2.7 USING ANOVA TO ESTIMATE THE RELATIVE MAGNITUDE OF UNCERTAINTY IN A SUITE OF CLIMATE CHANGE SCENARIOS

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1. INTRODUCTION

An emerging research focus in global change studies is the identification, quantification, and communication of uncertainty. Uncertainty is a particular concern for integrated assessments, including those involving the impact of climate, as the uncertainty associated with each component of an assessment can propagate through the assessment process. This uncertainty "cascade" (Mearns and Hulme, 2001) places severe constraints on policy recommendations derived from impact assessments.

Katz (2002) argues that a fully probabilistic approach should be the ultimate goal of uncertainty analysis. Previous attempts to assign probabilistic values have usually involved identifying the major sources of uncertainty, representing these uncertainty sources as probability density functions, driving a model (e.g., climate model) using multiple values from the probability density functions, and combining the model outcomes into an output probability density function (Wigley and Raper, 2001). A major difficulty of this approach is defining appropriate probability density functions for the uncertainty sources. Typically, either a uniform distribution is assumed or the distribution is defined subjectively based on expert judgment. A second important limitation is that uncertainty in the model structure is not considered. Jones (2000) proposed a somewhat simpler approach whereby multiple scenarios are used to estimate the "quantifiable range of uncertainty" for a particular source. Ideally, the quantifiable range approaches the total range of uncertainty if a diverse group of scenarios is selected. If more than one uncertainty source exists, then conditional probabilities can be calculated by first defining the second uncertainty source in terms of the first, next assuming a uniform distribution for each source, then randomly sampling the component uncertainties across their respective quantifiable uncertainty ranges and finally multiplying the samples from each source. An advantage of this approach is that uncertainty in model structure is included, although only implicitly. A limitation, of course, is the simplistic and likely unrealistic assumption of uniform distributions for the uncertainty sources. Also, it is difficult using this approach to simultaneously consider more than two sources of uncertainty.

We propose an alternative method for evaluating and communicating uncertainty that involves 1) the use of a large suite of local climate change scenarios to estimate a quantifiable range of uncertainty and 2) the application of analysis of variance (ANOVA) and related non-parametric procedures to determine the relative magnitude of multiple sources of uncertainty, the "interaction" between the uncertainty sources, and the statistical significance of the source and interaction terms. The motivation for this study is summarized by Katz (2002) who states that "The field of climate change impact assessment will be better off in the long run the sooner it is recognized how severely underestimated uncertainty presently is" (p. 182). For this demonstration, the ANOVA technique is applied to 240 annual scenarios and 960 seasonal scenarios of the projected change in the mean and standard deviation of temperature. The scenarios were originally developed to assess the potential impact of a perturbed (approximately 2xCO_2) climate on agriculture in the lake-modified zones surrounding the Great Lakes and are unique in terms of the shear number of scenarios for a region. Uncertainty sources were defined as 1) the downscaling methodology used to develop the scenarios, 2) the choice of coarse-scale GCM output to which the downscaling methodology was applied, 3) the location for which the scenario was constructed, 4) the predictand (i.e., maximum or minimum temperature), and 5) season. Admittedly, between-location, between-predictand and between-season differences are frequently of interest to users of climate scenarios and typically would not be considered uncertainty sources. However, inclusion of these terms in the ANOVA analysis allows their magnitude relative to the two primary uncertainty sources (i.e., downscaling methodology and GCM simulation) to be assessed.

2. DATA AND METHODS

Simulations from four GCMs (Canadian Climate Center (CCC) GCMII, the Hadley Center UKTR, Max Planck Institute (MPI) ECHAM3, and the Goddard Institute of Space Studies (GISS) Version IV) were used in the scenario development. As the scenarios were developed over an extended period of time, the characteristics of the GCMs vary widely. Two approaches were employed to downscale the GCM simulations to six locations surrounding the Great Lakes. First, the GCM-simulated series of daily maximum or minimum temperature from the land gridpoint nearest the station location were used directly (referred to as the GRDPT scenarios). Second, a regression-based statistical downscaling methodology,

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which relates large-scale free atmosphere variables to local temperature, was employed. Four "variants" on the empirical methodology were derived, as an earlier sensitivity analysis showed that the transfer functions and consequent downscaled scenarios were sensitive to subjective choices made when developing the functions, particularly the definition of the seasons used to calibrate the functions and the decision to adjust for bias in the GCM simulations of the predictor variables (Winkler *et al.*, 1997). The four variants are: 1) PN functions (no standardization, one annual specification equation), 2) PS functions (no standardization, four seasonal specification equations), 3) ZN functions (standardized predictor variables, one specification equation), and 4) ZS functions (standardized predictor variables, four specification equations). We considered the four variants (i.e., PN, PS, ZN, ZS) to be separate downscaling "methods" in order to maintain a balanced design for the ANOVA procedure.

The dependent variables were the projected changes in the annual and seasonal means and standard deviations and the categorical independent variables were the five uncertainty sources (METHOD, MODEL, LOCATION, PREDICTAND, and SEASON). Important assumptions of ANOVA are that the data within each cell are independent and normally distributed with equal variance. However, Levene's test suggested that the cell variance was unequal for some of the dependent variables. Consequently, ANOVA was performed on both the original values and on log-transformed values. In addition, the parametric ANOVA procedures were supplemented by non-parametric tests (i.e., Kruskal-Wallis test). A source (i.e., main effect) term was considered significant only if judged so by both the parametric and non-parametric methods. The significant main effect terms were then used to rank and quantify the uncertainty sources. Interaction terms were limited to two-way interactions, which we felt were the most insightful for interpreting and annotating the scenarios. For all analyses, Bonferroni critical values (i.e., the probability of a Type I error adjusted for multiple comparisons) were used to test the significance of the main effect and interaction terms. A critical (alpha) level of 0.05 was used for all significance tests.

3. RESULTS

The maximum quantifiable range of uncertainty for this suite of scenarios is substantial (Table 1). For example, the range of uncertainty is 4.8°C for the projected change in annual mean temperature and 10.2°C for the projected change in seasonal mean temperature. The projected changes in annual and seasonal standard deviation range from substantial reductions in temperature variability to substantial increases.

Table 1: Maximum quantifiable uncertainty for climate change projections for a doubled CO_2 environment for the Great Lakes region.

VARIABLE	QUANTIFIABLE UNCERTAINTY RANGE	MINIMUM CHANGE (°C)	MAXIMUM CHANGE (°C)
Annual mean temperature	4.83	1.75	6.58
Seasonal mean temperature	10.19	-0.95	9.24
Annual standard deviation	4.12	-2.29	1.83
Seasonal standard deviation	9.64	-5.43	4.21

Histograms of the projected changes, which are a reflection of the underlying probability density functions, differ noticeably for the four variables (Figure 1). The histogram for the projected change in annual mean temperature approaches a uniform distribution, whereas the histogram for the projected change in the seasonal means more closely resembles a normal distribution, although a modest negative skew is noticeable. The histograms for the projected change in annual and seasonal standard deviations are non-normal and non-uniform. Both histograms indicate that a few scenarios are disproportionately contributing to the quantifiable uncertainty range for these two variables.

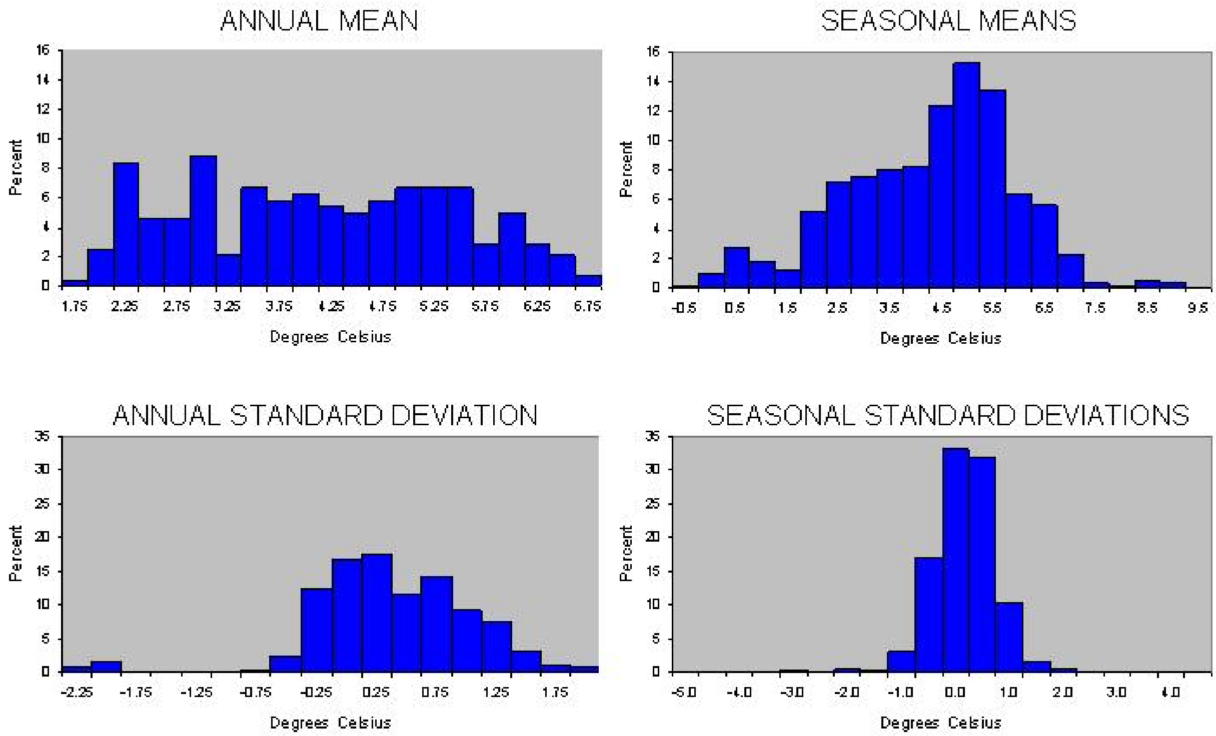

Figure 1. Histograms of the projected change in annual and seasonal mean temperature and of the projected change in annual and seasonal standard deviation.

For the projected change in annual mean temperature, two sources of uncertainty, MODEL and METHOD were significant (Table 2). Between-category differences are more than twice as large for the MODEL main effect term than for any of the other main effects. The range in the category averages for MODEL is 3.0°C, compared to 1.1°C for METHOD. SEASON and PREDICTAND were also significant for the scenarios of projected change in seasonal mean temperature. Note, however, the between-season and especially the between-predictand differences are smaller than the uncertainty introduced by the choices of GCM model and downscaling methodology. For the projected change in annual standard deviation, the two significant terms were MODEL and METHOD with the MODEL main effect term contributing the most (1.4°C compared to 0.4°C) to the quantifiable range of uncertainty. In the case of the projected changes in seasonal standard deviations, the MODEL and SEASON main effect terms were significant. The choice of downscaling method was not significant for this variable. For all variables, locational differences were not significant.

Table 2: Statistically significant sources of uncertainty (alpha = 0.05).

SOURCE OF UNCERTAINTY	***DIFFERENCE IN CATEGORY MEANS (°C)***	***NUMBER OF SCENARIOS PER CATEGORY***
ANNUAL MEAN TEMPERATURE		
MODEL	2.99	60 (240)*
METHOD	1.13	48(192)*
SEASONAL MEAN TEMPERATURE all of the above plus		
SEASON	0.91	240
PREDICTAND	0.21	480
ANNUAL STANDARD DEVIATION		
MODEL	1.43	60
METHOD	0.42	48
SEASONAL STANDARD DEVIATION		
MODEL	0.72	240
SEASON	0.46	240

**Value in parentheses is the number of scenarios used to calculate the category mean for seasonal mean temperature.*

Difference in means tests were then applied to the category means for those main effect terms that were shown above to be statistically significant sources of uncertainty. Again parametric (i.e., t-test) and non-parametric (i.e., Mann-Whitney U test) methods were used to account for non-normal distributions. When test results differed, the most conservative interpretation was used (i.e, the fewest number of significant differences). For the parametric tests, both the Bonferroni and Scheffe adjustments were used to account for multiple comparisons. For the non-parametric comparisons only the Bonferroni adjustment was employed. The results for annual and seasonal mean temperature indicate that for this suite of scenarios, the projected changes were significantly different for all four GCM models (Table 3). In terms of the downscaling methodology, the projected changes in annual and seasonal mean temperature derived from the ZN and PS methodologies differed the most, whereas the projected changes derived from the GRDPT, PN, and ZS methodologies were not significantly different from each other. In terms of seasonal variations, the projected changes in mean temperature differed significantly between each of the traditionally-defined seasons.

The ANOVA analysis also indicated that a number of the two-way interaction terms were significant. In the case of seasonal mean temperature, significant two-way interactions included MODEL and SEASON, MODEL and METHOD, METHOD and SEASON, METHOD and PREDICTAND, and PREDICTAND and SEASON. Inspection of plots of the category means for the interaction terms provides interesting insights on the nature of uncertainty. For example, between-model differences in the projected change in seasonal mean temperature are smallest during the summer season and largest in winter (Figure 2). Also, between-season differences are fairly small for the CCC GCMII and the GISS Version IV models, but large for the MPI ECHAM3 and Hadley Center UKTR models.

Table 3. Comparison of category means for annual and seasonal mean temperature. Means with the same letter are not significantly different.

Category	***Category Means***	***Groups***
MODEL		
CCC	5.35	A
GISS	4.76	B
UKTR	3.60	C
ECHAM	2.37	D
METHOD		
ZN	4.55	A
PN	4.12	B
GRDPT	4.08	B
ZS	3.94	B
PZ	3.42	C
PREDICTAND		
TMAX	4.13	A
TMIN	3.92	B
SEASON		
Summer	4.51	A
Fall	4.13	B
Spring	3.83	C
Winter	3.60	D

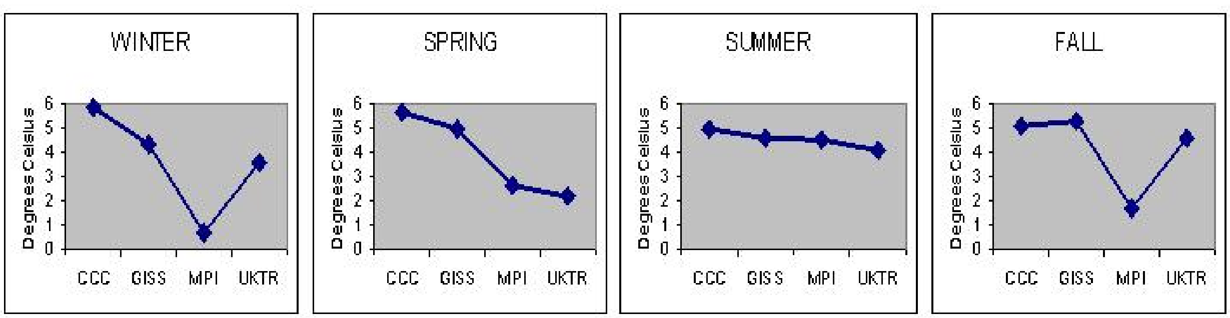

*Figure 2. Plot of the MODEL*SEASON two-way interactions for the projected changes in annual and seasonal mean temperature.*

4. DISCUSSION AND CONCLUSIONS

The analyses presented above illustrate the importance of having available a large suite of local climate scenarios when undertaking a climate impact assessment. A suite of scenarios allows for the calculation of a quantifiable range of uncertainty associated with the projected change in a climate variable. Confidence in the adequacy of the uncertainty range increases with an increase in the number of available scenarios. Furthermore, the scenario suite provides an estimate of the form of the underlying probability density function. In addition, ANOVA can be applied to the scenario suite to determine the statistical significance of different uncertainty sources and the interaction of different sources which heretofore has not been considered. For the suite of scenarios presented in this paper, it was shown that the choice of GCM simulation used to develop the scenario introduced the greatest uncertainty. It should be noted that we considered the choice of GCM as only one source of uncertainty but in reality a number of uncertainty sources are combined within this term, such as the choice of emissions scenario, the inclusion/omission of aerosols, and model structure. These sources could be explored more explicitly by designing an ANOVA analysis that includes scenarios that, for example, used the same model structure but employed different emissions scenarios. Obvious constraints are access to the appropriate simulations and the time and effort required to create the additional scenarios.

Our results also point to considerable uncertainty in local/regional climate change projections. In fact, the ranges presented here are likely underestimates of the uncertainty range as the scenarios were constructed from “early vintage” models, primarily equilibrium models and uncoupled transient models, and were either based on a simultaneous doubling of CO_2 or an assumed one percent per year increase (roughly the IS92a emission scenario) rather than the recently-developed SRES emission scenarios (Nakicenovic *et al*., 2000). As pointed out by Wigley and Raper (2001), the switch to the new emissions scenarios along with the use of state-of-the-art coupled atmosphere-ocean GCMs resulted in an increase in the projected range of global warming from only 0.8^{o}C to 3.5^{o}C in the IPCC Second Assessment Report to 1.4^{o}C to 5.8^{o}C in the IPCC Third Assessment Report. We expect a similar increase in the quantifiable uncertainty range when the downscaling methodologies are applied to more recent GCM versions. However, comparison of local/regional climate change projections derived using older GCM vintages to those derived from newer GCM versions can provide valuable insights on the stability of the quantifiable uncertainty range associated with the projections. We urge developers of climate scenarios to take care that the addition of new members to a scenario suite is done in a manner that facilitates statistical analysis of the magnitude and significance of the uncertainty sources. We particularly encourage scenario developers to consider ANOVA methods, either the simple balanced design used here or more complex nested designs, to evaluate the statistical significance and interaction of the different sources of uncertainty.

In sum, ANOVA provides one means of communicating to users the uncertainty contained in a large suite of climate scenarios. Application of ANOVA to temperature scenarios for the Great Lakes region suggests that uncertainties introduced by the choice of GCM simulation and downscaling methodology are larger than the seasonal and spatial variations in the projected changes in the mean and standard deviation of maximum and minimum temperature. These findings are a caution to impact analysts to not over interpret climate change scenarios.

5. ACHKNOWLEGEMENTS

The scenarios used in the analysis were developed with funding from the Midwestern Regional Center of the National Institute for Global Environmental Change (NIGEC) and the NATO Collaborative Research Grants Programme.

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