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Climate of Illinois and Central United States: Comparison of Model Simulations of the Current Climate, Comparison of Model Sensitivity to Enhanced Greenhouse Gas Forcing, and Regional Climate Model Simulations

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Abstract

A diagnostic analysis of climate model data examined precipitation, surface air temperature, and related atmospheric features for Illinois and the central US. Data were obtained for 21 global general circulation models (GCMs) participating in the Atmospheric Model Intercomparison Project (AMIP) and 9 models participating in the Coupled-Model Intercomparison Project (CMIP). Comparisons between models and observations included annual and seasonal means of precipitation, surface air temperature, southerly flow at 850 hPa, westerly flow at 200 hPa, specific humidity at 850 hPa, and total precipitable water. Model values of annual mean precipitation range from 1.5 to 3.4 mm/day (548 to 1240 mm/year, 21.5 to 48.9 inches/year) for AMIP models and from 2.0 to 3.2 mm/day (730 to 1168 mm/year, 21.5 to 46.0 inches/year) for CMIP models, compared to an observed value of 2.7 mm/day (986 mm/year, 38.8 inches/year). Model values of the mean annual temperature range from 8.9 to 14.2°C (48.0 to 57.5°F) for AMIP models and from 9.1 to 12.3°C (48.3 to 54.1°F) for CMIP models, compared to an observed value of 10.8°C (51.4°F). Nearly all models reproduce the timing of the extremes in the seasonal cycles of these variables, although amplitudes of the seasonal cycles vary considerably. There are no specific systematic biases that characterize all models with one prominent exception: all AMIP and all but one CMIP models are drier than observed in the fall. Composite maps indicated that both AMIP and CMIP models produce simulations of the 850 hPa and 200 hPa flow patterns that contain the essential features of the observed flow, although there are subtle differences that may be important to the simulation of Illinois climate conditions. Although a number of the models reproduce many observed features, no single model is clearly superior to all others. A few models exhibit glaring biases that reduce confidence in their use. Precipitation biases appear to be related in a systematic manner to biases in circulation patterns. In particular, biases in 850 hPa southerly flow over the Gulf of Mexico and southern Gulf coast states are correlated to the biases in the central US precipitation. The results do not clearly indicate whether the AMIP or CMIP model simulations are superior in simulating the present-day climate.

The CMIP doubled-CO_2 (inclusion of other greenhouse gases and aerosols varied among models) transient runs show warming for all models and seasons, ranging from 2-7°C in summer to 6-9°C in winter with respect to their control simulations. These changes are larger than the natural variations that are observed in the 20th Century and the model variations in the control simulations. Precipitation changes with respect to the control simulations are mostly upward, but the magnitudes of changes are mostly less than the natural variations that are observed in the 20th Century and less than the model variations in the control simulations. Model simulations of time series of 20th Century climate conditions were not available. These simulations did not include all forcings and thus are not appropriate for projecting the magnitude of future changes.

A comparison of an NCAR PCM (a coupled GCM) simulation with a mesoscale regional climate model (RCM) simulation driven by the PCM indicates that the higher resolution and more detailed physics in the RCM produces a more credible simulation of the central US climate, especially precipitation. The RCM downscaling provides a credible tool to improve the GCM climate simulations and projections, and hopefully reduce the uncertainties among GCMs, for local-regional climate change and impact assessments.

1. Introduction

The mission of the Illinois State Water Surveys (ISWS) is to evaluate the availability, quality, and use of the water resources of the State, and to make resulting data and information available to the public, decision makers, planners, and managers. Illinois receives almost 40 inches of precipitation per year and is well endowed with water resources. About 20 billion gallons of water are used each day for domestic, municipal, commercial, manufacturing, industrial, mining, livestock, irrigation, power generation, recreation, navigation, and waste dilution purposes. Large quantities of water are also needed to sustain healthy ecosystems, including habitat, fish and wildlife. The sources of water in Illinois are Lake Michigan, rivers, streams, lakes, reservoirs, shallow aquifers, and deep aquifers. All these sources are dependent on precipitation, and variations or changes in precipitation can affect the supply and demand for public and private water supplies. Temperature also affects supply and demand through its impact on evaporation rates. Data and information on precipitation amount, evaporation rates, recharge rates, and other variables are needed by water resource managers to determine available quantities of water and to design reservoirs, well-fields, and water distribution systems. This information is also needed to prevent over-use and depletion of the precious water resources of the state. A major issue confronting the future of Illinois water supplies is climate change due to changes in atmospheric composition and land use. Reliable estimates of future precipitation and evaporation rates with uncertainty bounds are needed for management of the state's water supplies.

General Circulation Models (GCMs) are sophisticated computer models of the earth's climate system. They are the principal tools used by scientists to study the potential effects of increasing greenhouse gas concentrations and changes in aerosol concentrations and land use on the climate. The Intergovernmental Panel on Climate Change (IPCC), a United Nations body, has recently released its Third Assessment Report (TAR, IPCC 2001), a comprehensive analysis of all aspects of the climate change issue. The IPCC conclusions rely in large part on GCM projections of significant climate change during the 21st Century. However, there remains considerable uncertainty and lack of consistency on a global scale about the rate of warming and changes in other aspects of the climate, such as precipitation. Furthermore, the TAR recognizes that uncertainties and lack of consistency on a regional scale are greater than those on a global scale. Since most impacts are realized on the local and regional scale, these uncertainties are critical for assessing the impacts of future climate change and evaluating management strategies and policy options.

GCM simulations of 21st Century performed during the 1990s had widely varying projections of Illinois precipitation in the 21st Century. Since precipitation is the primary source of surface and groundwater resources, it is critical to understand the reasons for the wide variations and perform research to narrow the uncertainties. The principal objective of this project is to contribute to assessment and understanding of uncertainties in GCM projections of 21st Century precipitation and temperature in Illinois and the central US by documenting and analyzing differences among models in controlled experiments. Thus, this study focuses on uncertainties arising from model-to-model differences in how the current climate system is represented, but not uncertainties arising from external factors, such as future emissions scenarios, land use changes, or aerosol concentrations. Also, the experiments do not explore the full range of possible model-to-model differences that might affect future projections, but are targeted to some basic model aspects.

2. Background

Precipitation occurs when atmospheric water vapor rises and is cooled to its saturation point. Thus, precipitation requires a source of water vapor and a mechanism to lift the water vapor for condensation.

Evaporation of water from oceans is the primary source of water vapor. For Illinois, the most important source is the moisture transport from the Gulf of Mexico via southerly wind flows. Although water vapor can be transported by westerly winds from the Pacific Ocean into Illinois, this is minor because most of that water vapor is removed when the winds rise over the several mountain ranges to the west. An additional source is evaporation of soil moisture from local and regional (accompanying advection) land surfaces; however, this is a secondary source in the sense that the soil moisture resulted from precipitated water vapor originating in the oceans.

In Illinois, the primary mechanism for lifting condensation of water vapor is the atmospheric imbalances occurring in the extratropical cyclone (EC), more familiar as the low pressure system on weather maps. In these low pressure systems, there is general rising motion, often concentrated along the warm and cold fronts that are part of these systems, that leads to the condensation and precipitation of water vapor. ECs are a consequence of the differences in temperature between the equatorial and polar regions. The resulting differences in air density create forces that tend to equalize these differences by moving warm air to the poles and cold air toward the equator. The EC is the manifestation of this equator-pole exchange of air. The EC typically develops in the vicinity of the mid-latitude westerly upper-level jet stream and is manifested in the jet stream by a wave pattern. It is often accompanied with the Great Plains southerly low-level jet, especially in summer.

Our diagnoses focused on these dominant processes to assess and understand the performance of GCMs, including their climate biases as compared with observations, future climate projections in response to greenhouse gas increases and inter-model differences. McAvaney et al. (2001) have provided a multi-faceted description of the strengths and weaknesses of models used for climate change assessments. This study focuses on a particular geographical region and is more specific and detailed in its analysis for that region.

3. Data

Different GCMs have been developed by a number of research groups around the world. For the purposes of this project, it was necessary to obtain detailed data from a large number of models. Fortunately, two recent projects have been undertaken that provided the needed data. These are described below.

The Atmospheric Model Intercomparison Project (AMIP, Gates et al. 1998) was undertaken to provide a framework for comparisons of atmospheric GCMs (AGCMs). AGCMs do not simulate ocean circulations; instead, the ocean surface conditions, which are needed by the atmospheric model to determine transfers of heat, moisture, and momentum, are specified from data or an idealized situation. In general, it can be difficult to compare simulations from different models. For example, when examining 21st Century simulations, different projections may be due to differences in model formulations or different assumptions about increases in greenhouse gas concentrations and other forcings (it should be noted that 21st Century simulations require coupling with an ocean model; AMIP only examines the atmospheric component). The underlying principal of AMIP is that each participating modeling group agrees to undertake the identical experiments. Thus, differences in simulations will be due solely to differences in model formulations. One of the experiments was an historical simulation of the period 1979-1995. The sea surface temperatures (SSTs) were specified as monthly mean variations based on actual observations. In this experiment, all AGCMs use the same "perfect" ocean surface conditions to determine the fluxes of heat, moisture, and momentum needed to drive the atmosphere. ("Perfect" here refers to the use of actual data, as compared to the use of ocean model output which usually contain some biases.) Each model also used the same values of atmospheric CO_2 concentration (345 parts per million) and solar constant (1365 W m^{-2}). Specification of the land surface and inclusion of the radiative effects of other greenhouse gases and aerosols was left up to each modeling group and thus varied among models. Data from this experiment include 21 AGCMs, all of which were used for this diagnostic analysis.

The Coupled Model Intercomparison Project (CMIP, Meehl et al. 2000) is similar to AMIP except that the models include both an atmospheric component and an ocean component that are fully coupled. Coupled models (CGCMs) are the state-of-the-art for climate change studies and perhaps more relevant for assessing differences in future projections. However, the results can be more difficult to interpret. Differences between models can result from differences in the atmospheric models, the ocean models, or both. One of the experiments consisted of a control run of at least 80 years duration in which greenhouse gas concentrations were fixed followed by a transient run of at least 80 years duration in which CO_2-equivalent concentration increases at the rate of 1%/year. A variety of methods are used to determine the initial state of the atmosphere and ocean at the beginning of the control run; these are briefly described at http://www-pcmdi.llnl.gov/modeldoc/cmip/table2.html. In both runs, the solar constant and land use did not change and the inclusion of aerosol effects other greenhouse gases varied among models. Thus, these simulations are not appropriate for comparing with historical variations or for projecting the magnitude of future climate changes. Rather, they are meant for use in evaluating models' ability to simulate the present climate and for comparing models' sensitivities to certain changes in forcing. In the transient run, CO_2-equivalent concentrations reach a doubling compared to initial concentrations around year 70. Data from this experiment include 9 CGCMs, all of which were used for this diagnostic analysis. Several of the models participating in both AMIP and CMIP use the same or a very similar atmospheric component.

Table 1 lists the AMIP climate models used in this study along with certain model characteristics. The spatial resolution of the models varies considerably. For example, the horizontal grid spacing of the Japan Meteorological Agency (JMA) GCM is 1.875° (or grid boxes of about 130 miles in latitude by 100 miles in longitude) compared to 5.6° (or grid boxes of about 400 miles in latitude by 300 miles in longitude) for the Center for Climate System Research (CCSR) GCM. The number of vertical levels varies from 7 to 30. One might expect that models with smaller grid boxes would perform better because they are able to simulate smaller scale features of climate. However, other studies do not show a consistent relationship between resolution and model performance. Physics parameterizations can play a more critical role in model performance. The table shows that there are differences among the models in physics parameterizations for convection, cloud formation, precipitation, the planetary boundary layer, the land surface, and the soil. The models have been shown to be very sensitive to differences in these parameterizations.

Table 2 lists the CMIP climate models used in this study along with certain model characteristics. Since these models contain an ocean component and ocean surface conditions are computed by the model rather than specified, the SSTs can differ among models and from observations. In fact, most of the early generation CGCMs tended to drift in temperature away from observations. This presumably resulted from errors in the exchange (flux) of energy between the atmosphere and ocean. To prevent such errors from becoming too large, modelers introduced a correction factor (called a "flux adjustment") to keep temperatures close to observed. More recent versions of these models have improved to the extent that flux adjustments are no longer considered necessary. The first line in the table indicates which models have eliminated this adjustment.

There are some notable differences between the CMIP and AMIP experiments. In the AMIP experiment, the CO_2-equivalent concentration was fixed at 345 ppm while in the CMIP control simulation it varies from 290 to 355 ppm. Likewise, the solar constant was fixed in AMIP at 1365 W m^{-2} while in CMIP it varies from 1365 to 1370 W m^{-2}.

Two major sources of observational data were used. For comparison of wind, humidity and pressure patterns, the reanalysis data set of Kanamitsu et al. (2002) was used. For comparison of surface air temperature and precipitation, data from the National Weather Service's cooperative observer network, as archived in the TD-3200 data set of the National Climatic Data Center, was used.

4. Results

The impacts of climate on society occur primarily as the result of the characteristics of the surface climate. Thus, one focus of the analysis was on a comparison of the model's ability to reproduce major features of the surface climate, specifically precipitation and temperature. However, we were also interested in understanding the reasons for GCMs' performance. Thus, a second focus of the analysis was on characteristics of the atmospheric circulation on a continental scale to understand possible causes for any model differences.

For both AMIP and CMIP, various climate elements were available as monthly means at each grid point with varying grid spacings (see Tables 1 and 2). The following climate elements were chosen for diagnostic analysis:

- precipitation
- surface air temperature
- wind and pressure level height at 850 hPa (about 5000 ft above sea level)
- wind and pressure level height at 200 hPa (about 35,000 ft above sea level)

The analysis at 850 hPa was chosen because much of the moisture transport into Illinois from the Gulf of Mexico occurs at and below this level. The analysis at 200 hPa was chosen because this is near the usual high-level jet stream and jet stream patterns will be reflective of EC activity.

Analyses were done for different regions. One region was the state of Illinois; only grid boxes located within the state boundaries were used. The second region was larger, including

Illinois but also parts of several surrounding states (southern Wisconsin, southwestern Michigan, most of Indiana, eastern Iowa, eastern Missouri, western Kentucky). Most of the figures present results for the larger ("central US") region. The reason is that the state of Illinois typically encompasses very fewer grid boxes. The larger region obviously contains more boxes, more likely to be resolved by the coarse resolution GCMs, and the statistical reliability of the results is therefore better. Also, the main climatic features of Illinois are common to the larger central US region

a. Precipitation

(1) AMIP results

Figure 1 compares AMIP annual precipitation values for the central US region with values for Illinois for the 1979-1995 simulation period. In most cases, there is very little difference between values for the two regions. Seasonal comparisons (not shown) exhibit similar close agreement. This provides confidence that our assessment for the central US region will be applicable to Illinois. Of course, there are some small-scale climatic features specific to Illinois that are not captured in a larger region average. However, the resolution of GCMs is too coarse to capture these. Figure 2 shows annual precipitation values for AMIP models for the central US ranked in order of increasing precipitation and compared with observations for the period 1979-1995. The same order is used in subsequent model comparisons. Model values of annual mean precipitation range from 1.5 to 3.4 mm/day (548 to 1240 mm/year, 21.5 to 48.9 inches/year), compared to an observed value of 2.7 mm/day (986 mm/year, 38.8 inches/year). About half of the models are within 10% of observed. Figure 3 displays the seasonal precipitation values for the AMIP models. Model values of winter precipitation range from 1.0 to 2.9 mm/day (91 to 260 mm/season, 3.6 to 10.2 inches/season), compared to an observed value of 1.6 mm/day (147 mm/season, 5.8 inches/season. Model values of spring precipitation range from 2.3 to 5.0 mm/day (214 to 458 mm/season, 8.4 to 18.0 inches/season), compared to an observed value of 3.0 mm/day (272 mm/season, 10.7 inches/season. Model values of summer precipitation range from 1.1 to 4.5 mm/day (99 to 418 mm/season, 3.9 to 16.4 inches/season), compared to an observed value of 3.4 mm/day (311 mm/season, 12.2 inches/season. Model values of fall precipitation range from 1.0 to 2.7 mm/day (94 to 248 mm/season, 3.7 to 9.8 inches/season), compared to an observed value of 2.8 mm/day (254 mm/season, 10.0 inches/season. The behavior is not always consistent across seasons. For example, the NCAR model had the best results for annual precipitation, but the model produces too much precipitation in summer and not enough in the fall. This is an example where a good simulation of annual precipitation may be for the wrong reasons. All models are too dry in the fall and most are too wet in the spring, although in several models the differences are not too large. In addition, almost all models produce the correct shape of the seasonal variations with high values in the warm season and low values in the cold season.

Figure 4 shows the pattern of precipitation for the winter season for observations, the GLA (driest) model, the ECMWF (wettest) model, and the NCAR model (closest to observations for annual values). The observed pattern exhibits wetness along the west coast and in the southeast US. Over the central US, there is a rapid decrease in values from southeast to northwest. All three models exhibit these general characteristics. However, both the GLA and NCAR models are too dry in the southeast. The ECMWF is most similar to observations in the general spatial pattern over the eastern and central US, although wetter than observed.

Figures 5-7 show similar maps for spring, summer, and fall, respectively. For spring (Fig. 5), the observed pattern is similar to that in winter although precipitation amounts are higher in the central US and lower along the west coast. This increase of precipitation in the central US is simulated by all models to some extent. The pattern of increase in ECMWF matches observations very well, although again the absolute magnitudes are high. The increase in the dry GLA is smaller than observed while the increase in NCAR is similar to observed. For summer (Fig. 6), the observed distribution of precipitation is rather uniform in the central US with amounts adequate to support rainfed agriculture. The GLA is much drier, failing to reproduce the basic features of the summertime precipitation climate. Both NCAR and ECMWF simulated precipitation is somewhat greater than observed. Again, the spatial pattern in ECMWF is close to observed. In the NCAR, there is a maximum in the central Great Plains that is not observed. For fall (Fig. 7), the observed pattern is similar to that of spring over the central US. Both the GLA and NCAR are too dry, failing to reproduce the basic pattern. The ECMWF is somewhat wetter, but the observed north to south gradient is not reproduced.

A key factor that influences precipitation in the central US is the transport of water vapor from the Gulf of Mexico by the wind. This movement takes place primarily in the lower levels of the atmosphere below 10,000 ft. Figure 8 shows observed average flow patterns at a pressure level of 850 hPa, which is located around 5,000 ft above sea level. In winter, the average flow in the central US is from the west and northwest. Because flow from the Gulf of Mexico does not usually penetrate into the central US, the winter season is relatively dry. Significant winter precipitation can occur during transient episodes when flow from the Gulf of Mexico penetrates into the central US. During the spring, summer, and fall, the mean flow is still from the west, but it is part of a curved pattern that originates in the Gulf of Mexico, moves across Texas, and curves northeastward into the central US. Thus, moisture is more abundant in these three seasons. This pattern is most pronounced in the summer, the wettest season.

A second key factor is the location and orientation of the high-level jet stream, which reflects the frequency and intensity of EC activity. Fig. 9 shows average flow patterns at a pressure level of 200 hPa, which is around 39,000 feet above sea level. In all seasons, the average flow is westerly over the central U.S. The average position of the jet stream, the region of highest wind speeds, is to the south of the central US in winter and spring, over the region in fall, and to the north in summer. Highest wind speeds occur in the winter when the north-to-south temperature gradient is strongest.

Analysis of observed precipitation and flow indicated that precipitation episodes were highly correlated with southerly flow over the Mississippi River valley at the pressure level of 850 hPa (Fig. 10). Correlations of greater than 75% are seen for some areas. There are slight variations by season with a westward shift in the pattern in the summer. However, high correlations are seen in all seasons from central Texas to Louisiana. At a pressure level of 200 hPa (high-level jet stream), high correlations are found generally in a belt from California to the Great Lakes (Fig. 11). This reflects the average location of the jet stream during periods when extratropical cyclones are causing precipitation over the central U.S. There are some seasonal variations in the strength of the correlations, but the location of the high correlations is about the same in all seasons, although correlations in the central US are very low in the fall. The results shown in Figs. 10 and 11 were used to identify 3 regions for analysis of the GCM data (Fig. 12). The box covering eastern Texas and Oklahoma corresponds to an area of high correlations illustrated on the 850 hPa map (Fig. 10) and reflects the importance of low level moisture transport from the Gulf of Mexico; this area will be referred to as the "LLJ" (low level jet) region. The box covering Iowa and portions of adjacent states corresponds to an area of high correlations illustrated on the 200 hPa map (Fig. 11) in 3 of the 4 seasons (except for fall); this will be referred to as the "IA" (Iowa) region. The box covering California and Nevada corresponds to a second area of high correlations illustrated on the 200 hPa map (Fig. 11); this area will be referred to as the "CA" (California) region.

We compared the low level southerly flow at 850 hPa (v850) by season for the AMIP models with observations (Fig. 13). In winter, the observed flow is slightly northerly (-0.6 m s^{-1}, -1.2 mph). In spring, the average flow is southerly at 2.0 m s^{-1} (4.5 mph). The southerly flow increases to about 4.4 m s^{-1} (9.8 mph) in the summer and then decreases to 1.9 m s^{-1} (4.5 mph) in the fall. Most models exhibit this same qualitative behavior of northerly flow in the winter and southerly flow in the other 3 seasons, reaching a maximum value in the summer. The wind speeds are also similar to observed in many of the models, indicating that the large scale circulation features are in basic agreement with observations. The UIUC model does not exhibit a seasonal cycle. The CCSR model exhibits weak northerly flow in the spring and fall. Several models also exhibit weak (near zero mean southerly wind speed) flow in the fall, which may account in part for the general model tendency to underestimate precipitation in that season. Model values of winter southerly flow range from –5.1 m s^{-1} (-11.4 mph) to 0.3 m s^{-1} (0.6 mph). Model values of spring southerly flow range from –0.6 m s^{-1} (-1.4 mph) to 3.6 m s^{-1} (8.1 mph). Model values of summer southerly flow range from –0.7 m s^{-1} (-1.6 mph) to 7.3 m s^{-1} (16.4 mph). Model values of fall southerly flow range from –1.2 m s^{-1} (-2.7 mph) to 3.2 m s^{-1} (7.2 mph).

In addition to the southerly wind flow, a second factor that is required for precipitation is the presence of water vapor. We analyzed specific humidity (mass of water vapor in a volume divided by the total mass of air in the volume) values at the 850 hPa pressure level at the same location as the southerly mean flow (Fig. 14; no values were available for GISS). The observed values exhibit a strong seasonal dependence with a minimum value in the winter (0.0029 kg H_2O /kg air) and a maximum value in the summer (0.010 kg H_2O/kg air). All models exhibit this same qualitative behavior. The UIUC model is inconsistent in lacking the proper seasonal cycle for southerly flow at 850 hPa but exhibiting a reasonable seasonal cycle for specific humidity; the reasons for this inconsistency are not clear. The magnitudes of the minimum (winter) values are about the same as observations. The magnitudes of the maximum (summer) values are more variable, ranging from about 0.006 kg H_2O /kg air to 0.012 kg H_2O /kg air. The CCSR and COLA are quite dry while the CNRM is very moist. Interestingly, the values in the fall are relatively close to observations, suggesting that the deficiency in precipitation is not completely related to the humidity of the air flowing from the Gulf of Mexico. However, there is a general tendency for increasing moisture from left to right in Fig. 15, particularly in spring and summer. Thus, the models with higher precipitation have greater amounts of water vapor in the northward flow from the Gulf of Mexico. Model values of winter specific humidity range from 0.0022 to 0.0037 kg H_2O/kg air. Model values of spring specific humidity range from 0.0037 to 0.0066 kg H_2O/kg air. Model values of summer specific humidity range from 0.0066 to 0.0122 kg H_2O/kg air. Model values of fall specific humidity range from 0.0043 to 0.0075 kg H_2O/kg air.

Another way to examine availability of water vapor is through a variable called total precipitable water (TPW), which is the total amount of water vapor in a vertical column from the surface to the top of the atmosphere. This is the maximum water vapor that can be condensed by precipitation-producing systems. A comparison of TPW values for AMIP models is shown in Fig. 15 for the central US region. The seasonal cycle is similar to that of 850 hPa specific humidity (Fig. 14). Observed values range from a winter minimum of 9 kg m^{-2} to a summer maximum of 30 kg m^{-2}. All models produce the basic seasonal cycle. In most cases, model values are close to observed in winter, spring, and fall. There is somewhat more model variability in summer. Eight models have values of 5-10 kg m^{-2} higher than observed while two models are about 6 kg m^{-2} lower than observed. Again, there is a tendency for increasing values of TPW from left to right, although there are exceptions. Model values of winter TPW range from 6 to 12 kg m^{-2}. Model values of spring TPW range from 13 to 23 kg m^{-2}. Model values of summer TPW range from 24 to 40 kg m^{-2} while fall TPW range from 14 to 28 kg m^{-2}.

Correlations between central US precipitation and the 850 hPa southerly wind component in the LLJ region (Fig. 12) were calculated for AMIP models by season (Fig. 16). Observed correlations range from 33% in the spring and 54% in the winter to around 60% in the summer and fall. There is considerable variability in model results. Many models have similar high correlations, particularly in winter, spring, and fall, but in each season there are models with low correlations. There is not always consistency in the behavior. For example, the correlations in SUNYA are close to observed in winter and fall, but they are near zero in spring. The correlations in UKMO are too low in the summer, but reasonably close to observations in the winter and fall. The correlations in NCAR are low in spring and summer. In summer, all models have correlations that are lower than observed. Model values of winter correlations range from 18 to 67%. Model values of spring correlations range from -14 to 53%. Model values of summer correlations range from -11 to 46%. Model values of fall correlations range from 13 to 65%.

Correlations for the Iowa region between central US precipitation and the westerly wind component at the 200 hPa level are shown in Fig. 17. Observed correlations are 44% in winter, 39% in spring , 67% in summer, and 29% in fall. Most models have correlations lower than observed in winter. The models exhibit the most variation in the spring, with 9 having negative correlations, but several having values close to the observed value. All models but one have a positive correlation in the summer, about half of them above 30%. Interestingly, most models have rather large positive correlations in the fall, in contrast to the rather low observed correlation. Model values of winter correlations range from -13 to 60%. Model values of spring correlations range from -30 to 39%. Model values of summer correlations range from -9 to 58%. Model values of fall correlations range from -1 to 56%.

Correlations for the California region between central US precipitation and the westerly wind component at the 200 hPa level are shown in Fig. 18. Observed correlations are 19% in winter, 44% in spring, 49% in summer, and 36% in fall. Although most models have positive correlations, the magnitudes of the correlations exhibit substantial variability. Model values of winter correlations range from -12 to 49%. Model values of spring correlations range from -20 to 48%. Model values of summer correlations range from -23 to 47%. Model values of fall correlations range from -12 to 39%.

(2) CMIP results

The annual precipitation results for the control runs of CMIP models are shown in Fig. 19. In the case of the AMIP simulations, the SSTs are specified from the period 1979-1995 and thus a direct comparison with observations for that same period is appropriate. However, in the

CMIP control runs, the SSTs are calculated by the model and the CO_2 concentration is fixed. Thus, it is not obvious what historical observational period should be chosen to compare with the model simulations. We have chosen the same 1979-1995 period for convenience, but it should be recognized that small differences between a model and observations may not be physically significant. Model values of annual mean precipitation range from 2.0 to 3.2 mm/day (730 to 1168 mm/year, 21.5 to 46.0 inches/year), compared to an observed value of 2.7 mm/day (986 mm/year, 38.8 inches/year). Seven of the 9 models are within 10% of observations. The CSIR is about 25% drier than observed and the HAD3 is about 20% too wet. The comparison of seasonal precipitation (Fig. 20) indicates some inconsistencies across seasons. Model values of winter precipitation range from 1.3 to 2.5 mm/day (117 to 221 mm/season, 4.6 to 8.7 inches/season), compared to an observed value of 1.6 mm/day (147 mm/season, 5.8 inches/season. Model values of spring precipitation range from 3.0 to 3.9 mm/day (273 to 357 mm/season, 10.8 to 14.1 inches/season), compared to an observed value of 3.0 mm/day (272 mm/season, 10.7 inches/season. Model values of summer precipitation range from 2.5 to 4.0 mm/day (230 to 365 mm/season, 9.1 to 14.4 inches/season), compared to an observed value of 3.4 mm/day (311 mm/season, 12.2 inches/season. Model values of fall precipitation range from 1.4 to 3.0 mm/day (127 to 271 mm/season, 5.0 to 10.7 inches/season), compared to an observed value of 2.8 mm/day (254 mm/season, 10.0 inches/season. Similar to the AMIP results, most (but not all) models are drier than observed in fall. The CSIR model (Australian) is within 15% of observed in winter and spring, but more than 20% drier in summer and fall. Both the ECHA (European) and ECHO (European) models are within 10% of observed in winter, spring, and summer, but more than 20% drier in the fall. The GFDL (US) model is within 10% of observed in the winter, 20% wetter in the spring, and more than 15% drier in the summer and fall. The PCM (US) is within 10% of observed in the winter and spring, about 15% wetter in the summer, and more than 40% drier in the fall. The CSM (US) model is within 10% of observed in winter, wetter in spring and summer, and 30% drier in the fall. The CCCM (Canadian) model precipitation is within 10% of observed in winter and summer, about 20% wetter in spring and more than 20% drier in the fall. The HAD2 (UK) model is about 20% wetter in the winter and spring, within 5% of observed in summer, and about 25% drier in the fall. The HAD3 (UK) is about 50% wetter in the winter, 20% wetter in the spring, within 10% of observed in the summer, and about 10% wetter in the fall.

The results for the low level southerly component of the wind speed in the LLJ region are shown in Fig. 21 for CMIP models. All models produce the correct seasonal cycle with a maximum in the summer and a minimum in the winter. The amplitudes of the seasonal cycle are similar to observations for many models. One notable exception is ECHO whose seasonal amplitude of 1.6 m s^{-1} is much less than the observed value of 4.8 m s^{-1}. Both CCCM and HAD2 have somewhat larger amplitudes than observed. Model values of winter southerly flow range from –3.3 m s^{-1} (-7.4 mph) to 1.5 m s^{-1} (3.4 mph). Model values of spring southerly flow range from 0.5 m s^{-1} (1.0 mph) to 3.1 m s^{-1} (7.0 mph). Model values of summer southerly flow range from 3.2 m s^{-1} (7.2 mph) to 5.6 m s^{-1} (12.5 mph). Model values of fall southerly flow range from –0.4 m s^{-1} (-0.8 mph) to 2.2 m s^{-1} (4.8 mph).

For specific humidity at 850 hPa in the LLJ region (Fig. 22), the CMIP models generally simulate the seasonal cycle with a minimum in winter and a maximum in summer. Although magnitudes are generally within 15% of observations, the CCCM and HAD3 are more than 15% moister in spring, summer and fall. Model values of winter specific humidity range from 0.0026 to 0.0039 kg H_2O/kg air. Model values of spring specific humidity range from 0.0048 to 0.0054 kg H_2O/kg air. Model values of summer specific humidity range from 0.0079 to 0.0135 kg H_2O/kg air. Model values of fall specific humidity range from 0.0049 to 0.0083 kg H_2O/kg air.

Correlations between central US precipitation and the southerly wind component in the LLJ region (Fig. 12) were calculated for CMIP models by season (Fig. 23). The models are within 20% of observed in the winter except for HAD2. In the spring, three models (ECHO, PCM, and HAD2) differ from observations by more than 30%. In summer, CCCM, HAD2, and HAD3 differ from observations by more than 40%. In fall, the ECHA differs by about 40% and HAD2 by about 55%. Model values of winter correlations range from -6 to 68%. Model values of spring correlations range from -5 to 37%. Model values of summer correlations range from -5 to 52%. Model values of fall correlations range from 6 to 55%.

Correlations for the Iowa region between Central US precipitation and the westerly wind component at the 200 hPa level are shown in Fig. 24 for CMIP models. In winter, CSM and HAD2 differ from the observed correlation by more than 20%. In spring, ECHO is about 40% lower than observed. In summer, all models have somewhat lower correlations than observed. In fall, all correlations are within 20% of observed. Model values of winter correlations range from 17 to 47%. Model values of spring correlations range from 0 to 53%. Model values of summer correlations range from 16 to 55%. Model values of fall correlations range from 16 to 45%.

Correlations for the California region between central US precipitation and the westerly wind component at the 200 hPa level are shown in Fig. 25 for CMIP models. There is more variability in the model results than was found for the LLJ and Iowa regions, perhaps reflecting the greater distance from the region of interest. In winter, four models (ECHO, ECHA, HAD2, and HAD3) have correlations at least 20% more than observed. In spring, the correlations in ECHO and PCM are at least 20% less than observed. The CSM and CCCM have correlations at least 30% less than observed in summer. In fall, the ECHA and PCM correlations are at least 20% less than observed. In the fall, the left to right increase in U200 CA correlations corresponds in a general way to the left to right increase in precipitation (Fig. 20). Model values of winter correlations range from 15 to 61%. Model values of spring correlations range from 8 to 37%. Model values of summer correlations range from -5 to 47%. Model values of fall correlations range from 9 to 56%.

b. Temperature

Figure 26 compares AMIP annual temperature values for the central US with values for Illinois averaged for 1979-1995. There is a very consistent relationship. In all cases, the difference between values for the two regions is less than 1.0°C (1.8°F). Seasonal results (not shown) exhibit similar close correspondence. This provides confidence that our assessment for the central US region will be applicable to Illinois, similar to the results for precipitation (Fig. 1). Figure 27 shows annual temperature values for AMIP models for the central US region ranked in order of increasing temperature and compared with the observed value for 1979-1995. The difference between model and observations is less than 1°C (1.8°F) for 8 of the models. There is a tendency for the models to be warmer than observations. The largest difference between model and observations is about 3.3°C (6°F). Model values of annual temperature range from 8.9 to 14.2°C (48.0 to 57.5°F), compared to an observed value of 10.8°C (51.4°F).

Seasonal temperature values (Fig. 28) are plotted in the same order as Fig. 27 to facilitate identification of variations in the order by season. The ordering (increasing temperature from left to right) is roughly the same as the annual ordering for spring, summer, and fall, but not in winter; however, the difference among models in winter is not large. The GLA model is notable for a much larger seasonal amplitude with the coldest temperatures in winter among all models and rather warm temperatures in summer. Model values of winter mean temperature range from –8.4 to 0.8°C (16.8 to 33.4°F), compared to an observed value of –2.3°C (27.7°F) . Model values of spring mean temperature range from 7.3 to 12.7°C (45.1 to 54.9°F), compared to an observed value of 10.7°C (51.2°F) . Model values of summer mean temperature range from 21.8 to 30.6°C (71.2 to 87.1°F), compared to an observed value of 22.8°C (73.0°F) . Model values of fall mean temperature range from 10.9 to 16.1°C (51.6 to 60.9°F), compared to an observed value of 11.9°C (53.4°F). In summer, 12 models are more than 2°C (4°F) warmer than observations.

Figure 29 shows the pattern of surface air temperature for the winter season for observations, the GLA (coldest) model, the MRI (warmest) model, and the UKMO model (an intermediate model close to observations). The observed pattern exhibits the expected strong north-to-south gradient; coldest temperatures occur in the central US near the Canadian border with the warmest temperatures over Florida. The model maps do not have the observed small scale features (such as are observed over the western mountains) which reflects the coarse resolution of the model grids. Over the central US, the general spatial pattern is similar to observed for all 3 models. A closer examination shows that the magnitude of the spatial gradient is slightly smaller than observed in the models.

Figures 30-32 show similar maps for spring, summer, and fall, respectively. For spring (Fig. 30), the observed pattern shows considerable warming, compared to winter, over the north-central US so that the north-to-south gradient is smaller than in winter. Again, the model patterns are very similar. The magnitude of the gradients is similar to observed for GLA and UKMO and somewhat larger than observed for MRI. For summer (Fig. 31), the observed pattern shows a further decrease in the magnitude of the north-to-south gradient. The spatial pattern over the central US is similar to observed. Interestingly, all 3 models show a center of warmth over eastern Texas and surrounding areas that is considerably warmer than observed. The extension of this warm area into southern areas of the central US results in a north-to-south gradient whose magnitude is somewhat larger than observed. For fall (Fig. 32), the observed pattern exhibits an increase in the magnitude of the gradient compared to summer. The GLA's gradient over the central US is slightly larger than observed while the gradients in UKMO and MRI are similar to observed.

The comparison of mean annual temperature in CMIP models, shown in Fig. 33, indicates that all models are within 1.5°C (2.8°F) of the 1979-1995 observed mean. Model values range from 9.1 to 12.3°C (48.3 to 54.1°F). This range is smaller than that for the AMIP models, principally because there are no very warm models in the CMIP group. Somewhat larger differences are observed for the seasonal values (Fig. 34), although the amplitude of the seasonal cycle is similar to observed for most models. The HAD3 and CSIR models exhibit a somewhat larger amplitude in the seasonal cycle with colder temperatures in the winter and warmer temperatures in the summer compared to observations. The CCCM model exhibits very cold temperatures [about 5°C (9°F) less than observed] in the spring, but is within 2.0°C (3.6°F) of observations in the other 3 seasons. Model values of winter mean temperature range from –

6.4 to –0.4°C (20.5 to 31.2°F), compared to an observed value of –2.3°C (27.7°F) . Model values of spring mean temperature range from 5.5 to 11.7°C (42.0 to 53.1°F), compared to an observed value of 10.7°C (51.2°F) . Model values of summer mean temperature range from 21.3 to 25.0°C (70.4 to 77.0°F), compared to an observed value of 22.8°C (73.0°F) . Model values of fall mean temperature range from 9.7 to 13.7°C (49.4 to 56.6°F), compared to an observed value of 11.9°C (53.4°F).

c. Regional Climate Model Downscaling Capability

Differences between GCMs and observations can arise from a number of sources. GCMs may not simulate with enough fidelity the large-scale circulation patterns that are the principal determining factor in local climatic features. However, regional and local influences are also important; the coarse spatial resolution and simplified physical parameterizations in GCMs may cause these local climatic influences to be inaccurately simulated. An experiment was conducted to explore this issue using a Regional Climate Model (RCM, an updated version of Liang et al. 2001). This RCM, under development at the Water Survey, was run at a spatial resolution of 30 km covering a rectangular domain that includes the entire US, southern Canada, most of Mexico, the Gulf of Mexico, the eastern Pacific Ocean, and the western Atlantic Ocean. An RCM requires a GCM or observations to provide the boundary conditions on the 4 sides of the domain.

The experiment consisted of two RCM simulations. In one simulation, the boundary conditions were provided by the NCEP-DOE AMIP-II reanalysis (R-2, Kanamitsu et al. 2002), which is based on observations. Because it is driven by actual observations, this simulation provides an upper bound on the accuracy of the RCM. In the second simulation, the boundary conditions were provided by one of the coupled GCMs, NCAR's Parallel Climate Model (PCM). Any biases in these boundary conditions may be reflected in the RCM simulation by lesser accuracy. A comparison between the PCM and PCM-driven RCM simulations provides an assessment of the additional accuracy provided by the RCM. Both simulations were run for the period 1991-1995.

Figure 35 illustrates results for winter precipitation. The RCM driven by R-2 is able to simulate some important features of the US climate. The accurate simulation of many small-scale features in the west illustrates that topographic forcing is quite accurate in the RCM. The gradient across the central US and the peak precipitation in the southeast are simulated, although the RCM produces too little precipitation in the southeast. In the PCM, the spatial details in the west are not simulated because of the coarse resolution. Also, precipitation in the southeast is considerably less than observed. The RCM driven by the PCM produces a rather accurate depiction of the spatial details in the west. Also, the RCM precipitation in the southeast is still less than observed, but is closer than the PCM to observed.

Figure 36-38 show similar results for spring, summer, and fall, respectively. In spring, the RCM driven by R-2 produces a generally accurate simulation including the spatial variations in the west and the high values in the southeast. The PCM has too much precipitation in the Great Plains and not enough in the southeast. The RCM driven by PCM produces a much improved simulation of precipitation in these areas. In summer, the RCM driven by R-2 accurately captures the maximum of precipitation in the central US. The PCM simulates the correct amount of precipitation in the central US, but the maximum precipitation is far too high and displaced well to the west. The RCM driven by the PCM has a much improved simulation with the peak moved back to the east close to the observed position. However, the RCM does not capture the peak in precipitation over Florida in either simulation. In fall, the RCM driven by R-2 has a maximum over the central US that is similar to observed in location although the magnitude of precipitation is smaller than observed. However, the RCM is too dry along the east coast. The PCM is too dry in the central US, a characteristic of almost all of the GCMs. The RCM driven by PCM is wetter in the central US, an improvement, but still drier than observed.

Figure 39 illustrates results for winter temperature. The RCM driven by R-2 is able to simulate many small-scale features in the west, as was the case for precipitation. The gradient across the central US is simulated, although the RCM is slightly warmer in the northern portions of this region. In the PCM, the spatial details in the west are not simulated because of the coarse resolution. Also, the PCM is somewhat cooler than observed. The RCM driven by the PCM produces a rather accurate depiction of the spatial details in the west. Also, the RCM is somewhat warmer and closer to observations.

Figure 40-42 show similar results for spring, summer, and fall, respectively. In all three season, the results are similar. The RCM driven by observations reproduces the observed spatial features in the west and the spatial gradient in the central U.S., although it is slightly cooler than observations in the northern central U.S. The PCM does not capture the spatial detail in the west and is somewhat cooler than observed in the central U.S. The RCM driven by the PCM reproduces the spatial detail in the west. Also, the RCM is warmer than the PCM and closer to observations in the central U.S.

Overall, the RCM provides an improved simulation of precipitation and temperature in all seasons. This suggests that regional and local forcing is important and the RCM is able to improve on the simulation of these forcing factors. Therefore the RCM provides a credible tool for downscaling the GCM climate simulations. This is particularly important for climate projection studies.

d. Model Sensitivity to Enhanced Greenhouse Gas Forcing

The sensitivity of CMIP models to certain changes in forcing was also analyzed. Each CMIP model performed the following experiment. Carbon dioxide concentrations were increased in the model by 1%/yr and a model simulation of at least 80 years was performed. With this rate of increase, there is a doubling of concentrations around year 70 of the simulation. We examined the period of years 65-75 and compared precipitation rates for this period with the last 30 years of the control (no increase in CO_2) simulation. The results are presented in terms of differences between the two periods, rather than displaying the absolute magnitudes of precipitation in years 65-75. This approach to estimating changes due to anthropogenic forcing assumes that any model biases in simulating the present climate will also apply to model simulations of the future. However, it is not possible to rigorously test this assumption and it is conceivable that model biases may be quite different for a climate system with different forcings than the present. The alternative approach of displaying the absolute magnitudes of model simulations of the future and using that information as an estimate of the range of possible future outcomes assumes that any model biases in simulating the present climate become insignificant when simulating a future scenario. That assumption may be less defensible than the assumption that the biases do not change significantly.

Figure 43 shows the difference in precipitation rates for the 4 seasons. The models show either little change or increases of at least 0.2 mm/day (0.7 inches/season) in winter and spring. In fall, the models show either little change or decreases of more than 0.2 mm/day (0.7

inches/season) except for increases of about 0.3 mm/day (1.1 inches/season) for HAD3. There is more variability in summer. The ECHO, HAD3 and ECHA show increases of at least 0.2 mm/day (0.7 inches/season). By contrast, the CCCM and HAD2 show sizeable decreases 0.6 mm/day (2.1 inches/season). How do these changes compare to precipitation variations that would occur naturally, that is, without enhanced greenhouse warming? This question was investigated by performing a more detailed analysis of the control simulations of the CMIP models. The length of the control simulation varied among models, but was at least 79 years in length. Time series of seasonal precipitation were smoothed with a 11-year running average filter. The maximum, minimum, and mean values were identified and plotted (Fig. 44). A smoothing window of 11 years was chosen to match the length of the analyzed portion of the transient simulation plotted in Fig. 21. In winter, spring, and fall, the maximum and minimum values are generally 0.2-0.4 mm/day (0.7-1.4 inches/season) above and below the mean. In summer, the maximum and minimum values are mostly in the range of 0.3-0.8 mm/day (1.1-2.8 inches/season) above and below the mean. When comparing these variations to the transient changes shown in Fig. 43, in most cases the transient changes are within the envelope of the natural variations summarized in Fig. 44. Although rigorous statistical testing is necessary to verify, these results suggest that the transient simulations changes due to the specified anthropogenic forcing are in most cases not unambiguously different than natural variations observed in the 20th Century or simulated in the control runs.

Figure 45 shows the seasonal results of the transient simulation for temperature, specifically the difference between the average temperature for years 65-75 and the average temperature for the last 30 years of the control run. As expected, all models show warming in all seasons. The results are rather consistent for winter, the models being in the range of about 6-9°C (11-17°F) warming. In spring, there is considerable variation, the models ranging from 3 to 9°C (5-17°F) warming. In summer, warming is in the range of 2-7°C (4-13°F). In fall, warming ranges from about 4°C (7°F) to slightly more than 7°C (13°F). As was done for precipitation, an 11-yr running average filter was applied to the temperature time series of the control simulations to examine the internal variations of the models. The maximum and minimum values of the 11-yr running average time series (Fig. 46) indicate variations about the average of 0.4-1.3°C (0.7-2.1°F). All of the temperature increases found in the transient simulations exceed the range of internal model variations found in the control simulations, suggesting that warming in the models is unambiguously due to the models' anthropogenic forcing.

A simulation was performed for the period 2046-2050 (for the 1%/year increasing CO_2 experiment) using the PCM to drive the RCM. Precipitation and temperature differences between that period and 1991-1995 were analyzed. For winter precipitation (Fig. 47), the PCM shows changes of 0.1-0.5 mm/day (0.4-1.8 inches/season) between the present and future periods. However, the RCM driven by the PCM shows larger changes over the central US with some areas experiencing increases of up to 1 mm day^{-1} (3.5 inches/season). The southeastern portion of the central US exhibits decreases of about 0.3 mm day^{-1} (1.1 inches/season). For spring precipitation (Fig. 48), the PCM produces mostly decreases of 0.1-0.5 mm/day (0.4-1.8 inches/season). The RCM driven by the PCM is not too different except that there is more small-scale structure in the pattern. For summer precipitation (Fig. 49), the PCM changes in the central US are small or slightly negative. The RCM driven by the PCM shows a mix of positive and negative changes although negative changes predominate and the magnitudes are small. For fall precipitation (Fig. 50), the PCM generally shows decreases over the central US. The RCM driven by the PCM is wetter, exhibiting little change. In summary, the RCM results for 2046-2050 are wetter in the fall and winter than the PCM and similar to the PCM for spring and summer.

For winter temperature (Fig. 51 top), the PCM produces increases of around 3°C (5°F) in the central US. The RCM driven by the PCM shows smaller changes, in the range of 1-2°C (2-4°C). For spring temperature (Fig. 51 bottom), the PCM produces increases of 2-3°C (4-6°F) in the central US, very similar to the changes simulated by the RCM driven by the PCM. For summer temperature (Fig. 52 top), the PCM produces increases of around 2-3°C (4-6°F) in the central US. The RCM driven by the PCM shows much smaller changes, in the range of 0-1°C (0-2°F). For fall temperature (Fig. 52 bottom), the PCM produces increases of around 1-3°C (2-6°F) in the central US. The RCM driven by the PCM shows little or no changes. In summary, the RCM results for 2046-2050 are cooler than the PCM except for spring where they are similar.

5. Discussion

The major findings of this study are as follows:

(1) Annual precipitation in AMIP models ranges from 1.5 to 3.4 mm/day (548 to 1240 mm/year, 21.5 to 48.9 inches/year), compared to an observed value of 2.7 mm/day (986 mm/year, 38.8 inches/year), with about half of the models within +/- 10% of observed.

(2) The seasonal precipitation cycle in all AMIP models exhibits a minimum in the cold season and a maximum in the warm season. The amplitude of the seasonal cycle ranges from 0.9 to 3.5 mm/day (81 to 315 mm/season, 3.2 to 12.4 inches/season), compared to an observed value of 1.8 mm/day (158 mm/season, 6.2 inches/season).

(3) All AMIP models are drier than observed in the fall, with precipitation ranging from 1.0 to 2.7 mm/day (94 to 248 mm/season, 3.7 to 9.8 inches/season), compared to an observed value of 2.8 mm/day (254 mm/season, 10.0 inches/season).

(4) The seasonal cycle of southerly wind flow at 850 hPa in the LLJ region for AMIP models exhibits a cold season minimum and warm season maximum, except for the UIUC model. Three other models (GISS, YONU, UGAMP) have quite weak southerly flow in the summer. Thirteen models have weaker than observed southerly flow in the fall. The amplitude of the seasonal cycle varies from 2.3 to 11.1 m s^{-1} (5.3 to 25.3 mph), compared to an observed value of 4.9 m s^{-1} (11.2 mph).

(5) The seasonal cycle of specific humidity at 850 hPa in the LLJ region exhibits a cold season minimum and warm season maximum for all AMIP models. Model values of winter specific humidity range from 0.0022 to 0.0037 kg H_2O/kg air. Model values of spring specific humidity range from 0.0037 to 0.0066 kg H_2O/kg air. Model values of summer specific humidity range from 0.0066 to 0.0122 kg H_2O/kg air. Model values of fall specific humidity range from 0.0043 to 0.0075 kg H_2O/kg air. The amplitude of the seasonal cycle ranges from 0.0043 to 0.0093 kg H_2O/kg air, compared to an observed value of 0.0074 kg H_2O/kg air.

(6) Total precipitable water (TPW) in the central US in AMIP models exhibits the observed pattern of minimum values in the winter and maximum values in the summer. Model values of winter TPW range from 6 to 12 kg m^{-2}, compared to the observed value of 9 kg m^{-2}. Model values of spring TPW range from 13 to 23 kg m^{-2}, compared to the observed value of 17 kg m^{-2}. Model values of summer TPW range from 24 to 40 kg m^{-2}, compared to the observed value of

30 kg m^{-2}. Model values of fall TPW range from 14 to 28 kg m^{-2}, compared to the observed value of 19 kg m^{-2}. The amplitude of the seasonal cycle ranges from 17.4 to 31.2 kg m^{-2}, compared to an observed value of 21.4 kg m^{-2}.
(7) Correlations between precipitation and various circulation indices are mixed. For southerly flow at 850 hPa in the LLJ region, in each season except summer there are several models with correlations within 10% of observed values. In summer, two models are within 20% of the observed value. Only the PNNL model has correlations within 20% of observed in all four seasons. For westerly flow at 200 hPa in the California and Iowa regions, the average differences between model and observations are greater than for southerly flow at 850 hPa. No single model has correlations within 20% of observed in all 4 seasons.
(8) Annual precipitation in CMIP models is within 10% of observed in 7 of the 9 available models. The CSIRO and HAD3 models are 25% drier and 20% wetter than observed, respectively.
(9) The seasonal precipitation cycle in CMIP models ranges from 1.4 to 2.4 mm/day (130 to 220 mm/season, 5.1 to 8.7 inches/season), compared to an observed value of 1.8 mm/day (158 mm/season, 6.2 inches/season). Except for the fall season, the magnitudes of seasonal precipitation are within 0.5 mm/day (45 mm/season, 1.8 inches/season) of observed in most cases. However, each model exhibits a difference of greater than 20% in at least one season. In one case, the difference is about 50%.
(10) All CMIP models but one (HAD3) are drier than observed in the fall.
(11) The seasonal cycle of southerly wind flow at 850 hPa in the LLJ region exhibits a cold season minimum and warm season maximum in all CMIP models. The amplitude of the seasonal cycle varies from 1.7 to 8.8 m s^{-1} (3.9 to 20 mph), compared to the observed value of about 4.9 m s^{-1} (11.2 mph).
(12) The seasonal cycle of specific humidity at 850 hPa in the LLJ region exhibits a cold season minimum and warm season maximum for all CMIP models. The amplitude of the seasonal cycle varies from 0.005 to 0.011 kg H_2O/kg air, compared to an observed value of 0.007 kg H_2O/kg air.
(13) The correlations between precipitation and southerly flow at 850 hPa in the LLJ region are within 25% of observed in the winter for all CMIP models except HAD2. In the other 3 seasons, differences of greater than 25% are found for several models. The CSM is the only model within 25% of observations in all four seasons. For westerly flow at 200 hPa in the Iowa region, the correlations are within 25% of values for several models. However, correlations lower than observed in the summer for all models. The HAD2 has correlations within 25% of observed in all four seasons. For westerly flow at 200 hPa in the CA region, no model is within 25% of observed values in all four seasons.
(14) In the transient simulations, there is a mix of conditions at the time of CO_2 doubling, with some models simulating higher precipitation compared to the control simulation and others simulating decreased precipitation compared to the control simulation. However, in almost all cases the changes are smaller than the natural variations observed in the control simulations.
(15) Mean annual temperature in the AMIP models is within 1°C (1.8°F) of observed for 8 models. The largest error is about 3°C (5.4°F). The amplitude of the seasonal cycle varies from 23.4 to 32.2°C (42 to 61°F), compared to an observed value of 25.1°C (45°F).

(16) Mean annual temperature in the CMIP models is within 1.5°C (2.8°F) of observed for all models. The amplitude of the seasonal cycle varies from 23.1 to 30.5°C (42 to 55°F), compared to an observed value of 25.1°C (45°F).
(17) In the transient simulations, all models show substantial warming, compared with the control simulation, in all seasons at the time of CO2 doubling with the typical pattern of maximum warming in the winter and minimum warming in the summer. Overall, HAD3 is the warmest model while CSM and PCM are the coolest. In almost all cases, the temperature changes are larger than the natural variations observed in the control simulations.
(18) A comparison of the data from the PCM with data from an RCM driven by the PCM indicates the RCM is superior in simulating the present-day climate. Thus, the higher resolution RCM is likely to produce more reliable estimates of the future climate.
(19) A brief simulation for a climate sensitivity experiment indicates that the RCM produces higher precipitation in the central US for winter and spring and is cooler in winter, summer and fall, compared to the direct output of the PCM.
(20) There is a high correlation between values for Illinois and for the central US region. Thus, the above findings, based on analysis of the central US region, will also be applicable to Illinois.

In summary, the current status of the ability of GCMs to simulate the regional climate of the central US exhibits considerable model-to-model variability, particularly among the greater number of models participating in AMIP.

For precipitation-related variables, most models reproduce certain basic features of the climate. The general shape of the seasonal cycle is simulated. Most models are able to simulate the seasonal changes in southerly flow from the Gulf of Mexico and the atmospheric water vapor content there and in the central US. These results reflect the models' ability to reproduce the large-scale circulation patterns and basic processes of the hydrologic cycle. There is more variation among the models in reproducing the connections between specific circulation patterns and precipitation episodes in the central US. One question is whether a specific model's biases can be related in a quantitative manner to biases in other aspects of the climate system. An examination of the results reveals the following. For AMIP models, precipitation magnitude is generally correlated with specific humidity at 850 hPa in the LLJ region and with total precipitable water in the central US, although there are some exceptions. Thus, the availability of water vapor appears to be an important modulating factor. A relationship with southerly flow at 850 hPa in the Great Plains LLJ region or with the various circulation pattern correlations is not clear. In spring, the season with the strongest correlation between its precipitation and annual precipitation, the LLJ correlations are somewhat related to precipitation with many low correlations for models with low precipitation and many of the high precipitation models showing rather high correlations. The other seasons do not show an obvious relationship. However, the regions for which the correlations are calculated are rather small in spatial extent and any slight spatial shifts in precipitation-correlation patterns could confuse such relationships. A different analysis, discussed below, provides a broader perspective. For CMIP models, no relationship was found with any of the above variables, but the precipitation differences among CMIP models is somewhat smaller than for the AMIP models.

Composite (averages of all models) maps were produced to provide additional insights. The model composite maps for 850 hPa and 200 hPa flow are quite similar for the 1979-1995 AMIP period (Figs 53 and 54) and for the 30-year control CMIP period (Figs. 55 and 56) and are in impressively close correspondence with the observed patterns (Figs. 8 and 9). However, there are subtle differences that may be important for precipitation processes in the central US. In the winter, the minimum 850 hPa wind speed in the Gulf of Mexico extends further to the west to the Texas coast. In the spring, the 850 hPa comparison is quite close. In the summer, the 850 hPa minimum is shifted to the east and the high wind speed core over Texas is weaker and broader compared to the observed. This may explain in part the more variable correlation patterns in the models. In the fall, the 850 hPa minimum is shifted to the north and extended to the west. This shift in the fall may explain the low precipitation because the model composite pattern would lead to an overall weaker advection of moisture from the Gulf of Mexico. At 200 hPa, the location of the spring maximum wind speed is slightly to the north of observed. In summer, the 200 hPa maximum is somewhat higher than observed. The 200 hPa comparison for fall and winter is quite close.

Model composite maps were prepared for the correlation between precipitation biases and wind flow biases (model minus observed monthly means averaged over all years). These maps may help to identify mechanisms causing the precipitation biases. In the following discussion they are compared with the correlations maps between observed precipitation and observed wind shown in Figs. 10 and 11, even though the model composite maps show correlations among models for climatological mean biases while Fig. 10 and 11 show correlations among different years in the observed data. If the physical representation of precipitation processes is basically correct, then we might expect that model-to-model differences may be similar to the temporal variations occurring in the observed pattern. For southerly flow at 850 hPa (Fig. 57), the models on average have positive correlations in the same general regions as are found in the observed correlation maps (Fig. 10) during winter, spring, and fall. This suggests that model precipitation biases are related to biases in the 850 hPa southerly flow in these seasons. In summer, the composite high correlations in the eastern portion of the central US are located in the same area as observed high correlations (Fig. 10), but the composite correlations are near zero over Texas, an area of high correlations in the observed map (Fig. 10). This may indicate unrealistic or inconsistent representation of the LLJ-central US precipitation relationship among GCMs. Model composite maps for the correlation between precipitation and westerly flow at 200 hPa (Fig. 58) show a mixed picture. In the winter, the composite bias correlations are high over the eastern subtropical Pacific and low over the northwest US, in different positions than the observed maximum over the Great Lakes and minimum over the Gulf of Mexico. In the spring, the minimum over the northwest and maximum over the southwest are in similar positions to observed correlations, but the observed maximum extends into the Great Lakes region, a feature not seen in the bias correlations. In the summer, the maximum over the central U.S. and the minimum over the subtropics are in similar positions to the observed correlation pattern. In the fall, the minima over the northwest and the southeast are in similar positions to observed correlation minima, but the observed weak maximum over the central U.S. is not seen in the bias correlation map. Model composite maps of correlations were not produced for CMIP because of the small number of models available resulting in low statistical reliability.

The number of basic similarities between Figs. 10 and 11 and 57 and 58 suggest that fundamental physical processes are being simulated correctly in a general sense. The differences between Figs. 10 and 11 and 57 and 58 may arise from several sources. One is topography. The mountain chains in the western US play an important role in key features such as the LLJ and the development and path of ECs, especially in summer. The topographic variations in GCMs are a rather crude approximation of reality because of their coarse spatial resolution. A second source is the models' representation of precipitation. The parameterization of the precipitation processes occurring within a grid box are known to be one of the most challenging aspects of climate system modeling because many processes, such as individual thunderstorm cells, are of a much smaller scale than the size of a grid, yet are extremely important to the magnitude of precipitation. In the case of both topography and precipitation parameterizations, regional climate models, with their much smaller grid boxes, have the potential to greatly improve on the results of global models, as we demonstrated in this study.

For temperature, both AMIP and CMIP models generally reproduce the basic observed features. The seasonal cycle is well-simulated in most models. There is some variation in the magnitude of the spatial gradient across the central US, but the general spatial pattern is well simulated.

The experiment with the RCM, although limited to a single GCM, provides confidence that the RCM will produce significantly improved simulations, particularly for precipitation. This experiment appears to show the importance of regional and local factors that are simulated in the RCM but not in GCMs.

6. Conclusions

The following are the main conclusions of this study:

- Most models reproduce basic features of the circulation, temperature, and precipitation patterns in the central US, including the pronounced seasonal cycles that are characteristic of this region and the general flow patterns, although all models exhibit sizeable differences from observations for at least a few characteristics. The use of these models for regional climate change assessments must recognize that there will remain important uncertainties in such assessments because of the model biases documented in this study. The findings of this study can provide a foundation for such assessments since in each season there are some models whose performances are inferior to others, reducing confidence in their simulations. A few models, such as GLA and UIUC, have glaring biases and would be suspect for use in climate change assessments for the central US.
- No single model, either in the AMIP or CMIP, is unambiguously superior to all other models. As such, studies of the future climate of Illinois should use 2 or more models to represent uncertainties and biases due to model differences. The results do not indicate clearly whether the AMIP or CMIP models are superior as a group to the other group. Among AMIP models, as noted above the UIUC and GLA models stand out for certain glaring problems that make them less suitable. Among CMIP models, the CSIR and HAD3 models exhibit the largest precipitation biases. The HAD3 is also the coolest CMIP model. Although on the surface these problems seem to reduce confidence in use of HAD3, it is the only model to produce enough precipitation in the fall. On this basis alone, the model warrants consideration for use in evaluating uncertainties. A strategy worthy of consideration is to choose models whose performances are complementary and as a set has at least one model providing a good simulation of the current climate in all 4 seasons. An examination of Figs. 19 and 20 suggest PCM and HAD3 or CSM and HAD3 as possible pairs that fit this requirement and could be used for driving an RCM.
- The RCM produces simulations of the present climate that are more accurate than the direct output of the PCM and thus provides an important tool to produce more credible

simulations of the future climate. A 5-yr simulation shows that the RCM produces a wetter (compared to the direct output of the PCM) future precipitation climate for the central US and is generally cooler.

7. Future Work

This study is part of larger effort to reduce uncertainties in our knowledge of the future climate of Illinois. These uncertainties arise principally from model differences and biases and uncertainties about future emissions paths. This latter source cannot be reduced substantially because it depends on the unknown future of human society. The former source can be reduced by model improvements and such reductions will likely be of value to decision-makers. The improvement of CGCMs is a major effort by modeling groups around the world. The AMIP and CMIP projects are very important catalysts for this effort by providing an objective forum for model comparisons. We hope that this study's identification of certain common biases (e.g. low precipitation in fall) will spur modeling groups to devote some resources to examine such important regional issues and hasten model improvements that will directly benefit our knowledge of this region's climate future.

This study also suggests a continuing value for use of RCMs to downscale the CGCM simulations. The results here suggest that RCMs can measureably reduce that portion of the uncertainty due to inadequate physical resolution of local and regional processes in CGCMs. At least two barriers exist that prevent a full application of RCMs to the problem. One is the computational resources required to perform RCM simulations for multiple CGCMs; at present these are inadequate to carry this out. The human resources required to manage and analyze such simulations is also substantial. A second barrier is access to the required CGCM data. The RCM requires CGCM data at a 6-hour resolution for lateral boundary conditions. In some cases, CGCM data are not stored at this resolution. In other cases, modeling groups may not be able or willing to provide access to such large volumes of data.

Finally, the analysis performed here analyzed monthly data. A detailed analysis of individual weather events requiring examination of daily data might provide more definitive identification of model deficiencies. However, such a study would demand considerable resources.

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9. References

Gates, W. L., J. Boyle, C. Covey, C. Dease, C. Doutriaux, R. Drach, M. Fiorino, P. Gleckler, J. Hnilo, S. Marlais, T. Phillips, G. Potter, B. Santer, K. Sperber, K. Taylor and D. Williams, 1998: An overview of the results of the Atmospheric Model Intercomparison Project (AMIP I). *Bull. Amer. Meteor. Soc.*, **73**, 1962-1970.

Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.), 2001: *Climate Change 2001: The Scientific Basis. Contributions of Working Group 1 to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881 pp.

Kanamitsu, M., W. Ebisuzaki, J. Woollen, S.-K. Yang, J.J. Hnilo, M. Fiorino, and G.L. Potter, 2002: The NCEP-DOE AMIP-II reanalysis (R-2). *Bull. Amer. Meteor. Soc.*, **83**, 1631-1643.

Liang, X.-Z., K.E. Kunkel, and A.N. Samel, 2001: Development of a regional climate model for U.S. Midwest applications. Part 1: Sensitivity to buffer zone treatment. *J. Climate*, **14**, 4363-4378.

McAvaney, B.J., C. Covey, S. Joussaume, V. Kattsov, A. Kitoh, W. Ogana, A.J. Pitman, A.J. Weaver, R.A. Wood, Z.-C. Zhao, 2001: Model evaluation. In: *Climate Change 2001: The Scientific Basis. Contributions of Working Group 1 to the Third Assessment Report of the Intergovernmental Panel on Climate Change* [Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881 pp., 471-524.

Meehl, G.A., G.J. Boer, C. Covey, M. Latif, and R.J. Stouffer, 2000: The Coupled Model Intercomparison Project (CMIP). *Bull. Amer. Meteor. Soc.*, **81**, 313--318.

Table 1. Characteristics of AMIP Models

Center Name	Model Abbrev	Country	Horizontal Resolution	Vertical Resolution (levels)	Solar Constant	CO2	Convection	Precipitation	Cloud Formation	PBL	Snow	Soil	Vegetation Types
Canadian Center for Modeling and Analysis	CCCMA	Canada	3.75° X 3.75°	10	1365	345	moist convective adjustment	local supersaturation	Fc (R H)	not explicit	prognostic	1 layer, bucket	24
Center for Climate System Research	CCSR	Japan	5.6° X 5.6°	20	1365	345	relaxed Arakawa-Schubert	liquid water content	convective mass flux/liquid water cont	Mellor and Yamada 2nd order closure scheme		1 layer, bucket	32
National Center for Meteorological Research	CNRM	France	300 km	30	1365	345	bulk mass flux	convective mass flux/supersaturation	Fc (RH)	not explicit	prognostic	complex, Noilhan and Planton (1989)	13
Center for Ocean-Land-Atmosphere	COLA	US	1.8° X 2.8°	18	1365	345	Kuo convective scheme	supersaturation	Fc (RH)		prognostic	complex, SiB	12
Department of Numerical Mathematics	DNM	Russia	4° X 5°	21	1365	348	relaxed convective adjustment	supersaturation	Fc (RH)	local diffusion	prognostic	24 levels	11
European Center for Medium-Range Weather Forecasting	ECMWF	UK	2.8° X 2.8°	19	1365	345	mass-flux convective scheme	supersaturation	Fc (RH)		prognostic	2 layers	
Geophysical Fluid Dynamics Laboratory	GFDL	US	2.25° X 3.75°	14	1365	345	simple convection adjustment	supersaturation	Fc (RH)	not explicit	prognostic	1 layer, bucket	
Goddard Institute for Space Studies	GISS	US	4° X 5°	9	1365	345		liquid cloud water	Fc (RH)	similarity theory	prognostic	complex, 6 layers	32
Goddard Laboratory for Atmospheres	GLA	US	4° X 5°	17	1365	345	Arakawa-Schubert	supersaturation	Fc (RH)		prognostic	complex, SiB	12
Japan Meteorological Agency	JMA	Japan	1.875° X 1.875°	30	1365	348	Arakawa-Schubert	supersaturation	Fc (RH)	Nellor & Yamada 2nd order closure	prognostic	complex, SiB	8

Main Geophysical Observatory	MGO	Russia	3.75° X 3.75°	14	1365	345	Kuo scheme	supersaturation	Fc (RH)	not explicit	prognostic	3 layer	
Max-Planck Institute for Meteorology	MPI	Germany	2.8° X 2.8°	19	1365	345	mass flux convection (tied the 1989)	complex	Fc (RH)	similarity theory	prognostic	3 layers	
Meteorological Research Institute	MRI	Japan	2.8° X 2.8°	30	1365	345	Arakawa-Schubert	supersaturation	Fc (RH)	Mellor and Yamada 2nd order closure scheme		SiB	
National Center for Atmospheric Research	NCAR	US	2.8° X 2.8°										
National Centers for Environmental Prediction	NCEP	US	3° X 3°	18	1365	345	Kuo convective scheme	supersaturation	Fc (RH)		prognostic	3 layers	12
Pacific Northwest National Laboratory	PNNL	US	2.8° X 2.8°	18	1365	348	mass flux convection	moist convective scheme	complex	Bulk Ri #	prognostic	BATS	18
State University of New York at Albany	SUNYA	US	2.8° X 2.8°										
The UK Universities' Global Atmospheric Modelling Program	UGAMP	UK	2.5° X 3.75°	19	1365	348	mass-flux scheme of Gregory (1990)	complex	complex	Bulk Ri #	prognostic	4 layers, complex	23
University of Illinois at Urbana-Champaign	UIUC	US	4° X 5°	7	1365	345	Arakawa - Schubert	liquid cloud water	Fc (RH)	not explicit	prognostic		
United Kingdom Meteorological Office	UKMO	UK	2.5° X 3.75°	19	1365	348	mass-flux scheme of Gregory (1990)	complex	complex	Bulk Ri #	prognostic	4 layers, complex	23
Yonsei University	YONU	Korea	4° X 5°	7	1365	345	Arakawa-Schubert		Fc (RH)	not explicit			

Table 2. Characteristics of CMIP Models

	CCCMA	NCAR CSM	CSIRO	ECHAM-OPYC	ECHO	GFDL	HADCM2	HADCM3	DOE PCM
Flux Adjustment	Yes, heat, water	No	Yes, heat, water, momentum	Yes, heat, water	Yes, heat, water	Yes, heat, water	Yes, heat, water	No	No
Control Run CO2 (ppm)	330	355	330	353	353	360	322.6	289.6	355
Solar Constant (Wm-2)	1370	1367	1367	1365	1365	1365	1365	1365	1367
No Vertical Levels	10	18	9	19	19	14	19	19	18
Bottom, Top (hPa)	980, 5	992, 3	979, 21	996, 10	996,10	997, 15	997, 5	997, 5	992, 3
Cloud Vertical Overlap	mixed	random	random	mixed	mixed	full	mixed	mixed	random
Connection	moist convective adjustment	mass flux scheme applied successively in three layers	relaxed moist adjustment with shallow convection	bulk mass flux scheme with shallow convection	bulk mass flux scheme with shallow convection	moist convective adjustment	bulk mass flux scheme with updrafts/downdrafts	bulk mass flux scheme with updrafts/downdrafts	mass flux scheme applied succesively in three layers
Prognostic CLW	No	No	No	Yes	Yes	No	Yes	Yes	No
Prognostic Snow Mass	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Snow Thermal Effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Sea Ice Snow Accumulation	Yes	Prescribed	Yes	No	Yes	Yes	No, but snow cover affects albedo	No, but snow cover affects albedo	Prescribed
No of Soil Temperature Layers	1	4	3	5	5	0	4	4	4
No of Soil Moisture Layers	1	0	2	1	1	1	1	1	0
Soil Model Description	Deardorff (1978) force restore, variable bucket and ET factor	heat diffusion prescribed wetness	Heat diffusion, Deardorff (1977) force restore	Warrilow et al (1986), Duemenil and Todini (1992), Blondin & Boellger (1987)	Warrilow et al (1986), Duemenil and Todini (1992), Blondin & Boellger (1987)	no heat storage, bucket	heat diffusion, single moisture reservoir, Warrilow et al (1986), Shuttleworth (1988)	heat diffusion, single moisture reservoir, Warrilow et al (1986), Shuttleworth (1986)	heat diffusion, prescribed wetness
850 mb Field in July for 1979-1995	Pressure over Illinois is higher. Southerly flow over Great Plains is slightly stronger	Close to observed	Not available	Close to observed		Not available	Close to observed	Close to observed	Close to observed
500 mb field in July for 1979-1995	Strong upper level high over Illinois	Higher heights centered over southern Illinois	Not available	Higher heights but relative flow pattern may be similar to observed		Not available	Relative trough over southern Great Lakes and eastern Midwest	Relative trough over southern Great Lakes and eastern Midwest	Higher heights centered over southern Illinois