paper.

The predicted corn yields are also subject to uncertainty from the methods employed in this study. For example, Carter et al. (1999) noted that the main problem of pattern-scaling methods is based upon an assumption that the regional pattern of changes remains constant with different magnitudes of global warming. This assumption seems to be well verified for temperature, but the validity of the assumption for precipitation is still being debated (Mitchell et al. 2003). However, despite this criticism, the pattern-scaling method has been widely used (Ruosteenoja et al. 2003).

Next, the methods that the WG uses to simulate a daily time series of temperature and precipitation are based upon the assumption that specific weather sequences—namely, the length of wet and dry spells within a month—are constant. In reality, these sequences vary tremendously from year to year. Moreover, the extent to which the distribution of the length of wet and dry spells would change over the next half-century under various GCM scenarios is unknown because the daily regional-scale data necessary for LARS-WG to estimate these changes are insufficient for many of the GCMs.

In addition, the crop yield also depends on the interactions between water and other factors. For instance, the increase in CO_2 levels could offset the effects of climate change-induced water stress to crops. Richter and Semenov (2005) used a similar approach to derive the probability distributions of soil moisture deficit and crop yield from multiple climate change simulations using representative weather, soil types, and sowing dates. They found that the soil moisture deficit would likely increase in the future at some typical agricultural sites in the United States, but the actual yields would increase because of a CO_2 -related increase in radiation use efficiency, as well as the acceleration of plant development. They also found that grain yields would likely be less variable when this climate change effect is taken into account. In contrast, a sequel paper on sugar beet (a spring-sown crop; Richter et al. 2006) shows that summer drought caused by climate change is likely to increase yield losses from 17% to 35%, which is in line with the findings in this paper. Also, recent studies (e.g., Schimel 2006; Long et al. 2006) suggest that previous work might overestimate the positive effects of higher carbon dioxide concentrations on crop yields through an

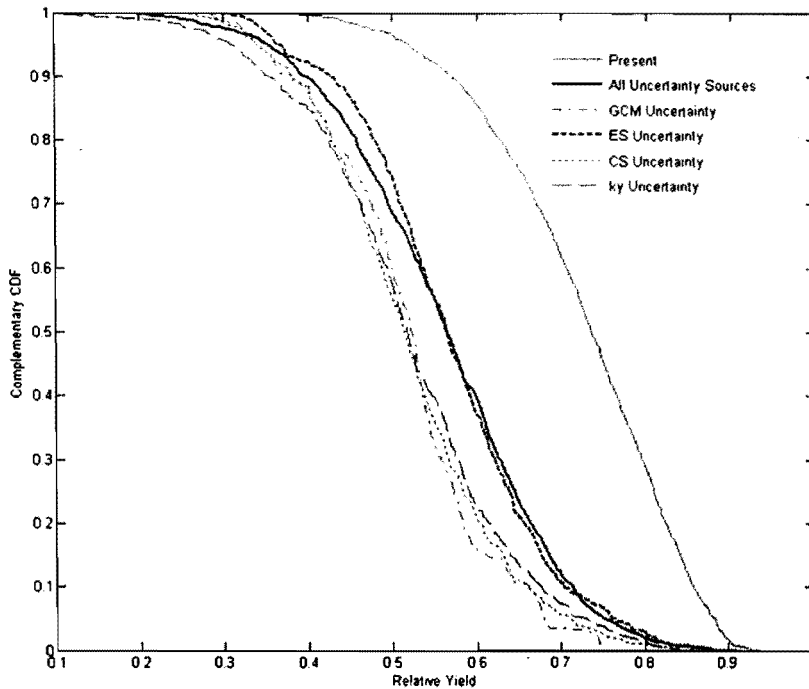


FIG. 13. The complementary CDF of relative yield ($K_y = 1.00$) for present and 2055 (RMSEM) for four scenarios that consider each uncertainty source of GCM, ES, CS, and all three uncertainty sources together.

analysis of recent data from a wide variety of field experiments.

Finally, it should be noted that the effect of climate change on groundwater availability is not accounted for in this study. In fact, climate change can aggravate the long-term effects of overpumping from the Mahomet aquifer in central Illinois, which may eventually affect the soil moisture in crop fields.

5. Conclusions

This paper evaluates the impacts of state-of-the-art climate change prediction and provides information applicable to rainfed agriculture. We combine the uncertainties of GCMs (i.e., regional response), emissions scenarios, and climate sensitivity in climate change prediction and crop models to explore the possible range of climate change effects on corn yields in central Illinois. Large intraseasonal variance with the changes in temperature, precipitation, and solar radiation is found in the corn belt region around year 2055. The average temperature during the corn growth season in central Illinois will most likely increase by 2°C by 2055. Although the total precipitation during the period of May–October (i.e., the current crop growth season) remains

about the same, precipitation in June–September will decline by 4%. This will increase soil water deficits, particularly during the flowering and yield formation stages, which could reduce corn yields substantially. From a water balance perspective, the expected relative yield of rainfed corn will decline by 23%–34%, whereas the range of probability of exceeding 50% of potential yield will decline from 87%–98% at present to 32%–70% by 2055.

More specifically, by 2055, larger soil moisture deficit (e.g., SWDI greater than 0.5) and crop yield reduction are likely to occur more frequently based on the larger occurrence probabilities. The negative effects of climate change are not apparent in the early stages of the corn growth period but could be very strong during the flowering and yield formation stages because soil moisture deficit may be higher during these stages when the crop is most sensitive to water stress.

The analysis presented in this paper also highlights important considerations regarding the use of multiple uncertainty sources when evaluating the effects of climate change on crop yield. First, the GHG emissions scenarios currently represented by the six illustrative scenarios with a uniform probability ($1/6$) may have a dominating contribution on the uncertainty of the crop

yield; and compensating effects exist among the various sources, which offsets the impacts to a certain degree. The use of a single uncertainty source—such as climate sensitivity (CS), regional response factor (RR), and yield response coefficient to water stress (Ky) with an average emissions scenario—may generate biased results. This implies that the uncertainty in socioeconomic development is the most important source of the uncertainty in the climate change impact assessment on rainfed crop yield in central Illinois—probably on other human activities, too. Therefore, we conclude that it is critical to develop more realistic emissions scenarios to predict the effects of climate change on crop yield with more certainty. Second, using 18 GCMs with an equal weight (SMMEM) and selected GCMs with unequal weights chosen based on RMSE (RMSEM), the mean of the predicted crop yield in the study area is only slightly different but the SMMEM may overestimate the risk of a particular soil moisture deficit or crop yield reduction (as shown in Tables 2 and 3 for the exceedance probabilities of the soil moisture deficit and crop yield).

Finally, these results imply that irrigation and other means of climate change adaptations may need to be undertaken to avoid reduced yields and resulting profit losses. Information on intraseasonal variability will be useful for adjusting the crop planting season. Soil moisture deficits suggest irrigation may be needed to maintain a certain level of yield. Knowledge of the relationship between climate change and corn yields in central Illinois will be critical for many decision makers, including farmers, business owners' and governments' agricultural insurance programs, government investment and subsidy programs for drought preparedness, and educational programs on climate change.

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