Climate change impact on agriculture: Devils Lake basin

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Abstract: Northern Great Plains is one of the most important agricultural regions worldwide. This is also a region expected to be heavily impacted by climate change. This and two other papers in this session concentrate on studying climate change impacts on water resources of the region, and on the impacts of these changes on agriculture. The major focus of our interest is Devils Lake watershed in North Dakota. The watershed is located in the Northern Great Plains, the area where intensive agriculture has caused an extreme change in land use and land cover, followed by substantial water pollution. Devils Lake is an endorheic (terminal) lake, which makes it especially sensitive to environmental pollutions, land use and climatic changes. Despite occasional severe droughts that heavily impact agriculture of the region, lake level has been steadily elevating since the 1940s, driven by a wetter climate phase. This paper concentrates on generation of a regional climate change scenario that would take into account the existing variability of climate parameters, on one hand, and data and structural uncertainty, on the other. We also introduce preliminary results of modelling climate change impacts on the production of spring wheat in the region.

Keywords: climate; agriculture; water; uncertainty; terminal lake

1. INTRODUCTION

Climate change, water, and food security are closely connected. Despite a huge progress in improving agricultural practices worldwide, in 2009 the number of undernourished exceeded 1 billion [FAO, 2009] for the first time. The Northern Great Plains (NGP), which include parts of North and South Dakotas, Minnesota, Montana, Nebraska, and Wyoming, is one of the principal world regions of intensive agriculture. Within the area, North Dakota is one of the most important producers of food and feed, ranking first in the nation in 14 commodities. That includes the first rank in production of red spring wheat, and the second rank in producing wheat overall [North Dakota Agriculture, 2009]. The total value of wheat production in North Dakota was almost $2.3 billion in 2008 [NASS, 2009].

It can be fairly said that the agriculture of North Dakota and the entire NGP region largely follows two climatic factors, thermal and moisture regimes, both of them frequently being far from optimal. While the region includes some of the worlds' most fertile lands, the steep north-south temperature gradient, and east-west precipitation gradient also makes the region one of the most sensitive to climate change [Ramankutty et al., 2002]. In the paper, we study the non-adaptation changes in agriculture production in the region due to several contrasting scenarios of climate change impacts.

The specific region of interest is Devils Lake watershed, located in the NE part of North Dakota. Similar to other endorheic lakes, the water surface area and elevation in Devils Lake are highly variable. From the early 1940s, the area of Devils Lake is continuously increasing. This increase leads to flooding of residential areas, loss of agricultural lands, and deterioration in water quality. The total cost of attempts to alleviate these problems is approaching $0.5 bil. (USGS 2010; for additional information see a discussion by Zhang in this volume). Because of the existing dynamic equilibrium between the lake area, from one

side, and climate, land cover and land use, from the other, variations in the lake water level are indicative of the climate and anthropogenic pressure throughout the entire watershed.

Our main objective is to study the impact of climate change on the hydrology and agriculture of the region and, eventually, to find the correspondence between the impacts of climate change and land conversion for agriculture. This paper primarily deals with developing a set of relevant climate change scenarios. We also show how these results can be applied to study the impacts of climate change on agricultural production in the region. Other parts of the project are discussed in this volume by Zhang and by Lim et al.

2.   CLIMATE

A coupled atmosphere-ocean general circulation model (AOGCM or GCM) is able to compute a multi-century climate forecast for a large set of meteorological variables, such as temperature and precipitation, at an hourly or even a minute time step, and at multiple altitudes; however, these projections can be hardly used without modification in an impact study. First, the GCM projections at a temporal scale below one month are not considered reliable (e.g., Kilsby et al., 1999). Then, the GCM simulations cover the entire globe with a grid of a few degrees latitude and longitude size; additionally, the projections are valid only for groups of cells. Finally, future climate projections differ both between GCMs and between single runs of same GCMs. Practical application of GCM projections of future climate in an impact study then requires:

- Temporal downscaling of GCM projections from monthly to daily or a finer temporal resolution;
- Spatial downscaling of GCM projections from hundreds of kilometres down to tens of kilometres or finer;
- Accounting for uncertainty in GCM integrations.

2.1   Downscaling

GCM projections are valid at a scale of multiple GCM cells, which corresponds to several hundred kilometres. All regional details, such as the effect of water bodies, altitude change, land cover and similar are lost at such a coarse resolution; additionally, the subgrid-scale processes such as cloud formation are impossible to reproduce. Multiple methods are being applied to downscale GCM projections both temporarily and spatially. The approaches range from simple interpolation to statistical downscaling to dynamic weather generators to regional GCMs (RGCMs). Simple interpolation does not introduce new details, however even simple distributing GCM projections to a finer grid in a coherent way is not a trivial task by itself. E.g., the IIASA global climate database, widely used in climate impact studies, in its early version projected 32 and more rainy days per month in some areas of the UK (the bug found and reported by the author) – a result of incorrect downscaling.

Statistical downscaling is more elaborate; it is based on finding the correlation between the measured parameters of climate (e.g., precipitation pattern) and GCM projections of current climate. The methods include multiple regression, artificial neural networks (ANN) and others. The major drawback of the method is, however, its assumption that the found correlations will stay same in the future climate. Since the method is, in this regard, based on extrapolation, it is difficult even to estimate the method uncertainty due to downscaling. An example of statistical downscaling is the Statistical Downscaling Model (SDSM, www.sdsm.org.uk), which combines a statistical weather generator for temporal downscaling with regression-based spatial downscaling.

The nested regional GCMs (RCMs) are considered by many to be the downscaling method of choice [Giorgi, 2006]. RCMs are "mini-GCMs" running on a regional scale, using GCM projections or the products of global climate reanalysis to drive their boundary conditions. An RCM then would use the fine-resolution details in forcing (e.g., topography) to model the atmospheric circulation within a small region. Currently, RCMs (e.g., the Weather

Research and Forecasting model WRF - Skamarock et al., 2007) are used frequently to simulate regional climate, and model projections are available for the impact studies on large territories. E.g., the North America Regional Climate Change Assessment program NARCCAP will eventually provide the projections of six RCMs (MCSS, RSM, HadRM3, MM5, RegCM3, and WRF) driven by four GCMs (CCSM, CGCM3, GFDL, and HadCM3) and by NCEP reanalysis. Nevertheless, there are indications that, even if computational complexity is not an issue, the RCM projections do not add skill to GCM projections [Castro et al., 2005; Rockel et al., 2008]. This is explained by strong dominating of GCM projections in RCM integrations. Alternative RCM downcasting methods may improve RCM results, generating more realistic fine-scale pattern of climate components [Lo et al., 2008]. For the purposes of our study, however, the major problem with the RCM approach is its high computational requirements, which precludes the researcher from using more than one or a handful of driving scenarios. E.g., in the (incomplete) NARCAPP simulations all GCM projections are driven by the IPCC Special Report on Emissions Scenarios (SRES) scenario A2. This drastically impacts the ability of both estimating the uncertainty and also including the uncertainty in impact projections.

2.2 Treatment of uncertainty

The uncertainties in projecting future climate are due to a variety of factors:
(1) Radiative forcing depends on anthropogenic activity, chiefly the amount of greenhouse gases (GHG) released to the atmosphere from agriculture and energy production and from land use change. SRES [IPCC, 2000] quantifies this forcing by defining different paths of economic and societal development.
(2) There are disagreements among the results of general circulation models.
(3) The intrinsic uncertainty: a GCM running under the same radiative forcing scenario will return different results due to stochastic nature of climate simulations.

A set of simulations combining a variety of model runs under a variety of scenarios is hence obligatory for comprehensive analysis of possible impacts of climate change.

2.3 Future climate scenarios for the Devils Lake basin

We elected to use a simple statistical downscaling approach. The approach is based on using ANUSPLIN for spatial downscaling and a statistical weather generator [Friend, 1998] for temporal downscaling. ANUSPLIN [Hutchinson, 1995; Hutchinson, 2004] uses a thin-plate smoothing spline to interpolate climate variables in three dimensions. The method was used to generate a widely used very high resolution global climate surfaces at a 30" (1-km) spatial scale [Hijmans et al., 2005] and was demonstrated to produce the results similar to other popular high-resolution climatology products [Stillman et al., 1996], e.g. PRISM.

Figure 1 illustrates the process of climate projection generation. We estimate future climate conditions in the region by combining the historical data on temperature, precipitation, air humidity, and wind speed with an ensemble of GCM projections. For base climate, we use the 1971-2000 measurements. For future climate, we extract monthly projections of seven different GCMs: CCMA_T63, CSIRO, GFDL_CM2, GISS_E-R, MPI, NCAR_PCM, and UKMO, for three pre-set time periods, 2020s, 2050s, and 2080s. Additionally, for each of the GCMs we employ three SRES scenarios (A1B, A2, and B1 - IPCC, 2000). To generate samples of weather at a daily temporal resolution, we employ a statistical weather generator [Friend, 1998] and generate 30 year-long samples of climate parameters, bringing the total number of a year long time series for each climatic parameter to 630 for each time slice. In generation of this ensemble we address all three sources of uncertainty, mentioned in (2.2):
(1) Scenario uncertainty is addressed through computations with three different scenarios of driving forces;
(2) Structural uncertainty is addressed through computations with seven GCMs;
(3) Intrinsic uncertainty of weather predictions is addressed through computations with a statistical weather generator.
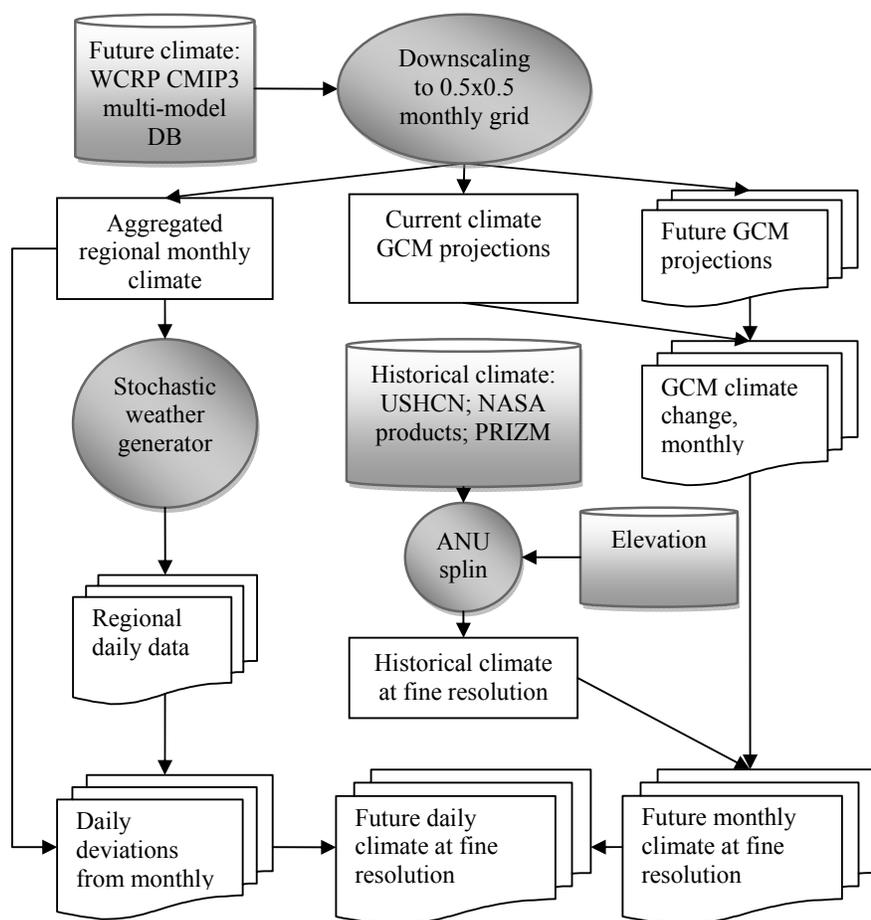
Figure 1. Developing climate scenario dataset

2.4 Validation

We compared the simulated GCM historical climate to measured daily temperature and precipitation from the Langdon Experimental Farm station of the US Historical Climate Network (USHCN, http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html), which is the closest to the Devils Lake basin USHCN meteorological station. The USHCN is essentially a subset of 1218 NOAA weather stations with the highest quality of data. Langdon experimental farm station is located approximately 80 km NNE of the city of Devils Lake and 60 km NE of the center of the Devils Lake basin. Due to this shift, we can expect the temperature, measured at the station, to be slightly lower as compared to the annual temperature of the entire basin over the same period.

We compared the distribution of 1971-1990 simulated temperature and precipitation with the data of Langdon station (Table 1). There were 10855 valid points; from these points, mean temperature was 2.6ºC according to measurements as compared to 3.5ºC according to GCM simulations. This difference is partially explained by the northern shift of the US HCN station. More important, observed data demonstrate higher variability. This is the most pronounced during winter months, with the observed extreme low temperature (-38.3ºC) being much lower than the simulated low (-25.5 - -20.8ºC). At the same time, warm period temperatures in the simulated and observed data sets are much closer (Table 1). The

frequency distribution of simulated and observed temperatures over the May-October period also demonstrates similarity. Similar to daily projections, distributions of mean monthly temperature and precipitation, observed and simulated, are very similar to the already discussed distribution of daily temperatures. Again, the simulated temperature is

slightly higher than the observed data, possibly due to the northern location of the meteorological station. Precipitation distribution is almost identical.

The distribution of precipitation over time is controlled by the number of rainy days. Even though GCM output

Table 1. Comparison of measured and simulated daily temperatures (T, °C) for annual and warm period (May-October) and warm period daily precipitation (P, mm). A mean of projections of seven GCMs.

		Annual T		Warm T		Warm P	
		Obs.	GCM	Obs.	GCM	Obs.	GCM
Mean		2.6	3.6	13.8	14.5	6.5	6.7
Std.		14.1	13.1	6.6	6.2	9.4	8.5
Min		-38.3	-25.4	-13.9	-9.2	0.3	0.1
Max		30.0	29.6	30.0	29.8	105	86.3
Per-cen-tiles	25	-7.8	-8.9	9.4	10.6	1	1.4
	50	3.9	5.7	15.0	15.6	3	3.8
	75	15.0	15.8	18.9	19.1	7.8	8.8

contains the number of rainy days, it does so at a GCM scale, typically 50,000-100,000 km^2. The immediate problem is that GCM output (and also gridded historical data) contains much higher number of rain days per month than the observed data at any specific location. To model the number of rainy days per month at a specific location, we used a linear model that connects this value with the total monthly precipitation, and used the result as an input of the statistical weather generator. For warm period precipitation, GCM projections are highly variable, especially when modeling high precipitation events. The heaviest precipitation varies from 46 to 139 mm between the models, while the observed daily precipitation maximum is 105 mm. However, distribution of precipitation shows much more similarity between the GCM and observed data, as demonstrated by comparison of percentiles and Figure 2.
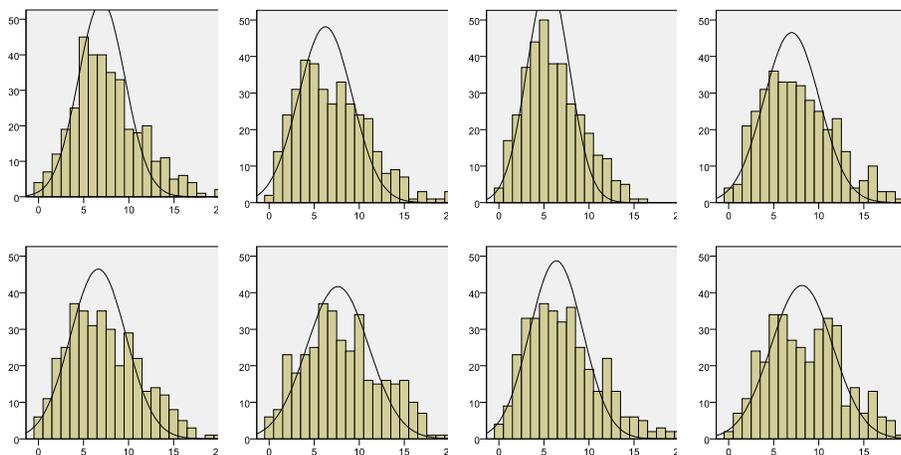

Figure 2. Distribution of observed (top left) and simulated (seven GCMs) monthly number of days with precipitation over 0.1 mm, 1971-2000.

2.5 Future climate

GCM integrations (Table 2, Figure 3) agree on a moderate temperature increase in the region under the "balanced" scenario A1B: annual temperature change by 0.9 – 1.6 °C in 2020s, 1.6 – 3.3 °C in 2050s, and 2.2 – 4.6 °C in 2080s. The projections under A2 scenario are similar: temperature increase by 0.6 – 1.5 °C in 2020s, 1.5 – 2.7 °C in 2050s, and 2.6 – 5.2 °C in 2080s. The temperatures under B1 scenario, with smaller carbon emissions, but also with reduced emissions in radiation blocking aerosols, result in larger change in 2020s: temperature increase by 0.8 – 1.7 °C, but the smallest changes after that: 1.2 – 2.5 °C in

2050s, and 1.5 – 3.3 °C in 2080s. Overall, the temperature will continue to increase; but the predicted increases vary among different GCMs and for different scenarios. The actual temperature distribution is likely to fall within the range of the predictions. As opposed to this universal increase in the temperature, there is much more diversity in precipitation projections, which vary from a small decrease by up to 12% to an up to 28% increase. The width of the projected corridor demonstrates a need to use model ensemble rather than results of just one GCM or one scenario.

Table 2. Comparison between the projections of seven GCMs under three SRES scenarios. Temperature (dt) is shown as a difference, and precipitation (dp) is shown as a percentage of change to the "current climate". No ccma_t63 A2 integrations are available from CMIP3 at this time.

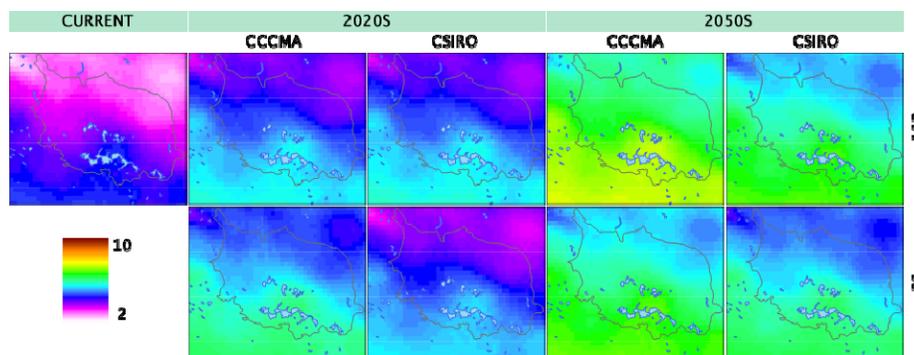|		A1B		A2		B1	
	GCM	**dt (°C)**	**dp (mm)**	**dt (°C)**	**dp (mm)**	**dt (°C)**	**dp (mm)**
2050s	**CCCMA_T63**	3.1	8.4			2.5	0.4
	CSIRO	2.3	1.2	2.7	0.0	1.9	-6.9
	GFDL_CM2	3.2	-2.2	2.5	2.6	2.3	4.5
	GISS_E-R	1.6	10.9	1.5	18.3	1.2	13.3
	MPI	3.0	4.4	2.3	8.5	1.9	13.4
	NCAR_PCM	2.2	3.0	2.3	5.9	1.4	3.3
	UKMO	3.3	3.5	2.7	4.5	2.3	2.7
	Mean	2.7	4.2	2.3	6.6	1.9	4.4

Figure 3. Mean annual temperature (°C) for the Devils Lake Basin. The projections are based on two GCM integrations under A1B and B1 SRES scenarios.

3. AGRICULTURE: MODEL VALIDATION AND SENSITIVITY ANALYSIS

Decision Support System for Agrotechnology Transfer (DSSAT) was used to study the impact of climate change on spring wheat production in the North Dakota. DSSAT has been used extensively to simulate crop yields across the U.S. under current climate and climate change scenarios [Tubiello et al. 1999]. The minimum data required for DSSAT includes weather, soil and management, and cultivar-specific data, which were extracted from North Dakota Agricultural Network (NDAWN, http://ndawn.ndsu.nodak.edu), USDA SSURGO (http://soils.usda.gov/survey/geography/ssurgo), and DSSAT databases, respectively.

To validate the model, we compared the results of model simulations with the synthetic daily weather from GCM monthly climate. Several warm season-long Markov chain sequences of random daily temperature and precipitation values were consequently used with the DSSAT; the results of multiple DSSAT runs with 15 different replicas of the synthetic weather for the same growing period were then averaged. We then compared the results of DSSAT simulated yield with the yield generated when using the actual historical NDAWN temperature and precipitation for the 1991-2000 period. We found that the mean

IPCC-climate and NDAWN-climate DSSAT-simulated wheat yields for the same time frame were not statistically different (at 0.05 level). Consequent model sensitivity analysis has demonstrated that the increasing temperatures in the region (with fixed precipitation), despite an extended growing season, negatively impact the yield (Table 3).

We completed preliminary simulations of climate change impacts on wheat production under the 2050s climate, using the 15 samples of temperature and precipitation during the growing season, generated as described above from the CCCMA projections under the SRES A1B scenario. Our analysis of the results shows 15% spring wheat yield decrease under the 2050s climate. This result is consistent with the studies done in other parts of the country, which has projected spring wheat yields to decline 10% to 15% by 2040, and 20% to 26% by 2080 [Stöckle et al. 2008].

Table 3. Simulations of spring wheat yield at changing temperature and precipitation

Change of temperature	Original	t+1ºC	t+2ºC	t+3ºC	t+3.5ºC	t+4ºC
	0	-2.5%	-7.7%	-7. 5%	-9. 5%	-11.5%
Change of precipitation	P-20%	P-10%	Original	P+10%	P+20%	P+30%
	-7.6%	-2.9%	0	1.4%	1.8%	2.0%

4.   DISCUSSION

Current public discussion of reliability of climate change projections has revived an interesting problem in public perception of climate, which, to the best of our knowledge, was first noticed in the beginning of 1990s, when the first wave of public concern about "global warming" has quickly subsided. Ungar (1992) speculated that the apparent lack of public interest was due to the fact that a person tends not to notice, or even misinterpret the signals from changing climate. To better communicate the information about climate change, a number of "common sense" climate indices have been proposed [Hansen et al., 1998], however the communication evidently needs further improvement. In this respect, the cumulative nature of an endorheic watershed makes an endorheic lake an ideal candidate to serve as a proxy for climatic changes in the region.

The same impact-accumulative nature of an endorheic lake makes the nearby communities, dependent upon its resources, particularly vulnerable to even small modifications in water balance in the watershed. Well-known examples of the impacts of such modifications include the Aral Sea and Lake Chad, where the unsustainable agricultural practices in the basin and, possibly, climate modifications, has led to dramatic lake degradation. Despite an existence of long-term probabilistic forecasts of Devils Lake water level [Vecchia, 2008], the uncertainty in climate change projections remains the major challenge to water managers in the region: the hydrological forecasts based on current climate conditions cannot be relied upon anymore. The major challenge here is producing the water managing plans that are robust to climate change-related uncertainty [Stakhiv, 1998].

In our study, presented by two additional papers in this volume by Zhang and by Lim et al., we are discussing the inter-connected effects of climate change, hydrology, agriculture, and land use change in the region. Here, we present a method to build a database of regional projections of climate change, based on an analysis of a multimodel ensemble of GCM results, which would take into account the scenario, the data, and the structural uncertainty in climate projections. Then, we show how this database can be used to project the consequent changes in performance of agriculture. This preliminary study includes studying the variation of wheat yield under one scenario of climate change; on the next step the methodology will be applied for a variety of the scenarios of socio-economic development, GCMs, and crops.

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