Integrating Climate Change into Water Management Design

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Abstract This paper presents a combination of methods to meet the challenge of incorporating global climate change models into predictions of meteorological events and trends using publicly available data to determine meteorological design values A purpose-built script was developed with the statistical language R to compile changes in multiple climate variables for a given longitude, latitude, and time period. Input information includes global climate change (GCC) models from Intergovernmental Panel on Climate Change Assessment Reports 1–5. The available GCC models were weighted equally during statistical evaluation of the overall cumulative results. Results were then compared to trends in historical data obtained from reanalysis climatic models. This overall procedure combines analysis of GCC models and historical data to define design values of the percentage change expected to use for civil structures and water management.

Key words Climate Change, GCC, applied engineering, hydrology, water management

Introduction

The lack of consistent processes to integrate global climate change (GCC) into engineering design acts as a barrier in the ability to address the effects of GCC on infrastructure (CSA 2012). Thus, the expectation exists within the engineering community and local governmental entities that GCC must be actively incorporated into engineering design.

This paper describes a method that uses computer programming to analyze GCC models and historical data in parallel. The results are then statistically compared to produce a single GCC design value. The method can help guide engineers during design of climate-dependent infrastructure and can be applied to any location in the world and for many climate variables. For example, in northern latitudes, tailings and waste rock freezing is used to control acidic runoff from facilities, and frozen core dams are often used to contain tailings and contaminated water. Projects in warmer climates with submerged tailings can be affected by an increase in temperature and thus evaporation. Globally, projects are dependent on water balances and predictions of mean annual precipitation.

The proposed method involves: (1) collating and evaluating baseline climate data, (2) querying available GCC prediction models, and (3) forecasting climate trends. Results are then graphically summarized. Baseline reanalysis data were sourced from ERA-Interim, produced by the European Centre for Medium-Range Weather Forecast (ECMWF), whereas GCC models from five Intergovernmental Panel on Climate Change (IPCC) Assessment Reports (ARs) were accessed through Environment and Climate Change Canada (ECCC) (2016). The entire procedure was accomplished using a purpose-built script developed with R software (Comprehensive R Archive Network 2016). The change in the mean air temperature of Yellowknife, Canada, was used to illustrate the procedure and analytical results.

Many GCC software packages are available through research institutions (e.g. the Pacific Climate Impacts Consortium). In some cases, GCC modelling provides highly detailed climate predictions, but these are usually only applied to specific regions. As well, most GCC modelling methods do not compare historical trends against available models. The major difference between the procedure described here and other GCC tools and sources is trend analysis of historical data. For example, ClimateWNA (described by Wang et al. 2012), ClimateBC, ClimateNA, and the Statistically Downscaled Climate Scenarios offered by the Pacific Climate Impacts Consortium (2016) produce detailed downscaled climate predictions based on a subset of available GCC models. They can only be applied for regions within North America. Although downscaling climate data allows for higher climate resolution, a trade-off exists between the geographical range of applicability and the increase in the time needed to produce results. In addition, increased performance and accuracy are not guaranteed with increasing resolution (Charron 2014).

Conceptual Methodology

The proposed methodology produces a conservative value (larger magnitude of GCC) when comparing historical trends and GCC models. For projects where historical trends show GCC is occurring more rapidly than predicted by GCC models, the historical trend is projected. For locations where GCC is predicted to exceed historical trend forecasting, the results from R are consistent with other GCC models.

Script Deployment

Assessment Reports

Design elements of a given project include the location, infrastructure risk associated with GCC, and climate variables deemed important for analysis. It is necessary to identify the GCC models available for each important climate variable. The five chosen IPCC AR models and scenarios contain monthly GCC modelling predictions for any location in the world:

- First Assessment Report (FAR) (IPCC 1990)
- Second Assessment Report (SAR) (IPCC 1995)
- Third Assessment Report (TAR) (IPCC 2001)
- Fourth Assessment Report (AR4) (IPCC 2007)
- Fifth Assessment Report (AR5) (IPCC 2014)

The GCC models and scenarios presented in AR1 to AR5 assume application of radiative forces (energy fluxes) through different anthropogenic sources that result in discharge of varying concentrations of atmospheric greenhouse gases. These radiative forces are not constant through time because they depend on global anthropogenic behavior, such as environmental policies, population growth, economic growth, energy sources, land use, and hydrocarbon usage. Each GCC model presented in the ARs represents these radiative forces differently and thus each presents a different GCC scenario, underscored by its own model assumptions and boundary conditions. The maximum projection time frame considered in this method is to the year 2100.

None of the GCC models are inherently superior or inferior. Likewise, the newer generation of ARs are not necessarily more reliable than older versions. Instead, they represent more detailed consideration of global anthropogenic forces. Typically, the user must apply professional judgment when choosing the most suitable model or generation of models for design, which is invariably biased. The proposed method aims to eliminate this bias by weighting the available models equally (Flato et al. 2013).

The AR1–AR4 data cover the years 1960–2100 for a variety of climate variables. The AR5 data cover the years 1900–2100 in NetCDF format (Unidata 2016) and provide temperature and total precipitation, but include fewer other meteorological variables in comparison. Significant data gaps exist in the ARs, depending on the report, scenario evaluated, and assessed variable.

Although the meteorological variables in AR1 to AR5 were used for most analyses, some GCC design values were calculated for other key variables through application of empirical models (e.g. extreme storm events and snowpack thickness using snowmelt energy models) (Walter et al. 2005).

Reanalysis: ERA-Interim

To best represent the historical trends, a reanalysis approach was used because the availability and timespan of records tend to be more consistent than regional meteorological stations. Reanalysis spans several decades and covers the entire planet. Publicly available reanalysis data from ERA-Interim (ECMWF 2016) comprise six-hour time interval data from 1979 to 2016, based on a 0.75° latitude by 0.75° longitude grid. If necessary, data from regional meteorological stations can be compared with the reanalysis data to validate the reanalysis data for a specific site, especially for projects in mountainous terrain.

The reanalysis models generally use 3D-variational (3DVar) and 4D-variational (4DVar) methods for data assimilation of the measured meteorological information when compared with short-term forecast information. 4DVar assimilation is more representative of the measured values because forecast information is corrected within the respective time step. ERA-Interim is one of few available and up-to-date reanalysis models with 4DVar data assimilation for a small grid size (Reanalyses.org 2016). These characteristics support the use of ERA-Interim for historical meteorological information.

Data Retrieval and Use of R

Data from AR1 to AR4 were downloaded from ECCC source files for a given site based on longitude and latitude. Data retrieval is automated within the R script, and data retrieval and analysis can be completed within minutes. The script is coded to be applicable to all projects, with few inputs and standardized outputs. AR5 information and ERA-Interim reanalysis databases were downloaded prior to use of the script. R software then facilitated presentation of the results in publication-quality figures.

Baseline Analysis

Using every model available in the five ARs, the GCC was projected with respect to a set baseline conditions over a time interval of 30 years, which is generally accepted as a statistically significant period (Baddour and Kontongomde 2007). The baseline and projected periods are defined as follows:

- The baseline period (1976–2005) coincides with that adopted for AR5 by ECCC. This is the estimation of the climate data based on the GCC models.
- Three projection periods, 2011–2040, 2041–2070, and 2071–2100, represent the future when GCC models are applied.

The projected change in a given climate variable for each time period can be automatically calculated using R script. Results can be presented in the form of a cumulative probabilistic curve. For the purpose of this method, only the overall cumulative probabilistic curve associated with data from all the available ARs combined is needed because all GCC models are equally weighted (IPCC 2014).

Trend Analysis

Historical reanalysis data from ERA-Interim were assessed by (1) identifying the trend and (2) estimating the statistical significance of the trend. Five trend analysis methods were used:

- Ordinary least square (Maidment 1992)
- Quantile regression (Koenker 1978)
- Mann-Kendall and Theil Sen (Mann 1945; Sen 1968)
- Zhang (Zhang et al. 2000)
- Yue and Pilon (Yue et al. 2002)

The outcome of the trend analysis is a figure illustrating the different trends and the statistical significance of each regression method. Significant trends ($p\text{-value}<0.05$) are displayed on the cumulative probabilistic curve (Figure 1).

Design Value Determination

Following completion of the baseline and trend analyses, a design recommendation is presented for the identified meteorological variable and time period. This design value is shown on the cumulative probabilistic curve (Figure 1), depending on which analysis outcome is deemed to be more representative of the location based on a simple calculation. If the previous trend analysis showed no historical statistical significance, then the design variable would be the percent change associated with 50% cumulative probability based on the GCC models. However, if there were statistically significant historical trends, then the design variable would be calculated based on the following equation:

$$\text{Climate Change Design Value} = \text{Max.}\left(\begin{array}{l}\text{50\% Cumulative Probability,}\\ \text{Mean}\backslash\{\text{Regression}_{\text{p value} < 0.05}\backslash\}\end{array}\right)$$

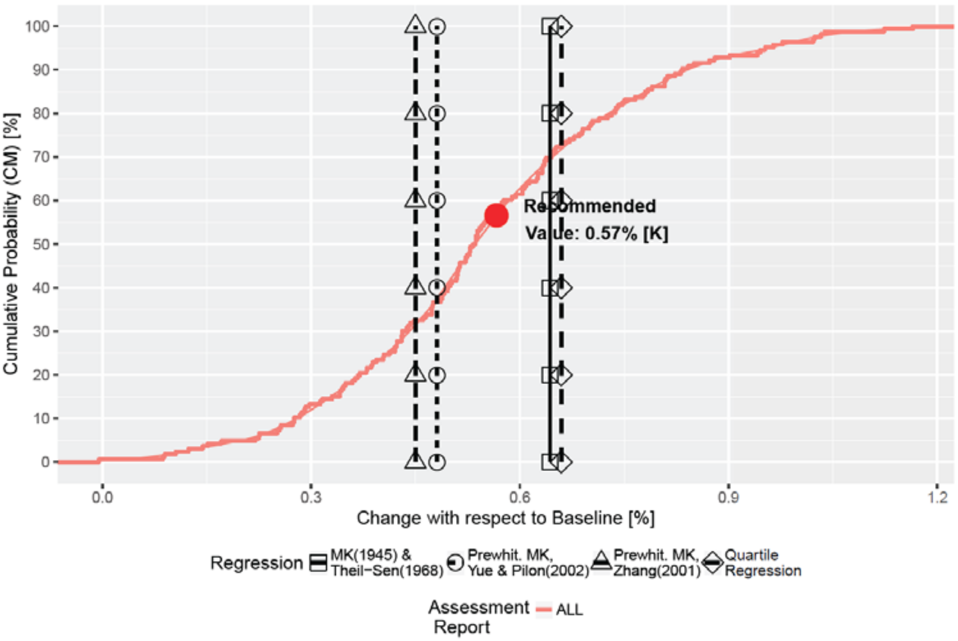

***Figure 1** Summary of baseline and trend analyses, including the cumulative probabilistic curve based on climate change models, and statistically significant historical trends. The design value represents the change in air temperature expected for 2011 to 2040 for Yellowknife, Canada.*

Discussion

The proposed method facilitates incorporation of GCC into engineering design in a practical way and is to be applied in addition to normal engineering best practices that are already implemented during engineering design. Such practices include the consideration of site-specific and engineering investigations, design codes, and the use of safety factors, risk management, and professional judgment.

GCC models inherently contain several assumptions, and there is no clear way to assess the accuracy of a given model. The proposed procedure statistically analyzes all climate predictions included in the IPCC ARs and identifies trends in historical data to produce the most representative GCC design variable for a given location and time period. The method eliminates the bias introduced by selecting a single model and compares GCC models with historical data.

The limitations of this procedure are inherent in GCC analysis. The source data are publicly available, and the software and methods that use these data share flaws associated with the data. Another limitation is the maximum time horizon over which the GCC models are projected. ECCC provides data access for models up to the year 2100. There are few GCC projections beyond 2100, and the uncertainty and variability in these models tends to be high (IPCC 2014). Therefore, it is considered appropriate to limit the use of models projecting beyond the year 2100 in engineering applications.

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