Transactions in GIS, 2008, 12(5): 613–631

Research Article

A GIS-Based Procedure for Downscaling Climate Data for West Africa

Felicia O Akinyemi
GIS and Remote Sensing Research and Training Centre
National University of Rwanda
Butare, Rwanda

James O Adejuwon
Department of Geography
Obafemi Awolowo University
Ile-Ife, Nigeria

Abstract
Local studies aimed at assessing the impact of climate variability on crop yield at the individual farm level require the use of weather and climate data. These are often collected at points known as meteorological stations. In West Africa, meteorological stations are sparsely distributed and as a result, are often unable to satisfy the data requirements for such studies. One major problem arising from this is how to estimate values for locations where primary data is not available. General Circulation Models (GCMs) have recently been deployed for weather forecasting and climate change projections but the resolution of their outputs is low requiring downscaling. This article describes a GIS-based procedure for downscaling GCMs' outputs for use in studies assessing the impacts of climate variability on crop yield at the farm level. The procedure is implemented with the Hadley Centre's GCM (HadCM2) data, although any other GCM can be used. Results in this study show that the model works best when representing drier months as compared to wet months in all three domains tested. For example, it estimated the rainfall for January (the driest month) better than that of July which is the peak of the rainy season in West Africa. There is also a north-south pattern influencing the accuracy of estimated rainfall distribution, with stations in the south better represented than those in the north. For the greater part of West Africa where similar climatic conditions persist as in Nigeria, this procedure can be considered suitable for interpolation and downscaling.

Address for correspondence: Felicia O. Akinyemi, GIS and Remote Sensing Research and Training Centre, National University of Rwanda, P.O. Box 212, Butare, Rwanda. E-mail: felicia.akinyemi@cgisnur.org

doi: 10.1111/j.1467-9671.2008.01120.x

1 Introduction

Primary information in respect of weather and climate are often collected at widely spaced points known as meteorological stations. Where observed weather data are available, they are used in local studies for assessing the impacts of climate variability on crop yield at individual farm sites. In West Africa, meteorological stations are sparsely distributed and as a result, are often unable to satisfy the data requirements for such studies. One major problem arising from this is how to estimate values for locations where primary data is not available. Consequently, crop model simulations at locations far from measured data or where essential variables or periods are missing must rely on estimated data (see Hansen and Jones 2000).

The most common estimate is to simply use the nearest weather station as a proxy for unmeasured weather at the location of interest. Spatial averaging and interpolation methods are often used to derive climate data values for all locations of interest in order to drive crop models (Priya and Shibasaki 2001). The reduction in the variability of daily time-series data when spatial averaging is used is a limitation. This is because crop models are sensitive not only to mean climate, but also to its variability within and between seasons. Spatial interpolation methods convert data from point observations to contiguous fields based on the rationale that, on average, climate values are more likely to be similar at points close together than at those further apart (see Hansen and Jones 2000). Low density of the weather observation network is the primary deficiency for interpolation methods (Tait et al. 2006). For example, interpolation of rainfall data into other areas, based on data from sampled stations sometimes several kilometres away, can cause significant discrepancies and it is also possible that some localised rainfall events may be missed entirely if no rain fell at the nearest observation stations.

Another source of estimated data is that provided by equilibrium General Circulation Models (GCMs) or coupled atmosphere-ocean general circulation model (AOGCM) simulations. Most impact studies now use climate change information from GCMs because of the ready availability of this information (Mearns et al. 2003). At present, GCMs are the best tools for providing a complete and coherent view of atmospheric dynamics. Although they provide reasonable climatic simulations in terms of annual and seasonal means, their resolution of several hundred kilometers is unsuitable for producing values either at a regional scale (i.e. a few tens of kilometres) or at a local scale (i.e. a few kilometres). Consequently, there is the need to downscale coarse GCM outputs to the scale of the studied system for simulated data to be of use in impact assessment studies (Hoff 2001).

In West Africa, weather data are sourced from both international and local organizations such as the Meteorological Office – United Kingdom (MO-UK), Centre de Recherche de Climatologie – France, the U.S. National Oceanic and Atmospheric Administration, the Central Forecasting Organisation (CFO) – Nigeria and the African Centre for Meteorological Applications for Development. These available data do not often satisfy the need of local impact assessment studies because the forecasting tools currently deployed are regional in approach and general in perspective. For example, the CFO divides Nigeria into five broad zones and makes its forecasts for each zone. The models developed are at such coarse spatial scales that they often fail at individual farm-level sites (Odekunle et al. 2005). According to Adejuwon et al. (2007), the zones are extensive and within the same zone, a wet season at one station may be a dry season at another. They noted that the disparities existing in forecasting skills between stations lying in the same ecological zones are probably a result of such intrazonal variability. Thus intrazonal variability is a limiting factor to the use of weather forecasts at farm-level sites.

The situation in West Africa requires scientifically accessible, sound and easy to use methods for studying climate change impact at local levels. This article seeks to address the growing requirement for climate and weather data by local applications in West Africa for assessing climate variability impacts on crop yield. It examines the suitability of a Geographic Information System (GIS)-based geostatistical interpolation procedure for downscaling low resolution climate and weather data from GCM outputs to high resolution data for use at the farm level. Interpolation is probably one of the most efficient methods for obtaining data at the required scale (Hoff 2001) and it is easily applied to output from different GCMs.

The primary objective of the larger project from which this study emanated is to examine the vulnerability of food crop production to inter-annual climate variability and extreme weather events in West Africa and to assess how extended weather and climate forecasts could be employed as a basic adaptation strategy to ameliorate the impact. The project is aimed at improving the management and decision-making associated with the production of food crops in West Africa.

2 Background

Climate models are used to simulate and quantify the climate response to present and future human activities. The present climate is initially simulated for extended periods, typically many decades, under present conditions without any change in external climate forcing. Then the quality of these simulations is assessed by systematically comparing the simulated climate with observations of the present climate. Once the model is evaluated and its quality established, projections of future climate change can be made (see Baede et al. 2001, Solomon et al. 2007).

The coarse spatial scale of the climate scenarios produced from GCMs is recognised as one of the major problems in applying GCM projections at local or regional levels (Kunstmann and Jung 2005). There are techniques for evolving regional and local details from the coarse resolution GCM data. One such method is to adopt changes in climate projected for each GCM grid box to project future climate for all locations within the larger box from observed climate (Rosenzweig and Parry 1994). Other more sophisticated approaches are high resolution and variable resolution 'time-slice' AOGCMs; regional (or nested limited area) climate models (RCMs); and empirical/statistical and statistical/dynamic methods (Wilby and Wigley 1997). With high resolution and variable resolution global models, identified periods of interest (or 'time-slices') within AOGCM transient simulations are modelled to provide additional spatial detail (Fox-Rabinovitz et al. 1997, Govindasamy et al. 2003).

The regional climate modelling technique involves the use of output from global model simulations to provide initial conditions and time-dependent lateral meteorological boundary conditions to drive high-resolution RCM simulations for selected time periods of the global model run (Giorgi 1990, Mearns et al. 2003). RCMs capture geographical details more precisely than the coarse-resolution GCM, although the computational requirements are demanding (Hay et al. 2002). Kunstmann and Jung (2005) investigated the impact of climate change on the temporal and spatial distribution of precipitation, temperature, evapotranspiration and surface runoff in the Volta Basin (400,000 km^2) of

West Africa. High resolution regional climate simulation using explicit dynamic downscaling of the IS92a ECHAM4 global climate scenario indicates a slight increase in total annual precipitation of 5%, but also a significant decrease (up to 70%) of precipitation in April, which marks the transition from the dry season to the rainy season. Statistical downscaling develops empirical relations between climate variables simulated by a GCM at grid-box scales and variables at subgrid (regional and local) scales. A summary of various climate scenario techniques and an evaluation of their advantages and disadvantages can be found in Mearns et al. (2003).

Some studies have examined the differences in the performance of different downscaling methods. Wilby et al. (1998) calibrated different statistical downscaling models using both observed and GCM-generated daily precipitation time series. Significant differences in the level of skill were found amongst the downscaling methods. Changes in precipitation between the present and future scenarios produced by the statistical downscaling methods were generally smaller than those produced directly by the GCM. Wilby and Dettinger (2000) found that hydrographs (hydrological response) simulated using dynamically downscaled precipitation and temperature for the Animas River basin of Colorado were not generally as realistic as those simulated using statistically downscaled precipitation and temperature.

Impact assessment applications using climate scenarios are recent (e.g. in agriculture – Mearns et al. 2001 and in water resources – Stone et al. 2003). The approaches are still not available to a large majority of researchers whose main interests lie in the assessments of impacts, vulnerabilities and adaptations. The methods are not always straightforward and remain much more computationally demanding than most people other than their developers could cope with. Statistical downscaling models are most suitable for use in regions where there is sufficiently good datasets available for model calibration (Mearns et al. 2003). Although not computationally as expensive as other downscaling models, the use of statistical downscaling in West Africa is limited by the dearth of observed data. Moreover, impact research requires climate modelling skills. This requirement is often not available to impact researchers in developing countries and working with regional modellers who have the expertise for generating RCM simulations may as well not be feasible.

3 Study Area

The Atlantic Ocean is the major, if not the only, source of moisture for the West Africa subcontinent. The moisture is brought to the land areas by the southwesterly winds moving in after the northward migrating Intertropical Convergence Zone (ITCZ). This zone is a discontinuity between the dry continental air and the humid southwesterly air, whose characteristics are determined by the nature of the sea surface temperature of the Gulf of Guinea. The ITCZ controls the number and duration of weather types experienced in different parts of West Africa with rainfall over the land reducing with increasing distance inland (Adedokun 1978, Oguntoyinbo 1978).

Since the climate of Nigeria represents a microcosm of the climate of West Africa (Oguntoyinbo 1978), Nigeria is used as the case study for sub-Saharan West Africa. The country truly represents the climatic profile from the very wet to the semi-arid ends of the subcontinent (see Figure 1). All the indicator vegetation types of the various climate types are present in the Nigeria except the Southern Sahara and Saharan vegetation.

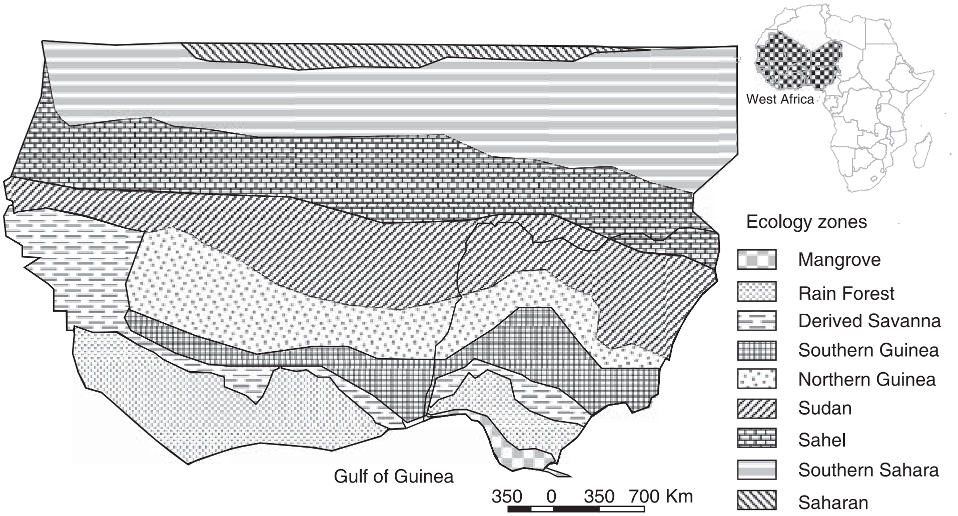

Figure 1 Location of Nigeria and agro-ecological zones of West Africa (adapted from Adejuwon et al. 2007)

From the very humid, eastern, coastal locations in the south to the drier northern margins, the agro-ecological zones include mangrove, evergreen rainforests (Koppen's Af; 1,500–2,200 mm year^{-1} precipitation), a transition zone of derived savannah (around 1,300 mm year^{-1}), Southern and Northern Guinea savannah (Koppen's Aw; around 1,200 mm year^{-1}), Sudan savannah (Koppen's BS; around 400–1,000 mm year^{-1}), and Sahel savannah (Koppen's BS; < 400 mm year^{-1}) (Kunstmann and Jung 2005, Adejuwon et al. 2007).

3.1 Data

In this study, rainfall is the meteorological parameter used as changes in the amount and distribution of rainfall have significant impacts on water availability and thereby directly influence socio-economic activities in the region. Over 70% of the inhabitants depend primarily on rain-fed agriculture for their livelihood. Since West Africa is a typical tropical region, rainfall is the principal controlling element of crop productivity because the crop plants are sensitive to the moisture situation both during their growth, development, and especially as they reach maturity. Hydropower is the main source of electric power generation, crucial for socio-economic development, and is strongly dependent on the availability of rainfall (Kunstmann and Jung 2005, Nieuwolt 1982 cited in Adejuwon et al. 2007).

3.1.1 Station data

A base map was created which depicts the locations of 30 meteorological stations as point objects. These stations are Bauchi, Benin, Bida, Calabar, Gusau, Ibadan, Ijebu-Ode, Ikom, Ilorin, Jos, Kaduna, Kano, Katsina, Lagos, Lokoja, Maiduguri, Makurdi,

Figure 2 Spatial distribution of meteorological stations

Minna, Nguru, Ogoja, Ondo, Onitsha, Osogbo, Owerri, Port Harcourt, Potiskum, Sokoto, Warri, Yola, and Zaria all located within Nigeria. Figure 2 shows the distribution of these stations selected from the various agro-ecological zones. Observed rainfall data from 1961–2000 is available for these stations which were acquired from the Nigerian Meteorological Agency.

Nigeria has a size of 927,000 km^2 with about 30 standard meteorological stations where observations of the main weather elements are made on a daily basis. If these stations had been regularly spaced, there would be one within each unit area of up to 30,000 km^2.

3.1.2 GCM output

The HadCM2 (Intergovernmental Panel on Climate Change) climate model data for Nigeria used in this analysis was downloaded from the IPCC Data Distribution Centre website (see http://ipcc-ddc.cru.uea.ac.uk/download_data/hadcom2/ for additional details). It is an output of the MO-UK Hadley Centre. It is a 19 layer atmospheric GCM coupled to a 20-layer ocean model whose surface horizontal resolution is 2.5 degrees

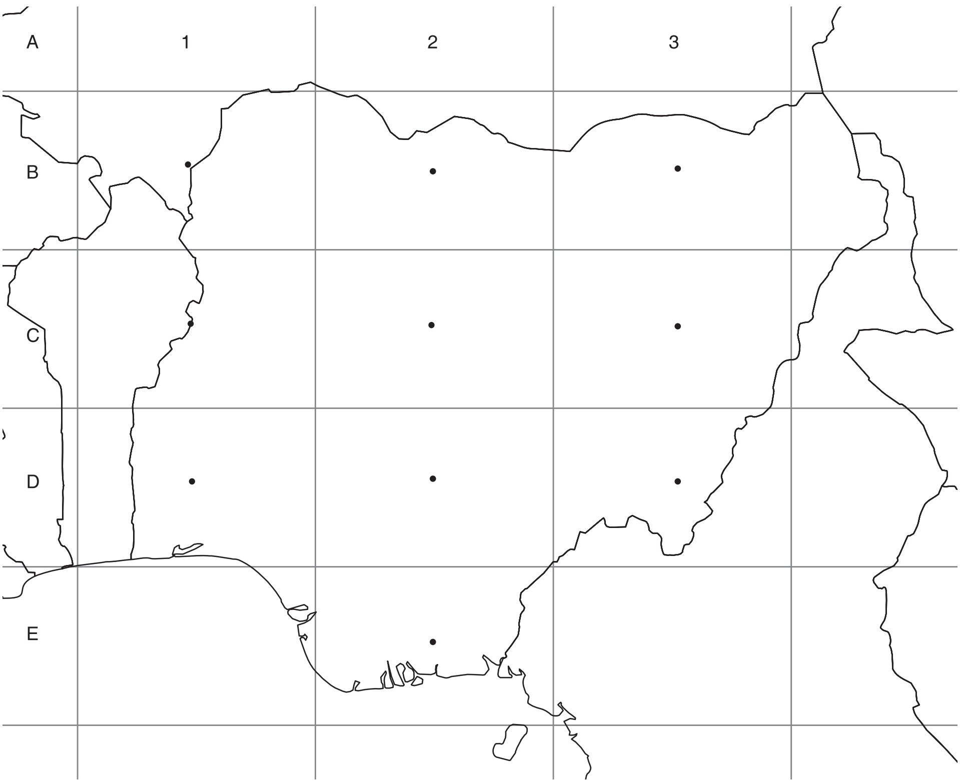

Figure 3 HadCM2 grid network over Nigeria

latitude by 3.75 degrees longitude. This has produced a grid-box resolution of 96 × 73 grid cells with each cell 417 km × 278 km at the equator reducing to 295 × 278 km at 45 degrees North and South (Gordon et al. 2000). For the HadCM2 output, each of the grid cells to which units of data are attached is about 115,000 km^2 in area near the equator. Nigeria's land area can accommodate 10 such grid cells each with an approximate size of 95,000 km^2 (Figure 3 and Table 1).

Figure 3 shows the HadCM2 grid network superimposed over Nigeria while the location of the 10 grid cells are shown as coordinates in Table 1. Only two cells, C-2 (10.0 N, 7.5 E) and D-2 (7.5 N, 7.5 E) are wholly contained within Nigeria. Thus the spatial resolution of the HadCM2 GCM is comparable to a network of 10 meteorological stations over Nigeria.

The spatial resolution of 5 degrees by 5 degrees GCM data over Nigeria is the same as the spatial resolution of a meteorological station network consisting of three to four regularly spaced stations. Near the equator, each of the grid cells is about 300,000 km^2 in size. Within Nigeria, each grid cell covers an area of about 270,000 km^2 which is between one-quarter and one-third the size of Nigeria. Thus, only one of these large GCM cells, (lying between 5° E and 10° E and, from 5° N to 10° N), lies entirely within the territorial limits of Nigeria. If GCM data were available at a resolution of 2 degrees latitude by 2 degrees longitude, they would be assignable to 25 grid cells within Nigeria

Table 1 HadCM2 grid details for Nigeria

Locator	ID	I	J	Lat	Long
B-1	2977	2	32	12.5	3.75
B-2	2978	3	32	12.5	7.5
B-3	2979	4	32	12.5	11.25
C-1	3073	2	33	10.0	3.75
C-2	3074	3	33	10.0	7.5
C-3	3075	4	33	10.0	11.25
D-1	3169	2	34	7.5	3.75
D-2	3170	3	34	7.5	7.5
D-3	3171	4	34	7.5	11.25
E-2	3266	3	35	5.0	7.5

Table 2 Spatial resolution of Grid Cells

	Grid cells lat × long	App. size in km^2	App. number of cells corresponding to meteorological station networks within Nigeria
1	5 × 5	270,000	4
2	HadCM2 GCM 3.75 × 2.5	95,000	10
3	2.5 × 2.5	62,500	15
4	2.5 × 2.0	50,000	20
5	2.0 × 2.0	40,000	25
6	2.0 × 1.5	30,000	30
7	1.5 × 1.5	22,500	40
8	1.0 × 1.0	10,000	95
9	0.5 × 0.5	2,500	400

each having an area of about 40,000 km^2. Four hundred grid cells of 0.5 degrees latitude by 0.5 degrees longitude will be needed to cover the entire land area of Nigeria (Table 2).

Table 2 shows the full range of grid cell sizes from 5.0° lat × 5.0° long to 0.5° lat × 0.5° long, their spatial equivalence in km^2, and approximate meteorological station networks over Nigeria.

4 Methodology

Where the climate and weather data have been collected at meteorological stations, interpolation procedures are used to estimate values for locations where data is not available. This is different where the data are the outputs of the GCMs, since the procedures for deriving values for locations between nodes are usually referred to as 'downscaling' in these instances. The relevant results of downscaling and interpolation in this context are the same in that they lead to the enhancement of the spatial resolution of the climate data surface. This forms the basic premise of this work in that GIS tools for interpolating from data collected at meteorological stations could logically be employed for downscaling coarse resolution data outputs of GCMs.

4.1 Spatial Interpolation Techniques

Spatial interpolation involves the estimation of the values of properties of unsampled sites within an area covered by sampled points, using the data from those points. Perhaps the most widely adopted version of this technique is the one which adopts the data collected at the nearest weather station for the location of interest (Burrough and McDonnell 1998). Other more sophisticated techniques used in interpolating climate values from point based data include: (1) Thiessen polygons (Thiessen 1911); (2) Splining (Fleming et al. 2000, Jeffrey et al. 2001); (3) Kriging (Hudson and Wachkernagel 1994); (4) Inverse Distance Weighting (IDW) (Hartkamp et al. 1999); (5) Gradient plus inverse-distance-squared (Price et al. 2000); and (6) Neural networks (Antonic et al. 2001, Rigol et al. 2001).

Although each of these spatial interpolation techniques has its own advantages and disadvantages, we consider the IDW interpolator the most appropriate in our case to illustrate the applicability of the GIS-based procedure for downscaling GCM outputs. This is because IDW attenuates the influence of distant points by its use of inverse distance weight given an assumption of positive spatial autocorrelation. In other words, it assumes that the influence of the nearby observed data on an interpolated point solely depends on the inverse of the distance between the interpolated point and the data point. Let $\hat{g}_j$ be the interpolated point, T_i be the observed data at the station $\hat{r}_i$, and $\hat{T}_j$ be the estimated value of the quantity T at the point $\hat{g}_j$. Then the inverse-distance-weighting scheme is:

$$\hat{T}_j = \left(\sum_{i=1}^{N} \frac{1}{d_{ij}} \right)^{-1} \sum_{i=1}^{M_j} \frac{T_i}{d_{ij}} \tag{1}$$

where $d_{ij} = | \hat{r}_i - \hat{g}_j |$ is the distance between $\hat{r}_i$ and $\hat{g}_j$, and M_i is the total number of the stations "nearby" $\hat{g}_j$. If the station $\hat{r}_i$ is on the grid point $\hat{g}_j$, then:

$$\hat{T}_j = T_i. \tag{2}$$

The stations T_i (where $i = 1, 2, \ldots, M_j$) are chosen according to the distance table for the grid $\hat{g}_j$. Station $\hat{r}_1$ is the station with data that is nearest to the grid $\hat{g}_j$, and station $\hat{r}_2$ is the second nearest station (Shen et al. 2001).

The implication of this assumption is that values closer to the unsampled locations are more representative of the value to be estimated than values from samples farther away. Weights therefore change according to the linear distance of the samples from the unsampled point in inverse proportions. In other words, the larger the distance between the data point and interpolated point, the smaller the weight given to the data point. In the ArcView IDW interpolator, the significance of the surrounding points upon the interpolated value is controlled using the power parameter. According to Adejuwon (2004), it is important for us to reduce to a minimum the influence of distant points because crop yield was found to differ between locations when all other parameters are the same. The distribution of observation points when interpolating is also very important as clustered points will carry an artificially large weight. For this study, the observation points are well spaced out which reduces the spatial bias to the estimates (see Shen et al. 2001 and Chapman and Thorne 2003 for detailed discussion on some of these other methods).

4.2 GIS-based Procedure for Downscaling

With particular focus on the West African situation, the aim of this GIS-based procedure is to procure weather data for crop modelling (Figure 4). This procedure could offer an

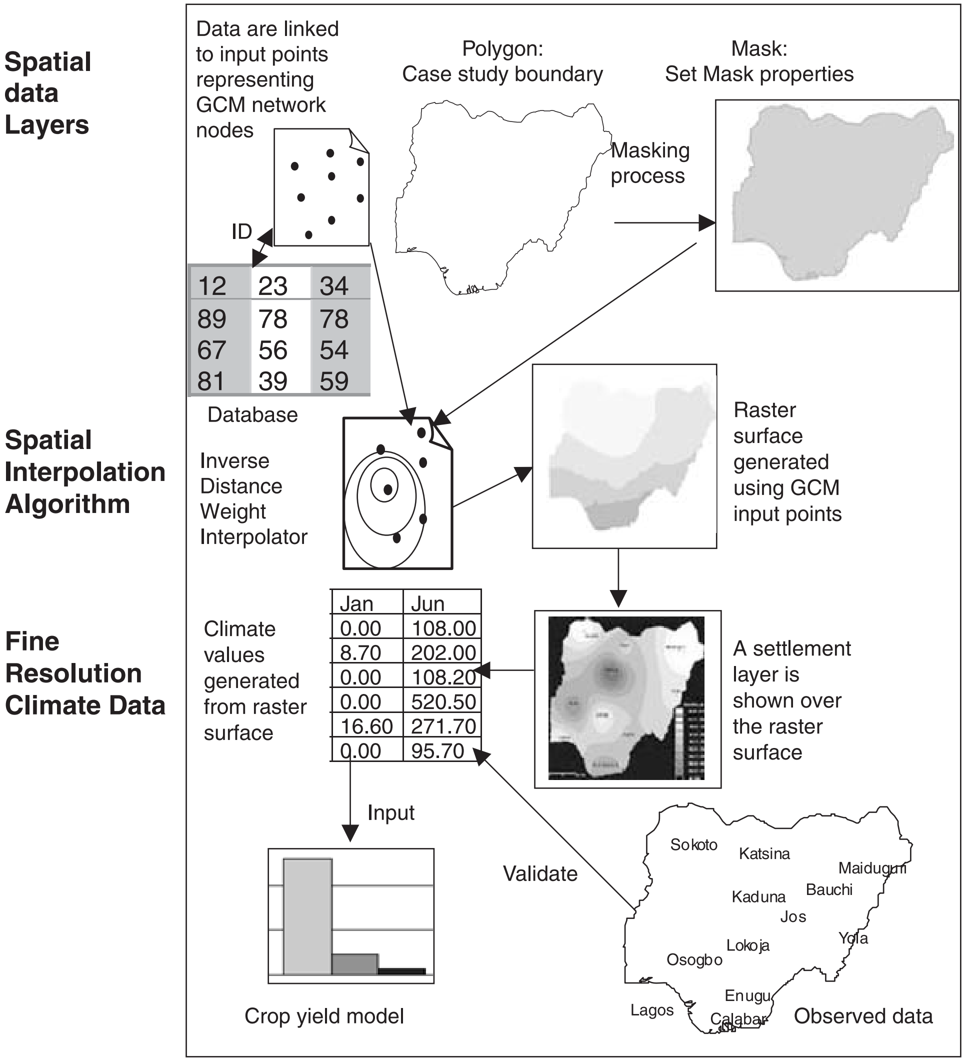

Figure 4 The GIS-based procedure for deriving fine resolution data for farm site crop modelling in West Africa

integration of GIS and crop model functionalities (Tan and Shibasaki 2003). Generally, crop simulation models require weather data as well as soil properties and cultivar characteristics.

Figure 4 shows the steps involved in the procedure developed and utilised in this study. Coarse resolution GCM output data are input into a GIS database with links to a point layer representing GCM network nodes. Using this point layer and a polygon mask layer of the Nigerian boundary (the case study), we run the IDW interpolator to produce a raster surface of continuous climate values (see Appendix 1 for details). Climate parameter values for settlements lying between the network nodes are generated from the raster surface. From this, a database of interpolated climate values is developed for settlements of interest. This database could serve as climate variable data input in a crop model for crop yield forecast. It is possible to incorporate terrain characteristics into the analysis for areas where topography affects the spatial patterns of climate with the GIS approach used. Since much of Nigeria consist essentially of low lying plateaus and coastal plains, the effect of topography was not assessed in this article. However, some studies in West Africa and East Africa have shown influence of altitude and relief on the occurrence of severe weather (Asnani and Kinuthia 1979, Fortune 1980 both cited in Nyakwada 2004).

As this work is carried out within a GIS environment there is considerable potential to couple the procedure developed with any agricultural impact model. The widespread applicability and obvious benefits of GIS has led to the development of several generic tools that link crop models and commercial GIS packages, thereby addressing the spatial deficiency of simulation models. Some examples are Spatial-EPIC (Satya 2002), GIS-CropSyst (Cropping Systems Simulation Model: Stockle et al. 2003) and AEGIS/WIN (Agricultural and Environmental Geographic Information System for Windows) which links the simulation system Decision Support System for Agrotechnology Transfer (DSSAT) v3 with the geographic mapping tool ArcView 2. AEGIS/WIN is a series of tools that link GIS to DSSAT family of crop models (Engel et al. 1997).

In order to test the reliability of this GIS-based procedure to reproduce observed rainfall, 30 Nigerian meteorological stations distributed from south to north were selected (refer to Figure 2). Observed rainfall data available from 1961 to 2000 for these stations were compared with estimated rainfall values in order to evaluate the ability of the proposed method to reproduce observed rainfall. R-squared (r^2) and root mean square error (RMSE) were calculated for each station as in Equations 3 and 4, respectively:

$$R^2 = 1 - \frac{\sum (X_i - \hat{X}_i)^2}{\left(\sum X_i^2\right) - \frac{\left(\sum X_i\right)^2}{n}} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \hat{X}_i)^2}{n}} \tag{4}$$

where X_i = observed rainfall, $\hat{X}_i$ = estimated rainfall from GCM, and n = number of sampled meteorological stations.

R^2 is the square of the Pearson product moment correlation coefficient through data points in observed rainfall (independent values – x) and modeled rainfall (dependent values – y). The R^2 value can be interpreted as the proportion of the variance in y

attributable to the variance in x. As an indicator whose values range from 0 to 1, it is most reliable when its value is at or near 1. The RMSE is a measure of how close a fitted line is to data points. For every data point, the distance is taken vertically from the point to the corresponding y value on the curve fit (the error), and the value is squared. Then we add up all those values for all data points, divide by the number of points and find the square root.

5 Implementation of the Procedure

This procedure is implemented using ESRI's ArcView 3.2 GIS software (Spatial Analyst extension). A significant advantage in using ArcView 3.x is the very large user base which continues to exist, despite the launch and implementation of the ArcGIS platform (Lowry 2006). Although the procedure was implemented using the Hadley Centre's GCM (HadCM2) data, it is also suitable for other GCMs. To demonstrate the suitability of the procedure for GCM generated climate data, we used the observed average rainfall for the period from 1961 to 2000 and 1985 rainfall values. Specifically we applied the procedure described earlier to the monthly means for January, April, July and September. The choice of months is important in that January was chosen as it is the middle of the "harmattan" (dry) season, April is at the beginning of the rainy season, and July and September are at the middle and end of the rainy season, respectively for West Africa.

Rainfall values were obtained from the GCM output for the months of January, April, July, and September for selected stations for which observed data were available. Three categories comprising 10, 20 and 30 meteorological stations were used and these are referred to as domain 1, domain 2 and domain 3, respectively for ease of reference. The domains incorporated 10, 20 and 30 stations with observed rainfall data because these domains approximate 10 2.5° lat × 3.75° long, 20 2° lat × 2.5° long and 30 1.5° lat × 2° long GCM grid cells, respectively covering Nigeria (see Table 2 for additional details).

6 Results and Discussion

Three point layers for the 10, 20 and 30 meteorological stations were created to which either observed 1985 precipitation values or 1961–2000 mean values were input. These layers are then displayed over the raster surface created from the GCM precipitation data output. Rainfall values for stations in the three different domains (10, 20 and 30 stations) can be read from the created raster surface (see Figure 5).

Figure 5 shows the interpolated precipitation surface derived from the GCM data output for Nigeria. This surface is for the month of January (1961–1990) under domain 3 (30 stations). The estimated and observed rainfall totals for Sokoto in the extreme north and Lagos in the extreme south-west are displayed on the map. In order to evaluate the ability to reproduce observed climate using the proposed procedure, a comparison between simulated mean monthly rainfall and observed rainfall was conducted for each domain. This is demonstrated in Figure 6, which presents a comparison between simulated and observed rainfall for each of the four months under domain 1.

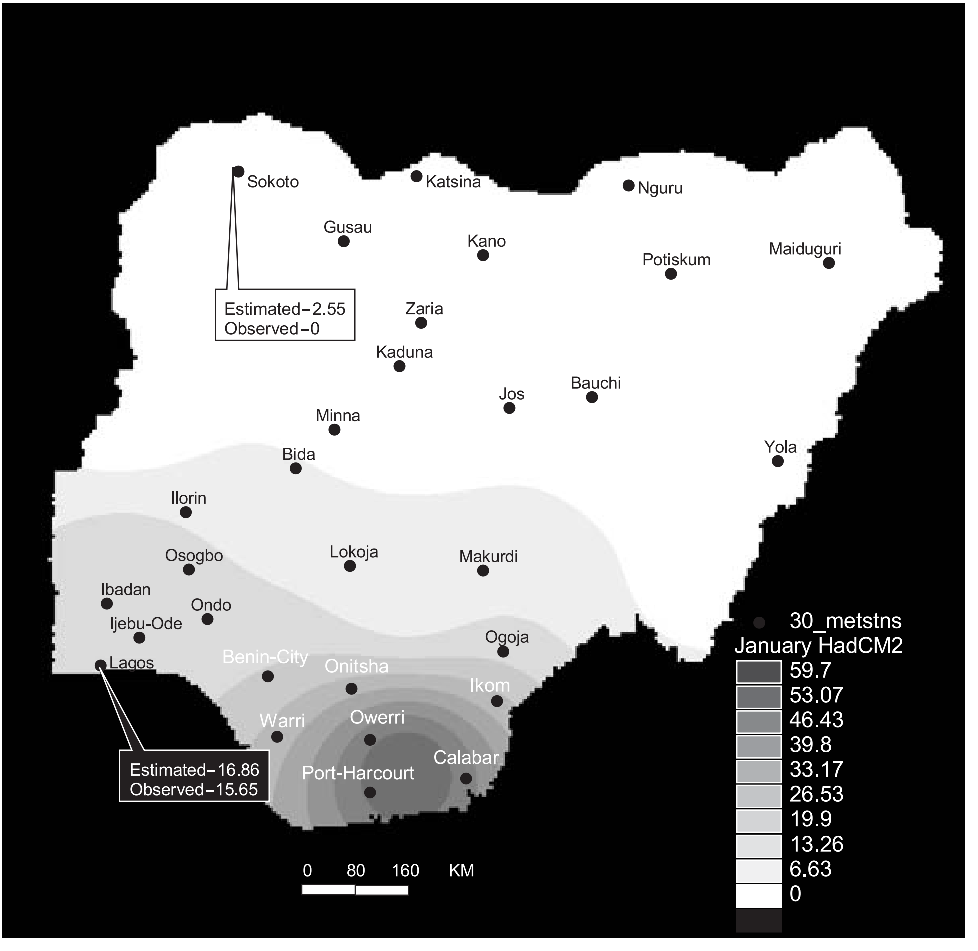

Figure 5 Estimated rainfall values for selected stations derived from interpolated GCM data output

Further results obtained from comparing estimated and observed rainfall for the time period 1961–2000 are shown in Table 3. A high positive correlation was found between the observed and simulated rainfall datasets used for all the months examined except for July in all domains. From Table 3, *r* values for every month with the exception of July range from 0.81 to 0.92. The R^2 values in Table 3 reveal that the model represents the drier months' rainfall (January – R^2 = 0.85 and April – R^2 = 0.84) better than that of the wettest month (July – R^2 = 0.24). That is 85, 84 and 24% of the variance in the estimated rainfall values can be explained by variation in the observed rainfall values for January, April and July, respectively. The RMSE values regarding the rainfall representation for January are better and were almost constant given values of 8.02, 8.25 and 7.84 for domains 1, 2 and 3, respectively.

Using results from domain 1 as the distribution of stations approximates the HadCM2 cell coverage for Nigeria, the model underestimated rainfall by 6.28%

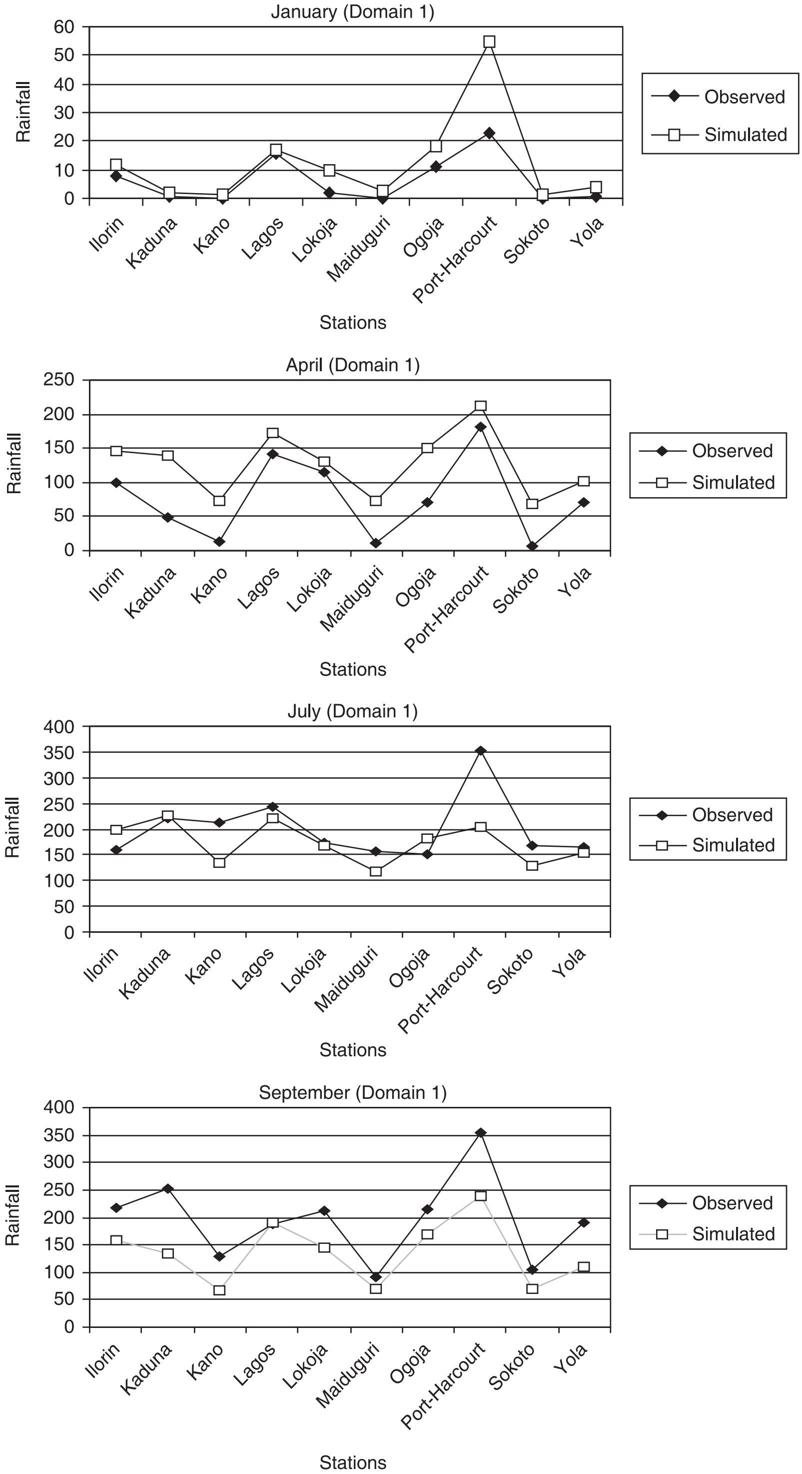

Figure 6 Comparison between simulated and observed rainfall for domain 1

Table 3 Summary of coefficients and reliability estimates for the estimation of rainfall

Domain	Month	Correlation (Pearson – *r*)	Results	
			R-squared – r^2	RMSE
Domain 1	January	0.9212	0.8487	8.01682848
(10 stations)	April	0.9177	0.8422	42.08303016
	July	0.4909	0.241	43.76635041
	September	0.8837	0.781	52.13726062
Domain 2	January	0.8824	0.7787	8.25076328
(20 stations)	April	0.9082	0.8248	37.91471319
	July	0.4629	0.2143	97.38173389
	September	0.8603	0.7401	60.3570106
Domain 3	January	0.9065	0.8218	7.84385857
(30 stations)	April	0.8968	0.8043	36.70400385
	July	0.4267	0.1821	75.79492899
	September	0.8144	0.6632	69.56901349

(1,119.96 vs. 1,194.96 mm) for the four months, especially for the very rainy months (July and September). Thornton et al. (2006) noted that the Hadley centre model is a "drier" model based on their study which compared rainfall differences between different models. The fact that the model captures the drier months better than the rainy months cannot be entirely attributed to its seemingly dry nature. We take cognisance of the fact that both the GCM and observed datasets used cover slightly different time periods which may have had some influence. The GCM data is from 1960–1990 while the observed rainfall data is from 1960–2000.

As an indication of its overall performance, the model underestimated total rainfall by 4.7% (2,799.1 vs. 2,935.98 mm) and 8.0% (1,303.12 vs. 1,415.8 mm) for southern and northern stations, respectively. Estimated rainfall values for stations in the south were better than those in the north. A contributing factor is probably that these southern stations enjoy a greater maritime influence due to their proximity to the Atlantic Ocean. Moreover, the density of stations which is much higher in the south than in the north may be an additional contributing influence.

6 Conclusions

This work describes a GIS-based procedure developed for downscaling coarse resolution data outputs of General Circulation Models to be used as input in crop models for crop yield forecast. The main GIS technique used is the IDW interpolation method which is adopted for deriving values for locations between the GCM network nodes. Our main objective is the use of simpler methods to generate high-resolution data from GCMs outputs for a technology and data sparse region as West Africa. Although the HadCM2 data was used for implementation, the procedure is meant to be generic. For climate change scenario construction, the GIS approach is subject, like the statistical approach, to the weakness of assuming that the current inter-element relations will continue to be valid under future radiative forcing. In other words, the GIS approach is basically time invariant.

To assess the ability of the GIS-based downscaling procedure to reproduce observed climate, the estimated rainfall values for meteorological stations were compared to the means of the observed data from 1961 to 2000. We reported coefficients of Pearson's correlation, R^2 and RMSE for the test using three domains comprising of 10, 20, and 30 stations for which observed data were available. The results in this study show that the model works best in representing drier months compared to wet months in all three domains tested. For example, it captured the rainfall for January (the driest month) better than that of July which is the peak of the rainy season in West Africa. With regards to accuracy, the model underestimated rainfall by 6.3% (1,119.96 vs. 1,194.96 mm), especially for the very rainy months (July and September). In relation to the north-south pattern of estimated rainfall distribution, stations in the south were better represented than those in the north with total rainfall underestimated by 4.7 and 8.0%, respectively.

At this stage, we cannot make the claim that the approach will be suitable for downscaling throughout tropical Africa where weather and climate similar to those of Nigeria are experienced. This is because Nigeria, consisting of essentially low lying plateaus and coastal plains, does not offer a good example for the remainder of tropical Africa which consists mainly of high altitude plateaus and mountainous regions. It may thus be necessary to conduct assessments similar to that performed in this article to test the applicability of the approaches in East, Central and Southern Africa. For the greater part of West Africa with similar climatic and terrain conditions as Nigeria, this procedure is considered suitable for interpolation and downscaling. Further refinements to the procedure would be to incorporate terrain characteristics in the analysis and use of future climate scenarios to study the spatial variability of climate and the temporal progression of changes.

With this GIS-based procedure, there is the possibility of downscaling to point resolution which is not always the case for the other approaches. There is also the chance to incorporate topographic effect where topography affects the spatial patterns of climate to give more accurate results. The GIS approach is definitely more user-friendly as it involves little or no computations since all that it requires are some knowledge of GIS-based spatial analysis functions and applications.

Acknowledgements

This article is an output of a research project funded and supported by START (SysTem for Analysis, Research and Training), US National Oceanic and Atmospheric Organization and AIACC (Assessment of Impacts of and Adaptations to Climate Change). The supporting organizations for AIACC are START, TWAS (Third World Academy of Sciences), and the United Nations Environment Programme. The useful comments of the anonymous reviewers are highly appreciated.

References

Adedokun J A 1978 West African precipitation and dominant atmospheric mechanisms. *Archiv für Meteorologie, Geophysik und Bioklimatologie, Serie A* 27: 289–310

Adejuwon J O 2004 *Assessing the Suitability of the EPIC Crop Model for Use in the Study of Impacts of Climate Variability and Climate Change in West Africa*. New York, Assessment of Impacts of and Adaptations to Climate Change (AIACC) Working Paper No 5 (available at http://www.aiaccproject.org/working_papers/WorkingPapers/AIACC_WP_No05.pdf)

Adejuwon J O, Odekunle T O, and Omotayo M O 2007 *Extended-Range Weather Forecasting in Sub-Saharan West Africa: Assessing a Potential Tool for Adapting Food Production to Climate Variability and Climate Change*. New York, AIACC Working Paper No 46 (available at http://www.aiaccproject.org/working_papers/WorkingPapers/AIACC_WP46_Adejuw.pdf)

Antonic O, Krizan J, Marki A, and Bukovec D 2001 Spatio-temporal interpolation of climatic variables over large region of complex terrain using neural networks. *Ecological Modelling* 138: 255–63

Asnani G C and Kinuthia J H 1979 *Diurnal Variation of Precipitation in East Africa*. Nairobi, Kenya, Institute for Meteorological Training and Research Report No 8

Baede A P M, Ahlonsou E, Ding Y, and Schimel D 2001 The climate system: An overview. In Houghton J T, Ding Y, Griggs D J, Noguer M, van der Linden P J, Dai X, Maskell K, and Johnson C A (eds) *Climate Change 2001: The Scientific Basis (Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change)*. New York, Cambridge University Press: 87–98 (available at http://unfccc.int/resource/cd_roms/na1/mitigation/Resource_materials/IPCC_TAR_Climate_Change_2001_Scientific_Basis/TAR-01.pdf)

Burrough P A and McDonnell R A 1998 *Principles of Geographical Information Systems*. New York, Oxford University Press

Chapman L and Thornes J E 2003 The use of geographical information systems in climatology and meteorology. *Progress in Physical Geography* 27: 313–30

Engel T, Hoogenboom G, Jones J W, and Wilkens P W 1997 AEGIS/WIN: A computer program for the application of crop simulation models across geographic areas. *Agronomy Journal* 89: 919–28

Fleming M D, Chapin F S, Cramer W, Hufford G L, and Serreze M C 2000 Geographic patterns and dynamics of Alaskan climate interpolated from a sparse station record. *Global Change Biology* 6: 49–58

Fortune M 1980 Properties of African Squall lines inferred from time-lapse satellite imagery. *Monthly Weather Review* 108: 153–68

Fox-Rabinovitz M S, Stenchikov G L, Suarez M J, and Takacs L L 1997 A finite-difference GCM dynamical core with a variable resolution stretched grid. *Monthly Weather Review* 125: 2943–68

Giorgi F 1990 Simulation of regional climate using a limited area model nested in a general circulation model. *Journal of Climate* 3: 941–63

Gordon C, Cooper C, Senior C A, Banks H, Gregory J M, Johns T C, Mitchell J F B, and Wood R A 2000 The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics* 16: 147–68

Govindasamy B, Duffy P B, and Coquard J 2003 High resolution simulations of global climate: Part 2, Effects of increased greenhouse gases. *Climate Dynamics* 21: 391–404

Hansen J W and Jones J W 2000 Scaling-up crop models for climate variability applications. *Agricultural Systems* 65: 43–72

Hartkamp A D, De Beurs K, Stein A, and White J W 1999 *Interpolation Techniques for Climate Variables*. El Batán, Mexico, International Maize and Wheat Improvement Centre (CIMMYT) Report No NRG-GIS 99-01

Hay L E, Clark M P, Wilby R L, Gutowski W J Jr., Leavesley G H, Pan Z, Arritt R W, and Takle E S 2002 Use of regional climate model output for hydrologic simulations. *Journal of Hydrometeorology* 3: 571–90

Hoff C 2001 Spatial and temporal persistence of mean monthly temperature on two GCM grid cells. *International Journal of Climatology* 21: 731–44

Hudson G and Wackernagel H 1994 Mapping temperature using kriging with external drift: Theory and example from Scotland. *International Journal of Climatology* 14: 77–91

Jeffrey S J, Carter J O, Moodie K B, and Beswick A R 2001 Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling and Software* 16: 309–30

Kunstmann H and Jung G 2005 Impact of regional climate change on water availability in the Volta basin of West Africa. In *Proceedings of the International Symposium on Regional Hydrological Impacts of Climatic Variability and Change*, Foz do Iguaçu, Brazil
Lowry J 2006 *Low-cost GIS Software and Data for Wetland Inventory, Assessment and Monitoring*. Gland, Switzerland, Ramsar Technical Report No 2 (available at http://www.ramsar.org/lib/lib_rtr02.pdf)
Mearns L O, Easterling W, Hays C, and Marx D 2001 Comparison of agricultural impacts of climate change calculated from high and low resolution climate model scenarios: Part I, The uncertainty due to spatial scale. *Climatic Change* 51: 131–72
Mearns L O, Giorgi F, Whetton P, Padon D, Hulme M, and Lal M 2003 *Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments*. Geneva, Task Group on Scenarios for Climate Impact Assessment, IPCC Data Distribution Centre (available at http://ipcc-ddc.cru.uea.ac.uk/guidelines/dgm_no1_v1_10-2003.pdf)
Nieuwolt S 1982 *Tropical Climatology: An Introduction to the Climates of the Low Latitudes*. New York, John Wiley and Sons
Nyakwada W 2004 The Challenges of Forecasting Severe Weather and Extreme Climate Events in Africa. In *Proceedings of the World Meteorological Organization Workshop on Severe and Extreme Events Forecasting*, Toulouse, France (available at http://www.wmo.ch/web/www/DPS/Meetings/WshopEEF_Toulouse2004/Doc4(4).doc)
Odekunle T O, Balogun E E, and Ogunkoya O O 2005 On the prediction of rainfall onset and retreat dates in Nigeria. *Theoretical and Applied Climatology* 81: 101–12
Oguntoyinbo J S 1978 Climate. In Oguntoyinbo J S, Areola O O and Filani M (eds) *A Geography of Nigerian Development*. Ibadan, Nigeria, Heinemann: 14–39
Price D T, McKenney D W, Nadler I A, Hutchinson M F, and Kesteven J L 2000 A comparison of two statistical methods for spatial interpolation of Canadian monthly mean climate data. *Agriculture for Meteorology* 101: 81–94
Priya S and Shibasaki R 2001 National spatial crop yield simulation using GIS-based crop production model. *Ecological Modelling* 136: 113–29
Rigol J P, Jarvis C H, and Stuart N 2001 Artificial neural networks as a tool for spatial interpolation. *International Journal of Geographical Information Science* 15: 323–43
Rosenzweig C and Parry M L 1994 Potential impact of climate change on world food supply. *Nature* 367: 133–8
Satya P 2002 GIS-Based Crop Production Model and Its Applications. WWW document, http://www.gisdevelopment.net/application/agriculture/production/agric0008pf.htm
Shen S S P, Dzikowski P, Li G, and Griffith D 2001 Interpolation of 1961–97 daily temperature and precipitation data onto Alberta polygons of ecodistrict and soil landscapes of Canada. *Journal of Applied Meteorology* 40: 2162–77
Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor M M B, Miller H L Jr, and Chen Z (eds) 2007 *Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. New York, Cambridge University Press (available at http://www.ipcc.ch/ipccreports/ar4-wg1.htm)
Stockle C O, Donatelli M, and Nelson R 2003 CropSyst: A cropping systems simulation model. *European Journal of Agronomy* 18: 289–307
Stone M C, Hotchkiss R H, and Mearns L O 2003 Water yield responses to high and low spatial resolution climate change scenarios in the Missouri River Basin. *Geophysical Research Letters* 30: 1186–9
Tait A, Henderson R, Turner R, and Zheng X 2006 Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *International Journal of Climatology* 26: 2097–115
Tan G and Shibasaki R 2003 Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. *Ecological Modelling* 168: 357–70
Thiessen A H 1911 Precipitation averages for large areas. *Monthly Weather Review* 39: 1082–4
Thornton P K, Jones P G, Owiyo T M, Kruska R L, Herrero M, Kristjanson P, Notenbaert A, Bekele N and Omolo A, with contributions from Orindi V, Otiende B, Ochieng A, Bhadwal S, Anantram K, Nair S, Kumar V, and Kulkar U 2006 Mapping Climate Vulnerability and

Poverty in Africa. Unpublished Report submitted to the Department for International Development, ILRI, Nairobi, Kenya

Wilby R L and Wigley T M L 1997 Downscaling General Circulation Model output: A review of methods and limitations. *Progress in Physical Geography* 21: 530–48

Wilby R L, Wigley T M L, Conway D, Jones P D, Hewitson B C, Main J, and Wilks D S 1998 Statistical downscaling of General Circulation Model output: A comparison of methods. *Water Resources Resources* 34: 2995–3008

Wilby R L and Dettinger M D 2000 Streamflow changes in the Sierra Nevada, CA, simulated using statistically downscaled general circulation model output. In McLaren S and Kniveton D (eds) *Linking Climate Change to Land Surface Change*. Berlin, Kluwer: 99–121

Appendix 1: Steps for Using the IDW Interpolation Method

Check and select the mask theme to make it active
From the **ANALYSIS** menu set the **PROPERTIES**
To run the IDW interpolator, make the point theme active
From the **SURFACE** menu click **INTERPOLATE GRID**

The **INTERPOLATE SURFACE** dialog box is displayed.

Choose for **method –** IDW (inverse distance weights)
Z-value Field – for example, Jan (January precipitation field in the database)
No. of Neighbours – 9 (10 HadCM2 nodes minus 1)
Power – 2
Barriers – No Barriers; **OK.**

Note that a choice of "No Barriers" will use all points specified in the "No. of Neighbours" or within a "fixed radius". On the other hand, each line in a barrier input line theme is used as a break that limits the search for input sample points. A line can represent a cliff, ridge, or some other interruption in a landscape.