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Using the Climate Forecast System Reanalysis as weather input data for watershed models

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Abstract:

Obtaining representative meteorological data for watershed-scale hydrological modelling can be difficult and time consuming. Land-based weather stations do not always adequately represent the weather occurring over a watershed, because they can be far from the watershed of interest and can have gaps in their data series, or recent data are not available. This study presents a method for using the Climate Forecast System Reanalysis (CFSR) global meteorological dataset to obtain historical weather data and demonstrates the application to modelling five watersheds representing different hydroclimate regimes. CFSR data are available globally for each hour since 1979 at a 38-km resolution. Results show that utilizing the CFSR precipitation and temperature data to force a watershed model provides stream discharge simulations that are as good as or better than models forced using traditional weather gauging stations, especially when stations are more than 10 km from the watershed. These results further demonstrate that adding CFSR data to the suite of watershed modelling tools provides new opportunities for meeting the challenges of modelling un-gauged watersheds and advancing real-time hydrological modelling.

KEY WORDS watershed modelling; meteorological forcing data; Climate Forecast System Reanalysis

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INTRODUCTION

A common challenge in modelling watershed hydrology is obtaining accurate weather input data (Kouwen, *et al*., 2005; Mehta *et al*., 2004), almost always one of the most important drivers for watershed models (Obled *et al*., 1994; Bleecker *et al*., 1995). Weather is often monitored at locations outside the watershed to be modelled, sometimes at a long distance from the watershed. As a result, the available records may not meaningfully represent the weather actually occurring over a watershed. An additional complication is that rain gauge data are effectively point measurements, which may represent precipitation poorly across a watershed, particularly if there are large hydroclimatic gradients (WMO, 1985; Ciach, 2003). Moreover, weather records are seldom complete, which requires substituting other measurements or incorporating some sort of 'estimated' weather conditions. To remedy this, some researchers have utilized radar data to provide precipitation inputs in hydrological modelling studies, especially for modelling flood events (Ogden and Julien, 1994; Habib *et al*., 2008), but these data pose their own challenges including discriminating different forms of precipitation such as hail, snow and rainfall and determining the appropriate relationship between radar reflectivity and rain rate (Villarini and Krajewski, 2010), not to mention that radar data are only available for a small fraction of the world's land surface. Thus, there is a need to consider additional methods to estimate weather conditions for watershed-scale modelling.

One possibility is to use multiyear global gridded representations of weather known as reanalysis datasets, of which there are several (Table I). Ward *et al*. (2011) found that the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) and the European Centre for Medium-Range Weather Forecasts' (ECMWF) 40-year (updated version of the ECMWF 15-year) datasets had significant variability between the reanalysis precipitation fields and suggested that higher spatial resolution data are likely better suited to capture higher frequency events when modelling small-sized to moderate-sized watersheds. In order to model these small-sized to moderate-sized watersheds, we utilized three

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Table I. Reanalysis datasets available to this project from the NCAR CISL RDA

Reanalysis dataset (CISL ID)	Date range	Time step (h)	PPT field	Res	Coverage
NCEP/NCAR (ds090.0)	1948–2010	6	PPT Rate	2.5° (~290 km)	Global
NCEP/DOE R2 (ds091.0)	1979–2012	6	PPT Rate	1.875° (~209 km)	Global
NCEP N. American Regional (ds608.0)	1979–2012	3	PPT Rate	~32 km (~0.25°)	North America
NCEP 51-Year Hydrological (ds607.0)	1948–1998	3	Total PPT	0.125° (~15 km)	Continental USA
ECMWF 15 Year (ds115.5)	1979–1993	6	Strat. + Conv. PPT	1.125° (~130 km)	Global
ECMWF 40 Year (ds117.0)	1957–2002	6	Strat. + Conv. PPT	1.125° (~130 km)	Global
ECMWF Interim (ds627.0)	1979–2012	6	Strat. + Conv. PPT	0.703° (~82 km)	Global
CFSR (ds093.1)	1979-present	1	PPT Rate	0.3125° (~38 km)	Global
Japanese 25-Year (ds625.0)	1979–2011	6	Total PPT	1.125° (~130 km)	Global

Note: All datasets include temperature. Japanese 25 year, ECMWF 40 Year, and ECMWF Interim reanalysis are restricted datasets not available to the public. CISL, Computational and Information Systems Laboratory; RDA, Research Data Archive; NCEP/NCAR, National Centers for Environmental Prediction; DOE, Department of Energy; PPT Rate, precipitation rate; Strat. + Conv., stratiform plus convective forms of precipitation; ECMWF, European Centre for Medium-Range Weather Forecasts; CFSR, Climate Forecast System Reanalysis.

criteria for dataset selection: (i) an openly available global reanalysis dataset that included temperature and precipitation rate; (iii) a spatial resolution on the order of 30 km; and (iii) the period of record should include adequate historical coverage to allow model calibration and validation and extend to the present. The only dataset that met all three of the aforementioned criteria was the NCEP Climate Forecast System Reanalysis (CFSR) dataset (Table I).

The CFSR dataset consists of hourly weather forecasts generated by the National Weather Service's NCEP Global Forecast System. Forecast models are reinitialized every 6 h (analysis hours = 0000, 0600, 1200 and 1800 UTC) using information from the global weather station network and satellite-derived products. At each analysis hour, the CFSR includes both the forecast data, predicted from the previous analysis hour, and the data from the analysis utilized to reinitialize the forecast models. The horizontal resolution of the CFSR is 38 km (Table I; Saha *et al*., 2010). This dataset contains historic expected precipitation and temperatures for each hour for any land location in the world. Moreover, as the precipitation is updated in near-real time every 6 h, these data can provide real-time estimates of precipitation and temperature for hydrologic forecasting.

The objective of this study was to determine whether CFSR-derived weather data can be reliably used as input data instead of traditional weather station data in simulating discharge from a watershed. We performed two studies to evaluate the utility of using CFSR data and traditional weather station data to simulate watershed discharge across a range of hydroclimate regimes. The first study utilized a watershed model as a filter to compare watershed model discharge predictions to observed discharge using models forced with both the CFSR and weather station data. The second study explores how model performance behaves as CFSR and weather station data are derived from progressively more distant locations. These two analyses elucidate under what conditions CFSR or land-based weather station are the most appropriate datasets for watershed modelling. Additionally, the second analysis provides information about how station density and/or distance influences watershed model results.

METHODS AND SITE DESCRIPTIONS

For these studies, we assume that the weather data that best correlate with watershed streamflow is the best representation of the weather occurring over the watershed. Unfortunately, traditional cross-correlation analysis between the weather variables and resulting streamflow is physically meaningless, as there are many linear and nonlinear systems between weather events and the resulting streamflow, as is often the case with many real-world time-series data (Podobnik and Stanley, 2008). Therefore, the description of the mutual correlation between the weather forcing variables and the resultant streamflow is presented using a hydrological model acting as a filter between the physical forcing variables and the resulting streamflow response, similar to the methods proposed in Podobnik and Stanley (2008). This eliminates the need for traditional methods of split-sample calibration and validation periods.

To perform these transformations, both studies utilized an adaptation of the Soil and Water Assessment Tool (SWAT) model (e.g. Arnold *et al*., 1998) that has been ported to the R modelling language and available through the CRAN repository (R Core Team, 2013). The SWATmodel package (Fuka *et al*., 2013) was utilized because it is widely implemented operationally as well as in research, and the integration into the R modelling language allowed for us to automate the optimization process using powerful tools such as the differential evolution optimization (DEoptim) package (Ardia and Mullen, 2009; Fuka *et al*., 2012) also freely available through the CRAN repositories. The hydrological subroutines in SWAT utilize a combination of empirical and process-based modelling approaches. Although SWAT is designed to predict a wide array of soil and water quality and flux characteristics, we only considered stream discharge in these studies. Additionally, because we are running this model in a variety of hydroclimatic regimes, and specific hydrological process vary among our test watersheds, we utilize the SWAT model solely as a response function or nonlinear scaling transformation, i.e. we are only trying to predict the watershed response to the weather input and not on validating specific internal model processes. Thus, we assumed that the model results for any given weather dataset used to force the model are an indicator of the relative representation of the weather occurring in the watershed (i.e. better model performance statistics points towards better weather representation over the watershed).

We also recognize that traditional SWAT watershed modelling initializations would result in many calibration degrees of freedom [e.g. hundreds to thousands of hydrological response units (HRUs)], and as stated earlier, the point of this work is to indicate which dataset better represents weather occurring over a watershed and not on over-fitting the watershed model. Thus, we drastically simplify the watershed conceptualization, effectively reducing the number of calibration parameters or degrees of freedom in the calibration, and thus reduce over parameterization or over-fitting issues. To do this, each watershed is initialized with three equal-sized sub-basins, idealized by three HRUs in each sub-basin. Each HRU was characterized by the calibration parameters in Table II. Dividing the watersheds into sub-basins facilitated stream channel routing within SWAT, which is important in any watersheds with a hydrologic delay greater than the model time step (e.g. 1 day). This creates a quasi-lumped model with parameterizations for surface runoff, interflow and ground water responses, as well as delay functions for in-stream routing. While this is an unconventional SWAT setup, three sub-basins are the minimum initialization that allows lumped surface responses combined with independent stream response delay functions.

In study 1, two watersheds (Table III, study 1) were selected that had previously published SWAT model results using weather data from nearby stations as input data (e.g. Easton *et al*., 2008; White *et al*., 2011). SWAT model performance using these weather datasets was compared to SWAT model runs using CFSR-derived weather data. This first study was performed to (i) evaluate how watershed models forced with CFSR-derived weather data compare to a typical modelling study where modellers aggregate multiple weather stations to derive or fill gaps in the weather data that are used in the watershed model; and (ii) determine how well the unconventional SWAT setup used in this study would represent results from traditional watershed modelling that uses high-resolution input data to initialize more distributed processes.

Table II. Calibrated parameters used for differential evolution optimization, with the optimization method and parameter range, or percent deviation for optimization

Variable	Definition	Method[a]	Range/percent
SFTMP	Snowfall temperature (°C)	Replace	−5–5 °C
SMTMP	Snow melt base temperature (°C)	Replace	−5–5 °C
SMFMX	Melt factor for snow on 21 June (mm H_2O/°C-day)	Replace	0–5 °C
SMFMN	Melt factor for snow on 21 December (mm H_2O/°C-day)	Replace	0–5 °C
TIMP	Snow pack temperature lag factor	Replace	0.01–1 °C
GW_DELAY	Groundwater delay (day)	Replace	1–180 days
ALPHA_BF	Baseflow alpha factor (day)	Replace	1–180 days
SURLAG	Surface runoff lag time (day)	Replace	1–180 days
GWQMN	Threshold depth of water in the shallow aquifer (m)	Replace	1–200 mm
LAT_TTIME	Lateral flow travel time (day)	Replace	1–180 days
ESCO	Soil evaporation compensation factor	Replace	0.2–0.99
EPCO	Plant uptake compensation factor	Replace	0.2–0.99
CN2	Initial SCS CN II value	Replace	65–85
Depth	Soil layer depths (mm)	Percent	50–150%
BD	Bulk density moist (g/cm^3)	Percent	50–150%
AWC	Average available water (mm/mm)	Percent	50–150%
KSAT	Saturated conductivity (mm/h)	Percent	50–150%
RCHRG_DP	Deep aquifer percolation fraction	Replace	0–1.0
REVAPMN	Depth of water in the aquifer for revap (mm)	Replace	0–500 mm
GW_REVAP	Groundwater 'revap' coefficient	Replace	0–0.2

[a] 'Replace' indicates that values were replaced within an initial range published in the literature, and 'percent' indicates that values were determined by adjusting the base initialization default variables by a certain percentage.

Table III. Table of watershed basin identifiers, characteristics and locations

	Name	USGS gauge	Area (km^2)	K-G[a] class	Latitude/ longitude	Study period	Gauge elevation (m)	Location
Study 1	Town Brook	01421618	36.6	Dfb	42.36/−74.66	1998–2004	784	Hobart, NY, USA
	Gumera	NA[b]	1200	Cwb	11.84/37.63	1995–2003	1800	Near Bahir Dar, Ethiopia
Study 2	Andreas Creek	10259000	22.1	Csa	33.76/−116.55	2000–2010	380	Palm Springs, CA, USA
	Tesuque Creek	08302500	30.0	BSk	35.74/−105.91	2000–2010	2170	Santa Fe, NM, USA
	Cross River	01374890	43.8	Dfa	41.26/−73.60	2000–2010	158	Cross River, NY, USA

[a] The Köppen-Geiger climate classification (Peel *et al*., 2007): BSk = semiarid, steppe, cold; Csa = Mediterranean, temperate, dry summer, hot summer; Dfb = humid, cold, without dry season, warm summer; Dfa = humid, cold, without dry season, cold summer; Cwb = temperate, dry winter, warm summer; http://people.eng.unimelb.edu.au/mpeel/koppen.html.
[b] Streamflow for the Gumara made available from the Ethiopian Ministry of Water Resources at http://www.mowr.gov.et/.

Table IV. Table of GHCN weather stations used in study 2 for (a) Cross River, (b) Tesuque Creek and (c) Andreas Creek, including Dist as well as %Miss, and TofOb in local time

Station name	GHCN ID	Dist (km)	%Miss	TofOb
(a) Cross River, Cross River, NY, USA				
Danbury Municipal Airport, CT, USA	USW00054734	15.4	3.2	24
West Point, NY, USA	USC00309292	33.4	0.9	7
Bridgeport Sikorsky Memorial Airport, CT, USA	USW00094702	−41.2	0.0	24
New York LaGuardia Airport, NY, USA	USW00014732	−58.3	0.0	24
New York J F Kennedy International Airport, NY, USA	USW00094789	−70.3	0.0	24
Falls Village, CT, USA	USC00062658	79.0	1.8	7
Oak Ridge Reservoir, NJ, USA	USC00286460	79.5	2.3	8
Newark International Airport, NJ, USA	USW00014734	−79.9	0.0	24
Bakersville, CT, USA	USC00060227	81.6	0.1	7
Burlington, CT, USA	USC00060973	81.9	2.9	7
Canoe Brook, NJ, USA	USC00281335	−85.4	2.4	8
Rock Hill 3 SW, NY, USA	USC00307210	92.1	1.6	8
(b) Tesuque Creek, Sante Fe, NM, USA				
Santa Fe 2, NM, USA	USC00298085	14.8	8.4	20
Glorieta, NM, USA	USC00293586	21.4	4.9	16
Santa Fe Co Municipal Airport, NM, USA	USW00023049	21.5	2.0	24
Pecos National Monument, NM, USA	USC00296676	28.8	1.0	16
Espanola, NM, USA	USC00293031	31.3	12.2	6
Los Alamos, NM, USA	USC00295084	39.8	3.3	24
Gascon, NM, USA	USC00293488	44.6	5.4	17
(c) Andreas Creek, Palm Springs, CA, USA				
Palm Springs Regional Airport, CA, USA	USW00093138	8.6	2.1	24
Palm Springs, CA, USA	USC00046635	9.3	2.3	16
Hemet, CA, USA	USC00043896	−36.2	0.2	16
Desert Resorts Regional Airport, CA, USA	USW00003104	38.2	0.4	24
Borrego Desert Park, CA, USA	USC00040983	59.9	0.6	8
Henshaw Dam, CA, USA	USC00043914	−61.7	1.2	7
Twentynine Palms, CA, USA	USC00049099	62.5	1.4	15
Redlands, CA, USA	USC00047306	−67.4	1.8	14
Carlsbad Mcclellan Palomar Airport, CA, USA	USW00003177	−97.5	1.9	24

Negative distances indicate stations closer to the ocean for Andreas Creek and Cross River.
GHCN, Global Historical Climatology Network; Dist, distance from USGS streamflow gage; %Miss, percentage of days with missing weather data; TofOb, time of observation in local time.

In study 2, three watersheds (Table III, study 2) were selected that had a variable density of weather stations located at increasing distances from the watershed outlet (Table IV). Discharge was simulated using SWAT models forced using both CFSR and weather station data. This second study evaluated how model performance in predicting discharge may diminish with increasingly distant weather stations and determines how CFSR-based results would diminish if interpolated at these same distances from the watershed.

Study 1

Two watersheds were chosen for this study: the Town Brook watershed (37 km^2) located in the Catskill Mountains, NY, USA, and the Gumera Watershed (1200 km^2) in the headwaters of the Blue Nile River in Ethiopia (Table III). Both watersheds have been modelled previously using SWAT (e.g. Easton *et al*., 2008, 2011; White *et al*., 2011). The weather station dataset for the Town Brook watershed was taken directly from the Easton *et al*. (2008) study and included data from the weather station at Stamford, NY, located just outside the northern watershed boundary, with gaps filled using weather data from the Delhi, NY, and Walton, NY, weather stations located 25 and 45 km from the outlet of the watershed, respectively. The Town Brook weather dataset was developed over time by several researchers studying a wide variety of models (e.g. Mehta *et al*., 2004; Agnew *et al*., 2006; Lyon *et al*., 2006; Schneiderman *et al*., 2007; Easton *et al*., 2008; Shaw and Walter, 2009; Easton *et al*., 2011). The weather station dataset for the Gumera watershed was taken directly from the White *et al*. (2011) study and was originally obtained from the National Meteorological Agency of Ethiopia for the three closest weather stations, Debre Tabor, Bahir Dar and Addis Zemen.

Study 2

For the second study, we selected three small (10–20 km^2) watersheds that represented distinct US hydroclimatic regions (Karl and Koss, 1984; Table III) and that had several weather stations within a 100-km radius from the outlet with nearly complete daily records (Table IV). One aspect of this investigation was to determine the distance from a small catchment at which land-based weather stations data produce worse stream discharge estimates than data from CFSR.

All weather station data for this study were downloaded using the National Climatic Data Center (NCDC) Interactive Map Application for daily datasets accessing the Global Historical Climate Network (Menne *et al*., 2011) database of temperature, precipitation and pressure records managed by the NCDC, Arizona State University and the Carbon Dioxide Information Analysis Center (http://gis.ncdc.noaa.gov/map/cdo/, accessed 2012/09/01).

CFSR data

CFSR data were obtained through the Data Support Section of the Computational and Information Systems Laboratory at the NCAR in Boulder, CO. For each catchment, we interpolated the CFSR temperature and precipitation rate fields to the centre of the catchment (the fields identified as tmp2m and prate, respectively). Daily maximum and minimum temperatures were determined from the hourly forecast values, and daily precipitation rates were determined by summing precipitation over 24-h periods. Maximum and minimum temperatures as well as precipitation were calculated using geographic midnight to midnight for each basin's location. For the analysis using weather stations at different distances from a watershed, we interpolated CFSR data to the coordinates of each weather station.

Analysis

All models were calibrated to maximize the Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970; Gupta and Kling, 2011) between observed and simulated stream discharge on a daily time step using the DEoptim package in the R computing environment (Ihaka and Gentleman, 1996; R Core Team, 2013). Separate model calibrations were performed for each meteorological dataset (e.g. for weather stations, and for CFSR interpolated to the centre of the watershed as well as interpolated to the locations of each of the weather stations). Streamflow at the Gumera watershed outlet was calibrated for an 8-year period, from 1996 to 2003, and

Table V. Table of NSE for the CFSR interpolated to the centre of each watershed, the closest weather station and the best meteorological weather station-based datasets

Name	Location	CFSR Center	Closest Met[a] weather	Closest Met distance (km)	Best Met[b] weather	Best Met distance (km)
Town Brook	Hobart, NY, USA	0.63	NA	NA	0.52	NA
Gumera	Bahir Dar, Ethiopia	0.71	NA	NA	0.68	NA
Andreas Creek	Palm Springs, CA, USA	0.71	0.36	9	0.67	9
Tesuque Creek	Santa Fe, NM, USA	0.49	0.08	15	0.34	45
Cross River	Cross River, NY, USA	0.67	0.63	15	0.63	15

Best meteorological weather is either a composite of stations in the case of Town Brook and Gumera, or a single weather station in the case of Andreas Creek, Tesuque Creek and Cross River.
NSE, Nash–Sutcliffe efficiency; CFSR, Climate Forecast System Reanalysis.
[a] Closest meteorological station to the centre of the watershed.
[b] Best performing meteorological station weather, or combination of weather stations in the case of Town Brook and Gumera.

streamflow in Town Brook was calibrated for a 5-year period from 1998 to 2002 to enable us to compare and contrast the results with prior published studies for these watersheds (Easton *et al*., 2008; White *et al*., 2011). For the remaining basins, streamflow at the watershed outlet was calibrated for an 11-year period from 2000 to 2010. In the DEoptim library, the number of guesses for the optimal value of the parameter vector (NP) was set to eight, and the number of iteration cycles over NP guesses (itermax) was set to 200. Each optimization converged near iteration 100, so this value did not seem to influence the optimization. Twenty model parameters were calibrated during optimization (Table II) (Moriasi *et al*., 2007). For the second analysis, we bootstrapped our data to determine the variability in our model performance. To do this, we sub-sampled 1000 random days from our time series and determined our mean and standard deviations in NSE from these data.

RESULTS

Study 1

For the Town Brook and Gumera watersheds, the simulated stream discharge using CFSR (NSE = 0.63 and 0.71, respectively) was similar to or slightly better than the results using weather station data (NSE = 0.52 and 0.68, respectively), as seen in Table V and Figures 1 and 2. Hydrographs for the two watersheds in Figure 3 also shows similar behaviour between the datasets for both watersheds. For Town Brook, the optimized results for our SWAT initialization are comparable to results from previous studies (Figure 1b, c) when using the same weather station data as the previous study (Easton *et al*., 2008). When using CFSR data, the performance was slightly better as shown comparing Figure 1(a) to Figure 1 (b, c). For Gumera, the NSEs were slightly better than those of previously published studies (Figure 2a, b; White *et al*., 2011).

Study 2

For the Cross River, Tesuque Creek and Andreas Creek watersheds in study 2, the modelled streamflow using CFSR data interpolated to the location of the stream gauge consistently had higher NSE values than the results generated using the nearest weather station (Table V and Figure 4). Hydrographs of measured *versus* simulated discharge are shown in Figure 5 for the closest weather station, and CFSR-based weather data. Although we initially hypothesized that model performance would diminish as the distance between the watershed and weather station increased, our results suggest somewhat more complex relationships. Figure 6 shows that in some cases (e.g. Tesuque Creek), weather stations located at a greater distance from the watershed actually provide better or more representative estimates of weather, as indicated by model performance.

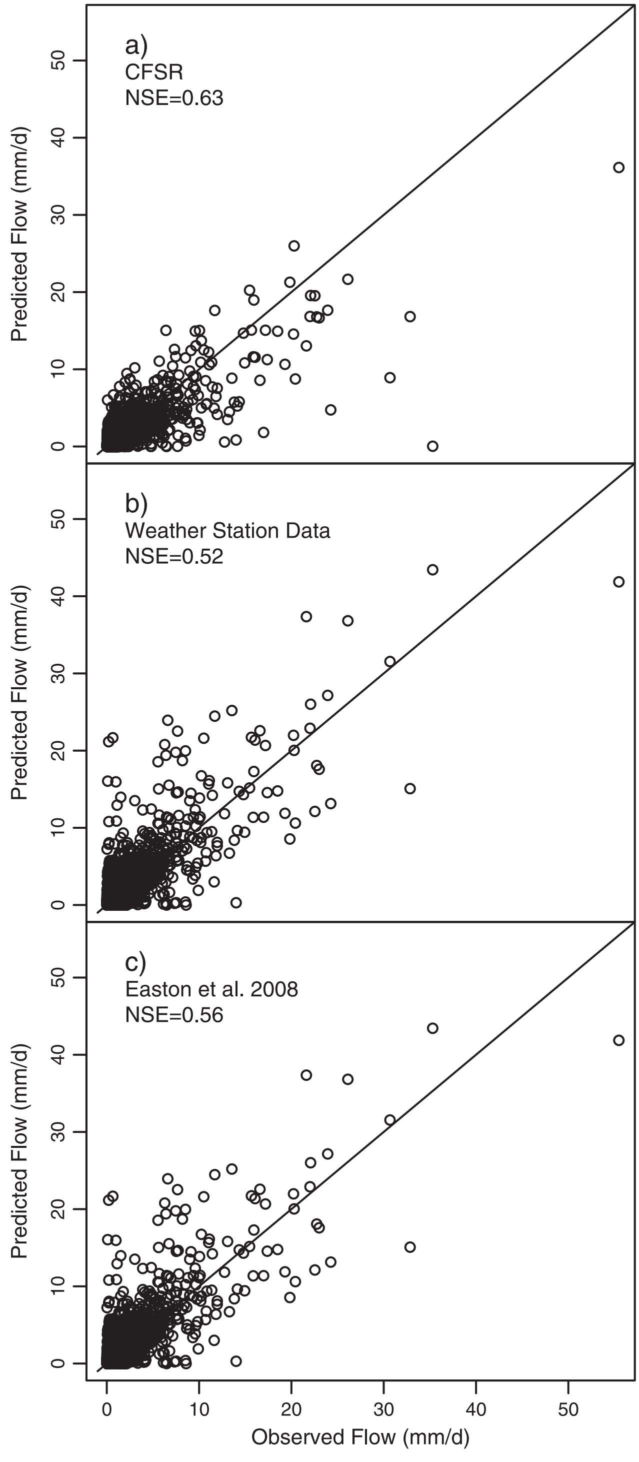

Figure 1. Comparison of the simplified nine HRU initializations in the Town Brook watershed for CFSR (a), ideal meteorological weather stations (b) and against the previous best values of the more complex SWAT model initialization shown in (c). The simplified initialization performs similarly to the complex initialization, and there is a significant increase in performance when the CFSR meteorological data are used to force the SWAT model

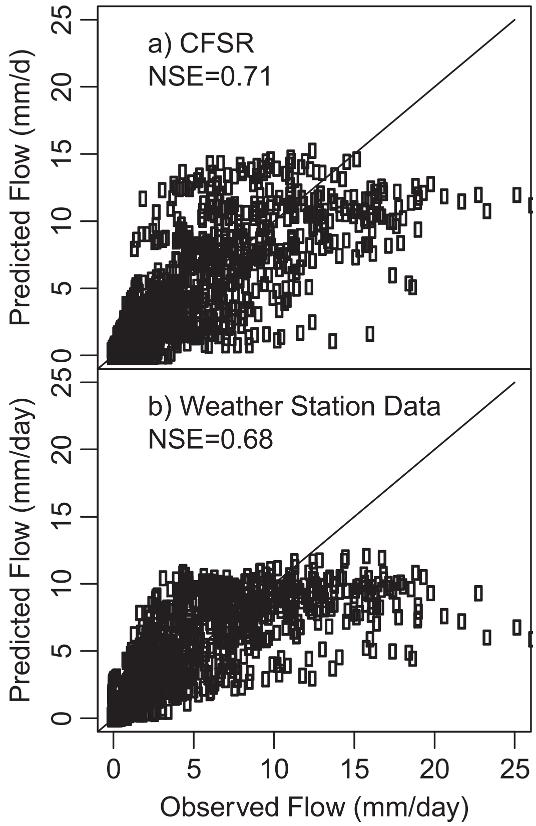

Figure 2. Comparison of the simplified nine HRU initializations in the Gumera watershed for CFSR (a) and ideal meteorological weather stations (b), and there is similar performance when the CFSR meteorological data are used to force the SWAT model *versus* using the closest weather stations

For Cross River and Andreas Creek, the NSE values declined less rapidly with increasing distance between the weather station and watershed moving towards the ocean than when considering stations further inland (Figure 6a, c). CFSR-based results showed a similar pattern at Andreas Creek, but a more or less symmetrical decline in NSE at Cross River. For Tesuque Creek watershed (Figure 6b), the best weather stations were actually the two furthest from the watershed, which are the most similar in terms of topography and land cover (e.g. mountainous and forested area of similar elevation). In general, the relatively arid watersheds, Andreas Creek and Tesuque Creek, were more difficult to model hydrologically (Figure 5b, c) than the humid Northeastern US watersheds (Figures 3a and 5a).

DISCUSSION

Using CFSR weather input to force the SWAT model delivered ‘satisfactory’ (NSE > 0.5) to ‘very good’ (NSE > 0.65) per Saleh *et al.* (2000) results for predicted *versus* observed flow on a daily time step, although care should be taken when comparing these results to those of different studies (Schaefli and Gupta, 2007). These results were consistently better than forcing the SWAT models using weather station records. Interestingly, the model results for Town Brook were better than those previously published by Easton *et al.* (2008), even though that study contained orders of magnitude more unique HRUs and

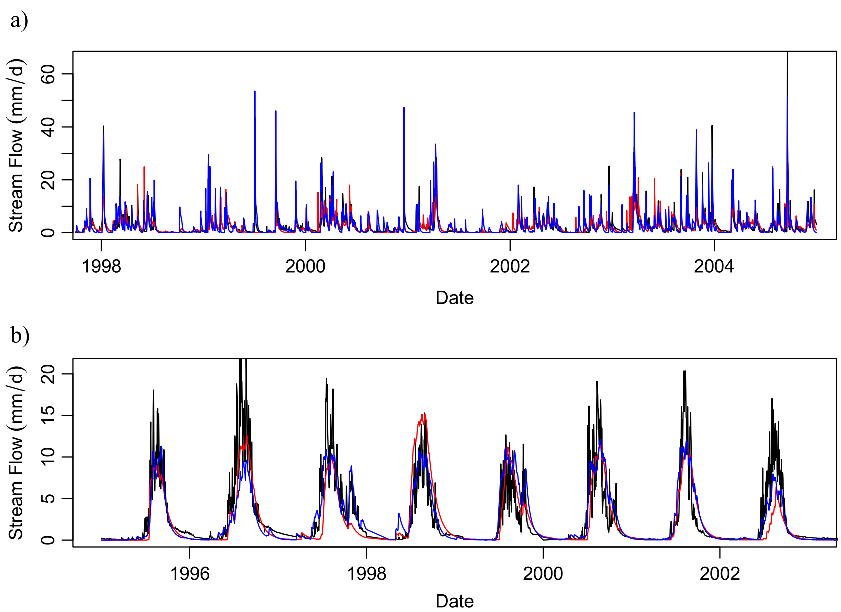

Figure 3. Hydrographs for Town Brook (a) and Gumera (b) watersheds, showing the measured streamflow (black) with the CFSR-based prediction (red) and nearest weather station (blue)

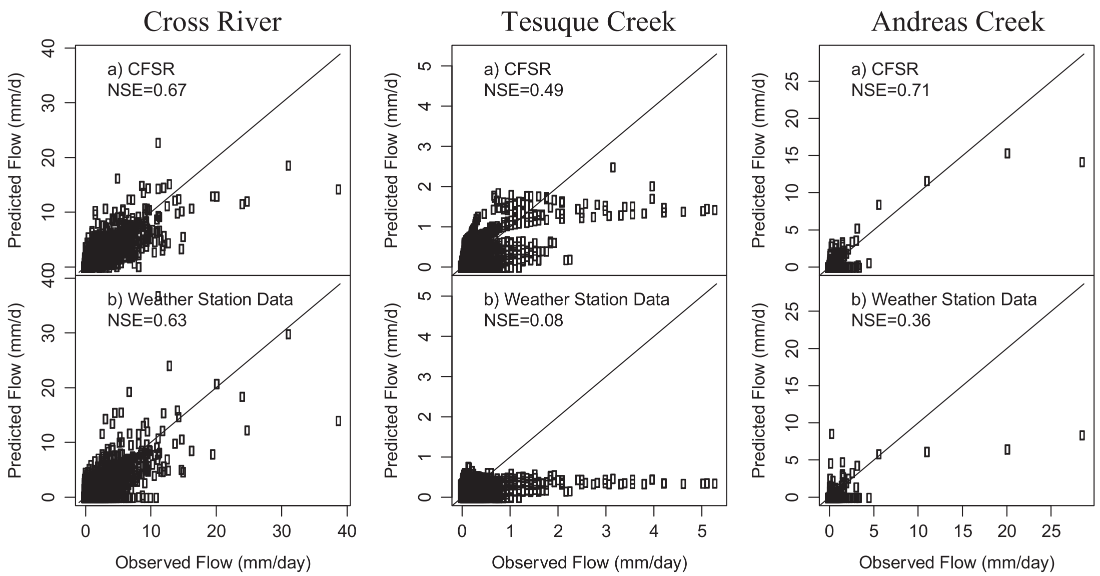

Figure 4. Comparison of the simplified nine HRU initializations in the Cross River, Tesuque Creek and Andreas Creek watersheds with the (a) frames showing the CFSR meteorological data results and (b) frames showing ideal meteorological weather station results used to force the SWAT model

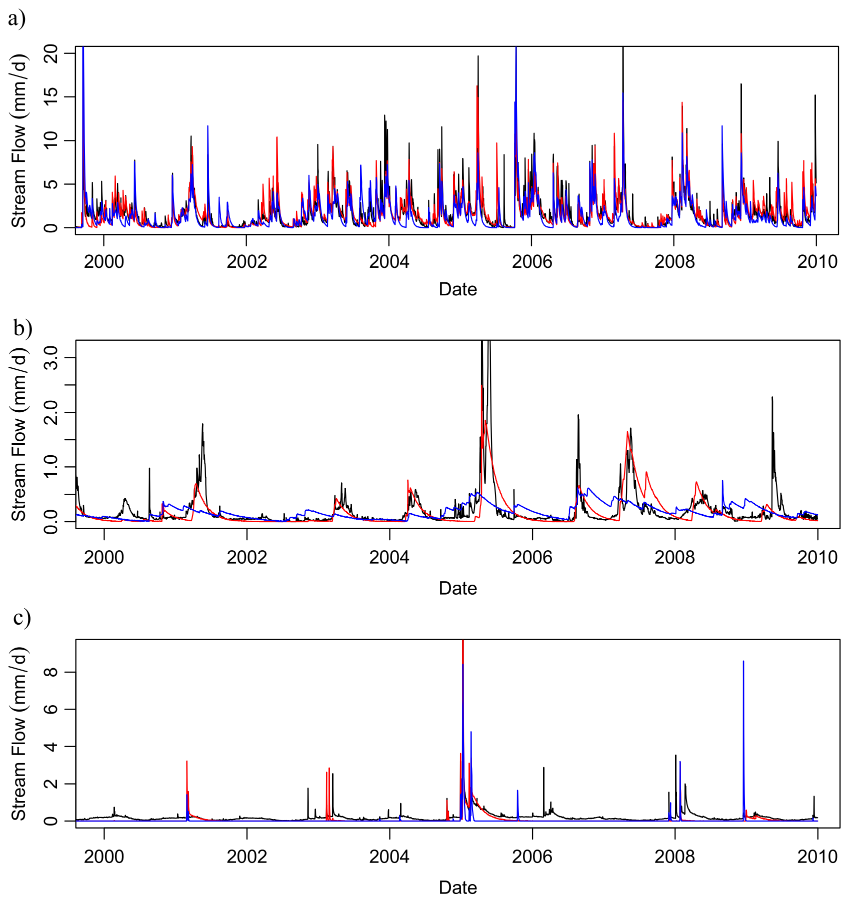

Figure 5. Hydrographs for Cross River (a), Tesuque Creek (b) and Andreas R (c) showing the measured streamflow (black) with the CFSR-based prediction (red) and nearest weather station (blue)

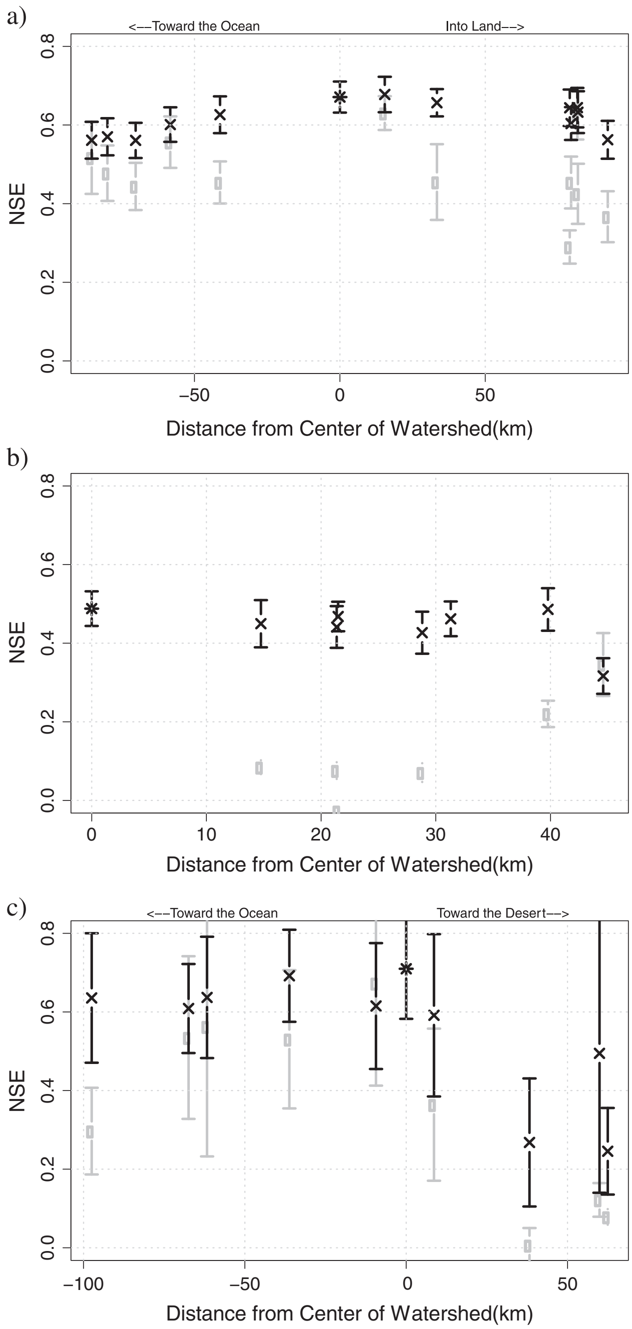

Figure 6. Optimal NSE for the CFSR (x) and weather stations (circle) at various distances from the centre of Cross River (a), Tesuque Creek (b) and Andreas Creek (c). The NSE model performance using the CFSR weather data interpolated to the centre of the watershed is shown with asterisks. Negative distances indicate stations that are towards the ocean (a and c only), with the exception of the 'Palm Springs' station, which is placed in the negative side at −9.3 km, to distinguish it from the 'Palm Springs Regional Airport' station at +8.6 km. Error bars indicate ±2 SD for 1000 bootstrap samples of predicted *versus* observed results

were thus afforded more degrees of freedom in the SWAT calibration and used a weather record consisting of multiple stations. This highlights one of the strengths of the CFSR dataset, in as much as it can outperform land-based stations even in research watersheds.

In general, the relatively arid watersheds, Andreas Creek and Tesuque Creek, were more difficult to model hydrologically (Figure 5b, c), than the Northeastern US watersheds, possibly because large storm runoff events are triggered by small, localized precipitation events that are not well represented by the relatively coarse-scale CFSR data or weather station data. The desert mountainous Southwest climate in NM demonstrated the most significant benefits of using the interpolated CFSR dataset. First, weather station density is substantially lower in this region relative to much of the rest of the conterminous USA. This results in fewer basins having weather stations close enough to adequately represent the streamflow. More importantly, even with weather stations in close proximity to the watershed, the precipitation events, characteristically small-cell-based storm systems of short duration and low frequency, were often not representative of weather occurring in the watershed. Stations within 10–20 km^2 had virtually no relationship with the observed streamflow for the basin (Figure 6b). It is interesting that weather stations located at a greater distance produced better results than the closest stations, possibly because they are located in similar terrains or microclimate regimes, i.e. more similar elevation, aspect and land cover. In this case, the microclimate similarities could be more important than the proximity of the weather station. We should also note that there could be other reasons for these results, such as the variability in the quality of NCDC gauge data, given all of the station types and collection methods (e.g. some are non-recording and have to be manually checked daily, and some are more susceptible to wind and splash loss). This type of climate is also challenging for CFSR-based modelling because the high-intensity local events may be overly 'dampened' in the relatively coarse scale of the CFSR data (e.g. Figure 6b, c).

One reason that the CFSR data may perform as well as it does for watershed modelling is that the weather data are effectively averaged over spatial scales that are more similar to many watershed extents or at least more similar than a typical point measurement of a weather station is to a watershed. Because the CFSR data represent averages over much larger areas than weather station data, CFSR appears able to maintain predictive capability even when interpolated to points far away from the watershed.

Although most hydrology textbooks note that the magnitude of point rainfall needs to be adjusted when considering the rainfall over a larger surrounding area (e.g. Miller *et al.*, 1973 cited in Dingman, 2008), few modellers do this explicitly and often account for these differences during model calibration. Using the spatial CSFR dataset, such adjustments are less important. As a result of the difference in spatial scales between CFSR data and weather station data, direct comparisons between the two provide little insight. This is not surprising and indeed has been noted in several other studies. For instance, Vasiloff *et al*. (2009) pointed out that comparisons of weather station data to higher-resolution radar and satellite precipitation products are hard due to the effects of wind, hail, missing gauge data and the storm tracks. In fact, Mehta *et al*. (2004) demonstrated that weather gauges located at distances less than the resolution of the CFSR have a low correlation ($r^2 < 0.3$). However, when the CFSR data are developed, there are automatic comparisons between CFSR and the ground-based weather data (Saha *et al*., 2010), which ensures some level of agreement.

Moving forward, it would be very useful to use regional watersheds with high-resolution weather station networks to determine what resolution of station density is needed in time, space and locality for weather estimates to adequately drive watershed models, especially more process-oriented models. As can be seen by comparing Figure 6(a–c), the result of such studies would be extremely location specific. Thus, it is recommended that such studies be performed prior to blindly accepting CFSR as a hydrological forcing dataset. Perhaps the most appropriate and most easily accomplished use for CFSR is to use it as an indication of the minimum acceptable model performance for any given hydrological study, although, as indicated by the results of this study, CFSR data might very well provide increased watershed model performance.

One valuable attribute of the CFSR data is that it is globally available and will allow modellers access to weather data (available at http://cfsr.bse.vt.edu/swat-cfsr-v02.pl) where there are no nearby weather stations. This is probably most valuable for data-poor regions such as in developing countries. In these regions, even when data are collected and archived, the effort and money required to access them can be substantial; the co-authors have personally experienced this specific difficulty in countries such as India and Chile, and several countries in Africa. One reason for the inclusion of the Gumera watershed in Ethiopia was to make this point explicit with a tangible example.

Another potentially valuable characteristic of the CFSR data for watershed modelling is that it is updated in real time, including short-term forecasts (6 h). This may facilitate more widespread efforts in real-time or near-real-time hydrological modelling. This could be beneficial for predicting flood likelihood and location or for crop forecasting. It could also allow modellers to predict areas in a watershed with a high risk of generating runoff and where land managers might avoid environmentally risky activities (Walter *et al*., 2000; Agnew *et al*., 2006; Easton *et al*., 2008).

While we attempted to explore a wide range of hydroclimatic settings in this study, a valuable next step would be to explicitly expand on these studies to determine where CFSR data work particularly well and where there may be problems. Also, although we looked at one large watershed (Gumera, 1200 km^2) and several on the order 40 km^2, the interplay between watershed size and CFSR data deserves more investigation. Probably the most valuable next-steps will be to apply CFSR to more physically based and complicated modelling efforts (e.g. realistic landscape representation instead of the quasi-lumped approach used here). The objective of this study was limited to evaluating whether CFSR data could theoretically work for providing weather inputs to watershed modelling, especially where good weather station data are not available. Thus, we did not make any attempts to bias correct the CFSR data, but the way we employed the SWAT model, as a black-box response function, likely resulted in parameters calibrations that offset any systematic biases in the weather data.

CONCLUSION

This proof-of-concept study demonstrated that CFSR data could be reliably applied to watershed modelling across a variety of hydroclimate regimes and watersheds. Surprisingly, the CFSR data generally resulted in as good or better streamflow predictions as the best (often nearest) weather station. We speculate that this is in part because the CFSR data are averaged over areas comparable to watershed areas we tested, at least more representative of watershed area than the area of a weather station. We note that this could be problematic for watersheds where the highest discharges are associated with very small, localized storms. In these cases, watershed modelling will be challenging regardless of the source of weather data. Adding CFSR data to the suite of watershed modelling tools provides new opportunities for meeting the challenges of modelling un-gauged watersheds and advancing real-time hydrological modelling across the globe.

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