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SDSM — a decision support tool for the assessment of regional climate change impacts

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Abstract

General Circulation Models (GCMs) suggest that rising concentrations of greenhouse gases will have significant implications for climate at global and regional scales. Less certain is the extent to which meteorological processes at individual sites will be affected. So-called 'downscaling' techniques are used to bridge the spatial and temporal resolution gaps between what climate modellers are currently able to provide and what impact assessors require. This paper describes a decision support tool for assessing local climate change impacts using a robust statistical downscaling technique. Statistical DownScaling Model (SDSM) facilitates the rapid development of multiple, low-cost, single-site scenarios of daily surface weather variables under current and future regional climate forcing. Additionally, the software performs ancillary tasks of predictor variable pre-screening, model calibration, basic diagnostic testing, statistical analyses and graphing of climate data. The application of SDSM is demonstrated with respect to the generation of daily temperature and precipitation scenarios for Toronto, Canada by 2040–2069.

Keywords: Downscaling; General circulation models; Climate change; Scenario; Canada

Software availability

Name of the product: SDSM (version 2.1)
Developed by: Robert L. Wilby and Christian W. Dawson
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Available since: 2000
Coding language: Visual Basic 6.0
Hardware requirement: PC Windows 95 or above
Program size: 3 MB RAM, 3 MB ROM
Availability: C.W.Dawson1@lboro.ac.uk
Cost: Freeware

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1. Introduction

> Even if global climate models in the future are run at high resolution there will remain the need to 'downscale' the results from such models to individual sites or localities for impact studies (Department of the Environment, 1996; p. 34)

General Circulation Models (GCMs) suggest that rising concentrations of greenhouse gases will have significant implications for climate at global and regional scales. Unfortunately, GCMs are restricted in their usefulness for local impact studies by their coarse spatial resolution (typically of the order 50,000 km^2) and inability to resolve important sub-grid scale features such as clouds and topography. As a consequence, two groups of techniques have emerged as a means of relating regional-scale atmospheric predictor variables to local-scale surface weather. Firstly, statistical downscaling is analogous to the 'model output statistics' (MOS) and 'perfect prog' approaches used for short-range numerical weather prediction (Klein and Glahn, 1974). Secondly, Regional Climate Models (RCMs) simulate sub-GCM grid-scale climate features dynamically using time-varying atmospheric conditions supplied by a GCM bounding a specified domain. Both approaches will continue to play a significant role in the assessment of potential climate change impacts arising from future increases in greenhouse-gas concentrations (IPCC-TGCIA, 1999).

As the following paragraphs indicate, statistical downscaling methodologies have several practical advantages over dynamical downscaling approaches. In situations where a low-cost, rapid assessment of highly localized climate change impacts is required, statistical downscaling (currently) represents the more promising option. In this paper we describe a software package, and accompanying statistical downscaling methodology, that enables the construction of climate change scenarios for individual sites at *daily* time-scales, using grid resolution GCM output. The software is named Statistical DownScaling Model (SDSM) and is coded in Visual Basic 6.0.

As far as the authors are aware, SDSM is the first tool of its type offered to the broader climate change impacts community. Most statistical downscaling models are generally restricted in their use to specialist researchers and/or research establishments. Other software, while more accessible, produces relatively coarse regional scenarios of climate change (both spatially and temporally). For example, SCENGEN (Hulme et al., 1995) blends and re-scales user-defined combinations of GCM experiments, and then interpolates monthly climate change scenarios onto a 5° latitude×5° longitude global grid. 'Weather generators' — such as WGEN (Richardson, 1981), LARS-WG (Semenov and Barrow, 1997) or CLIGEN (Nicks et al., 1995) — are widely used in the hydrological and agricultural research communities, but do not *directly* employ GCM output in the scenario construction processes (Wilks, 1992).

Following a brief review of downscaling techniques, we describe the structure and operation of SDSM with respect to five distinct tasks: (1) preliminary screening of potential downscaling predictor variables; (2) assembly and calibration of SDSM(s); (3) synthesis of ensembles of *current* weather data using observed predictor variables; (4) generation of ensembles of *future* weather data using GCM-derived predictor variables; (5) diagnostic testing/analysis of observed data and climate change scenarios. The paper concludes with an application of SDSM to climate change scenario generation for Toronto, Canada, comparing downscaled daily precipitation and temperature series for 1961–1990 with 2040–2069.

2. Downscaling techniques

The general theory, limitations and practice of downscaling have been discussed in detail elsewhere (see Giorgi and Mearns, 1991; Wilby and Wigley, 1997; Xu, 1999). These reviews group downscaling methodologies into four main types: (a) dynamical climate modelling, (b) synoptic weather typing, (c) stochastic weather generation, or (d) regression-based approaches. Each family of techniques is briefly reviewed below.

2.1. Dynamical

Dynamical downscaling involves the nesting of a higher resolution RCM within a coarser resolution GCM (see McGregor, 1997; Giorgi and Mearns, 1999). The RCM uses the GCM to define time-varying atmospheric boundary conditions around a finite domain, within which the physical dynamics of the atmosphere are modelled using horizontal grid spacings of 20–50 km. The main limitation of RCMs is that they are as computationally demanding as GCMs (placing constraints on the feasible domain size, number of experiments and duration of simulations). The scenarios produced by RCMs are also sensitive to the choice of boundary conditions (such as soil moisture) used to initiate experiments. The main advantage of RCMs is that they can resolve smaller-scale atmospheric features such as orographic precipitation or low-level jets better than the host GCM. Furthermore, RCMs can be used to explore the relative significance of different external forcings such as terrestrial-ecosystem or atmospheric chemistry changes.

2.2. Weather typing

Weather typing approaches involve grouping local, meteorological variables in relation to different classes of atmospheric circulation (Hay et al., 1991; Bardossy and Plate, 1992; von Storch et al., 1993). Future regional climate scenarios are constructed, either by resampling from the observed variable distributions (conditional on the circulation patterns produced by a GCM), or by first generating synthetic sequences of weather patterns using Monte Carlo techniques and resampling from observed data. The main appeal of circulation-based downscaling is that it is founded on sensible linkages between climate on the large scale and weather at the local scale. The technique is also valid for a wide variety of environmental variables as well as multi-site applications. However, weather typing schemes are often parochial, an inadequate basis for simulating rare or extreme events, and entirely dependent on stationary circulation-to-surface climate relationships. Potentially, the most serious limitation is that precipitation changes produced by changes in the frequency of weather patterns are seldom consistent with the changes produced by the host GCM (unless additional predictors such as atmospheric humidity are employed).

2.3. Stochastic weather generation

Stochastic downscaling approaches typically involve modifying the parameters of conventional weather generators such as WGEN (Wilks, 1999) or LARS-WG (Semenov and Barrow, 1997). WGEN simulates precipitation occurrence using two-state, first-order Markov chains: precipitation amounts on wet-days using a gamma distribution; temperature and radiation components using first-order trivariate autoregression that is conditional on precipitation occurrence (see the review of Wilks and Wilby, 1999). Climate change scenarios are generated stochastically using revised parameter sets scaled in direct proportion to the corresponding variable changes in a GCM. The main advantage of the technique is that it can exactly reproduce many observed climate statistics and has been widely used, particularly for agricultural impact assessment. Furthermore, stochastic weather generators enable the efficient production of large ensembles of scenarios for risk analysis. The key disadvantages relate to the arbitrary manner in which model parameters are defined for future climate conditions, and to the unanticipated effects that these changes may have on secondary variables.

2.4. Regression

Regression-based downscaling methods rely on empirical relationships between local-scale predictands and regional-scale predictor(s). Individual downscaling schemes differ according to the choice of mathematical transfer function, predictor variables or statistical fitting procedure. To date, linear and non-linear regression, artificial neural networks, canonical correlation and principal components analyses have all been used to derive predictor–predictand relationships (Conway et al., 1996; Schubert and Henderson-Sellers, 1997; Crane and Hewitson, 1998). The main strength of the regression downscaling is the relative ease of application, coupled with their use of observable trans-scale relationships. The main weakness of regression-based methods is that the models often explain only a fraction of the observed climate variability (especially in precipitation series). In common with weather typing methods, regression methods also assume validity of the model parameters under future climate conditions, and regression-based downscaling is highly sensitive to the choice of predictor variables and statistical transfer function (see below). Furthermore, downscaling future extreme events using regression methods is problematic since these phenomena, by definition, tend to lie at the margins or beyond the range of the calibration data set.

2.5. Relative skill of statistical and dynamical downscaling techniques

Given the wide range of downscaling techniques (both dynamical and statistical) there is an urgent need for model comparisons using generic data sets and model diagnostics. Until recently, these studies were restricted to statistical-versus-statistical (Winkler et al., 1997; Wilby et al., 1998a; Huth, 1999) or dynamical-versus-dynamical (Christensen et al., 1997; Takle et al., 1999) model comparisons. However, a growing number of studies are undertaking statistical-versus-dynamical model comparisons (Kidson and Thompson, 1998; Mearns et al., 1999a,b; Murphy, 1999; Wilby et al., 2000) and Table 1 lists some of the relative strengths and weaknesses that have been identified for the respective methods.

The consensus of model inter-comparison studies is that dynamical and statistical methods display similar levels of skill at estimating surface weather variables under *current* climate conditions. However, because of recognized inter-variable biases in host GCMs, assessing the realism of *future* climate change scenarios produced by statistical downscaling methods remains highly problematic. This is because uncertainties exist in *both* GCM and downscaled climate scenarios. For example, precipitation changes projected by the U.K. Meteorological Office coupled ocean-atmosphere model HadCM2, are known to be over-sensitive to future changes in atmospheric humidity (Murphy, 2000; Wilby and Wigley, 2000). Overall, the greatest obstacle to the successful implementation of both statistical and dynamical downscaling is the realism of the GCM output used to drive the schemes.

However, because of the parsimony and 'low-tech' advantages of statistical downscaling methods over dynamical modelling (Table 1), the following sections will report only the development and application of a multiple regression-based, decision support tool for regional climate change impact assessment.

3. Design and application of SDSM

Fig. 1 shows the Main Menu and functions of SDSM (version 2.1). The software reduces the task of statistically downscaling daily weather series into five discrete processes (denoted in Fig. 2 by the heavy boxes): (1) screening of predictor variables; (2) model calibration; (3) synthesis of observed data; (4) generation of climate change scenarios; (5) diagnostic testing and statistical analyses. Before describing the theory and practice underlying the software's five core operations, we first outline the assumed SDSM prerequisites and recommended file protocols.

Table 1
Comparison of the main strengths and weakness of statistical and dynamical downscaling

	Statistical downscaling	Dynamical downscaling
Strengths	•Station-scale climate information from GCM-scale output	•10–50 km resolution climate information from GCM-scale output
	•Cheap, computationally undemanding and readily transferable	•Respond in physically consistent ways to different external forcings
	•Ensembles of climate scenarios permit risk/uncertainty analyses	•Resolve atmospheric processes such as orographic precipitation
	•Flexibility	•Consistency with GCM
Weaknesses	•Dependent on the realism of GCM boundary forcing	•Dependent on the realism of GCM boundary forcing
	•Choice of domain size and location affects results	•Choice of domain size and location affects results
	•Requires high quality data for model calibration	•Requires significant computing resources
	•Predictor–predictand relationships are often non-stationary	•Ensembles of climate scenarios seldom produced
	•Choice of predictor variables affects results	•Initial boundary conditions affect results
	•Choice of empirical transfer scheme affects results	•Choice of cloud/convection scheme affects (precipitation) results
	•Low-frequency climate variability problematic	•Not readily transferred to new regions

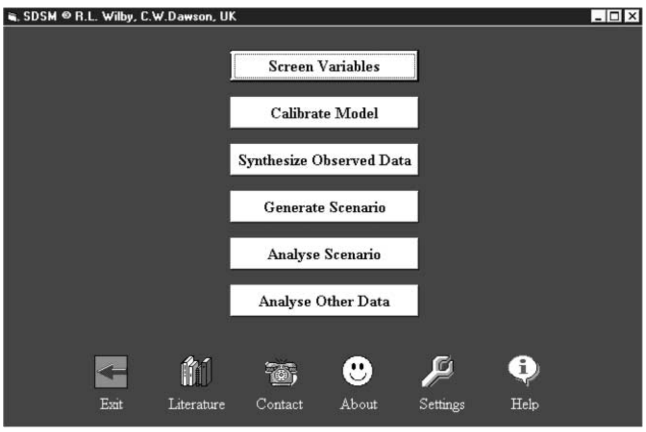

Fig. 1. Main menu of SDSM version 2.1.

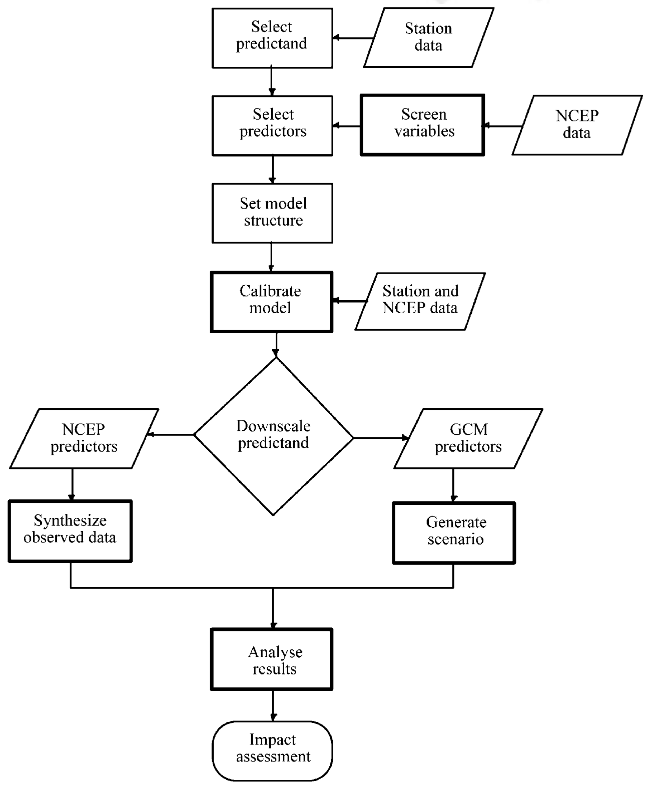

Fig. 2. SDSM climate scenario generation process.

3.1. SDSM *prerequisites and file protocols*

Downscaling is justified when GCM (or RCM) simulations of the required surface variable(s) are unrealistic at the temporal and spatial scales of interest — either because the impact scales are below the climate model's resolution, or because of model deficiencies — yet are considered realistic at larger scales and/or for other related variables. The choice of downscaling technique is governed largely by the availability of data for model calibration, and by the variables required for impact assessment. The same predictors should be available for target regions from both observed and GCM data.

Full technical details of the SDSM scheme are provided by Wilby et al. (1999). Within the taxonomy of downscaling techniques, SDSM is best described as a hybrid of the stochastic weather generator and regression-based methods. This is because large-scale circulation patterns and atmospheric moisture variables are used to linearly condition local-scale weather generator parameters (e.g. precipitation occurrence and intensity). Additionally, stochastic techniques are used to artificially inflate the variance of the downscaled daily time series to better accord with observations. To date, the downscaling algorithm of SDSM has been applied to a host of meteorological, hydrological and environmental assessments, as well as a range of geographical contexts including Europe, North America and Southeast Asia (Hassan et al., 1998; Wilby et al. 1999, 2000; Hay et al., 2000).

As Fig. 2 indicates, the SDSM procedure commences with the assembly of coincident predictor and predictand data sets. Although the predictands are typically individual daily weather series, obtained from meteorological observations at single sites (e.g. daily precipitation, maximum and minimum temperature, hours of sunshine, wind speed, etc.), the methodology is applicable to other environmental predictands (e.g. air quality parameters, sea levels, snow cover, etc.).

Assembly of a candidate predictor suite is, by comparison, a more involved process because virtually all statistical downscaling models employ gridded data such as the National Centre for Environmental Prediction (NCEP) re-analysis data set (Kalnay et al., 1996). This means that to apply SDSM to GCM data, both observed predictand and GCM data should ideally be available on the same grid spacing. However, observed and GCM predictor variables are seldom available at the same grid resolution, requiring interpolation and re-gridding of at least one of the data sets. Furthermore, the grid-box nearest to the target site does not always yield the strongest predictor–predictand relationships (see Wilby and Wigley, 2000). Therefore, the user should be prepared to consider geographically remote domains or arrays of grid points for *each* predictor variable.

As Karl et al. (1990) demonstrated, regression-based downscaling methods also benefit from the standardization of the predictor variables (by their respective means and standard deviations) so that the corresponding distributions of observed and present-day GCM predictors are in closer agreement. This ensures that future scenarios downscaled using GCM predictor variables (see below) are not compromised by systematic biases in climate model output. Furthermore, sufficient data should be available for both model calibration *and* validation. This is because the choice of the calibration period (and its length), as well as the mathematical form of the model relationship(s) and season definitions, all determine the statistical characteristics of the downscaled scenarios (the 'no analog' problem) (Winkler et al., 1997).

With the above prerequisites in mind, Table 2 lists the different file types employed by SDSM along with our recommended directory structure. All input and output files are single column, Text Only format. Individual predictor and predictand files (one variable to each file, time series data only) are denoted by the extension *.DAT. The equivalent GCM predictors should have the same file name but the extension *.GCM (e.g. T_{mean}.GCM is used instead of T_{mean}.DAT). This is necessary in order for the SDSM 'Synthesize' and 'Generate Scenario' functions (see below) to locate the correct predictor variables listed in the calibration output files, *.PAR, and underlines the importance of a clear directory structure. The *.SIM file records meta-data associated with every downscaled scenario (e.g. number of predictor variables, ensemble size, period, etc.), and the *.OUT file contains an array of daily downscaled values (one column for each ensemble member, and one row for each day of the scenario). Finally, the SCENARIO.TXT file is created whenever the 'Analyse' options are activated and records summary statistics for individual ensemble members or for the ensemble mean. This file is over-written each time either option is used.

3.2. Screen variables

Identifying empirical relationships between gridded predictors (such as mean sea level pressure) and single-site predictands (such as station precipitation) is central to all statistical downscaling methods. The main purpose of the 'Screen Variables' operation is to assist the user in the choice of appropriate downscaling predictor variables. This remains one of the most challenging stages in the development of any statistical downscaling model since the choice of predictors largely determines the character of the downscaled climate scenario (Winkler et al., 1997; Charles et al., 1999). The decision process is also complicated by the fact that the explanatory power of individual predictor variables varies both spatially (Huth, 1999) and temporally (Wilby, 1997).

Table 3 provides an example suite of daily predictor variables that might *potentially* be used to downscale surface variables such as daily precipitation, maximum

Table 2
SDSM file names and recommended directory structure

File extension	Explanation	Recommended directory
*.DAT	Observed daily predictor and predictand files employed by the calibrate and synthesize operations (input)	SDSM/calibration
*.PAR	Meta-data and model parameter file produced by the calibrate operation (output) and used by the synthesize and generate operations (input)	SDSM/calibration
*.GCM	GCM-derived predictor variable file employed by the generate operation (input)	SDSM/scenario_n
*.SIM	Meta-data produced by the synthesize and generate operations (output)	SDSM/results
*.OUT	Daily predictand variable file produced by the synthesize and generate operations (output)	SDSM/results
SCENARIO.TXT	Summary statistics produced by the analyse operations (output)	SDSM/results

Table 3
Candidate predictor variable definitions

Abbreviation	Description
Lag-1	Predictand value from previous day
Wet	Precipitation occurrence ('1'=wet, '0'=dry)
T_{mean}	2 m daily mean temperature (°C)
SH	Near surface specific humidity (gm/kg)
RH	Near surface relative humidity (%)
Mslp	Mean sea level pressure (hPa)
U[a]	Zonal component of geostrophic airflow (hPa)
V[a]	Meridional component of geostrophic airflow (hPa)
F[a]	Geostrophic airflow (hPa)
Z[a]	Vorticity (hPa)
z500	500 hPa geopotential height (m)

[a] Secondary variable derived from Mslp following the method of Jones et al. (1993).

and minimum temperatures, wind speed, solar radiation, etc. Ideally, candidate predictor variables should be: physically and conceptually sensible with respect to the predictand; strongly and consistently correlated with the predictand; readily available from archives of observed data and GCM output; and accurately modelled by GCMs. It is also recommended that the candidate predictor suite contain variables describing atmospheric circulation, thickness, stability and moisture content.

Having specified the target predictand along with an appropriate suite of potential predictor variables (including the lag-1 predictand in the case of autocorrelated time series), SDSM reports to the user only statistically significant predictor–predictand relationships. Significant pairs are expressed as percentages of explained variance, by month, at the specified confidence level. Unfortunately, as Fig. 3 indicates, the explanatory power of individual predictors can vary markedly on a month to month basis even for closely related predictands such as maximum and minimum daily temperatures (as shown). The user should, therefore, be judicious concerning the most appropriate combination(s) of predictor(s) for a given season and predictand. One solution may be to evaluate a predictor suite via off-line partial correlation or step-wise regression analyses. The local knowledge base is also invaluable in determining sensible combinations of predictors.

3.3. Calibrate model

The 'Calibrate Model' operation takes a user-specified predictand along with a set of predictor variables, and computes multiple linear regression equations (forced entry method). The user specifies the model structure: whether monthly, seasonal or annual sub-models are required; whether the process is unconditional or conditional; and whether or not a lag-1 autocorrelation function is required. The parameters of the regression model are obtained via the efficient dual simplex algorithm of Narula and Wellington (1977) and are written to a standard format file (*.PAR).

Unconditional models assume a direct link between the regional-scale predictors and the local predictand. For example, local wind speeds may be a function of gridded airflow indices such as the zonal or meridional velocity components. Conditional models, such as for daily precipitation amounts, depend on an intermediate variable such as the probability of wet-day occurrence. In this case, the two-state occurrence process (i.e. wet or dry day) is first modelled as a function of the regional forcing. Then, assuming that precipitation occurs, the wet-day amount is modelled conditional upon a different set of predictor weights (see below). Similarly, daily sunshine (h) might be modelled conditional on the presence or absence of precipitation.

Wet-day precipitation amounts are assumed to be

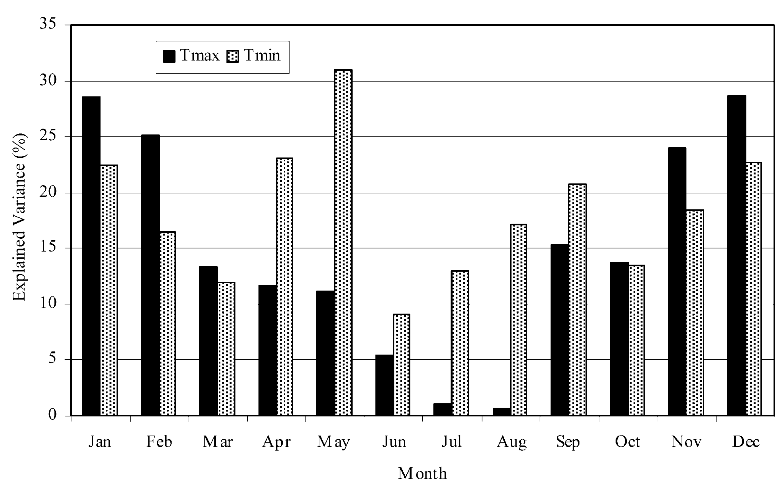

Fig. 3. Monthly variations in the percentage of variance explained in maximum and minimum daily temperatures by the meridional flow component of the surface geostrophic wind at Toronto, during the model calibration period 1981–1985.

exponentially distributed and are modelled using the regression procedure of Kilsby et al. (1998). The expected mean wet-day amount is empirically constrained by the algorithm to equal the observed mean wet-day amount of the calibration period. Note that precipitation amounts are a special case in which an autocorrelation function is *not* explicitly included by the regression equation. Instead, serial correlation between successive wet-day amounts may be incorporated implicitly by lagged predictor variables. This maximizes the availability of precipitation data for calibration by including wet-days that are preceded by dry-days.

Finally, the calibration algorithm reports the percentage of explained variance and standard error for each regression model type (monthly, seasonal or annual averages). These data should inform assessments of the *significance* of climate changes projected by the statistical downscaling (see below). For example, if the standard error of the model's maximum daily temperature is 4°C, and projected future temperature changes are smaller than this, then the model sensitivity to future climate forcing is less than the model accuracy (i.e. the temperature change could be an artefact of the model parameters rather than regional forcing).

Similarly, the percentage of explained variance indicates the extent to which daily variations in the local predictand are determined by regional forcing. For spatially conservative variables such as temperature 70%+ explained variance is not unusual; for heterogeneous variables such as daily precipitation occurrence/amounts <40% is more likely. Unfortunately, it is not possible to specify an 'acceptable' level of explained variance since model skill varies geographically, even for a common set of predictors. For example, precipitation models tend to be most skillful for locations on western seaboards where zonal airflows transport moisture directly from the ocean (McCabe and Dettinger, 1995).

3.4. Synthesize observed data

The 'Synthesize' operation generates ensembles of synthetic daily weather series given daily observed (or re-analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (ideally using independent data) as well as the synthesis of artificial time series for subsequent impacts modelling. The user simply selects a *.PAR file which contains references to all necessary *.DAT files (both predictand and predictors) along with associated regression model weights. The user must also specify the period of record to be synthesized as well as the desired number of ensemble members. Finally, synthetic time series are written to a user specified output file (*.OUT) for subsequent analysis and/or use for impacts modelling.

Individual ensemble members are considered equally plausible local climate scenarios realized by a common suite of regional-scale predictors. The extent to which time series of different ensemble members differ depends on the relative significance of the deterministic and stochastic components of the regression models used for downscaling. For example, local temperatures are largely determined by regional forcing whereas precipitation series display more 'noise' arising from local factors. The magnitude of deterministic forcing is indicated by the percentage of variance explained by the regression model (see above); the significance of the indeterminate or noise fraction by the standard error of the calibrated model.

SDSM version 2.1 uses the standard errors to stochastically reproduce the distribution of model residuals. Following the method of Rubinstein (1981), a pseudo random number generator reproduces values from a normal distribution with standard deviation equal to the calibration standard error. This stochastic residual is added to the deterministic component on each day to inflate the variance of the downscaled series to accord better with daily observations. By adjusting a kurtosis parameter (in the 'Settings' screen) it is also possible to accommodate leptokurtic (peaked) or platykurtic (flat) distributions of residuals. Alternatively, if the model residuals are not homoscedastic, or if a fully deterministic model is preferred, the stochastic component may be rendered inactivate by setting the kurtosis parameter to zero.

Conditional models incorporate an additional stochastic process. In the case of wet-day occurrence, regional predictors are used to determine the probability of precipitation (a value between zero and one), and a pseudo random number generator is used to determine the outcome (whether wet or dry). For example, if regional forcing indicates that the probability of precipitation occurrence, p=0.65, and the random number generator returns, $r \leq 0.65$, then rainfall occurs; if $r > 0.65$ then the day is dry.

Two parameters in the 'Settings' screen can be adjusted to modify this unconditional process. Firstly, the 'Event Threshold' can be increased so that non-zero days are treated as first-state days during model calibration. For example, when downscaling daily precipitation occurrence the parameter might be set to 0.3 mm/day to treat trace rain-days as dry-days. Similarly, the threshold for sunny versus cloudy days might be set at 1.0 h/day instead of the non-zero default. Secondly, the 'Bias Correction' parameter compensates for any tendency in the downscaling model to over- or under-inflate the variance of the conditional process.

3.5. Generate scenario

The 'Generate' scenario operation produces ensembles of synthetic daily weather series given observed daily atmospheric predictor variables supplied by a GCM (either for current or future climate experiments). The procedure is identical to that of the 'Synthesize' operation in all respects except that it may be necessary to specify a different convention for model dates. For example, HadCM2 assumes 12 months, each with 30 days, giving a fixed year length of 360 days. Alternatively, the Canadian Climate Center's CGCM1 model has 365 days in every year (i.e. does not recognize leap days). Note that there is a facility in the 'Settings' screen to de-activate leap years for downscaling using GCM data of this format. Note also that the input files (*.GCM) for both the 'Synthesize' and 'Generate' options need *not* be the same length as those used to obtain the regression weights during the calibration phase.

3.6. Analyse scenario/other data

The two 'Analyse' operations provide basic descriptive statistics for SDSM derived scenarios (both synthetic series and GCM derived scenarios) as well as for observed data in the standard *.DAT file format. The user specifies the file to be analysed, the required sub-period, ensemble member or mean, where appropriate. In return, SDSM computes the sample size, (percentage of days wet and monthly precipitation totals if rainfall is the specified variable), mean, maximum, minimum and variance of synthetic (or observed) daily weather series on a calendar month, and annual basis.

4. An illustration of SDSM application

Application of SDSM is demonstrated with respect to future precipitation and temperature scenario generation for Toronto, Canada. The procedure commenced with the selection of a limited set of regional-scale predictor variables from a larger suite of candidate variables describing atmospheric circulation, thickness, stability and moisture content over the target site (Table 3). All candidate variables were either obtained directly from the NCEP re-analysis (Kalnay et al., 1996), or were secondary variables derived from re-analysis data (e.g. daily vorticity is derived from mean sea level pressure). Predictors for the period 1981–1990 were extracted from the global fields (having first re-gridded the NCEP data to the GCM grid) for the re-analysis grid-box nearest to the target site. All predictors were standardized by their respective 10-year means and standard deviations. The first five years data (i.e. 1981–1985) were used for model calibration; the remaining five (i.e. 1986–1990) for independent model validation.

Candidate predictor variables were evaluated using the 'Screen Variables' operation and a partial correlation analysis conducted offline. Table 4 reports the most promising combinations of daily predictor variables (and corresponding predictand) when all data in the calibration period were combined (i.e. data were not stratified by month). The percentage of explained variance and standard error for daily precipitation amounts, maximum and minimum temperatures are also shown. In line with previous studies (Burger, 1996; Wilby et al., 1998b), calibrated models explain approximately 70%+ of the variance for daily temperature (maximum and minimum) and specific humidity (not shown), 40–60% for daily sunshine duration, solar radiation, wind speed and relative humidity (not shown), and less than 40% for precipitation. However, as shown by Fig. 3, these summary values conceal considerable seasonal variations in the skill of individual predictor variables.

Table 4
Partial correlation coefficients for predictor variables at Toronto 1981–1985. The **bold** values denote predictor variables selected for model calibration. The average percentage of explained variance (E%), and standard error (SE) for monthly models are also shown

Predictor	Predictand		
	T_{max} (°C)	T_{min} (°C)	Prec (mm)
Lag-1	0.15	**0.42**	0.03
Wet	−0.13	0.07	n/a
T_{mean}	**0.45**	**0.35**	−0.04
SH	0.14	0.03	**0.06**
RH	−0.20	0.02	−0.01
Mslp	−0.08	−0.03	−0.08
U	0.20	0.10	−0.04
V	−0.02	0.13	**0.40**
F	−0.01	0.12	0.04
Z	**−0.34**	−0.19	**0.20**
z500	0.11	0.07	−0.05
E (%)	73	72	28
SE	2.8	2.6	3.9

Fig. 4 compares observed and downscaled monthly mean wet-day occurrence and maximum wet-/dry-spell lengths at Toronto for the validation period 1986–1990. (Note that maximum spell-length statistics were chosen because these are notoriously difficult to reproduce in conventional weather generator models.) Monthly precipitation models were trained using daily observations at Toronto and the three regional predictors listed in Table 4 (specific humidity, meridional airflow and vorticity). Autocorrelation between successive wet-days was not explicitly incorporated (i.e. the lag-1 predictor was omitted). Nonetheless, the model captured the seasonal cycle of wet-day frequencies (winter maximum, summer minimum), and the weak autocorrelation between daily precipitation amounts (in both cases, r=+0.08). Overall, the model slightly over-estimated the frequency of wet-days, so the length of the average monthly maximum wet-spell was too long by +0.7 days, and the longest dry-spell too short by −1.8 days.

Mean wet-day amounts were downscaled using the same predictors, and conditional on the precipitation

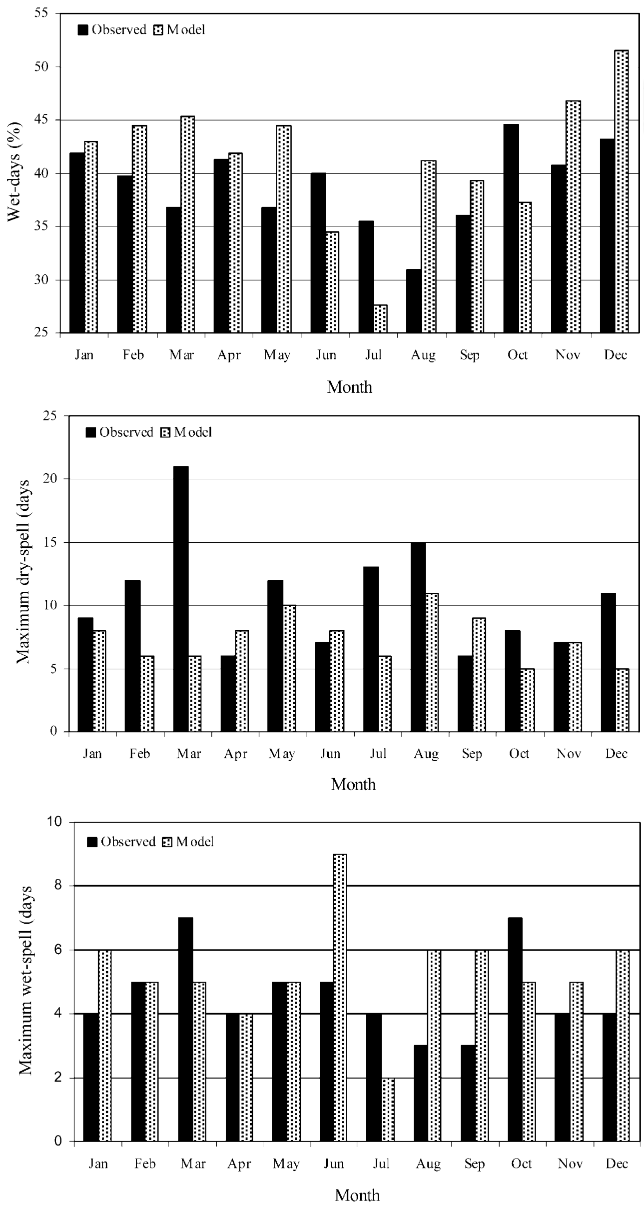

Fig. 4. Validation of downscaled monthly mean wet-day frequencies (% days), maximum dry-spell, and maximum wet-spell lengths (days) at Toronto, 1986–1990.

occurrence process. The global Bias Correction parameter was set to 0.62, and the kurtosis parameter to 3 (indicating a truncated distribution of residuals). This combination of parameters was found to best describe the variance of daily wet-day amounts in the calibration period. As Fig. 5 shows the resultant downscaling model reproduced the seasonal cycle of precipitation amounts and variance of the validation period, as well as the August/September maxima in each parameter. However, in line with other stochastic rainfall models, the variance of daily precipitation amounts was generally underestimated, most notably in summer.

Observed monthly means of maximum and minimum daily temperature at Toronto for 1986–1990 were reproduced by the downscaling model with an average error of 0.8°C (not shown) using the predictor variables listed in Table 4. In both cases, the residuals of the daily temperature models were found to be normally distributed and, therefore, amenable to stochastic simulation. As Fig. 6 illustrates, with variance inflation, the downscaling model better reproduced the observed variance of maximum daily temperatures in each month. Without variance inflation, the model consistently underestimated monthly variance.

Having re-trained the daily precipitation and temperature models using observed predictor–predictand relationships for the full 10 year record (1981–1990), the models were next used to downscale equivalent regional predictor variables supplied by the Canadian Climate Center's CGCM1 greenhouse-gas-plus-sulphate-aerosols experiment (Boer et al., 2000). Two 30-year time-slices were considered: 1961–1990 (indicative of current climate forcing) and 2040–2069 (indicative of future climate forcing). Following Karl et al. (1990) all predictor variables were standardized by the respective means and standard deviations of the corresponding predictor variables in 1961–1990 model output. For comparative purposes, changes in CGCM1 monthly mean precipitation and temperatures were computed for the grid-box closest to Toronto.

Fig. 7 shows percentage changes in monthly mean wet-day amounts at Toronto between 1961–1990 and 2040–2069 suggested by CGCM1 and the statistical downscaling model. According to SDSM, annual precipitation totals at Toronto are projected to increase by +9%, compared with +3% in CGCM1. Both models show decreases in August–September precipitation and a large increase in January totals. However, there is less agreement about the magnitude of expected increases in March, June–July, and November. Remaining months return conflicting results in terms of the direction of precipitation changes.

Figs. 8 and 9 show changes in monthly mean temperatures at Toronto between 1961–1990 and 2040–2069, for maximum and minimum daily values, respectively. For both variables, CGCM1 suggests greater warming than SDSM. Annual mean maximum daily temperatures change by +3.2°C in the CGCM1 scenario and by +2.9°C in the SDSM scenario. The equivalent changes in annual mean minimum temperatures are +4.0 and +2.9°C, respectively. Both methods indicate that the greatest warming will occur in the period January–April, with much less warming in the remainder of the year. It should also be noted that the downscaled changes in maximum and minimum temperatures are greater than the standard error of the model during these four months (see Table 4).

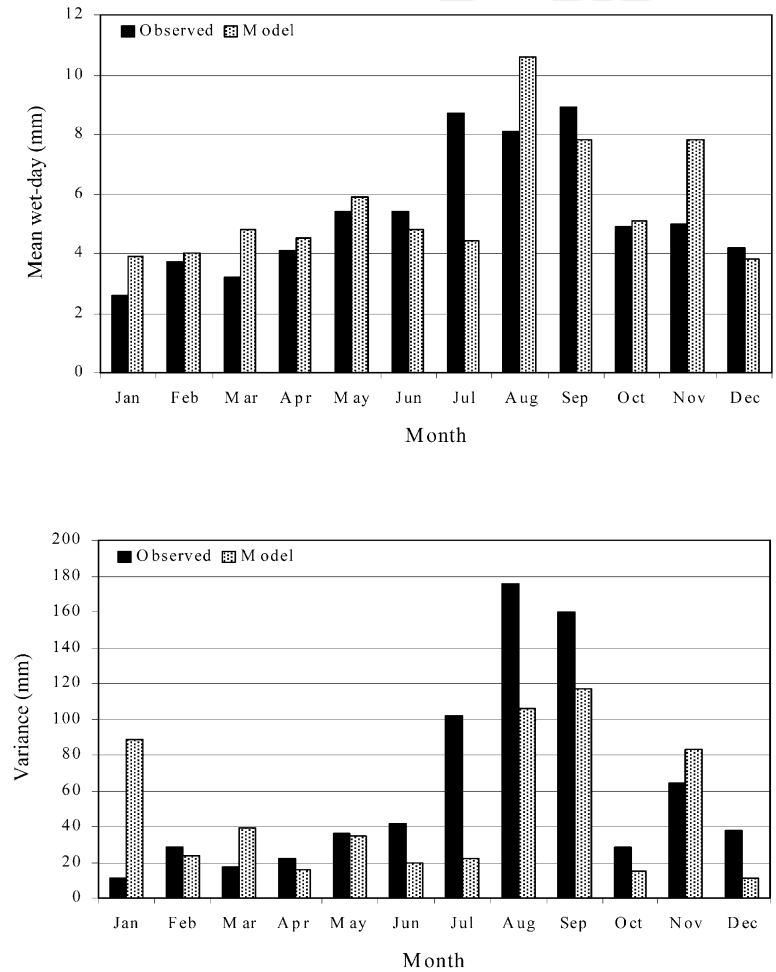

Fig. 5. Validation of downscaled monthly mean and variance of wet-day amounts (mm) at Toronto, 1986–1990.

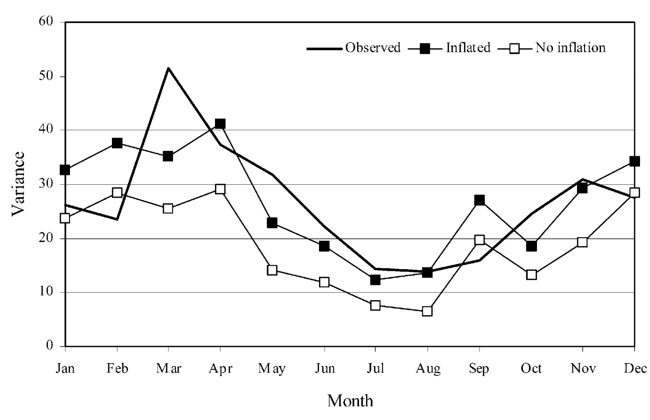

Fig. 6. Validation of downscaled monthly variances of maximum daily temperatures at Toronto, 1986–1990, with, and without, variance inflation.

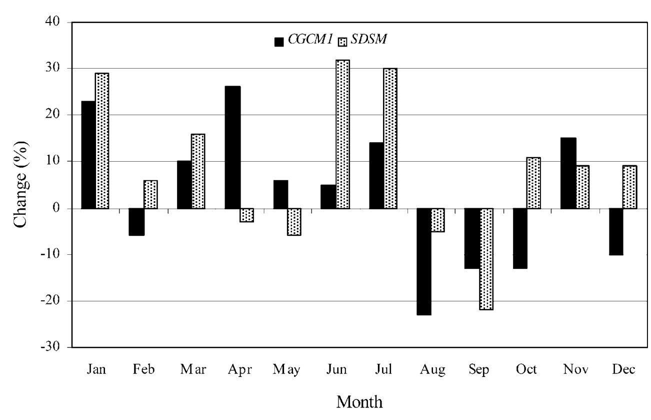

Fig. 7. Changes (%) in monthly mean wet-day amounts at Toronto between 1961–1990 and 2040–2069.

5. Conclusions

SDSM is a Windows-based decision support tool for the rapid development of single-site, ensemble scenarios of daily weather variables under current and future regional climate forcing. Version 2.1 performs the tasks required to statistically downscale GCM output, namely: screening of candidate predictor variables; model calibration; synthesis of current weather data; generation of future climate scenarios; diagnostic testing and basic statistical analyses. We note in passing, that many of these pro-

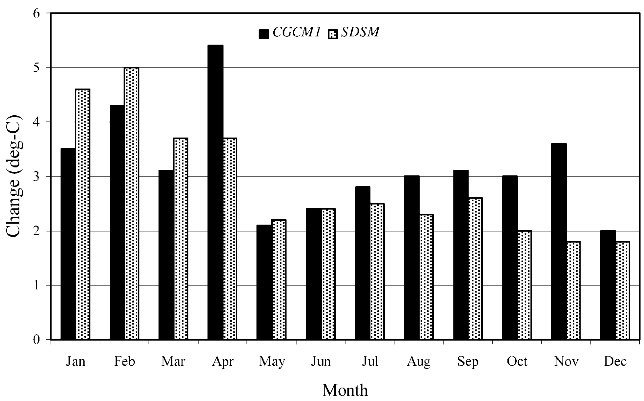

Fig. 8. Changes (°C) in monthly mean maximum daily temperatures at Toronto between 1961–1990 and 2040-2069.

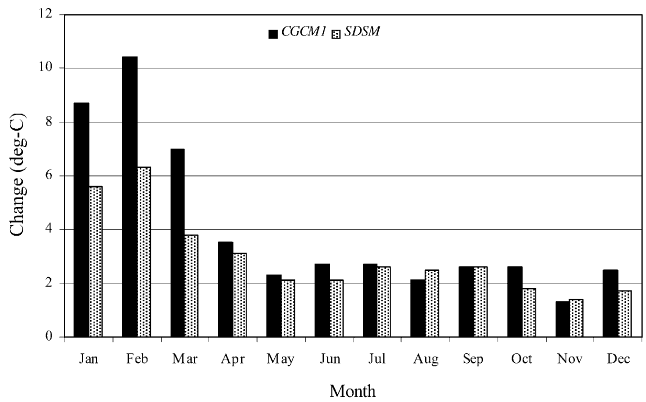

Fig. 9. Changes (°C) in monthly mean minimum daily temperatures at Toronto between 1961–1990 and 2040-2069.

cedures are transferable to seasonal forecasting of local weather variables using coarse-resolution numerical weather predictions (as in Lau et al., 1999).

As far as the authors are aware no comparable tool exists in the public domain — for downscaling ensembles of daily station data from the output of transient GCM runs. Nonetheless, the authors strongly caution that the software should not be used uncritically as a ‘black box’. Rather the selection of predictor variables should be based on physically sensible linkages between large-scale forcing and local meteorological response. Therefore, best practice demands the rigorous evaluation of candidate predictor–predictand relationships prior to downscaling.

To this end, several refinements of the existing software are currently in progress

- Presently, many predictor variables such as airflow indices (e.g. divergence and vorticity) must be computed outside SDSM. A web-based tool will enable the user to generate such variables directly from archives of observed and GCM-derived data by simply pointing and clicking on a map of the target region. Any re-gridding of observed predictors to conform to GCM grids will also be handled at the same time.
- Few meteorological stations have 100% complete and/or fully accurate data sets. Handling of missing and imperfect data is necessary for most practical situations. Simple quality control checks will also enable the identification of gross data errors prior to model calibration.
- More sophisticated data transformation and screening of candidate predictor variables are required. It is recognized that this step in the procedure still assumes a degree of local knowledge concerning the choice of most appropriate predictors. Additional statistics such as the cross-correlation matrix and partial correlations will enable the user to identify collinearity amongst potential predictors.
- A greater range of diagnostic tests will facilitate more comprehensive statistical analyses of observed and downscaled weather series. Favoured diagnostics include: skewness; peaks above/below thresholds; percentiles; wet- and dry-spell lengths; and measures of high-frequency persistence, such as the autocorrelation function. Graphing options that allow simultaneous comparisons amongst two data sets will also enable more rapid assessment of downscaled versus observed, or current versus future climate scenarios. Furthermore, the user will be able to specify suites of diagnostics from a generic list of statistical tests.
- A graphical interface will enhance the visualization of model outputs, to facilitate rapid reporting of model skill and/or local climate changes. This will be in the form of time-series plots, simple scatter plots and seasonal/monthly bar charts.

All the above enhancements are being included in SDSM version 2.2, scheduled for release in September 2001. Daily precipitation amounts at individual stations continue to be the most problematic variable to downscale, and research is ongoing to address this limitation. Multisite downscaling may also be tackled in subsequent versions of SDSM. In the meantime, the authors would welcome any further suggestions about the design or application of SDSM, particularly from the wider climate change impacts community.

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