京都大学防災研究所年報 第 54 号 B 平成 23 年 6 月
Annuals of Disas. Prev. Res. Inst., Kyoto Univ., No. 54 B, 2011

# Statistical Analysis of Present and Future River Water Temperature in Cold Regions Using Downscaled GCMs Data

Bin HE*, Kaoru TAKARA, Yosuke YAMASHIKI,
Kenichiro KOBAYASHI* and Pingping LUO**

* Center for Promotion of Interdisciplinary Education and Research,
Educational Unit for Adaptation and Resilience for a Sustainable Society, Kyoto University
** Graduate School of Engineering, Kyoto University

**Synopsis**

Stream water temperature has a direct impact on the water quality and ecosystem through its influences on many chemical processes. The main objectives of this study is to investigate the long term monthly and yearly variation of stream water temperatures in cold regions for both historical and future periods. Firstly, the long-term trends (1961-2001) in the monthly and yearly time series of water temperature at Sapporo were identified. Then, to predict the future water temperatures, the approach of downscaling the outputs of a global climate model (GCM) to a local scale was investigated by employing the Statistical Downscaling Model to downscale air temperature (T) in both the present and future climate scenarios. The above downscaling approach was applied to the Sapporo meteorological station in Japan by simulating the local scale daily temperature based on large scale atmospheric variables including National Center for Environmental Prediction (NCEP) reanalysis datasets (1961-2000) and a general circulation model (HadCM3) outputs (1961-2099).

**Keywords**: Cold region, river water temperature, downscaling, statistical analysis

## 1. Introduction

As a fundamental physical characteristic describing properties of surface waters, stream water temperature has a direct impact on the flora and fauna of aquatic systems through its influences on many chemical processes in river systems. High stream temperatures can have adverse effects on fisheries resources by limiting fish habitat and mortality. Most of the variations in stream water temperatures is affected by a number of variables such as the depth of water, cloud cover, solar radiation, low flow, etc. In recent decades, climate change has been reported as an important source of aquatic disturbance on a large scale and global scale (Fig. 1). A good knowledge of stream water temperature is therefore essential in the management of stream water and aquatic resources (Webb et al., 1993). The main objectives of this study is to investigate the long term monthly and yearly variation of stream water temperatures in cold regions for both historical and future periods. For this purpose, the observation and scenarios data of air and water temperature was collected in this study.

As for the future scenarios data of air temperature, the output from General circulation models (GCMs) was used. The GCMs representing physical processes in the atmosphere, ocean, cryosphere, and land surface are the most advanced

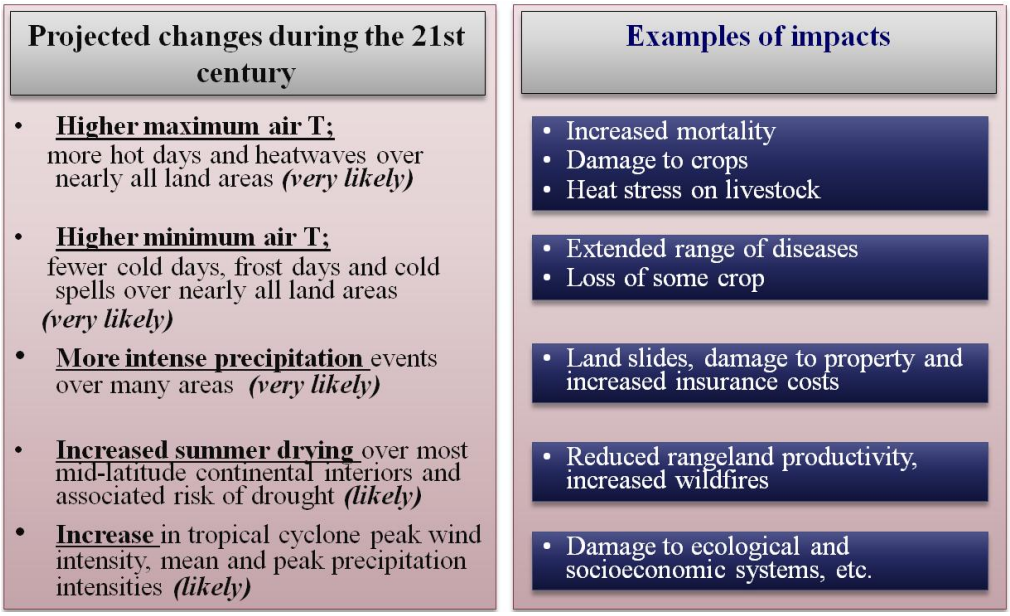


Fig.1 Schematic representation of the climate change and examples of impacts summarized from literatures (IPCC, 2007; etc.).

numerical tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations (Mendes and Marengo, 2010). While they demonstrate significant skill at the continental and hemispherical scales and incorporate a large proportion of the complexity of the global system, they are generally not designed for local or regional climate change impact studies and are inherently unable to present local subgrid-scale features and dynamics owing to their coarse spatial resolution (Coulibaly, 2004). Thus, GCMs simulations of local climate at individual grid points are often poor, especially in areas near mountains or coastlines (IPCC, 2007). As a result, GCMs are not directly suitable for local impact studies, since local climate depends on topographical features, such as elevation or aspect (Sailor et al., 2000). For applications to impact studies such as hydrological impacts of climate change, impact models are usually required to simulate sub-grid scale phenomenon and therefore require input data (such as precipitation and temperature) on a similar sub-grid scale (Schoof and Pryor, 2001). There is need to convert the GCMs outputs into higher spatial resolution scenarios (Giorgi et al., 2001).

The methods used to convert GCMs outputs to regional high-resolution meteorological fields required for reliable hydrological modeling are usually referred to as “downscaling” techniques (Hewitson and Crane 1992). There are two major approaches established well at the moment, namely the dynamic downscaling and the empirical (or statistical) downscaling. The former is a method of extracting local scale information by developing and using limited-area models or regional climate models (RCMs) with the coarse GCMs data used as boundary conditions. In this approach, the outputs of GCMs grid cells are used to provide boundary conditions for other models with higher resolution, which better represent local topography and provide a more realistic simulation of fine-scale weather features. Recent studies have shown the capacity of RCMs to reproduce fine-scale features of different regional climates, however, they still exhibit systematic errors due to imperfect representation of even smaller-scale features (Hulme et al. 2002). The latter seeks to derive the local scale information from the larger scale through inference from the cross-scale relationship using some

random or deterministic functions (Wilby et al., 2002). They are generally based on the assumption that GCMs are reliable predictors of both large-scale variables and atmospheric conditions which are sufficiently far removed from the surface of the earth (Cavazos, 1999). This approach does not require lengthy computation times and is based on finding clear relationships between large-scale atmospheric variables and local climate (Schoof et al., 2001). To date, linear and non-linear regression, artificial neural networks, canonical correlation and principal component analysis have all been used to derive predictor-predictand relationships (Xu, 1999; Busuioc et al., 1999). Even though it is not yet clear which method provides the most reliable and accurate downscaling results (Schoof and Pryor, 2001), the most widely used empirical downscaling method is the Statistical Down-Scaling Model (SDSM) which implements a simple linear regression (Wilby et al., 2002).

In this study, to investigate the long term monthly and yearly variation of stream water temperatures in cold regions for both historical and future periods, firstly, the long-term trends (1961-2001) in the monthly and yearly time series of water temperature at Sapporo were identified. Then, to predict the future water temperatures, the approach of downscaling the outputs of a global climate model (GCM) to a local scale was investigated by employing the Statistical Downscaling Model to downscale air temperature (T) in both the present and future climate scenarios. The above approach was applied to the Sapporo meteorological station in Japan by simulating the local scale daily temperature based on large scale atmospheric variables including National Center for Environmental Prediction (NCEP) reanalysis datasets (1961-2000) and a general circulation model (HadCM3) outputs (1961-2099).

## 2. Methodology

### 2.1 Statistical Downscaling Model

The SDSM is a multiple regression-based tool for generating future scenarios to assess the impact of climate change and it has the ability to capture the inter-annual variability better than other statistical downscaling approaches, e.g. weather generators, weather typing (Wilby et al. 1998; 1999). It is a combination of a stochastic weather generator approach and a transfer function model (Wilby et al. 2002; 2004) needing two types of daily data. The first type corresponds to local predictands of interest (e.g. temperature, precipitation) and the second type corresponds to the data of large-scale predictors (NCEP and GCMs) of a grid box closest to the study area. Correlation and partial correlation analysis are performed in SDSM between the predictand of interest and predictors to select a set of predictors most relevant for the site in question (Wilby et al. 1999; Wilby and Dawson, 2007).

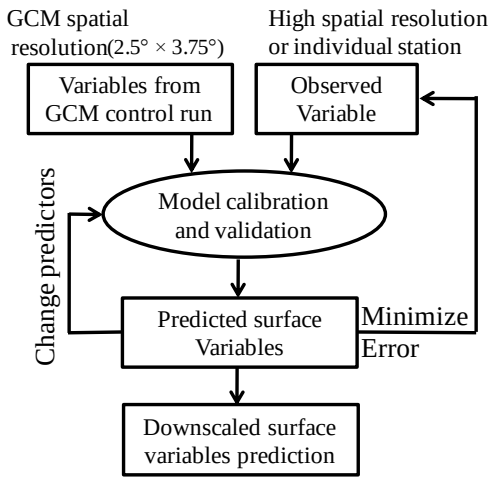


Fig.2 Schematic representation of the downscaling methodology used in this paper for generating local air temperature using historical surface temperature data and NCEP data.

### 2.2 Selection of predictor variables

For SDSM, selecting the most relevant predictor variables is the first and an important task in the downscaling process. The selection of the most relevant predictor variables is achieved with linear correlation analysis and scatter plots (between the predictors and the predictand variables). In this study, the observed daily data of large scale predictor variables (NCEP data) is used to investigate the percentage of variance explained by each predictand–predictor pair. The influence of individual predictors varies on a month-by-month

basis. Therefore, the most appropriate combination of predictors has to be chosen by checking the analysis output of all of the 12 months. Finally, only one set of selected predictors is used as input to the downscaling models of all of the months. Figure 2 demonstrated the schematic representation of the downscaling methodology used in this paper for generating local air temperature using historical surface temperature data and NCEP data.

## 3. Data description

### 3.1 Observation data

Observed local variables of air temperature and river water temperature for Sapporo site (Fig. 3) were collected from the observation database of Automated Meteorological Data Acquisition System (AMeDAS) and The Ministry of Land, Infrastructure, Transport and Tourism (MLIT) database. The temporal resolution of temperature is daily.

### 3.2 NCEP

Observed large-scale atmospheric variables for the period 1961–2000 were obtained from the reanalysis of NCEP-NCAR (National Centers for Environmental Prediction-National Center for Atmospheric Research) data. The dataset consists of large-scale predictor variables presented in Table 1 (Asian domain: 80.0°N-10.0°S, 56.25-191.25°E; NCEP dataset: http://www.cics.uvic.ca). Daily mean of predictors including geo-potential height at 500 and 850 hPa (ncepp500as, ncepp850as), relative humidity at 500 hPa (ncepr500as), mean sea level pressure (ncepmslpas) with a grid resolution of 2.5° × 2.5° were interpolated to match GCMs spatial resolution (2.5° Lat. × 3.75° Long.). The resulting time series of the grid cell nearest to Hokkaido (45° N, 142.5° E) were used as predictor variables to develop and test the SDSM model with observed air temperature data (1961–1990), and to validate the capability of SDSM to reproduce large-scale variables and atmospheric conditions (1991–2000).

### 3.3 HadCM3

The GCM adopted in this work were the HadCM3, developed by the Hadley Centre, UK. HadCM3 is a coupled atmosphere–ocean GCM described by Gordon et al. (2000) and Pope et al. (2000). The atmospheric component of HadCM3 has 19 levels with a horizontal resolution of 2.5° Lat. × 3.75° Long., while the oceanic component has 20 levels with a horizontal resolution of 1.25° Lat. ×1.25° Long. A number of scenarios of future changes in greenhouse gases and aerosols were used to drive the model run. In order to simulate climate change, the emission scenario A2 was selected among those proposed by the Special Report on Emission Scenarios (SRES) (IPCC, 2007) for their wide and representative range of changes in temperature patterns. The predictors which are similar to NCEP (Table 1) were simulated from HadCM3 for the periods 1961–2099 and were extracted for the respective grid cell closest to Sapporo. In particular, as mentioned above, the HadCM3 data for the present climate were compared with the NCEP-NCAR data to test the capability of the GCM to reproduce large-scale variables and atmospheric conditions. All predictors in these datasets (presented in Table 1) have been normalized with respect to the 1961–90 mean and standard deviation.

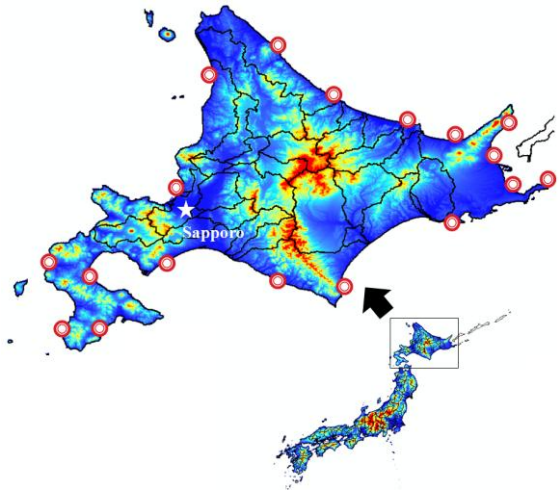


Fig.3 Location of study areas in Hokkaido (The red circles represent the observation sites of water temperature)

Table 1 Description of all predictors in NCEP.

| NCEP code | Predictors (NCEP reanalysis) | NCEP code | Predictors (NCEP reanalysis) |
|---|---|---|---|
| ncepmslpas | Mean sea level pressure | ncepp500as | 500 hPa geopotential height |
| ncepp5_fas | 500 hPa airflow strength | ncepp850as | 850 hPa geopotential height |
| ncepp5_uas | 500 hPa zonal velocity | ncepp__fas | Surface airflow strength |
| ncepp5_vas | 500 hPa meridional velocity | ncepp__uas | Surface zonal velocity |
| ncepp5_zas | 500 hPa vorticity | ncepp__vas | Surface meridional velocity |
| ncepp5thas | 500 hPa wind direction | ncepp__zas | Surface vorticity |
| ncepp5zhas | 500 hPa divergence | ncepp_thas | Surface wind direction |
| ncepp8_fas | 850 hPa airflow strength | ncepp_zhas | Surface divergence |
| ncepp8_uas | 850 hPa zonal velocity | ncepr500as | Relative humidity at 500 hPa |
| ncepp8_vas | 850 hPa meridional velocity | ncepr850as | Relative humidity at 850 hPa |
| ncepp8_zas | 850 hPa vorticity | nceprhumas | Near surface relative humidity |
| ncepp8thas | 850 hPa wind direction | ncepshumas | Surface specific humidity |
| ncepp8zhas | 850 hPa divergence | nceptempas | Mean temperature at 2 m |

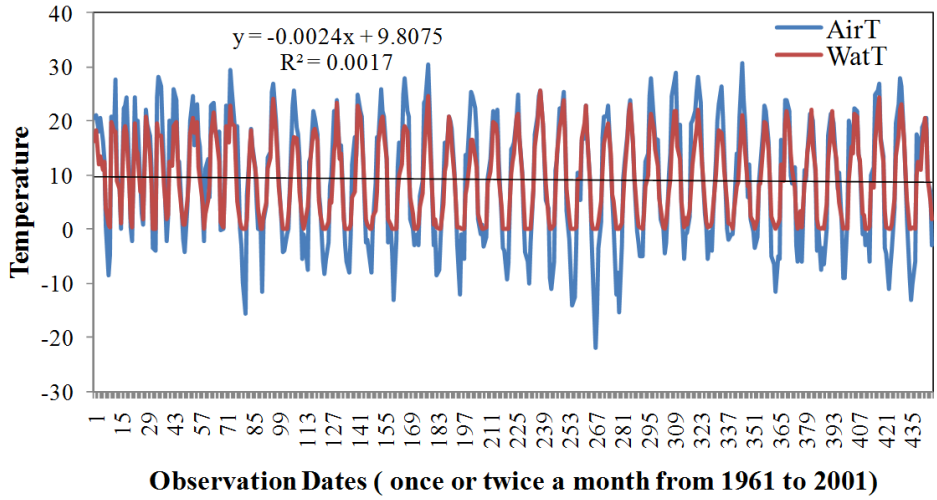


Fig.4 Time series variation of observed daily air and water temperature (Unit: °C) from 1961 to 2001.

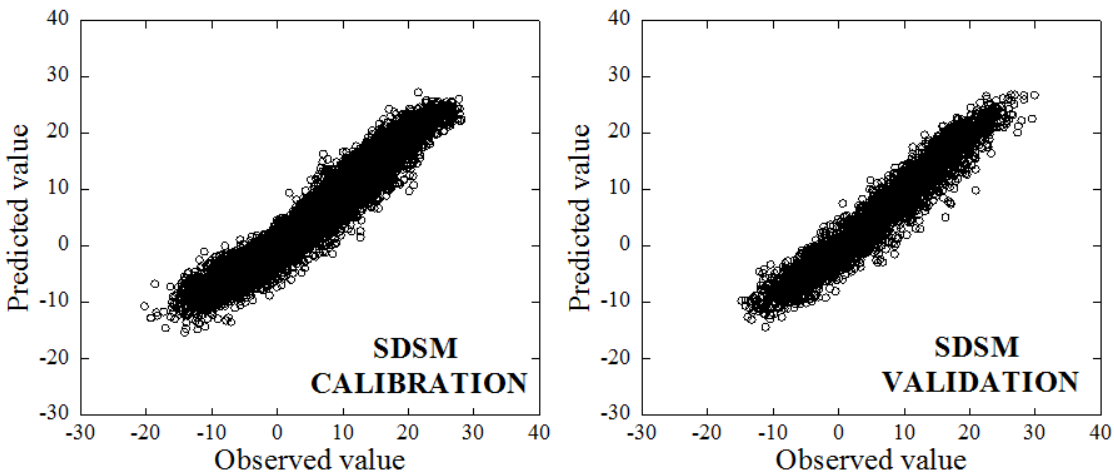


Fig.5 Scatter plots of observed and simulated daily temperature (Unit: °C) for both calibration and validation of SDSM model.

## 4. Results and analysis

### 4.1 Long term variation

The long-term trends (1961-2001) in the monthly and yearly time series of water temperature at Sapporo (Hokkaido, Japan) were identified. Figure 4 shows the time series variation of observed daily air and water temperature from 1961 to 2001. The data was observed once or twice a month. From Fig. 4, it is obvious that the river water temperature has high correlation with air temperature. Using the multiple regression techniques, an empirical relationship can be derived between monthly stream water temperatures and monthly atmospheric temperatures, monthly discharge, and some other factors as well, using the observed data between 1961 and 2001. Here, as the preliminary stage of this study, the simple relationship between air temperature and river water temperature was employed.

### 4.2 Future air temperature

To predict the future stream water temperatures, the approach of downscaling the outputs of a global climate model (GCM) to a local scale is investigated by employing the Statistical Downscaling Model (SDSM) to downscale air temperature (T) in both the present and future climate scenarios (IPCC scenarios A2). The above approach were applied to the Sapporo meteorological station in Japan by simulating the local scale daily temperature based on large scale atmospheric variables including National Center for Environmental Prediction (NCEP) reanalysis datasets (1961-2000) and a general circulation model (HadCM3) outputs (1961-2099) with a coarse spatial resolution of 2.5º latitude by 3.75º longitude.

Results also show that atmospheric predictors such as surface specific humidity, mean air T at 2 meter, and 500 hPa geopotential height are identified as the most relevant inputs to the downscaling model. Furthermore, the performance of the downscaling methods is compared for both calibration period (1961-1990) and validation period (1991-2000). Figure 5 shows the scatter plots of observed and simulated daily temperature for both calibration and validation of SDSM model.

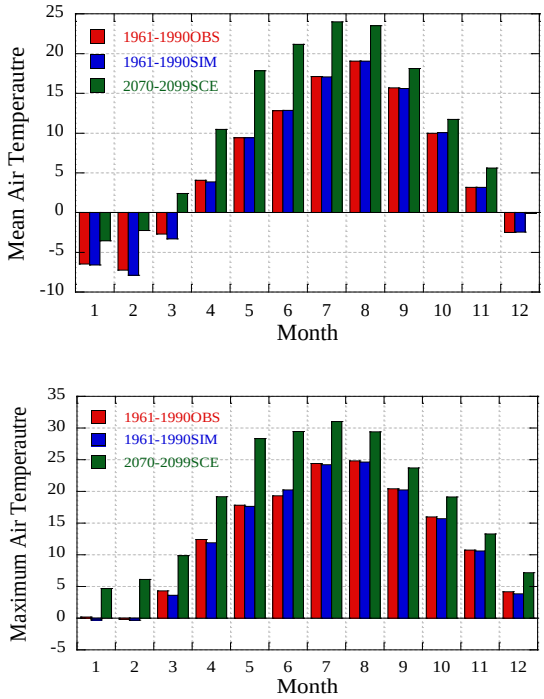


Fig.6 Histogram of observed and simulated monthly minimum and maximum extreme T (Unit: °C) for historical climate (1961-2000) and future climate (2070-2099). (OBS: observation of T by AmeDAS; SIM: simulation of T using current HadCM3 data; SCE: scenarios of T using future HadCM3 data)

The downscaling model's performance shows that SDSM is efficient for downscaling daily air T with $R^2$ index higher than 90%. The simulated monthly average air T (1961-2000) by using HadCM3 datasets also reproduced well the observed ones in the local station (Fig. 6).

As for yearly variation, Fig.7 shows the histogram of observed (using AMeDAS data) and simulated (using HadCM3 data) yearly average and maximum extreme air temperature from 1961 to 2099.

### 4.3 Future river temperature

Using the empirical relationship derived between stream water temperatures and atmospheric temperatures, monthly discharge, and some other factors as well, using the observed data between 1961 and 2001, it is possible for us to predict the future river water temperature. In this paper, the simple relation between air temperature

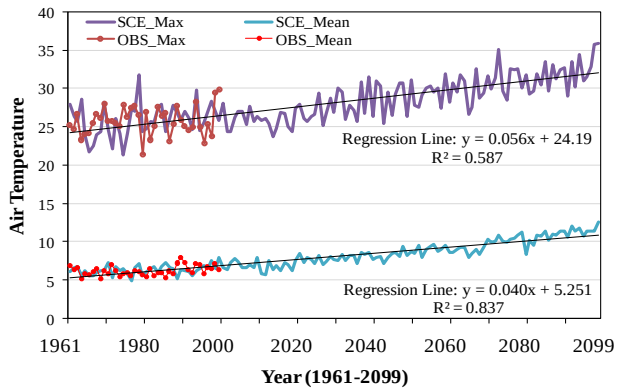


Fig.7 Histogram of observed (using AmeDAS data) and simulated (using HadCM3 data) yearly average and maximum extreme air temperature (Unit: °C) from 1961 to 2099.

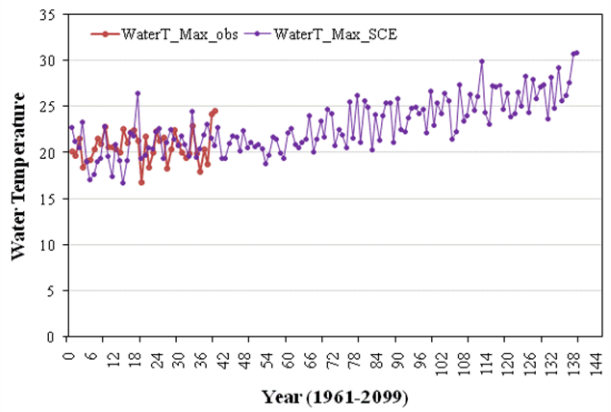


Fig.8 Histogram of observed and simulated yearly average and maximum river water temperature (Unit: °C) from 1961 to 2099.

and river water temperature was applied to predict the future river water temperature in Ishikari River. Figure 8 shows the histogram of observed and simulated yearly average and maximum river water temperature (Unit: °C) from 1961 to 2099.

## 5. Conclusions

In this paper, the statistical downscaling method is presented to simulate local scale daily air temperature and monthly extreme (maximum and minimum) temperatures based on large scale atmospheric variables. They were applied to a weather station in Hokkaido, Japan along with NCEP reanalysis datasets. Results show that atmospheric predictors such as surface specific humidity, mean air T at 2 meter, and 500 hPa geopotential height are identified as the most relevant inputs to the downscaling models. The performance of the downscaling methods is compared for both calibration period (1961-1990) and validation period (1991-2000). The downscaling models' performance show that SDSM is efficient for downscaling daily air T with $R^2$ index higher than 90%. This study demonstrates the applicability of downscaling technique in evaluating the reliability of the downscaled data for climate scenarios development. The results obtained from this study show the predicted river water temperature reproduced well the yearly variation of observed river water temperature. From the Fig. 8, the river temperature has the increasing trend. However, the results of Fig. 8 were highly influenced by the output of GCMs data, which has many potential uncertainties currently. Even though those uncertainties, this study still proposed a way to predict the future river water temperature.

## Acknowledgements

This study was supported by the Kyoto University Global COE program "Sustainability/Survivability Science for a Resilient Society Adaptable to Extreme Weather Conditions" and the JSPS Grant-in-Aid for Young Scientists (B) (KAKENHI Wakate B, 90569724). The authors are grateful for their supports.

## References

Busuioc, A., Von Storch, H. and Schnur, R. (1999): Verification of GCM generated regional seasonal precipitation for current climate and of statistical downscaling estimates under changing climate conditions, J. Climate, 12, pp.258–272.

Cavazos, T. (1999): Large-scale circulation anomalies conducive to extreme precipitation events and derivation of daily rainfall in Northeastern Mexico and Southeastern Texas, J. Climate, 12, pp.1506–1523.

Coulibaly, P. (2004): Downscaling daily extreme temperatures with genetic programming,

Geophysical Research Letters, 31, L16203, pp.1-4.

Giorgi, F., Hewitson, B., Christensen, J., Hulme, M., Von Storch, H., Whetton, P., Jones, R., Mearns, L. O. and Fu, C. (2001): Regional climate information-evaluation and projections. In: Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the IPCC (ed. by J. T. Houghton, Y. Ding, D. J. Griggs, M. Noguer, P. J. van der Linden, X. Dai, K. Maskell & C. A. Johnson), 583–638. Cambridge University Press, Cambridge, UK.

Gordon, C., Cooper, C., Senior, C.A., Banks, H., Gregory, J.M., Johns, T.C,, Mitchell, J.F.B. and Wood, R.A. (2000): Simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments, Clim. Dyn., 16, pp.147–168.

Hewitson, B.C. and Crane, R.G. (1992): Large-scale atmospheric controls on local precipitation intropical Mexico. Geophys Res Lett, 19, pp.1835–1838.

Hulme, M., Jenkins, G.J., Lu, X., Turnpenny, J.R. et al. (2002): Climate change scenarios for the United Kindom: the UKCIP02 Scientific Report. Tyndall Centre for Climate Change Research, University of East Anglia, Norwich

IPCC (Intergovernmental Panel on Climate Change) (2007): Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC (ed. by S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor & H. L. Miller). Cambridge University Press, Cambridge, UK.

Mendes, D. and Marengo, J.A. (2010): Temporal downscaling: a comparison between artificial neural network and autocorrelation techniques over the Amazon Basin in present and future climate change scenarios, Theor Appl Climatol, 100, pp.413–421.

Pope, V.D., Gallani, M.L., Rowntree, P.R. and Stratton, R.A. (2000): The impact of new physical parameterizations in the Hadley Centre climate model: HadAM3, Clim. Dyn., 16, pp. 123–146.

Sailor, D.J., Hu, T., Li, X. and Rosen, J.N. (2000): A neural network approach to local downscaling of GCM output for assessing wind power implications of climate change, Renew Energy, 19, pp.359–378.

Schoof, J. T. and Pryor S. C. (2001): Downscaling temperature and precipitation: A comparison of regression-based methods and artificial neural networks, Int. J. Climatol., 21, 773–790.

Webb BW and Walling DE (1993): Longer term water temperature behaviour in an upland stream. Hydrol Process, 7:19-32.

Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J. and Wilks, D.S. (1998): Statistical downscaling of general circulation model output: a comparison of methods, Water Res., 34, pp.2995–3008

Wilby, R.L., Hay, L.E. and Leavesley, G.H. (1999): A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado, J. Hydrol., 225, pp.67–91

Wilby, R. L., Dawson, C. W. and Barrow, E. M. (2002): SDSM: A decision support tool for the assessment of regional climate change impacts, Environ. Modell. Software, 17, pp.147– 159.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P. and Mearns, L. O. (2004): Guidelines for Use of Climate Scenarios developed from Statistical Downscaling Methods. Task Group on Data and Scenario Support for Impact and Climate Analysis, Environment Agency of England and Wales, UK.

Wilby, R. L. and Dawson, C. W. (2007): Using SDSM Version 4.1 – A decision support tool for the assessment of regional climate change impacts. User Manual.

Xu, C. Y. (1999): From GCM to river flow: A review of downscaling methods and hydrologic modeling approaches, Prog. Phys. Geogr., 23(2), pp.229–249.

# ダウンスケーリングしたGCMデータによる寒冷地域における河川水温の統計解析

賀　斌*・寶　馨・山敷　庸亮・小林　健一郎*・羅　平平**

*学際融合教育研究推進センター・極端気象適応社会教育ユニット
**京都大学・工学研究科

## 要　旨

河川水温の上昇は，水質や生態系に重大な影響を及ぼすことが懸念される。本研究は，寒冷地域における河川水温の長期間(現在と将来)変動の解析を目的とする。まず，札幌における長期間（1961年-2001年）の季節変動と年変動を解析する。その後，将来の水温を予測するため，統計的ダウンスケーリング法を用い，北海道における将来の日単位気温をダウンスケーリングする。また，札幌における観測された日単位の気温と水温の関係を解析し，米国大気海洋庁の NCEP 再解析データ(1961-2000)と英国ハドレーセンター(Hadley Centre)のHadCM3(Hadley Climate Model)のGCMデータ(1961-2099)を用い，札幌における将来の河川水温を予測する。

**キーワード**：寒冷地域，河川の水温，ダウンスケーリング，統計解析