Weather generator utilization in climate impact studies: Implications for water resources modelling

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Abstract: Weather generators are increasingly used in water resources studies, and more so with current concerns on climate change and its implications on the water resource. In general, generated weather data should go beyond matching values with observed data to mirroring statistical properties of observed data. With the use of generated data in future-cast studies, it is additionally important that generated data capture anticipated variabilities in climate. The generators, thus need to be evaluated prior to being applied in new areas and/or those with climate characteristics distinct from those in which they were developed. Furthermore, considering the stochasticity of weather, it is important that several realizations be generated to capture the range of variability in climate. We present some considerations based on experience with three commonly used climate generators: CLIGEN, LARS-WG, and WeaGETS. We then present a discussion on realizations and their impacts on the suitability of generated data. Finally, we discuss implications for water resources modelling.

Key words: Weather generators, statistical properties, realizations, modelling, water resources

1. INTRODUCTION

Weather generators are increasingly used in water resources studies to: provide model input, particularly where observed data are not consistent or available in sufficient quantities and consistence for modelling (Yu 2003, Fodor et al. 2013, Lemann et al. 2016); develop datasets for ungaged stations (Fodor et al. 2013); obtain localized predictions based on observed data (Al-Mukhtar et al. 2014); downscale from coarse resolution predictions (Semenov and Barrow 1997, Fatichi et al. 2011, Farzanmanesh et al. 2012); and provide flexibility needed for Monte Carlo simulations. Daily weather data are needed to run hydrologic, water quality, and crop-growth models. Thus, in addition to evaluating generated values on a daily time scale, it is especially important that these values also mirror the statistical properties (Semenov and Barrow 1997, Chen et al. 2012) and other essential characteristics of observed data. We discuss some important considerations in this regard with examples from work done with three commonly used generators CLIGEN (Nicks et al. 1995), LARS-WG (Racsko et al. 1991), and WeaGETS (Chen et al. 2012).

2. CONSIDERATIONS FOR WEATHER GENERATOR UTILIZATION

2.1 Selection of base time period from which to parameterize the generator

Parameterization generally involves obtaining average characteristics computed on a monthly or bi-weekly time period. The length of observed input data from which parameters are generated (base time period) is, therefore, important as it translates to the nature of the parameters. For example, considering a 75-year record and comparing daily precipitation values averaged on a
monthly basis across the entire dataset to those obtained on a 25-year and 10-year basis (Figure 1a): 1) For 25-year means, the period from 1966-1990 had lower mean daily values than that computed across the dataset while mean values were higher in 1991-2015; 2) For 10-year means, values were higher in 1941-1960 and 2011-2015 and generally lower in 1961-2000 than values obtained across the dataset. Means for the period 2011-2015 were substantially higher than those for all other periods, although these means were only calculated for the first 5 years of the decade and patterns might vary once a complete 10-year dataset is available. Ideally, a longer base period should provide a better representation of climate; for example, a 20-year period is recommended to provide a suitable set of input parameters (Semenov and Barrow 1997). However, variations inherent in different time periods and data lengths, as shown in Figure 1a, imply that the selection of base time period could well translate into an overestimation or under estimation of expected values. Furthermore, data from a more recent albeit shorter time period would be better suited for future-cast predictions than historical data over a longer time period. Thus, a longer period is not necessarily better; a more suitable approach to selecting a base time period would be to analyse the data for trends and select periods in which the data are either consistent or show consistent trends.

2.2 Determining the length of the generated dataset

With a base time period selected or determined, oftentimes simulated values are obtained for a time period equal to the base time period- for example, 55 years (Min et al. 2011) and 30 years (Hayhoe and Stewart 1996). However, at times data are generated for a period less than or greater than the base time period e.g. 10-year simulation from 20-year base data (Al-Mukhtar et al. 2014) and 300-year simulation from 30-year data (Kou et al. 2007), respectively. Commonly used generators generally produce weather time series of a specified length X which are not necessarily matched in a pair-wise fashion with the base input data. Where the length of generated data is equal to that of the base data, such a pairwise relationship might be assumed. However, if the length of the generated data (Y) is shorter than X, generated data could represent any of the many different potential combinations of time series each of length Y (Figure 1b: X=30, Y=20). This might present a challenge where data are generated for use with modelling applications, and especially when model outputs are used in parameter optimization. A challenge may also present where data are extrapolated beyond the length of the base input data. This is sometimes done, for example, to evaluate what-if scenarios for factors other than climate, in which case the desire is to fix the climate data to a certain or prevailing pattern so as not to confound the analysis. With extrapolating beyond the base data, pertinent changes and variabilities might not be captured, for example in Figure 1b where there is a discernible increase in daily mean values.

2.3 Utilizing a suitable number of realizations

Because weather generators produce random outputs, it is unlikely that any two simulation runs will produce the same output, pointing to the need for multiple realizations. The number of realizations used based on current literature varies from one (Farzanmanesh et al. 2012, Fan et al. 2013, Al-Mukhtar et al. 2014) through 100 (Min et al. 2011) to 1000 (Brisson et al. 2015). In some cases, generated data have been obtained for a large number of years and then divided into a number of different sets, for example 300 years divided into ten sets each 30 years in length (Kou et al. 2007). Based on a comparison of LARS-WG output for 50 realizations each of length 50 years with the corresponding values obtained from one realization 2500 years in length split into 50 sets of length 50 years (pseudo-realizations), the choice of method did not seem to make a difference for
maximum and minimum temperatures, and standard deviation of precipitation (Figure 2). Mean precipitation was, however, better represented with 50 realizations based on which it was possible to capture observed values. With the pseudo-realizations, the entire dataset was a reflection of the single realization (in this case an underestimation) and errors were simply propagated across the dataset. The same picture might be expected if the realization had resulted in an overestimation of values thus the need for several realizations to better capture the range of variability in climate, and especially so when looking at possible future climate. A comparison of 1, 25, 50, and 100 realizations showed that 25 realizations were sufficient to represent the essential characteristics of observed data. Results from 50 realizations were generally not different from those obtained using 25 realizations and there was no advantage of going over 50 realizations.

Figure 1. Fort Wayne, Indiana daily time series showing: a) variations in data during 1941-2015; and, b) 30-year base time period (1981-2010) with possible representation of a 20-year time period (dotted) and extrapolation beyond the base time period (dashed).
Figure 2. Use of realizations in simulating weather data I) results from 50 realizations each of length 50 years; II) results from 1 realization length 2500 years with data split into 50 equal parts each length 50 years (pseudo-realizations). Dotted line shows respective observed data value computed for a period of 50 years.
2.4 Representation of essential characteristics of observed climate

Primary statistical properties of observed data include daily mean, standard deviation, skewness, kurtosis, and percentiles (e.g. Zhang and Garbrecht 2003, Min et al. 2011, Chen and Brisette 2014). Generally, there needs to be some reasonable agreement between observed and simulated data at this point since values are aggregated. Other essential characteristics include the minimum and maximum values and inter-annual variations. A detailed knowledge of wet and dry spells (including sequences, monthly distributions, and lengths) is important for water resources allocation and distribution, and water management planning in general. This information is also important for crop management. Temperature characteristics are also important as they influence components of the hydrologic cycle, in particular evapotranspiration. They also influence the nature of precipitation and whether it is more likely to fall as rain or snow (particularly where snow-melt hydrology is of importance). Other characteristics that are important include those related to the growing season. In the U.S. midwest for example, corn is an economically important crop; ideal temperatures for corn growth are 20-25 °C. Adverse impacts occur when temperatures rise above 35 °C or drop below 10 °C. Thus, depending on the intended use of the synthetic data, it is also important that the generators are able to capture the variety of associated characteristics (Table 1).

Table 1. Example weather generator performance for select stations in Indiana, Michigan and Ohio

<table>
<thead>
<tr>
<th></th>
<th>Fort Wayne, IN</th>
<th>Adrian, MI</th>
<th>Norwalk, OH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Precipitation</td>
<td>Obs† 111.8</td>
<td>CLIGEN 147.0</td>
<td>LARS-WG 111.5</td>
</tr>
<tr>
<td></td>
<td>120.4</td>
<td>120.8</td>
<td>229.1</td>
</tr>
<tr>
<td>Max Temperature, °C</td>
<td>41.1</td>
<td>45.4</td>
<td>38.8</td>
</tr>
<tr>
<td>Min Temperature, °C</td>
<td>25.6</td>
<td>31.9</td>
<td>25.6</td>
</tr>
<tr>
<td>% days with Min Temp ≤ 0.5 °C</td>
<td>34.8</td>
<td>34.8</td>
<td>36.2</td>
</tr>
<tr>
<td>Wet Sequences Count</td>
<td>18.0</td>
<td>24.0</td>
<td>24.0</td>
</tr>
<tr>
<td>Dry Sequence Count</td>
<td>213.0</td>
<td>279.0</td>
<td>223.0</td>
</tr>
<tr>
<td>% days with Max Temp &gt; 35 °C*</td>
<td>0.4</td>
<td>8.7</td>
<td>0.2</td>
</tr>
<tr>
<td>% days with Mean Temp &gt; 10 °C*</td>
<td>47.3</td>
<td>47.1</td>
<td>47.6</td>
</tr>
</tbody>
</table>

*Observed; † precipitation more likely to fall as snow; *impacts on corn growth

Statistical tests of significance (t- and F-test) have been used to compare synthetic data to observed data (Kou et al. 2007, Min et al. 2011, Chen and Brisette 2014). For output other than temperature and aggregated precipitation data, assumptions of normality and equal variances inherent in these tests are violated. These violations are, however, likely to be of little consequence when sample sizes are large (Ott and Longnecker 2015). Several authors have called to question the validity of standard tests of significance (e.g. Cohen 1977, Kirk 1996, D’Errico 2009) and especially so when sample sizes are large (Royall 1986, McBride 2002, Denis 2003). Thus, care must be taken in using and interpreting results from such tests. Alternatives to significance testing have been suggested including equivalence testing, effect sizes, confidence intervals, and graphical techniques (Cohen 1977, Lecoutre et al. 2001, Denis 2003, Ngatia et al. 2010). Where more than a single realization is generated, visual comparisons become especially important as these allow a more detailed examination of the data where numerical presentation of the data would be overwhelming. The K-S test has been used to check that datasets come from the same distribution (e.g. Hayhoe and Stewart 1996, Zhang and Garbrecht 2003, Fan et al. 2013, Al-Mukhtar et al. 2014). This test has been found to work better than the χ² test (Massey Jr 1951).

2.5 Implications for water resources modelling

Precipitation is the primary driver in water resources applications and how well precipitation is represented ultimately impacts the ability to model other aspects of water resources. Temperature is also important due to its impacts on components of the hydrologic cycle and implications for crop
growth as previously discussed. Generator selection for water resources modelling will largely depend on study or project objectives. In that regard, the suitability of generated data with respect to simulated water resource responses also needs to be determined. The use of multiple realizations in water resources modelling will generate large datasets, presenting specific challenges related to analysis of output. If the purpose is to obtain a single climate dataset for use as model input, then the performance of individual realizations will help find the best fitting set. This simplifies the analysis of output. If, however, the data have been extrapolated beyond the base input data, have been generated for a period shorter than the base time period, or the interest is in future scenarios, individual realizations need to be maintained in order to capture the possible range of variability in climate. This may present additional challenges with respect to computational efficiency and the handling of model output especially with distributed models. A high-throughput computing framework has been used to perform over 43,000 model runs resulting from a combination of weather realizations and pollutant control practice scenarios (Gitau et al. 2012). Today facilities to handle such runs and associated data output are more readily available.

3. DISCUSSION AND CONCLUSIONS

With the increasing use of weather generators in water resources applications, it is important that the generators be evaluated for their suitability for the area in which they would be applied. In particular, the generators need to be evaluated for their ability to represent statistical properties and essential characteristics of observed data in addition to matching values. The choice of characteristics to evaluate will largely depend on the intended use for the synthetic output. Other important considerations include the base time period from which input parameters will be generated and the length of the synthetic data relative to the base time period. Generally, a number of realizations are needed in order to capture the range of variability in climate. However, the number of realizations will be of no consequence for a particular weather variable if the generator is incapable of simulating that variable relative to observed data. The use of weather realizations in water resources modelling studies could potentially be computationally expensive and produce large datasets all of which will likely require computing resources beyond the standard workstation. There is the need to determine how the effectivenss of a weather generator in simulating climate variables translates to effectiveness with respect to simulated water resource responses.

REFERENCES


