

The statistical downscaling model- decision centric (SDSM-DC): conceptual basis and applications

Article

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1 **The Statistical DownScaling Model – Decision Centric**
2 **(SDSM-DC): Conceptual basis and applications**

3

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19

20 **Abstract**

21 Regional climate downscaling has arrived at an important juncture. Some in the research
22 community favour continued refinement and evaluation of downscaling techniques within a
23 broader framework of uncertainty characterisation and reduction. Others are calling for
24 smarter use of downscaling tools, accepting that conventional, scenario-led strategies for
25 adaptation planning have limited utility in practice. This paper sets out the rationale and new
26 functionality of the Decision Centric (DC) version of the Statistical DownScaling Model
27 (SDSM-DC). This tool enables synthesis of plausible daily weather series, exotic variables
28 (such as tidal surge), and climate change scenarios guided, not determined, by climate model
29 output. Two worked examples are presented. The first shows how SDSM-DC can be used to
30 reconstruct and in-fill missing records based on calibrated predictor-predictand relationships.
31 Daily temperature and precipitation series from sites in Africa, Asia and North America are
32 deliberately degraded to show that SDSM-DC can reconstitute lost data. The second
33 demonstrates the application of the new scenario generator for stress testing a specific
34 adaptation decision. SDSM-DC is used to generate daily precipitation scenarios to simulate
35 winter flooding in the Boyne catchment, Ireland. This sensitivity analysis reveals the
36 conditions under which existing precautionary allowances for climate change might be
37 insufficient. We conclude by discussing the wider implications of the proposed approach and
38 research opportunities presented by the new tool.

39

40 **Key words**

41 Downscaling; Climate scenario; Weather generator; Stress test; Data reconstruction;
42 Adaptation

43 **1. Introduction**

44 Attitudes are changing about the production and utility of regional climate change scenarios.
45 The notion that climate model output can be used in a deterministic sense to direct adaptation
46 decisions is increasingly hard to defend in the face of recognised uncertainties in global and
47 regional climate modelling – both statistical and dynamical (Pielke Sr & Wilby 2012, Stakhiv
48 2011). There are a few cases where downscaled products have been applied, such as
49 establishment of precautionary allowances for flood risk in Australia, Denmark, Germany
50 and the UK (Wilby & Keenan 2012). However, some believe that climate models are still not
51 yet “ready for prime time” (Kundzewicz and Stakhiv, 2010). Others advocate an *assess-risk-*
52 *of policy over predict-then-act* framework (Lempert et al. 2004, Weaver et al. 2013).

53 Conventional uses of downscaling include production of scenarios, data inputs for impacts
54 modelling, evaluation of the consequences relative to present climate, and discussion of
55 appropriate adaptation responses. Typically, large uncertainties attached to climate model
56 scenarios cascade into even larger uncertainties in downscaled regional climate change
57 scenarios and impacts (**Figure 1**). The decision-maker is then left with a bewildering range of
58 possibilities, and often defaults to “low regret” decisions (World Bank 2012). A few studies
59 use regional downscaling to explore the relative significance of uncertainty components, for
60 example in future snowmelt (Dobler et al. 2012), high (Smith et al. 2014), low (Wilby &
61 Harris 2006), or mean river flows (Bastola et al. 2011).

62 The Statistical DownScaling Model (SDSM) was originally conceived as a regional climate
63 change scenario generator to support climate risk assessment and adaptation planning. A
64 meta-analysis of the first decade of published work using SDSM showed that over half the
65 200+ studies to date refer to water and flood impacts, often with regards to the production of
66 climate scenarios, benchmarking with other scenario tools, or refinement of downscaling
67 techniques (Wilby & Dawson 2013). A modest but growing number of studies apply the tool
68 in adaptation planning or climate risk management¹.

69 Some assert that downscaling should be used to appraise adaptation options through
70 vulnerability-led rather than scenario-led methodologies (Wilby & Dessai, 2010). In this
71 ‘bottom-up’ framework, the scenario is used to evaluate the performance (some say “stress
72 test”) adaptation measures. As such, the scenario does not need to be explicitly tied to a given

¹ For a bibliography of SDSM studies see: <http://co-public.lboro.ac.uk/cocwd/SDSM/Bibliography.pdf>

73 climate model or ensemble; plausible futures can be described by representative climates or
74 generated from weather sequences using simple narratives of the future (such as “warmer”,
75 “drier”, “more variable”) (Whetton et al. 2012). Scenarios are then used to test the sensitivity
76 of the system or decision set, ideally to reveal non-linear behaviours or break-points under
77 prescribed climate-forcing (e.g., Prudhomme et al. 2010, Stakhiv 2011, Brown & Wilby,
78 2012, Lempert et al. 2012, Nazemi et al. 2013, Steinschneider & Brown, 2013; Turner et al.,
79 2014).

80 Accordingly, this paper describes a suite of tools for producing daily weather series and
81 climate scenarios **without explicit use of climate model output**. Our Decision-Centric (DC)
82 version of SDSM is built on the premise that downscaled scenarios should be informed by
83 but not determined by climate models. This increases the range of plausible scenarios that can
84 be evaluated in an adaptation context. The new *Weather Generator* in SDSM-DC also
85 provides tools for in-filling missing data and interrogating local climate information based on
86 re-analysis predictor variables. These functions enable application in data sparse regions and
87 leads to deeper understanding of regional climate systems.

88 The purpose of this paper is to introduce the new functions of SDSM-DC and to demonstrate
89 their usage with two case studies. The following section describes the technical basis of
90 SDSM-DC as applied to single and multiple sites. We then illustrate how SDSM-DC can be
91 used for data reconstruction in contrasting climate regimes. These analyses address the often
92 asked question about how much data is needed to calibrate the model to achieve a given level
93 of skill. The second worked example shows how SDSM-DC can be used in a ‘stress testing’
94 situation. In this case, we refer to the definition of safety margins for flood risk under a
95 changed climate in Ireland. Finally, we identify some of the research opportunities emerging
96 from a ‘bottom-up’, vulnerability-based paradigm for downscaling.

97

98 **2. SDSM-DC**

99 Earlier versions of SDSM have been described elsewhere (Wilby et al. 2002, 2003, Wilby &
100 Dawson 2013) but for completeness are brought together here. The tool enables the
101 production of climate change time series at sites for which there are *daily* observations (the
102 predictand) and re-analysis products describing large-scale atmospheric properties (the
103 predictors) for model calibration. In the vintage version of SDSM, archived General

104 Circulation Model (GCM) output may then be used to generate scenarios for future decades.
 105 The SDSM-DC User is guided through each stage of the downscaling process by a set of
 106 screens (**Figure 2**). These address key functions such as basic quality control and
 107 transformations (as required) of input data; predictor variable selection; model set-up and
 108 calibration; weather and scenario generation; diagnostics for interrogating model output
 109 (summary statistics, frequency and time-series analysis, graphing). The following section
 110 reprises the key features of the single- and multi-site versions of SDSM then introduces the
 111 new functions of SDSM-DC.

112

113 **2.1 Downscaling single sites**

114 SDSM is best described as a conditional weather generator because atmospheric circulation
 115 indices and regional moisture variables are used to estimate time-varying parameters
 116 describing daily weather at individual sites (e.g., precipitation occurrence or daily mean
 117 temperatures). The downscaled process is either unconditional (as with wet-day occurrence or
 118 air temperature), or is conditional on an event (as with rainfall amounts).

119 For wet-day occurrence W_i there is a direct linear dependency on n predictor variables X_{ij} on
 120 day i :

$$W_i = \alpha_0 + \sum_{j=1}^n \alpha_j X_{ij}$$

121 under the constraint $0 \leq W_i \leq 1$. Precipitation occurs when the uniform random number $[0,1]$
 122 $r \leq W_i$. The threshold (mm) for a wet-day varies between locations, depending on the
 123 definition of trace rainfalls or precision of measurement. Here we define a wet-day as any day
 124 with non-zero precipitation total.

125 When a wet-day is returned, the precipitation total P_i is downscaled using:

$$P_i^k = \beta_0 + \sum_{j=1}^n \beta_j X_{ij} + e_i$$

126 where k is used to transform daily wet-day amounts to better match the normal distribution.
 127 Here we apply the fourth root transformation (i.e., $k = 0.25$) to P_i . Note that the same

128 predictor set is used to downscale W_i and P_i and that all predictors v_{ij} are standardised with
 129 respect to the 1961-1990 mean \bar{V}_j and standard deviation σ_j :

$$X_{ij} = \frac{v_{ij} - \bar{V}_j}{\sigma_j}$$

130 For unconditional processes, such as temperature, there is a direct linear relationship between
 131 the predictand U_i and the chosen predictors X_{ij} :

$$U_i = \gamma_0 + \sum_{j=1}^n \gamma_j X_{ij} + e_i$$

132 The model error e_i is assumed to follow a Gaussian distribution and is stochastically
 133 generated from normally distributed random numbers and added on a daily basis to the
 134 deterministic component. This white noise enables closer fit of the variance of the observed
 135 and downscaled distributions, but is known to degrade skill at replicating serial
 136 autocorrelation implicit to daily predictor variables. The stochastic process also enables the
 137 generation of ensembles of time-series to reflect model uncertainty.

138 All downscaling parameters (α_j , β_j , and γ_j) are obtained via least squares calibration of the
 139 local predictand(s) against regional predictor variables derived from the National Center for
 140 Environmental Prediction (NCEP) re-analysis (Kalnay et al. 1996) using data for any period
 141 within 1961-2000. Users are advised to calibrate SDSM using data drawn from this period
 142 because it is assumed that these decades have relatively high data quality/availability with
 143 modest risk of nonstationarity in predictor-predictand relationships due to anthropogenic
 144 forcings. Predictands are downscaled separately so any covariance must be conveyed by
 145 common predictor variables and/or correlation between predictors. Model testing suggests
 146 that this is a reasonable assumption (Wilby et al. 1998).

147 In common with all downscaling methods, SDSM predictor-predictand relationships are
 148 assumed to be unaffected by anthropogenic influences during the calibration period, and are
 149 applicable to conditions outside the training set. In practice, the parameters of all empirical
 150 and dynamical downscaling models are observed to vary over decadal-time scales, not least
 151 because of natural variability. Furthermore, the climate effects of land-surface changes
 152 cannot be captured by conventional statistical downscaling models (Pielke Sr. & Wilby 2011).
 153 For instance, previous work in the western US suggests that winter snow/ice cover feedbacks

154 can lead to lower temperatures than expected by downscaling models (Wilby & Dettinger
155 2000). All these caveats undermine the case for applying downscaling in predict-then-act
156 modes.

157

158 **2.2 SDSM-DC functionality**

159 Perhaps the most contentious aspect of SDSM-DC is that climate scenarios are not
160 determined explicitly by climate model output. Rather, the range of the adjustments may be
161 informed by palaeoclimatic evidence, expert judgement, or climate model experiments.
162 Alternatively, the range may be designed to bracket conditions that would stress the target
163 system(s) to failure (Steinschneider & Brown 2013). These methods represent a marked
164 departure from main-stream downscaling ideology which is wholly contingent upon the
165 realism of future driving variables supplied by climate models. Nonetheless, there is
166 acceptance that even massive climate model ensembles may understate the true uncertainty in
167 regional climate change (Stainforth et al. 2007, Deser et al. 2012). Therefore, tools are
168 needed to generate scenarios that can test adaptation decisions and system vulnerabilities over
169 a much wider (yet still plausible) range of climate variability and change (Steinschneider &
170 Brown 2013, Brown & Wilby, 2012, Nazemi et al. 2013).

171 SDSM-DC enables the User to apply such *Treatments* to daily predictands. These are User-
172 defined factors and functions that manipulate the unconditional occurrence process, mean,
173 variance and trend of the original series. Input series may originate from observations² or
174 from output produced by a weather generator (as in **Figure 3a**) if multiple realisations are
175 required. Four main types of single and multiple treatments are described below.

176

177 **2.2.1 Occurrence**

178 In the following explanation we refer to precipitation as an example manipulation of event
179 occurrence. However, this treatment might apply to any other phenomena with zero and non-
180 zero values (such as sunshine hours). For precipitation the event threshold might be any non-
181 zero total. In this case, the percentage change entered represents the amount by which event
182 frequency should change. For example, a value of 10% applied to rainfall series would

² For sample input data, predictor variables and parameter file see: <http://co-public.lboro.ac.uk/cocwd/SDSM/sdsmmain.html>

183 increase the number of rain days by 10%; a value of -20% would reduce the number of wet-
184 days by a fifth (**Figure 3b**).

185 When increasing event frequencies, new wet-days are not generated randomly across the
186 entire range of the series but are weighted according to the baseline occurrence profile. This
187 ensures that (for precipitation occurrence) wet months remain generally wetter than dry
188 months and vice versa. This process involves four stages. First, input series are analysed to
189 determine the frequency of events in each month (e.g., January 16%; February 20%, etc.).
190 Second, a random month is selected based on the overall likelihood of occurrence (in this
191 case, February would have a slightly higher chance of being selected than January). Third, a
192 random non-event (dry) day in this month is selected from the concatenated series. Fourth, in
193 order to convert this dry day into a wet day an appropriate event magnitude (wet-day amount)
194 must be determined. This is achieved by sampling a non-zero event from the month. Steps
195 two to four are then repeated until the required percentage change in rain days has been
196 achieved.

197 Removal of events from the series operates in a similar way to the process outlined above. As
198 before, the series is first analysed to determine the monthly occurrence profile. This
199 likelihood is used to weight the chance of removing an event: those months with the greatest
200 frequency of zero days are most likely to lose a non-zero event. A non-zero day is randomly
201 selected and then removed from that month (anywhere within the entire series) by replacing it
202 with the event threshold value. This process is repeated until the required percentage of
203 events has been achieved.

204 The above processes are conditionally stochastic since addition or removal of events is
205 weighted by monthly event frequencies, but individual days are randomly changed within
206 months. This effectively amplifies the initial seasonality of event occurrence. Alternatively,
207 the User can prescribe the change in occurrence for each month by setting the target
208 likelihood profile. In this case, SDSM-DC then calculates whether to randomly add or
209 remove events from each month in turn (across the entire series). In cases where a month has
210 no events, magnitudes are sampled from adjacent months.

211 Stochastically adding or removing events from a series can affect the mean of the series. If
212 the user wishes to preserve the initial mean despite adjusting the occurrence process, SDSM-
213 DC scales the final series such that the overall total is the same as pre-treatment. SDSM-DC
214 stores the event total for the series before the occurrence process is manipulated. The model

215 then calculates how much the final series needs to be adjusted in order to preserve this
 216 original total. For example, under this set-up, reducing the frequency of events by 10% would
 217 necessitate scaling the remaining non-zero events by 10% to preserve the pre-treatment mean.

218

219 **2.2.2 Mean**

220 The mean treatment enables adjustments to individual daily values by the chosen amount. For
 221 a conditional process this treatment is only applied to values above the event threshold (for
 222 example, non-zero rainfall amounts). The treatment may be applied either as a factor (such as
 223 for precipitation) or by addition (such as for temperature). Note that this also affects other
 224 properties of the series including the maximum, quantile distribution, and variance.

225

226 **2.2.3 Variance**

227 In order to change the variance and preserve the coefficient of variation (mean divided by
 228 standard deviation) only the mean need be scaled (see above). Otherwise, for an
 229 unconditional process, the mean is first removed from each value then each data point is
 230 multiplied by the square root of the required percentage change in variance. The mean is then
 231 added back to the result thereby increasing the variance by the desired amount overall and
 232 leaving the mean unchanged. This treatment is summarised as:

$$U_m = [(U_i - \bar{U}) * (\sqrt{1 + r})] + \bar{U}$$

233 where U_m is the transformed value, U_i is the original value, \bar{U} is the mean of the series, and r
 234 is the change entered by the user ($0 \leq r \leq 1$). This simple procedure cannot be applied to
 235 highly skewed distributions (such as wet-day amounts) because the treatment would yield
 236 negative values. In this case, the variance treatment is applied after a Box-Cox transformation
 237 (Hinkley 1977, Sakia, 1992):

$$238 \quad U_m = (U_i^\lambda - 1)/\lambda \quad \text{where } \lambda \neq 0;$$

$$239 \quad U_m = \ln(U_i) \quad \text{where } \lambda = 0;$$

240 where λ lies in the range $[-5, +5]$ and is set to minimise the skewness of the distribution of U_m .
 241 SDSM-DC determines λ via iteration until skewness is minimised. In order to evaluate the

242 effectiveness of the transformation for each λ Hinkley's (1977) nonparametric measure of
 243 symmetry is applied, d_{IQR} . This does not depend on knowledge of the underlying distribution
 244 and may be computed using either the standard deviation or inter-quartile range as the
 245 denominator:

$$d_{IQR} = \frac{(mean - median)}{inter_quartile\ range}$$

246 The inter-quartile range is used in preference to the standard deviation in SDSM-DC because
 247 the latter tends to drive values of d towards zero for larger values of λ . As the algorithm
 248 employed by SDSM-DC is iterative, the standard deviation may well result in large (positive
 249 or negative) values of λ being selected which by no means minimise the skewness of the data.
 250 Conversely, d_{IQR} provides similar λ value as d_{SD} but does not suffer from convergence as
 251 values increase and decrease.

252 Having transformed the series it is now possible to apply the factor to achieve the required
 253 variance inflation as with normally distributed data. This is not straightforward as there is no
 254 direct relationship between the required variance transformation and the Box-Cox
 255 transformed data. Therefore, SDSM-DC applies an iterative approach to determine an
 256 appropriate value of r . For increased variance r ranges from 0 to a maximum of value of 0.3;
 257 for decreases r ranges from 0 to a minimum value of -0.5. Through iteration, SDSM-DC
 258 derives an appropriate value of r to achieve the intended variance treatment, such as +50%
 259 **(Figure 3c)**.

260

261 **2.2.4 Trend**

262 SDSM-DC allows three types of trend to be applied to a series: linear, exponential or logistic.
 263 A linear trend simply adds (or subtracts) the value entered at each annual increment, scaled
 264 within years by Julian day number. For example, 10 would add values from 0 to 10 in the
 265 first year, 10 to 20 in the second year, 20 to 30 the following year, etc. For a calendar year
 266 each day has added $10/365.25$ multiplied by the Julian day number.

267 For a conditional process, event values are adjusted multiplicatively. For example, if the
 268 factor is 5, events in the first year are increased by 0 to 5% linearly (for days 1 to 365); then
 269 by 5% to 10% in the second year; and so forth. In this case, the first day would be

270 approximately unchanged; a value in the middle of the year would be increased by ~2.5%;
271 and a value at the end of the year by 5%.

272 Exponential and logistic trends are applied across the entire range of the series, rather than
273 annually as in the linear treatment. An exponential trend adds (or subtracts) an exponential
274 function across the entire range of the data. For example, entering +5 would add between 0
275 (for the first data point) to +5 (for the final data point) with intervening values scaled
276 exponentially between these end-points (**Figure 3d**). For a conditional process the treatment
277 is multiplicative rather than additive. For example, +10 would result in exponential scaling by
278 1 to 1.10 between the first and last non-zero value in the series.

279 The logistic trend applies an S-shaped function by addition of the chosen value between the
280 first and last points of the unconditional series. For a conditional process the change is
281 multiplicative rather than additive. For example, 5 results in events being scale by 1 to 1.05
282 across the full length of the series following the logistic curve. The logistic function is useful
283 for introducing step changes into generated series.

284

285 **2.2.5 Multiple treatments**

286 Treatments can be implemented in isolation or combination to create more complex
287 transformations of the series. If the latter, treatments are applied by SDSM-DC in fixed order
288 (*Occurrence, Mean, Variance and Trend*). For instance, it is possible to adjust the occurrence,
289 by say -20%, whilst preserving the mean annual precipitation total (**Figure 3e**). In this case,
290 the generated series would have fewer wet-days but with greater mean intensity. More
291 elaborate scenarios can be produced by simultaneously changing the occurrence, variance and
292 trend (**Figure 3f**). These complex treatments might be applied to mimic a specific scenario,
293 or to explore known system vulnerabilities. However, the task of interpreting associated
294 impacts becomes much more demanding. Hence, most cases where synthetic series have been
295 used for stress testing are uni- or two-dimensional (e.g., Prudhomme et al. 2010; Nazemi et
296 al., 2013, Steinschneider & Brown, 2013).

297

298

299

300 **2.3 Extension to multiple sites**

301 Although the public domain version of SDSM-DC is for single sites, the basic model can be
302 modified for multi-site applications (following Wilby et al., 2003). This involves two steps.
303 First, a ‘marker’ series based on daily area averages from several sites (or a single key site) is
304 generated using predictors X_{ij} . Second, the area-average is disaggregated to observed daily
305 series recorded at the constituent sites. This is achieved by resampling multi-site values on
306 the date with observed area-average closest to the downscaled area-average. For example,
307 **Figure 4** shows that SDSM-DC reproduces the observed range of inter-site correlations for
308 both rainfall and temperature in the Upper Colorado River Basin. Across 76 stations in this
309 catchment, the spatial autocorrelation in daily temperature (mean $r_{\text{obs}} = 0.98$; $r_{\text{SDSM}} = 0.98$) is
310 found to be more homogeneous than that of precipitation (mean $r_{\text{obs}} = 0.72$; $r_{\text{SDSM}} = 0.69$).

311 Since actual patterns of values are re-sampled by SDSM-DC, both the area average of the
312 marker series and the spatial covariance of the multi-site array are preserved (Wilby et al.
313 2003, Harpham & Wilby 2005). Area averages are favoured over single site marker series
314 because there is less risk of employing a non-homogeneous or non-representative record, and
315 predictability is generally increased (because of larger signal-to-noise ratio). As with other
316 resampling methods, the maximum daily value generated cannot exceed the maximum daily
317 amount in the observations without invoking the treatments described above.

318

319 **3. Worked example 1: Data reconstruction**

320 Many of the regions that are most vulnerable to climate variability and change are also the
321 most data sparse. For example, major data gaps exist in the Congo basin, Sahel, central Asia,
322 and Amazon basin. One solution is to support intensive field campaigns (such as the EU
323 African Monsoon Multidisciplinary Analysis [AMMA]) to collect data on poorly understood
324 processes or climate regimes, especially in the Tropics. An alternative strategy is to locate,
325 rescue, digitize, archive and share historic climate data that may be held only as paper or
326 physical copies (as is the mission of the International Environmental Data Rescue
327 Organization [IEDRO]). A third way is to synthesize or infill missing data using a stochastic
328 weather generator. In the following application SDSM-DC is used to reconstruct daily
329 temperature and precipitation series and to demonstrate the trade-off between model skill and
330 information content of available data.

331

332 3.1 Strategies for weather simulation

333 There are broadly three main approaches to stochastic weather generator calibration. The
334 most conventional way involves tuning model parameters against available series for
335 precipitation occurrence, then dependent variables such as rainfall amount, temperature,
336 sunshine duration and so forth (Wilks & Wilby 1999). The resulting model replicates
337 important properties of the data (such as wet-day frequencies and amounts, wet- and dry-spell
338 durations, and covariance amongst variables) or can be used to synthesize much longer series
339 for analysis of extreme events. More sophisticated mixture-model variants can be tuned to
340 simulate low-frequency behaviour of annual to multi-decadal time-scales. Such tools have
341 found important applications in hydrologic design and crop-modelling, but are not suited for
342 data reconstruction because of their stochastic outputs.

343 Others apply weather generators based on parameters (e.g., rainfall occurrence or the alpha
344 and beta parameters of the gamma distribution) that have been prepared from gridded data
345 (e.g., Semenov et al., 2010, 2013) or interpolated from sites where such data exist to locations
346 where they do not (e.g., Camberlin et al. 2014, Semenov & Brooks 1999). In some cases,
347 landscape properties such as local slope aspect, distance from coast and altitude are extracted
348 from digital elevation models (e.g., the 1 km resolution Shuttle Radar Topography Mission of
349 the US Geological Survey) to explicitly account for topographic controls via weighted local
350 regressions (e.g., Wilby & Yu 2013). Such techniques are particularly helpful for estimating
351 weather generator parameters in regions of complex topography but are not so well suited to
352 repairing or infilling partial series.

353 This is where SDSM-DC potentially offers hope: observed (NCEP) predictor-predictand
354 relationships constructed for each calendar month, season, or series as a whole can be used to
355 estimate values on days for which there are no data, or for independently testing suspect
356 values. If it can be assumed that other (non-climatic) forcings are constant, the main practical
357 questions become how much data are needed for reconstruction, and what are the expected
358 uncertainty bounds for reconstructed series? Both aspects are explored below using
359 experiments in which daily series have been deliberately degraded in order to emulate
360 SDSM-DC capabilities under realistic ‘field conditions’.

361

362 3.2 Minimum data requirements

363 The effect of reducing daily data availability is demonstrated using contrasting sites:
364 Charlottetown on Prince Edward Island, Canada and Tunis in Tunisia (for temperature);
365 Addis Ababa, Ethiopia and Chang wu, China (for precipitation). In each case, the length of
366 observations presented for model calibration was varied between 10% and 100% of the
367 available record (equating to about 4 to 40 years of data). Individual days or blocks of years
368 were randomly removed to represent situations in which data records might be patchy or
369 where longer sequences of data are missing. SDSM-DC skill at reproducing the artificially
370 removed days was assessed using the Root Mean Squared Error (RMSE) for temperature; the
371 proportion correct wet-day occurrence (PCW); and the non-parametric Kolmogorov-Smirnov
372 (KS) *D*-statistic to test similarity of wet-day amount distributions.

373 Distributing “lost” data via missing year blocks yielded marginally larger RMSEs in
374 temperature reconstructions than random data gaps, but only for records less than 10 years
375 (**Figure 5**). This is because the random data reduction might still sample information content
376 for extreme periods or on trends within the series that are otherwise missed when whole year
377 blocks are removed. Both sets of results suggest that beyond 20 years of calibration data there
378 is little reduction in RMSEs for temperature. A similar pattern emerges for precipitation
379 occurrence with the most dramatic reduction in PCW for calibration sets less than 10 years
380 (**Figure 6**). However, unlike temperature, there appears to be little difference between data
381 degraded by random or block omission. In both cases, the presence or absence of a wet-day
382 (non-zero precipitation) is simulated correctly on average ~75% of the time.

383 Ability to reproduce wet-day amount distributions was assessed by comparison of cumulative
384 distributions (**Figure 7**) and the *D*-statistic (**Figure 8**). These reveal that the assumed fourth
385 root distribution provides a fair approximation of observed wet-day amounts at both sites,
386 particularly for occurrence of days >30 mm. The distribution of downscaled wet-day amounts
387 appears to be robust to data reduction until very low levels (10%) of information are available
388 for model calibration whether random days or years are removed. The type of data reduction
389 is less important for Addis Ababa (**Figures 7a and 7b**) than for Chang wu (**Figures 7c and 7d**)
390 because even the initial data set for the former site is partially fragmented.

391 *D*-statistics show little change in ensemble median but variance in the metric grows with
392 increasing levels of data reduction, most notably at Addis Ababa (**Figure 8**). For this site,
393 model skill at reproducing wet-day amounts is resistant to 10% random data loss. At Chang

394 wu, where initial data quality is superior, the D -statistic is largely unchanged even after 80%
395 reduction (by random day removal). The instability of the D -statistic for large data reduction
396 at Addis Ababa is due to the diminished number of wet days available for downscaling
397 parameter estimation within individual months. For example, with 90% data reduction there
398 are fewer than 10 wet-days for model calibration in December. Large D can then arise when
399 the stochasticity of the downscaling algorithm generates unexpectedly large wet-day amounts
400 (as in **Figure 7d**). Likewise, small D may occur in a large ensemble when the small number
401 of generated wet-days closely matches observations by chance.

402 With diminished samples of observed wet-day amounts there is larger uncertainty in
403 parameter estimates and proportionately greater influence of any extreme event(s) captured in
404 the sub-set. **Figure 8a** suggests that ~30 events are needed to obtain stable wet-day
405 parameters for a given month. Moreover, choice of distribution (whether exponential, long-
406 normal, fourth root, gamma, etc.) may be as important as the amount of data available for
407 model calibration. The ramifications for minimum record lengths are most significant for
408 semi-arid and hyper-arid regions where there may be very few wet-days even when there are
409 many years of record, or when data are stratified by season rather than by calendar month.
410 Conversely, as **Figure 6** shows, wet-day occurrence estimates are relatively robust to
411 variations in record length and data gaps.

412

413 **3.3 Reconstructed time-series**

414 SDSM-DC was used to reconstruct daily temperature and precipitation series at the same
415 sites as above. Models were fitted to all available data but assessed against metrics that were
416 not applied in calibration, including extreme temperatures and annual precipitation totals. An
417 ensemble of 20 daily series was produced in each case using NCEP predictors for the period
418 1961-2000. **Figures 9a** and **9b** show that SDSM-DC provides a close approximation of
419 observed annual mean ($r=0.87$) and maxima ($r=0.91$) temperatures at Prince Edward Island
420 and Tunis respectively. In both cases, the observations lie within the ensemble range of the
421 downscaled series for the majority of years. The correlation between observations and
422 downscaled series was also high for the annual frequencies of cold ($r=0.76$) and hot ($r=0.91$)
423 days (**Figures 9c** and **9d**). Again, the majority of the hindcast values lie within the ensemble
424 range. Results for Tunis demonstrate that even when there are strong trends in observations

425 the NCEP predictors and downscaling are able to replicate most of the inter-annual and inter-
426 decadal variability despite model calibration against daily performance metrics.

427 SDSM-DC was less skilful at replicating inter-annual variability in wet-day frequencies and
428 totals at Addis Ababa and Chang wu (**Figure 10**). Although the majority of observed annual
429 totals lie within the ensemble range, the correlation with the ensemble median is weak at
430 Addis Ababa ($r=0.36$) compared with Chang wu ($r=0.63$). Correlations for the annual wet-
431 day frequencies are marginally stronger: Addis Ababa ($r=0.41$) and Chang wu ($r=0.71$).
432 Differences in skill between the two sites may reflect the quality and length of data available
433 for calibration: 27 and 40 years respectively. The long-term mean at Addis Ababa is
434 reproduced to within 3%, but 36% of observed annuals totals fall outside the ensemble range.
435 Conway et al (2004) note that there is some ambiguity about the location of the site and that
436 the possibility of changes in instrumentation cannot be discounted. Hence, evaluation of the
437 downscaled series remains problematic for this site.

438

439 **4. Worked example 2: Stress testing**

440 In this application SDSM-DC is used to *stress-test* adaptation decisions for local flood risk
441 management (O'Connor, 2013). By focusing on a specific question rather than the traditional
442 "predict-then-act" approach the application can be categorised as a "bottom-up" approach to
443 adaptation (Brown & Wilby, 2012). First, the option is described. Second, an impact model is
444 calibrated for the system in question. Third, the scenario generator tool in SDSM-DC is used
445 to construct the inputs for the impact model, and then construct a response surface showing
446 the sensitivity of the system under a wide range of conditions. Finally, results obtained from a
447 given climate model ensemble (such as CMIP3 or CMIP5) may be mapped onto the
448 sensitivity surface to indicate likelihoods based on current knowledge.

449

450 **4.1 Identifying the adaptation question or concern**

451 In adapting to assumed increases in flood risk in Ireland, the Office of Public Works (OPW),
452 the agency responsible for flood risk management, advocate precautionary allowances in
453 design of flood defences (OPW 2009). Under this guidance an allowance of 20 % on design
454 peak flows is recommended under a mid-range future scenario, with a 30 % allowance under

455 a high-end future scenario. Note that OPW chose not to tie these allowances explicitly to any
456 emissions or climate model scenario.

457 The value chosen for the precautionary allowance has far-reaching consequences. If too low,
458 there is a danger of maladaptation and failure to protect lives, livelihoods and critical
459 infrastructure; if too high, the cost of flood defences may be prohibitive or outweigh the
460 intended benefits. Authorities have to weigh up these costs and benefits in the context of
461 uncertainty about climate change impacts. Using an example catchment in east Ireland,
462 SDSM-DC was used to explore the sensitivity of a 1-in-100 year design flood, to changes in
463 key precipitation parameters.

464

465 **4.2 Developing an impact model for the chosen system**

466 The Boyne at Slane Castle in east Ireland has a catchment area of 2460 km², average annual
467 precipitation 897 mm (1952-2009), Base Flow Index (BFIsoils) 0.69, and an undulating
468 landscape dominated by pasture. The conceptual rainfall-runoff model HYSIM (Manley
469 2006) was used to simulate streamflow within the catchment. The model has modest data
470 requirements and has been applied previously in Ireland (e.g., Harrigan et al. 2014, Murphy
471 et al. 2006, Bastola et al. 2012). Daily precipitation for three rainfall stations and potential
472 evapotranspiration for the period 1952-2009 were obtained from Met Eireann, while daily
473 streamflow for a gauge at Slane Castle was obtained from the OPW for the same period.

474 We recognise that HYSIM adds uncertainty due to non-uniqueness of model parameters
475 (Murphy et al. 2006), but apply a single behavioural parameter set for illustrative purposes.
476 Emphasis is placed on characterising uncertainties from GCMs and emission scenarios, given
477 their large contribution to overall uncertainty in local impacts (e.g. Dobler et al. 2012, Wilby
478 & Harris 2006). HYSIM was trained on daily flows for the period 1981-1995 and verified for
479 the period 1996-2007. Nash-Sutcliffe (NS) (Nash and Sutcliffe 1970) scores of 0.87 and 0.88
480 were derived for the full training and verification periods respectively, while NS scores of
481 0.80 and 0.90 for winter (DJF) flows were obtained for training and verification periods
482 respectively, indicating good model performance (**Figure 11**). To examine changes in flood
483 events the Generalised Logistic (GL) distribution was fitted to annual winter maximum flood
484 series simulated using original and perturbed precipitation series (Hosking and Wallis 1997).

485

486 **4.3 Generating the impact model inputs**

487 SDSM-DC was used to derive a response surface representing the sensitivity of changes in
488 the design (1-in-100 year) flood to prescribed changes in precipitation. The scenario
489 generator function in SDSM-DC was used to perturb observed catchment area-average
490 rainfall to produce daily rainfall series without explicit use of climate model inputs. Changes
491 in rainfall are expected to influence flooding through changes in seasonal wet-day occurrence
492 and amounts. Wide ranges of change for these precipitation attributes were employed to
493 construct bounds within which to perturb observed precipitation. Only winter (DJF) changes
494 are reported here for illustrative purposes.

495 The sensitivity domain for precipitation parameters was informed by the projections of the
496 Coupled Model Intercomparison Project CMIP3 for the nearest grid box, together with
497 previous impacts assessments for Irish catchments (e.g. Bastola et al. 2012; Murphy &
498 Charlton 2006). Changes in mean winter rainfall total ranging between -30 and +30 % and
499 changes in the occurrence of winter wet days (amounts > 0.1 mm) between -20 and +20 %
500 were sampled at 5% increments and applied to the observed rainfall series (1952-2009).
501 Changes in the likelihood of wet-day occurrence and amounts were applied simultaneously
502 so, for example, -20 % likelihood of rainfall with +10 % winter total yields an increase in
503 mean wet-day amounts. Preserving winter totals while adjusting occurrence allows sensitivity
504 to changes in intensity to be explored. Note that these treatments are specific to evaluation of
505 flood risk; sensitivity analysis of other characteristics such as drought would imply
506 alternative treatments to precipitation and potentially evapotranspiration.

507

508 **4.4 Constructing the response surface and mapping climate projections**

509 Perturbed rainfall series were input to HYSIM model to explore the sensitivity of the design
510 flood to changes in rainfall properties with results visualised in the form of a response surface
511 (**Figure 12**). PE was held constant at observed values given low losses during winter months.
512 The 1-in-100 year flood was found to be sensitive to changes in both mean rainfall amounts
513 and changes in the number of wet days. For the ranges of precipitation parameters
514 considered, changes in the magnitude of the 1-in-100 year flood span -40 to +120 %.

515 Even very modest changes in mean rainfall amounts (when combined with reduced wet day
516 occurrence) result in large changes in modelled flood magnitude, delivering rainfall in greater

517 daily amounts and resulting in elevated flood peaks. Even reductions of winter mean rainfall
518 by 10 %, when coupled with reductions in the number of wet days by 15 %, result in changes
519 in flood magnitude approaching the medium range scenario design allowance of an additional
520 20 %. With no change in wet day occurrence increases in winter mean rainfall of above 5 %
521 result in changes in flood magnitude approaching 20 %. The results highlight the sensitivity
522 of flooding within this catchment – not just to changes in rainfall amounts, but to how
523 changes in rainfall amounts are distributed through time. Such sensitivities are moderated by
524 physical catchment properties defining the rainfall-runoff response and will vary on a
525 catchment by catchment basis.

526 Climate change scenarios were then mapped onto the sensitivity response surface to examine
527 risk of exceedence of the precautionary allowances (**Figure 13**). The exemplar climate
528 change scenarios are regionalised outputs from 17 GCMs forced with three (A1B, A2 and
529 B1) SRES emissions scenarios from the Coupled Model Intercomparison Project CMIP3
530 (Bastola et al. 2012). A change factor method based on monthly output from GCMs was used
531 to infer changes in the parameters of a weather generator related to both the magnitude and
532 occurrence of precipitation and was employed to derive regional scenarios for synoptic
533 rainfall stations in Ireland (Bastola et al. 2011). Here 50 realisations of precipitation (based
534 on sampled change factors from GCMs) under each emissions scenario were used to
535 represent uncertainty in future scenarios. For each realisation percent changes in mean winter
536 precipitation amounts and occurrence were derived relative to control simulations for the
537 period 1961-1990. These are then plotted onto the sensitivity response surface, represented as
538 a contour plot, for three future time periods (**Figure 13**).

539 Based on the above sensitivity analysis it is concluded that flood defences with a short design
540 life (i.e. to the 2020s) with medium-range allowance of 20 % are likely to be adequate for the
541 Boyne catchment, but some scenarios under the A1B and B1 emissions fall close to the limit
542 of this allowance. However, given that most hard engineering defences have a design life in
543 excess of 50 years, particularly when designed for extremes with a low recurrence interval
544 (such as 1-in-100 year flood) this is unlikely to be the case for the 2050s and beyond. By the
545 2050s (2040-69) and especially by the 2080s (2070-99) a higher proportion of scenarios
546 exceed the medium range allowance of 20 %, under all emissions scenarios. By the 2080s a
547 number of projections under the A1B and A2 emissions scenario exceed even the high range
548 allowance of 30 %.

549 In summary, this case study reveals potential limitations in the medium range allowance to
550 rainfall driven changes in the design flood. By the 2080s there is greater residual risk,
551 indicated by the proportion of scenarios exceeding the 20 % precautionary allowance. Such
552 an 'assess risk of policy' approach allows decision makers to more readily appreciate the
553 sensitivity of the system without explicit reliance on climate models, while the latter can be
554 readily integrated to visualise risk as represented by a large ensemble of climate change
555 scenarios. The approach adopted also facilitates rapid appraisal of such threshold based
556 adaptation decisions and can be extended to national assessments (e.g., Prudhomme et al.
557 2010) or updated as new climate change projections become available.

558

559 **5. Conclusions**

560 This paper introduced the latest version of the Statistical DownScaling Model (SDSM) which
561 was engineered with the specific needs of adaptation options appraisal in mind – hence the
562 Decision Centric (-DC) extension. Consistent with other innovations in the downscaling
563 community we are moving away from complete dependence on GCM output for producing
564 regional climate change scenarios. Tools based entirely on weather generator techniques
565 enable synthesis of input variables for impacts modelling and adaptation planning (e.g.,
566 Nazemi et al. 2013; Steinschneider & Brown 2013) but they are not always well-suited to
567 reconstructing and/or infilling historic series. Most weather generators are also unable to
568 synthesize exotic variables (e.g., air quality and urban heat island metrics, wave and tidal
569 surge heights). SDSM-DC addresses these gaps by offering functionality to support data
570 reconstruction and basic weather generation, as well as direct simulation of decision-relevant
571 climate indices (**Table 1**). Moreover, tests reveal that SDSM performs as well as
572 conventional weather generators such as LARS-WG (see: Hashmi et al., 2011; Hassan et al.,
573 2014). Hence, with these capabilities, it is hoped that SDSM-DC will support decision-
574 making in some of the most vulnerable and data sparse regions of the world.

575 Two worked examples were presented to demonstrate some of these capabilities. The first
576 showed that with 10 years of data it is possible to achieve approximately the same level of
577 skill at simulating rainfall occurrence, amounts and temperatures as with 40 years at the
578 chosen sites. The analysis also confirmed that the downscaling is more robust to randomly
579 degraded data throughout a longer record than to lost year blocks. Hence, recovery and

580 digitization of even fragmentary observations may be beneficial and sufficient to allow
581 infilling. Moreover, the stochastic features of SDSM-DC enable confidence limits to be
582 attached to hindcast series so, even where the estimate may be uncertain, the model can at
583 least provide an upper and lower bound.

584 The second example study showed how SDSM-DC can be used to stress test an adaptation
585 decision – in this case a climate change safety allowance for flood defence schemes. The tool
586 enables arbitrary treatments to be applied to the synthetic series needed for systems
587 modelling. Treatments in the occurrence, mean, variance, and trend of events can be used to
588 elucidate thresholds in the pressure-response. The range of scenarios that are explored may be
589 guided by GCM output but importantly the tool enables exploration of consequences beyond
590 even a multi-model ensemble. Likelihoods can still be attached by overlaying the cloud of
591 model results on the response surface (as in Prudhomme et al. 2010). Moreover, by shifting
592 emphasis from the GCM, the decision-maker is free to consider more holistic narratives that
593 may be pertinent to the decision-making process (including perhaps changes in land cover,
594 fire risk, forest die back and so forth in the case of water resources).

595 To conclude, the rationale behind SDSM-DC is as much about what the specific tool can do,
596 as how downscaling in general can be used in smarter ways to support adaptation planning.
597 Planned technical enhancements include the ability to manipulate low frequency variability in
598 order to assess multi-season phenomena such as droughts or wet-spells persisting over more
599 than one year. New diagnostics are needed to evaluate expected levels of skill at series
600 reconstruction, perhaps based on more exhaustive cross-validation against whatever data are
601 available. Further exploration of direct downscaling potential is needed, such as for river
602 flows (as in Tisseuil et al., 2010) or other quantities that are typically derived by feeding
603 downscaled climate variables into impact models. Hindcasting performance needs to be
604 tested more thoroughly in a wider range of climate regimes, building on the knowledge base
605 that has been accumulated over the last decade of application. There is also a community-
606 wide need for practical guidance on setting bounds to weather generation for stress testing.
607 Again, this should look beyond the scenario-led framework that would conventionally turn to
608 the latest climate model ensembles but, instead, be guided by knowledge of the
609 vulnerabilities of the system of interest.

610

611

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614

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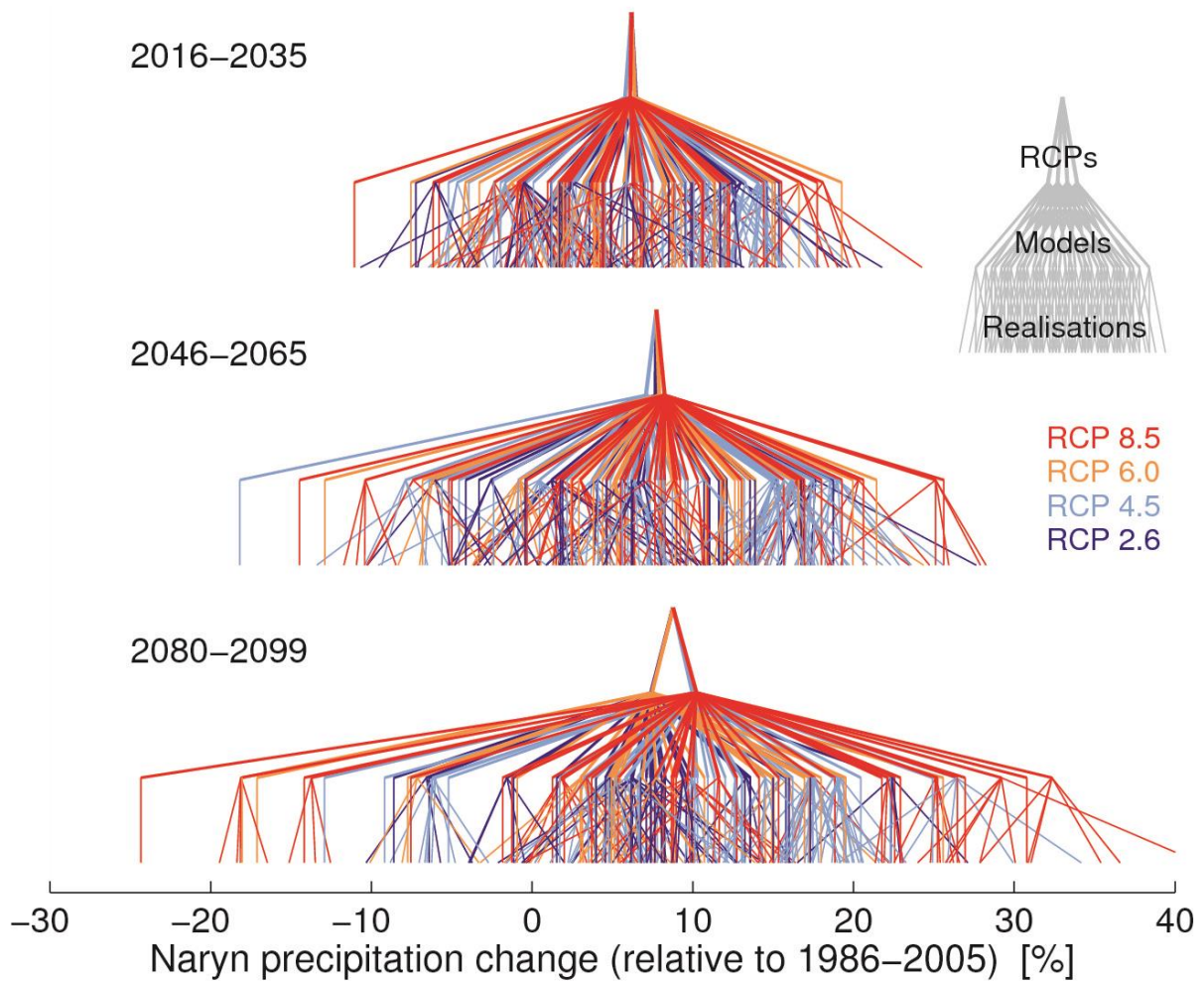
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- 769

770 **Table 1** Examples of direct downscaling of exotic variables using SDSM

Variable	Location	Source
Evaporation	Haihe, China	Chu et al. (2010)
	Loess plateau, China	Li et al. (2012)
	Tibetan plateau, Tibet	Wang et al. (2013)
	River Kennet, UK	Wilby et al. (2006)
	River Dongjiang, China	Yang et al. (2012)
Ground-level ozone and/or particulates	Chicago, US	Holloway et al. (2008)
	London, UK	Wilby (2008a)
	Tucson, US	Wise (2009)
Heat wave indices	Mexicali, Mexico	Cueto et al. (2010)
	London, UK	Wilby (2007)
Waves and tidal surge	North Sea, UK	Donovan (2003)
	Isle of Wight, UK	Hackney (2013)
	Thames Estuary, UK	Wilby (2008b)

771

Cascade of Uncertainty in CMIP5



772

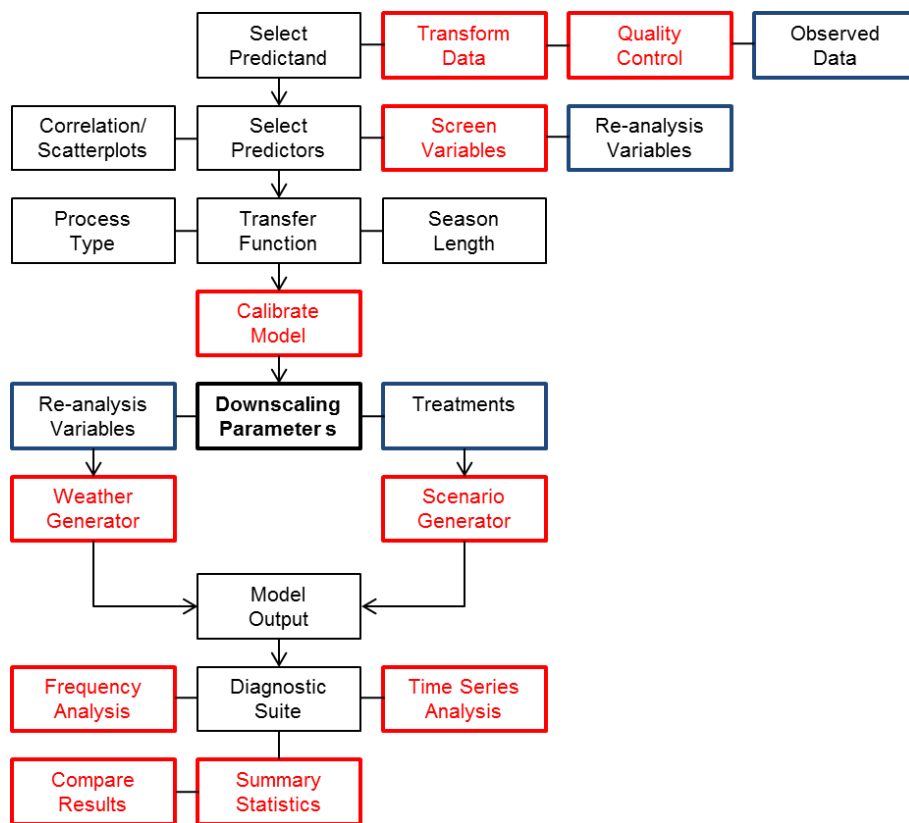
773

774 **Figure 1** A ‘cascade of uncertainty’ in precipitation changes projected by the CMIP5
 775 ensemble for the River Naryn basin, Central Asia (70-80°E, 40-45°N). The three levels of
 776 each pyramid illustrate uncertainty due to the choice of Representative Concentration
 777 Pathway (RCP), GCM and realisation of climate variability. Not all simulations have multiple
 778 realisations, resulting in a vertical line in the lowest layer. The intersection on the top row for
 779 each time period is the multi-scenario, multi-model, multi-realisation mean.

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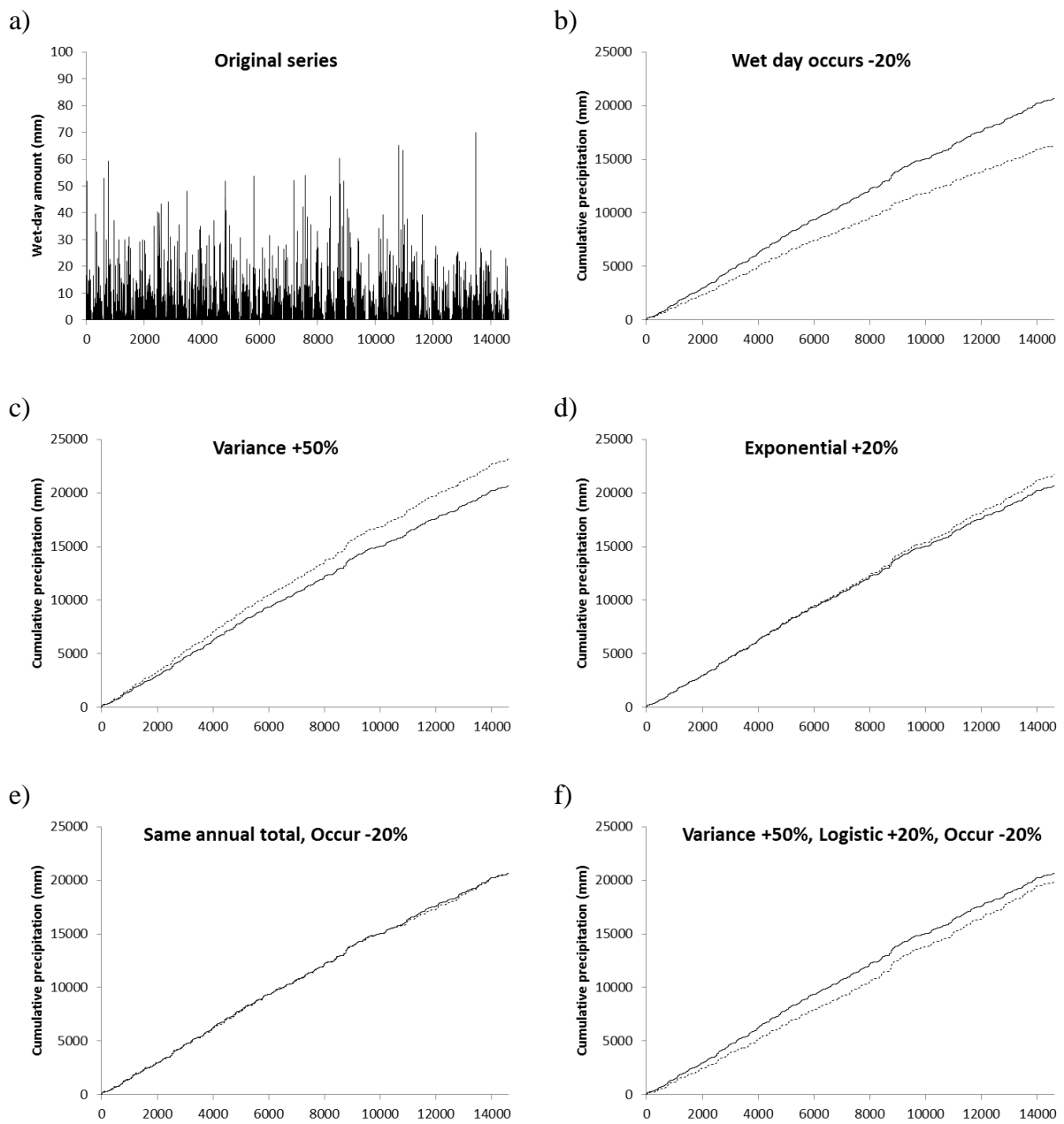


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785 **Figure 2** SDSM-DC architecture showing inputs (blue boxes) and screens (red boxes).

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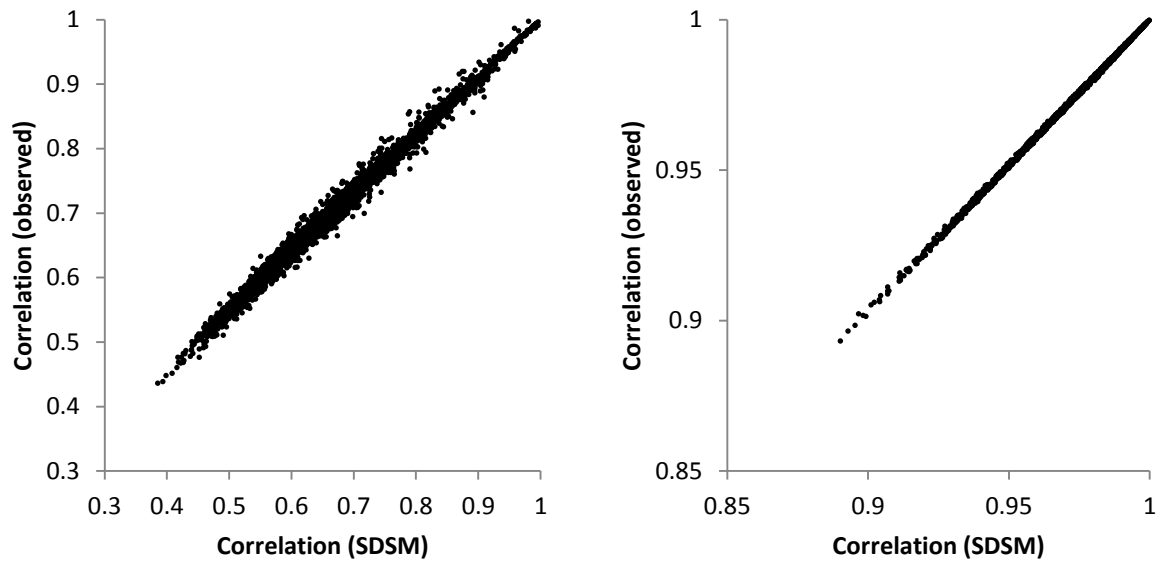
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788 **Figure 3** Example SDSM-DC treatments applied to a 40-year daily precipitation series. The
 789 dark line shows the original data and the grey line the treated series, both expressed as
 790 cumulative totals for ease of comparison.

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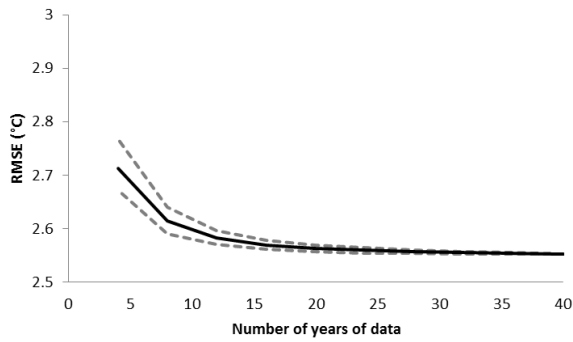
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795 **Figure 4** Pairwise correlation of observed and downscaled daily precipitation (left) and mean
796 temperature (right) in the Upper Colorado River Basin. Source: Wilby et al. (2013).

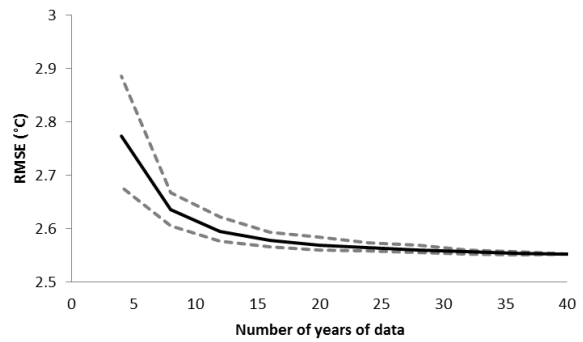
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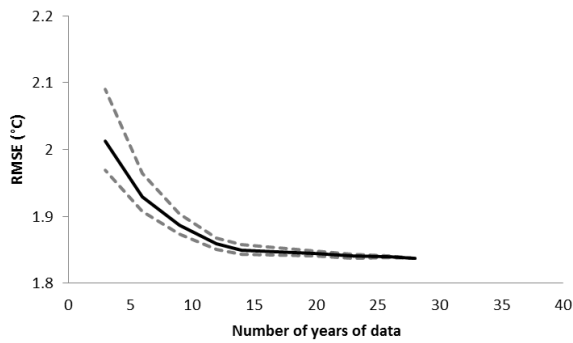
a) Prince Edward Island (day)



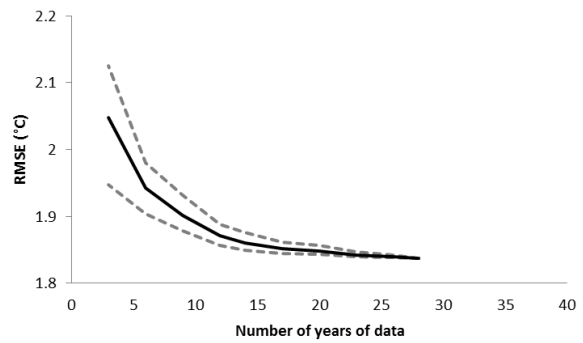
b) Prince Edward Island (year)



c) Tunis (day)



d) Tunis (year)



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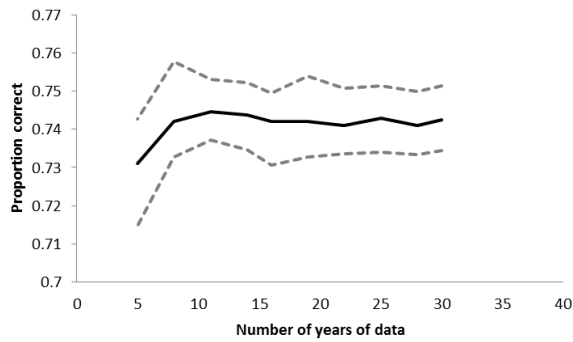
800 **Figure 5** Effects of missing data on the Root Mean Squared Error (RMSE) of downscaled
 801 daily mean temperature depending on whether random days or blocks of years are omitted for
 802 a,b) Charlottetown, Prince Edward Island, Canada and for c,d) Tunis, Tunisia. Each plot
 803 shows the range (dashed lines) and median (solid line) RMSE based on 100 simulations.

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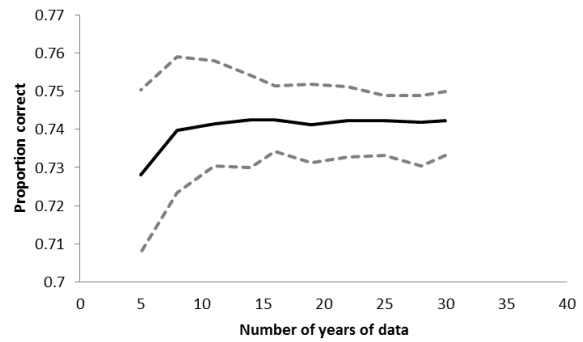
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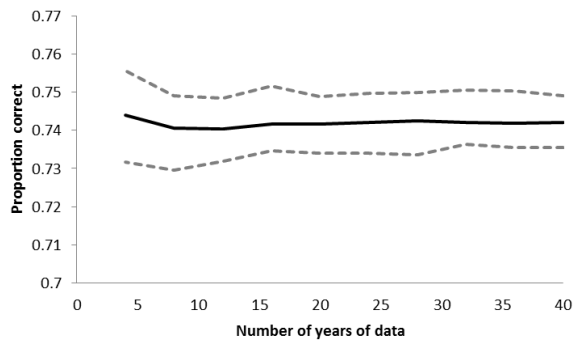
a) Addis Ababa (day)



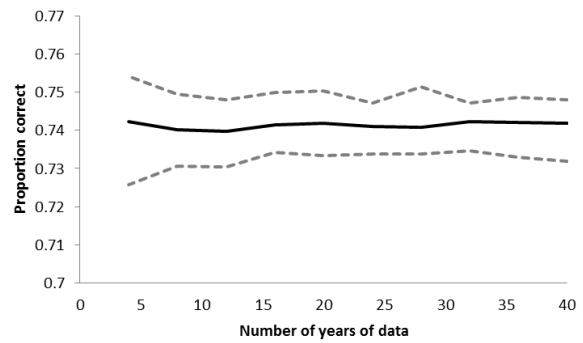
b) Addis Ababa (year)



c) Chang wu (day)



d) Chang wu (year)



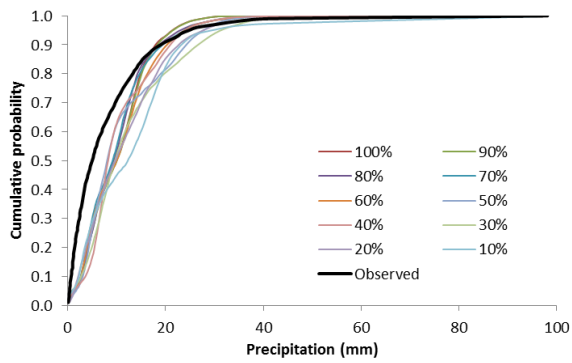
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808 **Figure 6** Effects of missing data on the proportion correct wet-day occurrence (PCW)
 809 depending on whether random days or blocks of years are omitted for a,b) Addis Ababa,
 810 Ethiopia and for c,d) Chang wu, China.

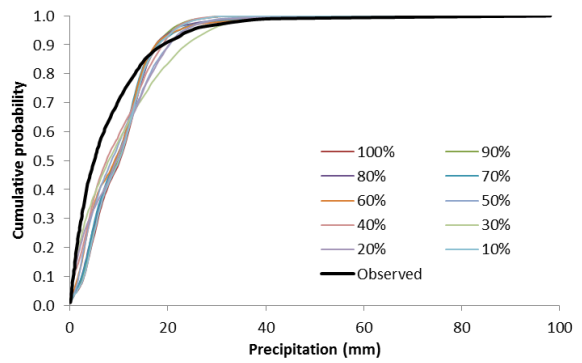
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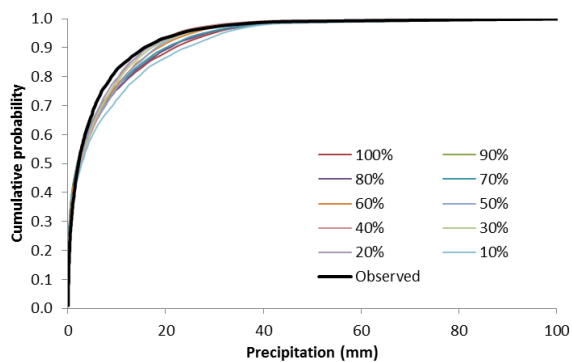
a) Addis Ababa (day)



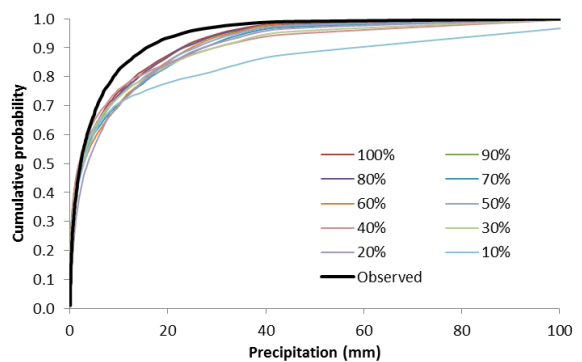
b) Addis Ababa (year)



c) Chang wu (day)



d) Chang wu (year)



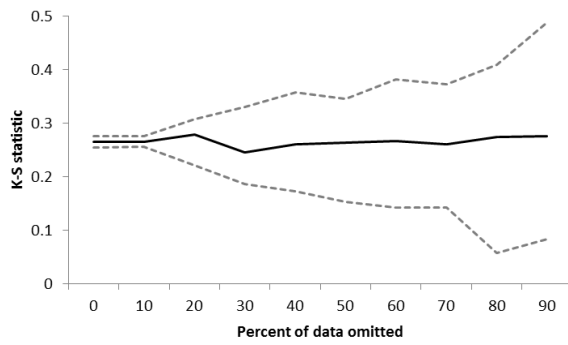
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814 **Figure 7** Sensitivity of downscaled daily precipitation distributions to percent of data omitted
815 by random day (left) or year (right) removal for Addis Ababa (upper) and Chang wu (lower)..

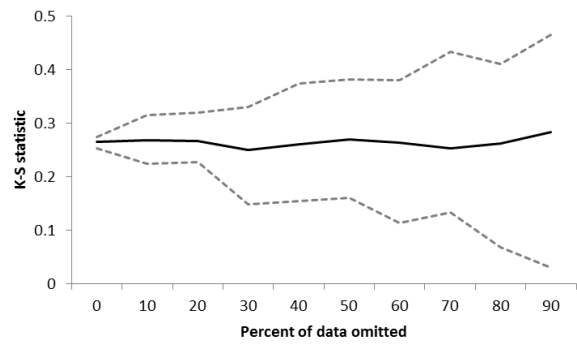
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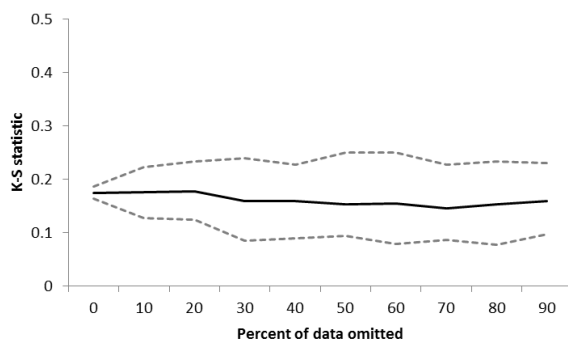
a) Addis Ababa (day) [0.8%]



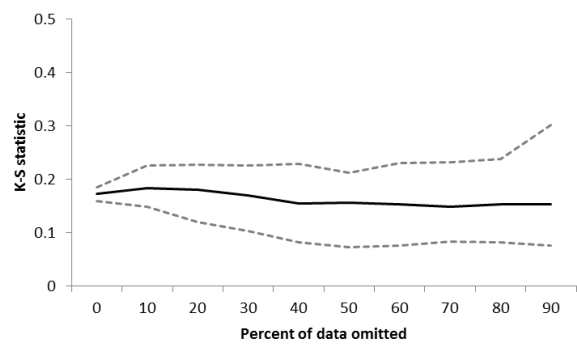
b) Addis Ababa (year) [1.2%]



c) Chang wu (day) [22.3%]



d) Chang wu (year) [22.3%]



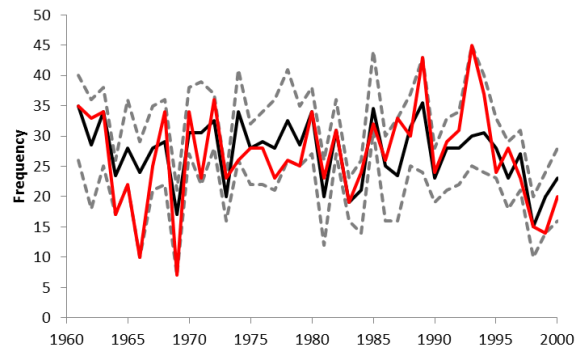
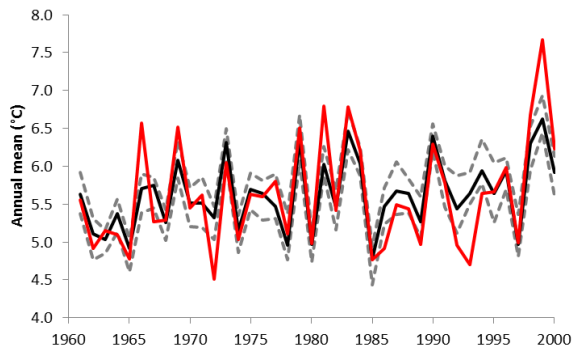
818

819 **Figure 8** Sensitivity of the Kolmogorov-Smirnov statistic to percent of data omitted by
 820 random day (left) or year (right) removal for Addis Ababa (upper) and Chang wu (lower).
 821 The percent of simulations with $KS < D_{crit}$ (0.14 at $p=0.05$) is given [in brackets].

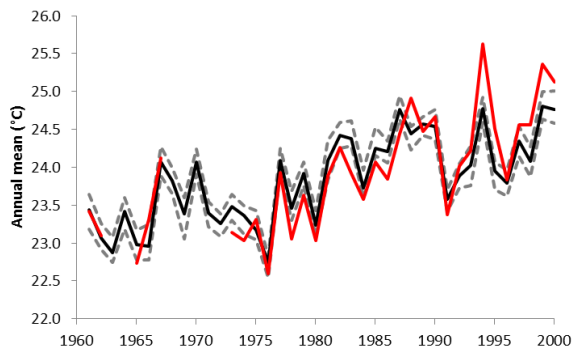
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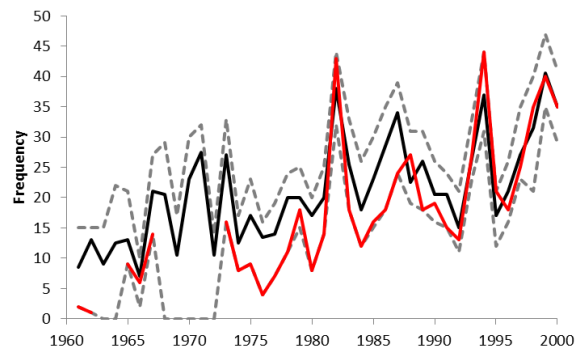
a) Prince Edward Island (annual daily mean) b) Prince Edward Island (days < -10°C)



c) Tunis (annual daily maximum)



d) Tunis (days > 35°C)



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825 **Figure 9** Reconstructed and in-filled (solid black line) temperatures compared with
 826 observations (red line) for a, b) Prince Edward Island, Canada and c,d) Tunis, Tunisia.
 827 Dashed lines show the downscaled ensemble range.

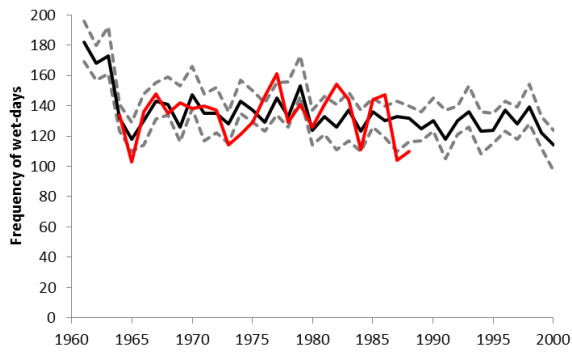
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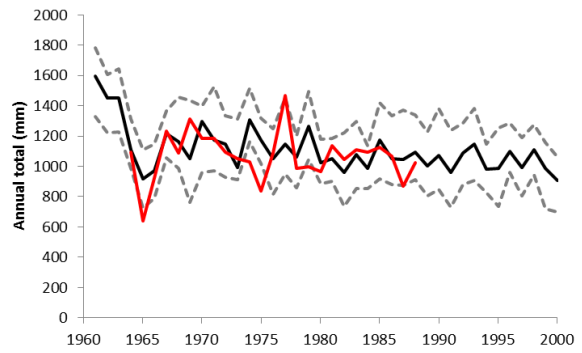
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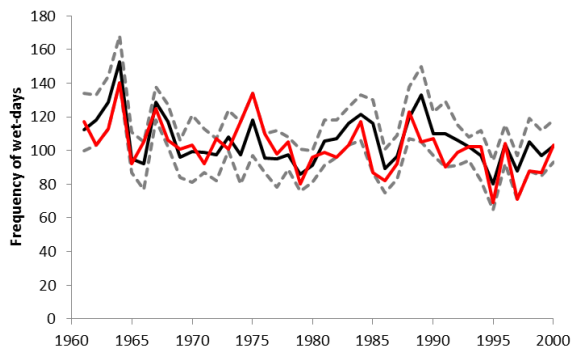
a) Addis Ababa (wet-days)



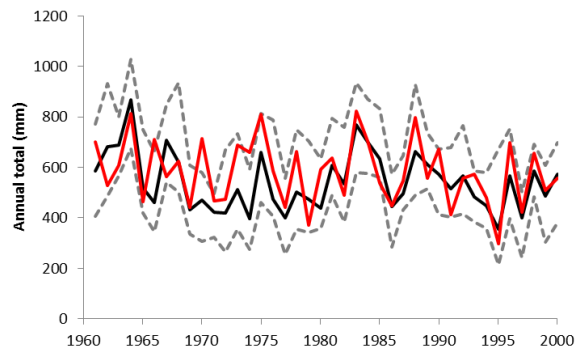
b) Addis Ababa (annual totals)



c) Chang wu (wet-days)



d) Chang wu (annual totals)



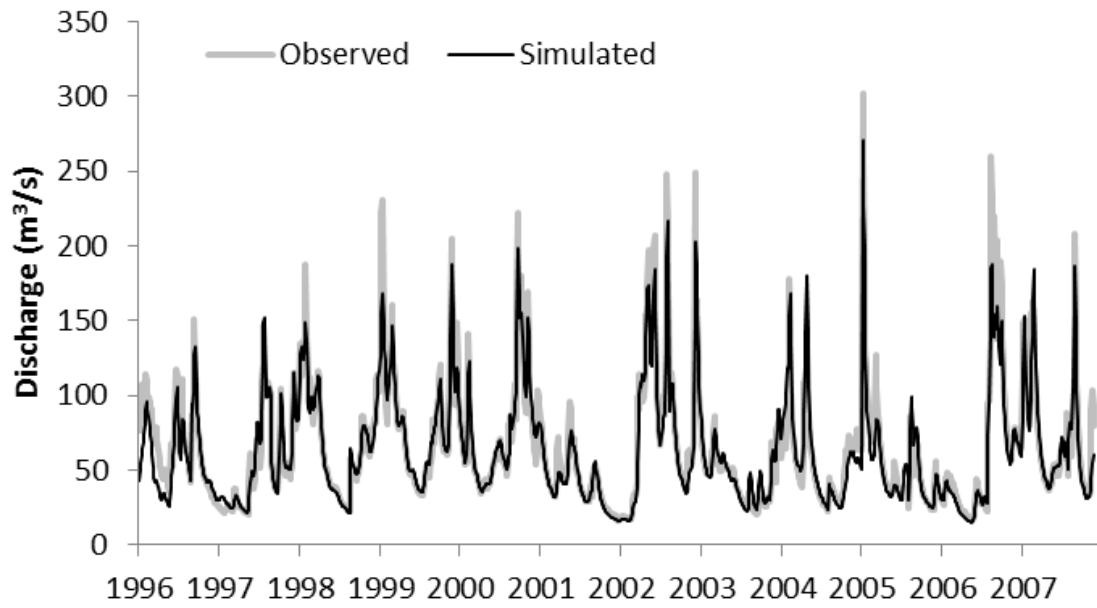
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833 **Figure 10** Reconstructed wet-day frequencies and annual precipitation totals for a,b) Addis
834 Ababa, Ethiopia and c,d) Chang wu, China.

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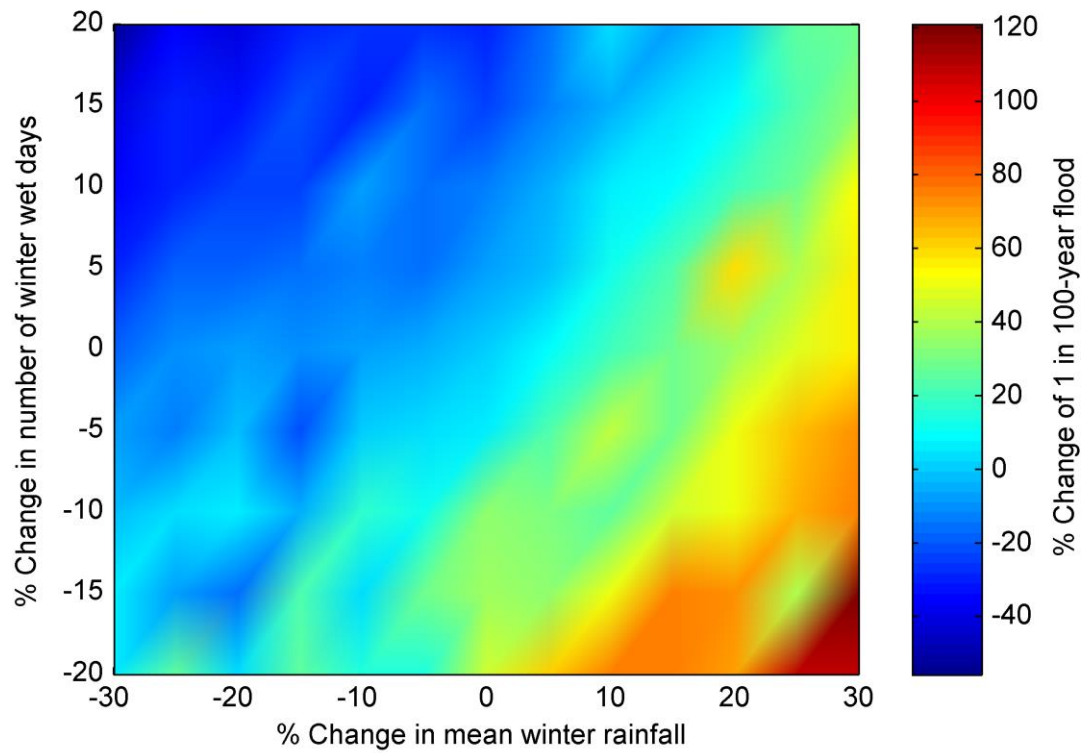
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839 **Figure 11** Comparison of observed (grey line) and HYSIM (black line) simulations of winter
840 daily flows in the River Boyne for the verification period 1997-2007.

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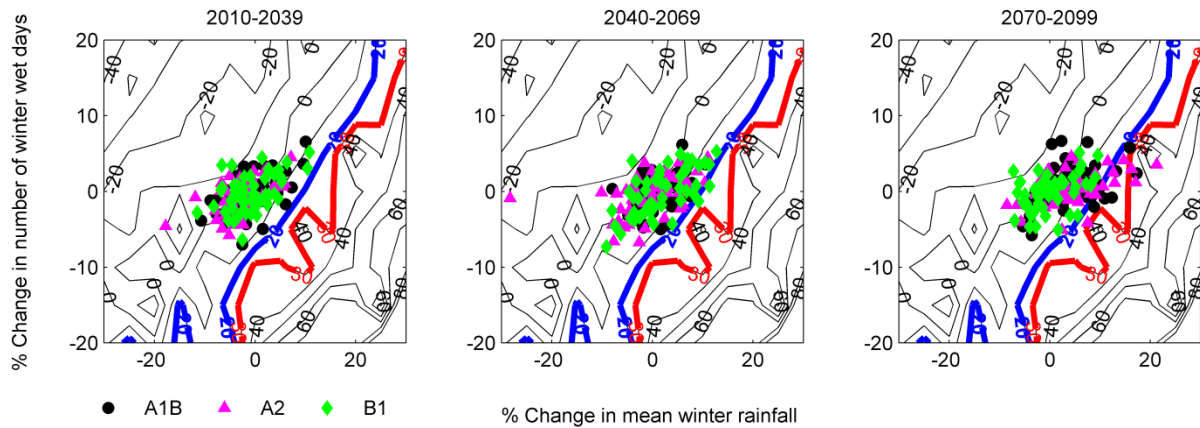
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843 **Figure 12** Response surface representing the sensitivity of percent changes in the magnitude
844 of the winter 1-in-100 year flood to changes in mean winter rainfall and occurrence of winter
845 wet days.

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850 **Figure 13** Sensitivity of precautionary allowances to projected changes in climate during
 851 winter months (DJF). Contours representing allowances of an additional 20 and 30 % of
 852 design flow (1-in-100 year flood) are highlighted in blue and red respectively. Climate
 853 change projections (Bastola et al., 2011) represent a sample of 17 GCMs from the CMIP3
 854 project forced with the A1B, A2 and B1 SRES emissions scenarios for the 2020s (2010-39),
 855 2050s (2040-69) and 2080s (2070-99).

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