AUTOMATED STATISTICAL DOWNSCALING

By Masoud Hessami, Philippe Gachon, Taha B.M.J. Ouarda, and André St-Hilaire

ASD User's Guide

For use with MATLAB

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ASD VERSION 1.1

November, 2007

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Chapter 1

Introduction

Climate change scenarios developed from Global Climate Models (GCMs) are the initial source of information for estimating plausible future climate. However, the spatial resolution of GCMs is too coarse to resolve regional scale effects and for the output to be used directly in local impact studies. Downscaling techniques potentially offer a way of improving regional or local estimates of variables from GCM outputs.

Downscaling methods, as reviewed in Wilby and Wigley (1997) and more recently in Wilby et al. (2004) and in Mearns et al. (2003), are divided into four general categories: regression methods (e.g. Hewitson and Crane, 1996; Wilby et al., 1999), weather pattern approaches (e.g. Yarnal, 2001), stochastic weather generators (e.g. Richardson, 1981; Racsko et al, 1991; Semenov and Barrow, 1997; Bates et al, 1998) and limited-area climate models (e.g. Mearns et al., 1995). Among these approaches, regression methods are regularly used because of their ease of implementation and their low computational requirements. Statistical downscaling is based on the fundamental assumption that regional climate is conditioned by local physiographic characteristics as well as the large scale atmospheric state. Based on this assumption, statistical relationships between local observed meteorological variables (the "predictands") and observed large scale climate fields (the "predictors") may be developed. GCM simulations can then provide information about future large scale atmospheric conditions and, in conjunction with these statistical models, be used to downscale to the local level. The major weaknesses of statistical downscaling methods are that the fundamental assumptions on which they are based are not verifiable, i.e. that the statistical relationships developed for the present day climate also hold under different forcing conditions of plausible future climate (e.g. Wilby et al., 2004), and that they cannot explicitly describe the physical processes that affect climate. In spite of these limitations, these methods may be helpful for impact studies in heterogeneous environments and/or for generating large ensembles or transient scenarios.

Automated statistical downscaling model

An automated regression-based statistical downscaling model (ASD, see Hessami et al., 2008), inspired by the existing Statistical Downscaling Model (SDSM; developed by Wilby et al., 2002) was developed within the Matlab environment (The Mathworks, 2002). Figure 1 shows the general scheme of the ASD framework for generating climate scenario information.

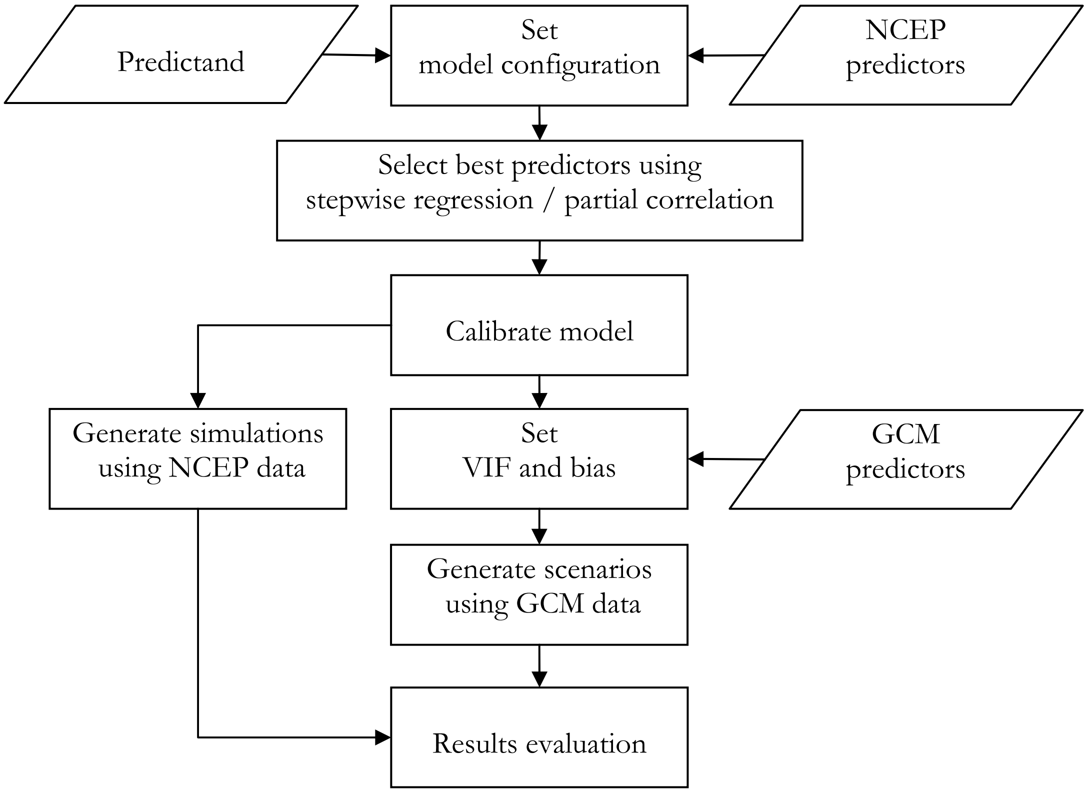

Figure 1: ASD architecture

The model process can be conditional on the occurrence of an event (i.e. for precipitation) or unconditional (i.e. for temperature). Hence, the modelling of daily precipitation involves the following two steps: modeling precipitation occurrence followed by the modeling of precipitation amounts (if precipitation occurs), as described in Wilby et al. (1999) and Hessami et al. (2008):

$$O_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j p_{ij} \ , \qquad R_i^{0.25} = \beta_0 + \sum_{j=1}^{n} \beta_j p_{ij} + e_i \quad (1)$$

where O_i is the daily precipitation occurrence, R_i are daily precipitation amounts, p_{ij} are predictors, *n* is number of predictors, α and β are model parameters and e_i is modeling error. The modeling of daily temperature is performed in one step:

$$T_i = \gamma_0 + \sum_{j=1}^{n} \gamma_j p_{ij} + e_i \qquad (2)$$

where T_i is the daily temperature (maximum, minimum or mean) and γ is the model parameter. Once the deterministic component is obtained, the residual term e_i is modeled under the assumption that it follows a Gaussian distribution:

$$e_i = \sqrt{VIF/12}\, z_i S_e + b \qquad (3)$$

where z_i is a normally distributed random number, S_e is the standard error of estimate, b is the model bias and VIF is the variance inflation factor. When calibrating the model, NCEP reanalysis data (e.g. National Centre for Environmental Prediction, Kalnay et al., 1996) must be used to represent observed large-scale atmospheric conditions, and the VIF and b values are set to 12 and zero, respectively, for generating scenarios to assess the performance of the model. When using GCM data for scenario generation, the VIF and the bias can be set automatically using the following equations:

$$b = M_{obs} - M_d \qquad (4)$$

$$VIF = \frac{12(V_{obs} - V_d)}{S_e^{\,2}} \qquad (5)$$

where V_{obs} is the variance of the observations during the calibration period, V_d is the variance of the deterministic part of model output during the calibration period, S_e is the standard error, M_{obs} and M_d are the mean of the observations and the mean of deterministic part of the model output during the calibration period, respectively.

Regression methods

Regression-based downscaling methods often use multiple linear regression, however the nonorthogonality of the predictor vectors can make the least squares estimates of the regression coefficients unstable. In addition to multiple linear regression, the ASD tool provides the option of using ridge regression (Hoerl and Kennard, 1970) to alleviate the effect of the nonorthogonality of the predictor vectors. The ridge regression coefficient b for the linear model y=Xb+e can be calculated from

$$b = (X^t X + kI)^{-1} X^t y \quad (6)$$

where I is an identity matrix and k is the ridge parameter. When k=0, b is the least squares estimator. The predictor variables should be first standardized to have zero mean and unit variance.

Predictor selection methods

In SDSM (Wilby et al., 2002), selection of predictors is an iterative process, partly based on the user's subjective judgment. In the ASD tool, we have implemented two methods based on backward stepwise regression (e.g. McCuen, 2003) and on partial correlation coefficients to select the predictors. Backward stepwise regression starts with all the terms in the model and removes the least significant terms until all the remaining terms are statistically significant. The partial *F*-test which can be used for either adding a predictor to the equation containing *q*-1 variables or removing a predictor from the equation containing *q* variables is :

$$F = \frac{(R_q^2 - R_{q-1}^2)(n-q-1)}{(1-R_q^2)} \quad (7)$$

where *n* is the number of observations, R_q and R_{q-1} are correlation coefficients between the criterion variable and a prediction equation having *q* and *q*-1 variables respectively. If *F* is greater than the critical *F* value, the predictor should be included in the equation. The critical *F* value is defined for a given level of significance and degrees of freedom 1 and n-q-1. A Bonferroni correction (Bonferroni, 1936) is used for the level of significance using the following formula:

$$\alpha = 1 - (1 - \frac{\alpha}{2})^{\frac{1}{q}} \quad (8)$$

where α is the level of significance and q is the number of predictors in the equation. The partial F-test must be computed for every predictor at each step of stepwise regression.

Partial correlation is the correlation between two variables after removing the linear effect of the third or more other variables. The partial correlation between variable *i* and *j* while controlling for third variable *k* is (e.g. Afifi and Clark, 1996):

$$R_{ij,k} = \frac{R_{ij} - R_{ik} R_{jk}}{\sqrt{(1 - R_{ik}^2)(1 - R_{jk}^2)}} \quad (9)$$

where R_{ij} is the correlation coefficient between variables i and j. For the partial correlation approach, the p-value is used for eliminating any one of the predictors. The p-value is computed by transforming the correlation *R* to create a *t*-statistic having *n*-2 degrees of freedom, where *n* is the number of observations:

$$t = \frac{R}{\sqrt{\frac{1 - R^2}{n - 2}}} \quad (10)$$

The probability of the *t*-statistic indicates whether the observed correlation occurred by chance if the true correlation is zero.

In the SDSM model, a recursive algorithm is implemented to compute partial correlations using equation 9. This recursive algorithm has a limitation, i.e. when the partial correlation between two variables is computed, the number of other variables that can be removed is limited to 12. However, the number of NCEP predictors used for partial correlation analysis is usually more than 20 (as suggested in Table 1). In the ASD tool, to control this limitation and allow fast computation, the following algorithm is used for partial correlation analysis. The correlation between y and x_1 controlling for x_2, x_3,…, x_m is obtained by computing the correlation between the residuals of the following two linear models:

$$y = f_1(x_2, x_3, ..., x_m) \quad (11)$$

$$x_1 = f_2(x_2, x_3, ..., x_m) \quad (12)$$

Chapter

2

Getting started with the ASD

The ASD tool is an easy to use graphical user interface for the statistical downscaling of GCM outputs to regional or local variables. ASD runs on all platforms that support MATLAB.

Before You Start

In order to run ASD you will need to provide daily observed local data (the predictand) and daily observed and GCM large-scale atmospheric data (the predictors). In Canada, daily observed local data can be obtained through Environment Canada – in particular daily data from the homogenised data set is available by contacting Lucie Vincent (temperature) and Eva Mekis (precipitation). Predictor data sets[1], including both observed (i.e. from NCEP reanalysis) and GCM outputs (i.e. three series of predictors currently available are from the last three versions of the Canadian coupled GCM and one series from the coupled British GCM, HadCM3), can be downloaded from the Canadian Climate Change Scenarios Network (www.cccsn.ca). These data sets contain the large-scale climate variables which are likely to have the largest influence on local climate (see Table 1). The ASD naming convention and file formats follow that of SDSM and predictor and predictand files prepared for use in ASD can also be used in SDSM. If you are planning on using the ASD tool for a number of sites, it is probably wise to set up separate directories for each site.

[1] Note: The GCM predictor files provided by the CCCSN are for the period 1961-2100. If you wish to downscale for particular time periods, e.g., the 2050s (2040-2069) you will need to extract the relevant period from the complete data set before using the ASD tool.

Table 1: Predictor variables available from the CCCSN and their associated acronyms. *Note that according to the considered GCM, relative humidity variables are not available and are replaced by specific humidity.

No.	Predictor	Code	No.	Predictor	Code
1	Mean sea level pressure	mslp	14	500hPa divergence	p5zh
2	1000hPa airflow strength	p__f	15	850hPa airflow strength	p8_f
3	1000hPa zonal velocity	p__u	16	850hPa zonal velocity	p8_u
4	1000hPa meridional velocity	p__v	17	850hPa meridional velocity	p8_v
5	1000hPa vorticity	p__z	18	850hPa vorticity	p8_z
6	1000hPa wind direction	p_th	19	850hPa geopotential height	p850
7	1000hPa divergence	p_zh	20	850hPa wind direction	p8th
8	500hPa airflow strength	p5_f	21	850hPa divergence	p8zh
9	500hPa zonal velocity	p5_u	22	Relative humidity* at 500hPa	r500
10	500hPa meridional velocity	p5_v	23	Relative humidity* at 850hPa	r850
11	500hPa vorticity	p5_z	24	1000hPa relative humidity*	rhum
12	500hPa geopotential height	p500	25	Specific humidity at 2 m	shum
13	500hPa wind direction	p5th	26	Mean temperature at 2m	temp

All input data files should be a single stream of data with each row representing a single daily value (see Figure 2), generally covering regular calendar year (including leap years) over 3 or 4 decades (e.g., 1961-1990 and/or 1961-2000). The predictor data sets are already in this format (and covering most of the time the 1961-1990 period), but you will probably need to reformat observed daily data files.

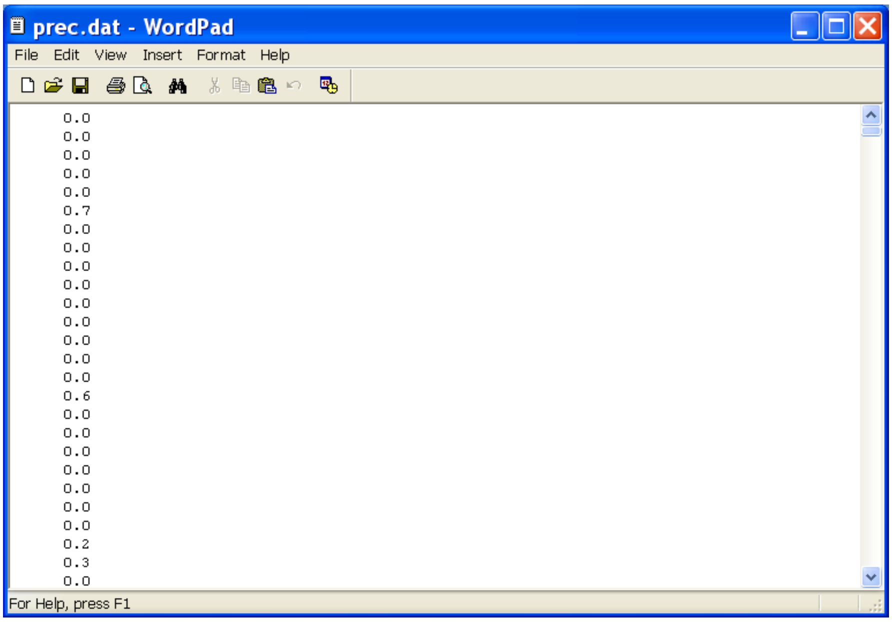

Figure 2: Example of the format required for the input data sets.

There are two other files which ideally need preparing before starting the ASD tool – **ncepdata.txt** and **gcmdata.txt**, although they may be created and/or edited whilst within the ASD environment. These files contain a list of the predictor files available for the NCEP data (observed large-scale atmospheric variables) and for the GCM in question. Examples of these files are provided with ASD (look in the c:\Program Files\ASD directory) and can be edited if necessary. The order of the file names contained in these two files must be exactly the same and for ASD to work correctly the same predictor variables should be available for both the NCEP and GCM data sets. There is little point in calibrating a statistical model containing a predictor variable which is not available in the GCM data set since, if it is identified as a significant variable and used in the statistical model, it will not then be possible to downscale future climate scenarios.

Starting ASD

Start MATLAB. At the top of the MATLAB main window you will see a Current Directory window containing the directory path of the MATLAB work directory (e.g., c:\MATLAB7\work). Change this directory path so that it shows the location of the ASD programs (e.g., c:\Program Files\ASD). To start ASD, type "asd" at the MATLAB prompt. The ASD main window opens (Figure 3).

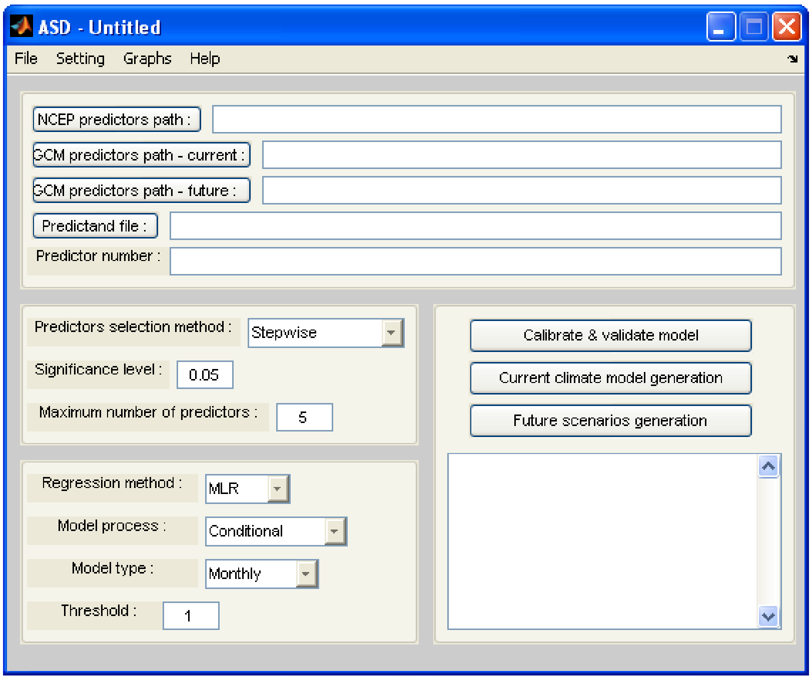

Figure 3: The main menu of the ASD (Automated Statistical Downscaling) tool

Summary of steps to use the ASD tool

The following list of steps outlines the main features of the ASD tool:

1. Click on the **Setting** menu at the top of the ASD main window and select the **NCEP predictors** or **GCM predictors** option from the drop-down menu to open **ncepdata.txt** or **gcmdata.txt** file (Figure 4). Both these files contain a list of the available predictor file names – the order of the list and the content in each file must be identical. Edit or replace the files if necessary.

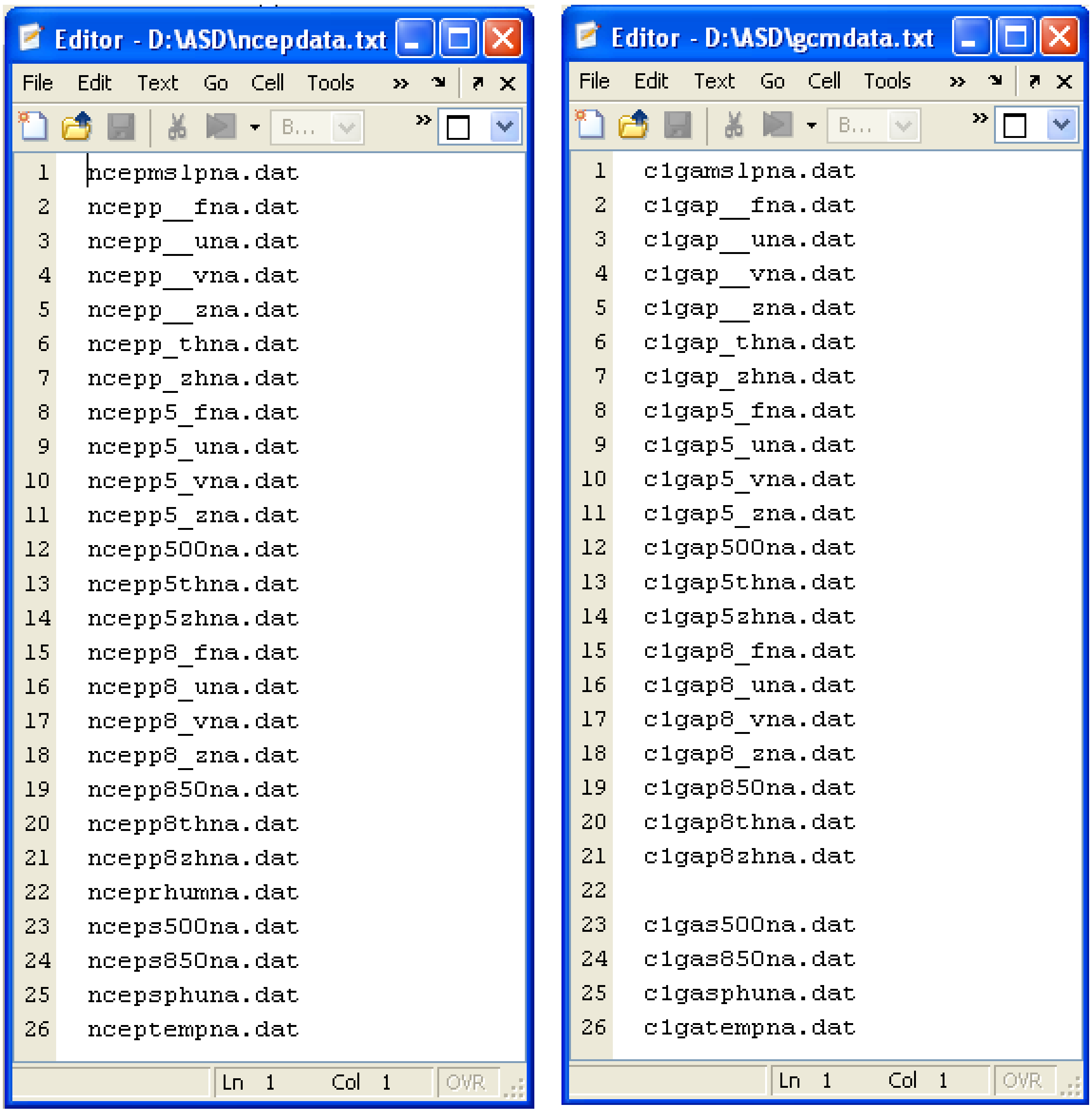

Figure 4: Predictors menu of ASD tool

2. Click on the **Setting** menu at the top of the ASD main window and select the **Parameters** option from the drop-down menu. Enter the start date of current data, the start date of future data, the calibration start and end dates, the validation start and end dates and the year length for GCM data[2] (Figure 5). Enter the Bias and VIF values manually or check the appropriate box to set them automatically (i.e. auto). These values are used only when generating scenarios using GCM predictor data. Enter the Percentile value that you would like to compute for the **Comparing Statistics** menu. Enter a threshold value for the identification of missing values (any values less than the threshold value will be treated as missing). Enter the number of scenarios you wish to generate (as for example in Figure 5, 100 synthetic data simulated series will be generated) and finally enter the projection periods (in Figure 5, 3 periods of 3 decades, centered over 2020s, 2050s and 2080s will be generated, respectively).

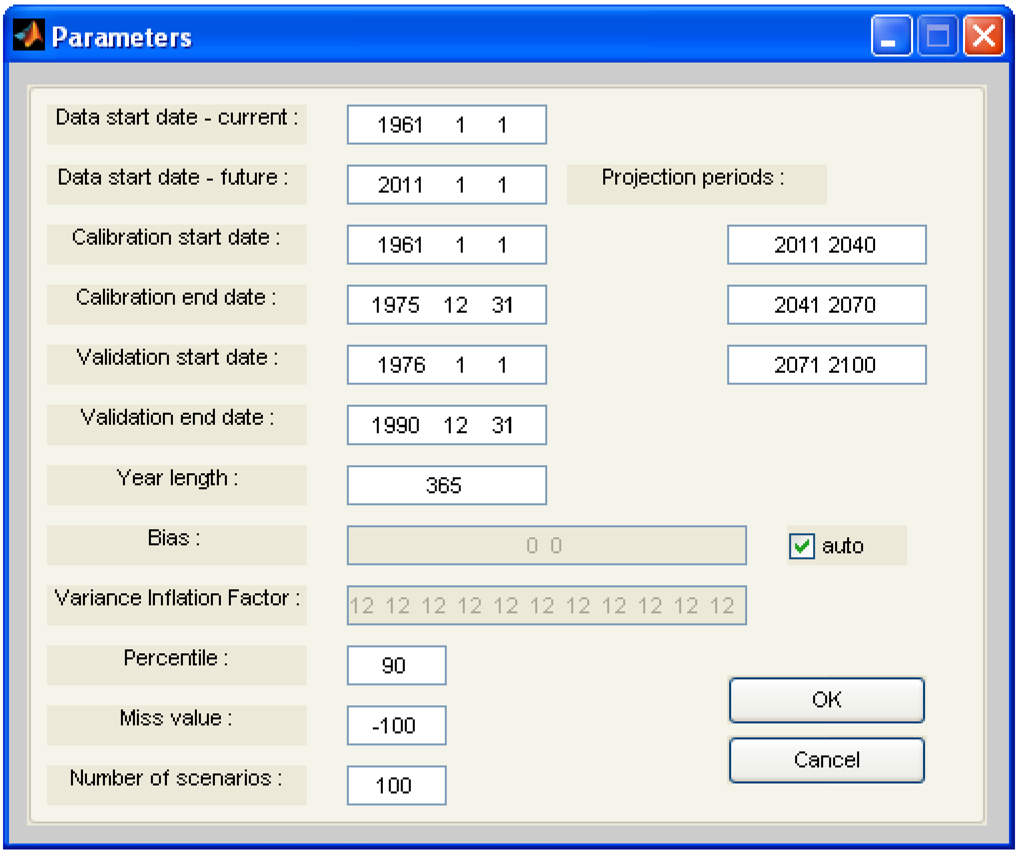

Figure 5: The ASD Parameters menu

[2] Some GCMs do not have a standard year length and most do not include leap years. You will need to check the number of days in a year for the GCM you are using. GCMs from the Canadian Centre for Climate Modelling and Analysis (e.g., CGCM1, CGCM2, CGCM3) have a 365-day year, whilst those from the Hadley Centre for Climate Prediction and Research (e.g., HadCM2, HadCM3) have a 360-day year.

3. Return to the ASD Main Menu and click on the NCEP predictors, GCM predictors and predictand buttons to browse through the directory tree to find the directory paths to the predictor and predictand data files (Figure 6). In the "predictor number" selection, enter the number of the predictors which you wish to be considered in the calibration process (e.g., 1:26 if the complete predictor data set is available, or, for example, 1:21 23 24, if only a subset of the complete suite is available). The predictor selection method gives three choices: stepwise, partial correlation or none (in this latter case, the process will be based on all predictors entered in the "predictor number"). In the present model, two methods are implemented based on backward stepwise regression and partial correlation coefficients to select the predictors (see further information in Hessami et al., 2008). The significance level value corresponds to the value used in the Partial F-Test equation (see eq. (8) in Hessami et al., 2008). You can select the level value at your convenience, as the default value is fixed at the 0.05 level (see Figure 6). The maximum number of predictors can be also selected, according to the number of available predictors used to develop the multi-linear regression equation. ASD offers the choice of two methods: in addition to multiple linear regression, the option of using ridge regression is allowed, especially to alleviate the effect of the nonorthogonality (i.e. colinearity) of the predictor vectors. One example about the usefulness of using the ridge regression is given in Hessami et al. (2008). The model process can be conditional on the occurrence of an event (i.e. for precipitation) or unconditional (i.e. for temperature). In the case of a conditional process, a transformation function is first applied (i.e. by default the fourth root transformation is used) in order to improve the performance of the multiple linear regression since these predictand data (i.e. precipitation) tend not to be normally distributed. For temperature, this not the case and the predictand data are generally used as is. Also, the model type can be based on monthly downscaling process or annual one (the two choices given in Model Type menu). As we are doing a statistical downscaling of precipitation in the example given in Figure 6, the model process is conditional and a threshold of 1mm/day (see the Threshold menu in Figure 6) is selected as the boundary between dry and wet days (< 1 mm/day and ≥ 1 mm/day, respectively). To calibrate the model and generate simulations using NCEP data, click on the **Calibrate & validate model** button. To generate scenarios using current and future GCM data, click on the **Current climate model generation** and **Future scenarios generation** buttons, respectively. (The actual values of the results of the calibration process and the data generated can be viewed in the Workspace window. If this window is not already displayed in the MATLAB main window, click on the **Window** menu and select **Workspace** or press

CNTL+3. Four variables will be displayed in this window: asdin (input variables), asdout (output variables), asdoutCGCM (output variables using the current period GCM data) and asdoutFGCM (output variables using the future period GCM data). If you double-click on any of the variables listed in the Workspace window, then the Array Editor opens with a list of the fields associated with each variable. Double-click on the desired field to display the values – these can be printed or you can select and copy them so that they can be pasted into another environment (e.g., Microsoft Excel.)

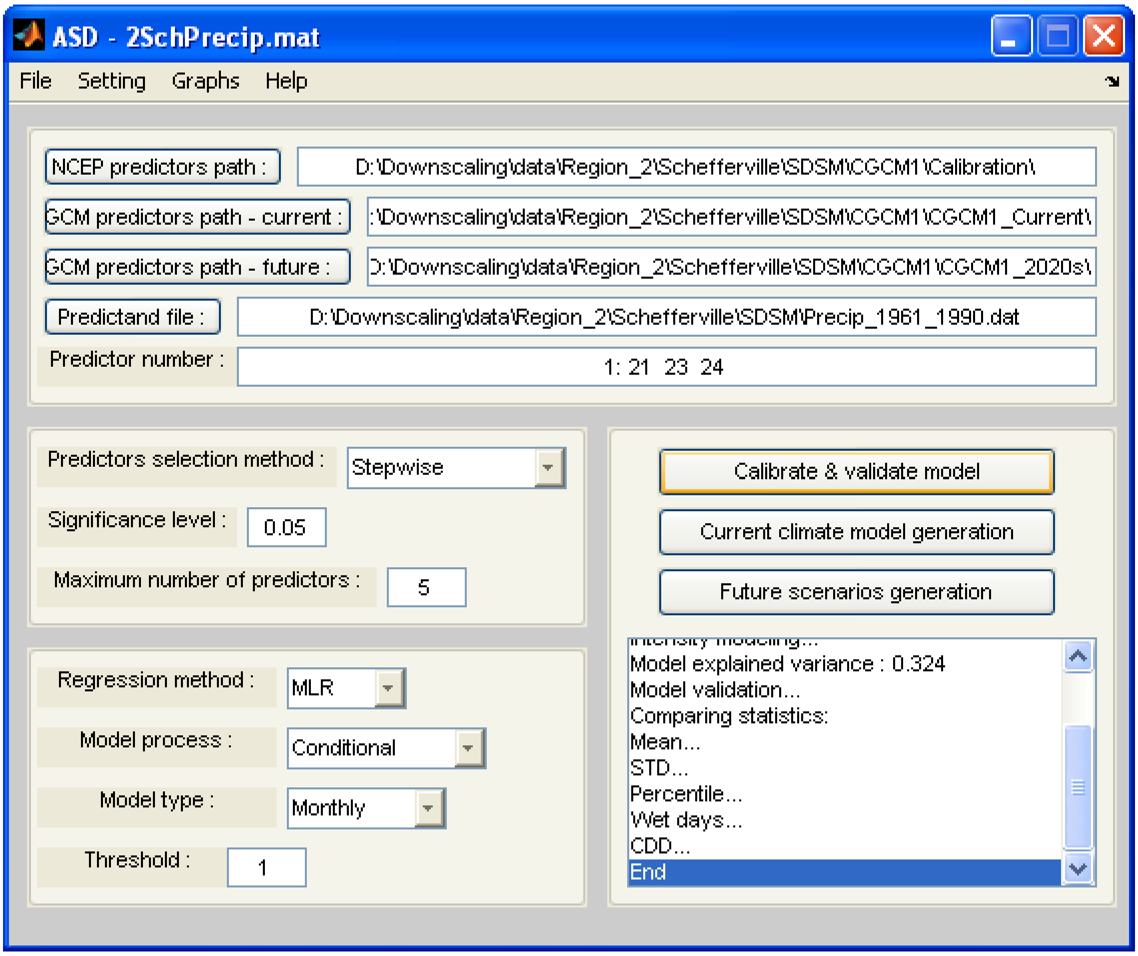

Figure 6: Main menu of the ASD tool

4. Click on the **Graphs** menu at the top of the ASD Main menu window and select **Correlation coefficients** from the drop-down menu. The correlations between the predictand and the NCEP predictors will be displayed (see Figure 7, 0 corresponds to the predictand and 1-26 to each predictor listed in Table 1). Click on the maximize window button in the top right-hand corner if the colour bar is not completely displayed. (All graphics can be customised by adding, for example, axis labels, titles etc. by clicking on the **Insert** menu on the graphics windows and

selecting the appropriate options. Graphics can also be copied and pasted into other applications using the appropriate commands on the **Edit** menu.)

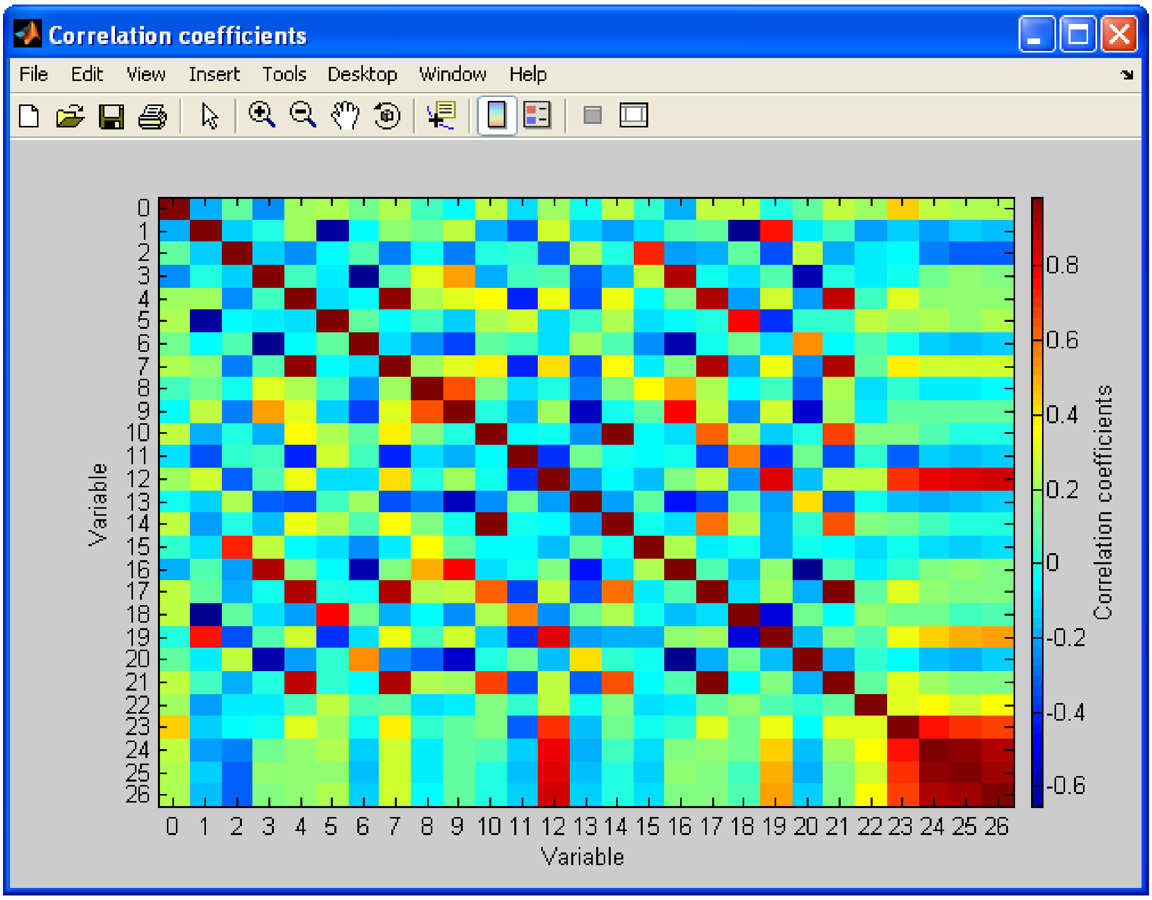

Figure 7: Correlation coefficients menu of ASD tool

5. Click on the **Graphs** menu at the top of the ASD Main menu window and select **Regression coefficients** from the drop-down menu. The model regression coefficients for the NCEP predictors identified as explaining the most variance in the predictand (up to the maximum number of predictors specified in the ASD Main menu) will be displayed per month (i.e. Model type is Monthly in that case as shown in Figure 8). Again, click on the maximize window button in the top right-hand corner if the colour bar is not completely displayed.

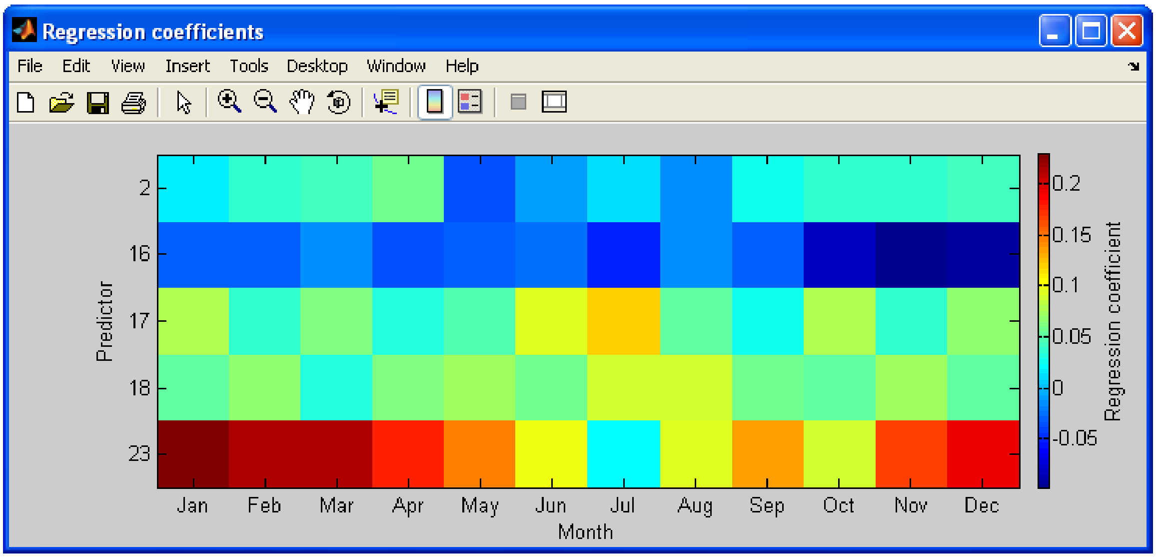

Figure 8: Regression coefficients menu of ASD tool

6. Click on the **Graphs** menu at the top of the ASD Main menu window and select **Boxplot** or **Bar-plot** from the drop-down menu. Then click on **NCEP**, **GCM–Current** and **GCM-Future** to compare the statistics for observations/NCEP data, observations/current GCM data and future GCM data respectively. Figure 9 shows the observed and simulated mean monthly values of precipitation obtained when using NCEP data, and the corresponding mean precipitation (mm/day) derived from observed data over the current period (1961-1990) and those downscaled over a future period (ex. 2011-2040) from the GCM predictors. Other statistical values which can be viewed are listed at the top of this window: standard deviation (STD), values for the selected percentile (i.e. that you have selected previously in the Parameters menu), percentage of wet days (Wet-day) and maximum number of consecutive dry days (CDD). For temperature variables, the mean, standard deviation, percentile, maximum and minimum absolute values can be viewed, printed or copied (as an image). All Box Plots are developed with the full ensemble runs, as the number was chosen in the Parameters menu (i.e. through the button "Number of scenarios", ex. 100 in Figure 5) from NCEP or GCM predictors. At the bottom of all Box Plots graphs, the Root Mean Square Error (RMSE) is given and this corresponds to annual mean values averaged from all monthly RMSE (for both the calibration and the validation periods).

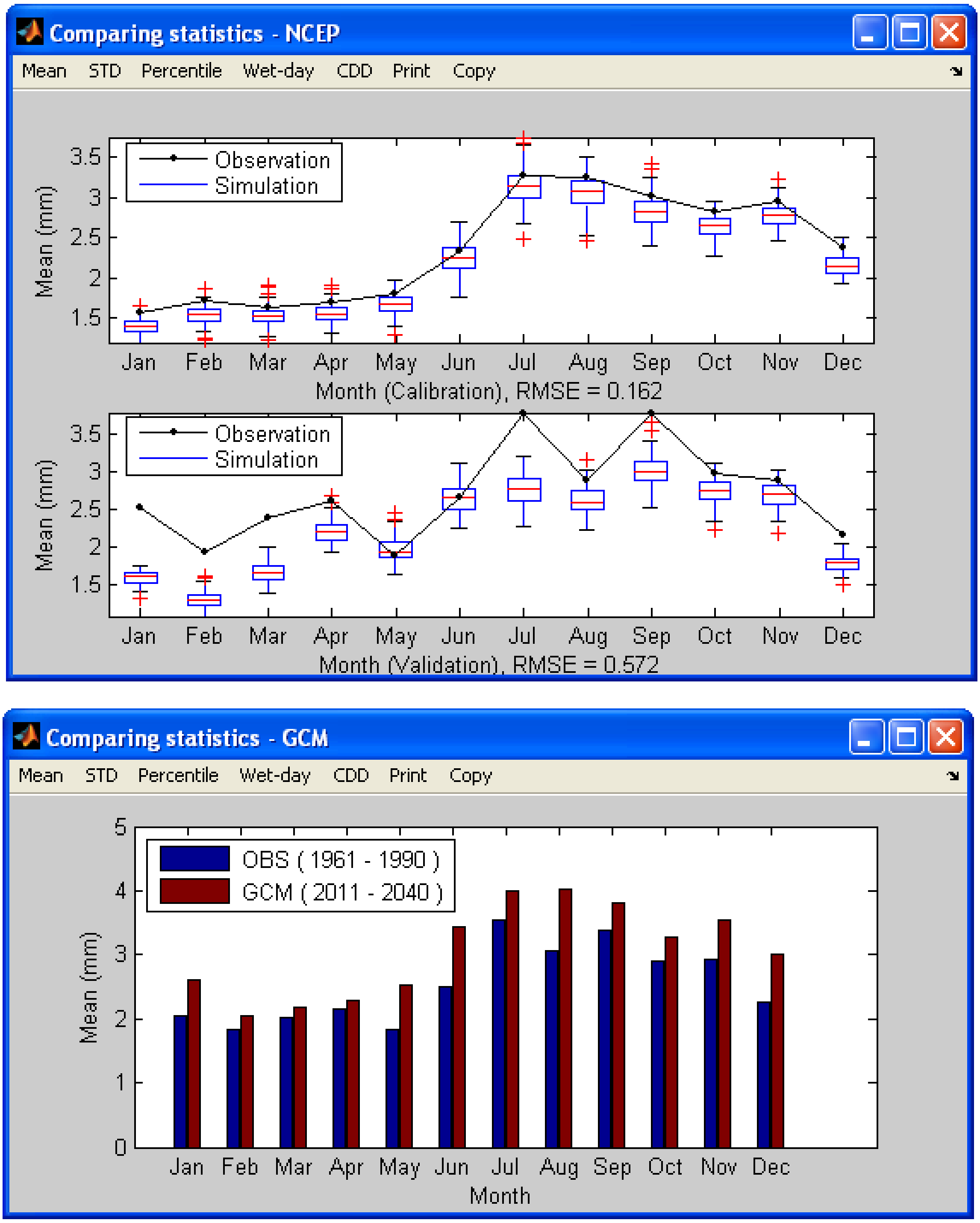

Figure 9: Comparing statistics menu of ASD tool

7. Click on the **Graphs** menu at the top of the ASD Main menu window and select **QQ-plot**[3] from the drop-down menu. Then click on **Calibration-NCEP**, **Validation-NCEP**,

[3] A quantile-quantile (q-q) plot can be used to determine if two datasets come from populations with a common distribution. In this type of plot, points are formed from the quantiles of the data and if the resulting points lie roughly on a line with a slope of 1, then the distributions are the same.

Calibration-GCM and **Validation-GCM** to see the Q-Q-plots between the observations and NCEP data and the Q-Q-plots between observations and GCM data for the calibration and validation periods (Figures 10 to 13, respectively). As for Box Plots, all Q-Q Plots are developed with the full ensemble runs, as the number was chosen in the Parameters menu (i.e. through the button "Number of scenarios", ex. 100 in Figure 5) from NCEP or GCM predictors. At the bottom of all Q-Q Plots graphs, RMSE is given and corresponds to mean values averaged over all 100 runs and quantiles (for both the calibration and the validation periods).

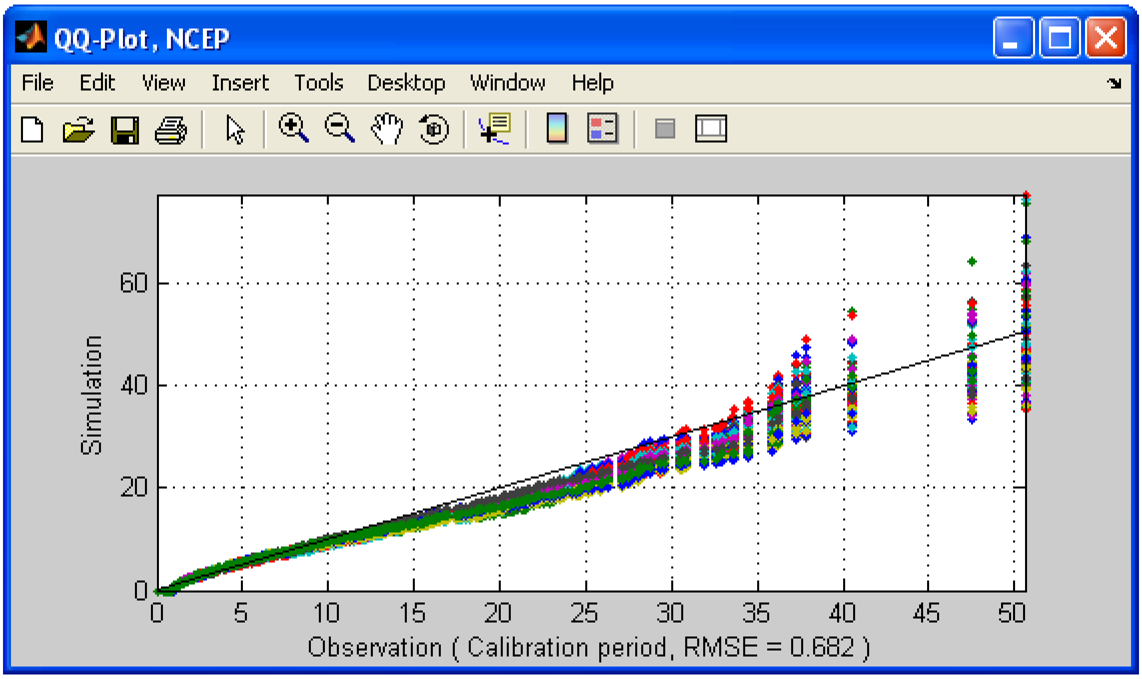

Figure 10: QQ-plot between observations and simulated values using NCEP data during the calibration period.

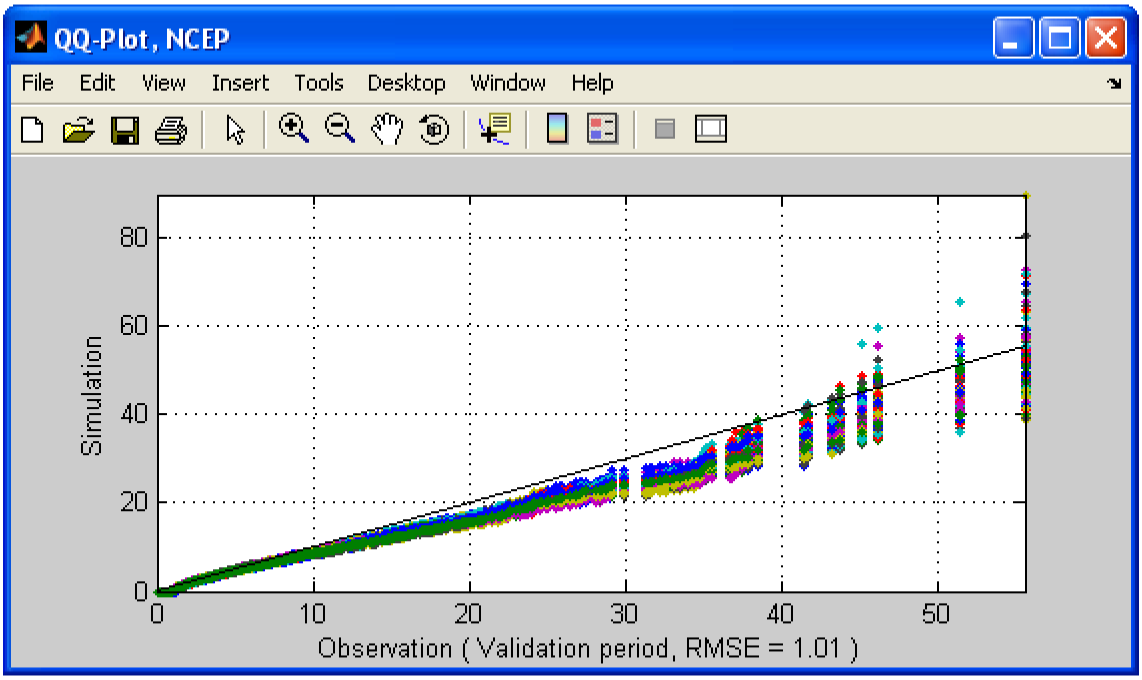

Figure 11: QQ-plot between observations and simulated values using NCEP data during the validation period.

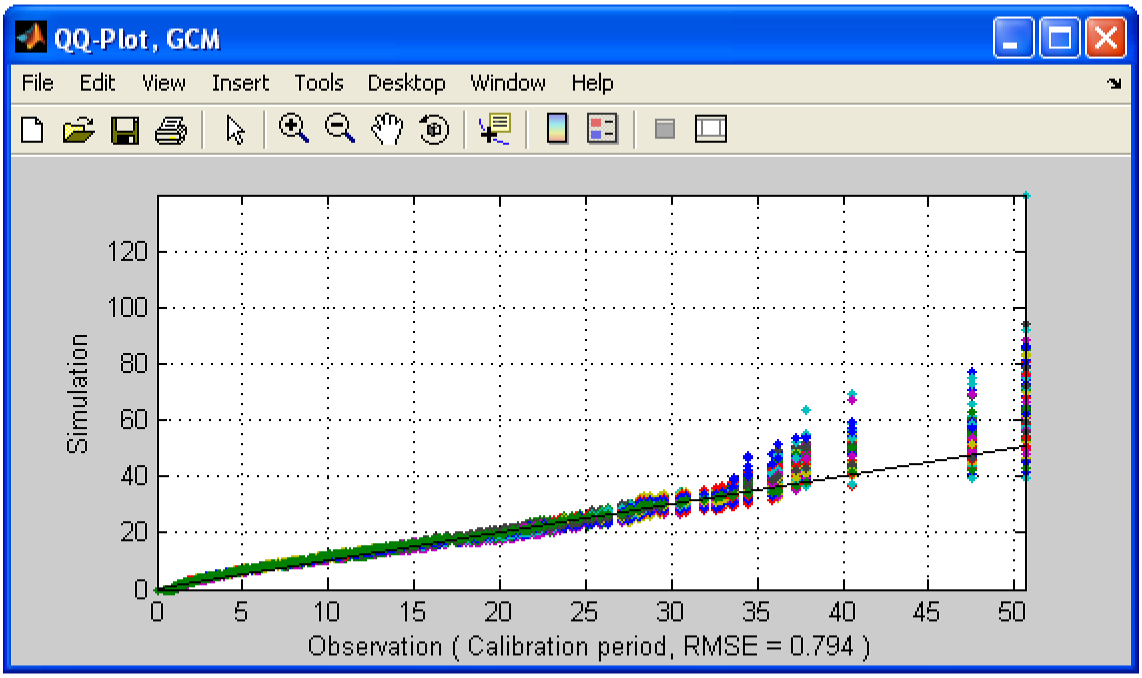

Figure 12: QQ-plot between observations and simulated values using GCM data during the calibration period.

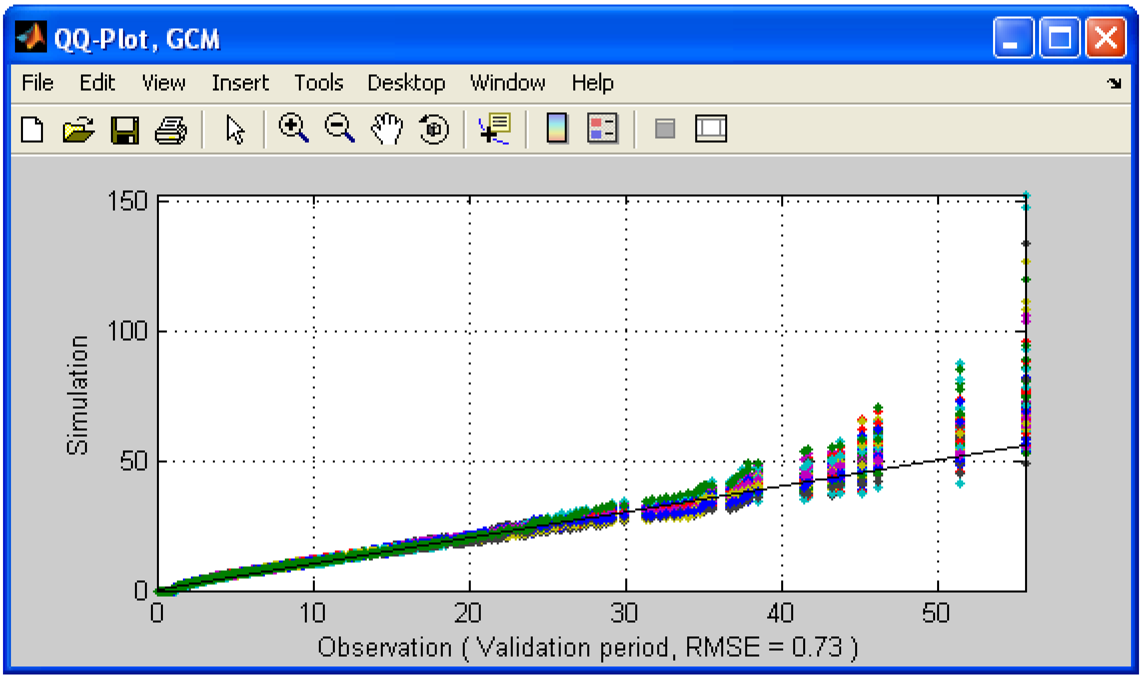

Figure 13: QQ-plot between observations and simulated values using GCM data during validation period.

Saving and retrieving parameters in ASD

To save the input and output parameters as well as the simulated runs from current and scenario data generated by the ASD tool, click on the **Save** option in the **File** menu on the ASD Main menu, browse to the desired directory and then type an appropriate filename. The output file extension will be *.mat. Next time, when ASD starts, you can easily retrieve the selected model parameters by clicking on **Open** in the **File** menu and selecting the file, or by typing **load *.mat** in the Command Window.

Examination of this *.mat file also provides the opportunity to view (and save or paste into other software packages) the values of the variables and data generated by ASD, including statistics and criteria of analysis as well as observed data for comparison over the current period. In order to view the values of the outputs, you need to have the MATLAB **Workspace** window displayed – if this is not already visible click on the **Window** menu and select **Workspace** from the drop-down menu, or press CNTL+3. Four variables will be displayed in this window: asdin (input variables), asdout (output variables), asdoutCGCM (output variables using the current period GCM data), and asdoutFGCM (output variables using the future period GCM data). (You can also see this list of variables by typing "who" at the command window prompt.) If you double-click on any of these variables listed in the Workspace window, then the Array Editor opens with a list of the fields associated with each variable. Double-click on the desired field to display the values – these can be printed or you can select and copy them so that they can be pasted into another environment (e.g., Microsoft Excel).

In the event that MATLAB cannot display the values for a particular field (there is a maximum number of elements that MATLAB can display) you can still save this information into an ASCII file. For example, if you wish to save the future scenario output, type asdoutFGCM.Scen at the command window prompt. The data for the number of scenarios generated will be displayed. If you type "who" again, a new variable is displayed – ans. To save this as an ASCII file, type (for example): save scenarios.dat ans –ascii. This file will be saved in the current directory (e.g., c:\Program Files\ASD) unless you specify a different directory path. More information about importing and exporting files can be found in the MATLAB Help facility.

Quitting the ASD

To quit the ASD tool, select **Exit** from the **File** menu, or click the close box.

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