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Note and record

AFRICLIM: high-resolution climate projections for ecological applications in Africa

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Introduction

Half of the African population, and most priority sites for conservation, are concentrated in mountain and coastal regions (Fig. 1). In these places, climatic gradients are steep and feedbacks between land, water and atmosphere are much more localized than the pixel resolutions of general circulation models (GCMs). Through the CORDEX initiative (Jones, Giorgi & Asrar, 2011), outputs from regional climate models (RCMs) have become available for Africa. Nested within GCMs, regional models simulate climate at finer spatial and temporal resolutions (Fig. 1). Yet at ~50 km, they remain too coarse-grained for many applications in ecology (Platts *et al.*, 2013). Here, we use a range of observational baselines to empirically downscale RCM outputs to resolutions amenable to ecological applications at local scales (up to 1 km). Results for the middle and late 21st century are available online https://webfiles.york.ac.uk/KITE/AfriClim/.

Materials and methods

RCM outputs for the period 1950–2100 were provided by the Swedish Meteorological and Hydrological Institute and the Canadian Centre for Climate Modelling and Analysis, at a resolution of ~50 km (0.44° × 0.44°). The Swedish model (SMHI-RCA4) was driven by boundary conditions from eight GCMs (Fig. 1a) and the Canadian model (CCCma-CanRCM4) by CanESM2. Future climates were projected under two IPCC-AR5 representative concentration pathways: RCP4.5 and RCP8.5, which project global temperature anomalies of 2.4°C and 4.9°C above pre-industrial levels by 2100 (Rogelj, Meinshausen & Knutti, 2012), with atmospheric CO_2 equivalents of 650 and 1370 ppm by 2100, respectively (Moss *et al.*, 2010).

We used change-factor downscaling to recover spatial variation at local scales and to correct for differences between observed and simulated baseline climates (Tabor & Williams, 2010). Due to uncertainty in observational baselines, we imposed RCM change-factors (future anomalies) onto four different data sets for rainfall and two data sets for temperature: CRU CL 2.0 (New *et al.*, 2002), WorldClim v1.4 (Hijmans *et al.*, 2005), TAMSAT TARCAT rainfall v2.0 (Maidment *et al.*, 2014); and CHIRPS rainfall v1.8 (Funk *et al.*, 2014). These grids, and thus downscaled projections, vary in resolution from 30″ (~1 km) to 10′ (~19 km).

To calculate change-factors, we first averaged RCM output for monthly 2-m air temperature (mean, minimum and maximum) and monthly rainfall over the period 1961–1990, matching to the time spans of CRU and WorldClim (Fig. 1a). Similarly, we calculated monthly rainfall around the year 2000 (1986–2015) to match the midpoints of TAMSAT and CHIRPS. Future anomalies were obtained by subtracting these simulated baselines from 30-year averages around the 2050s (2041–2070) and 2080s (2071–2100). Anomalies were spline-interpolated to higher resolutions (Mitasova & Mitas, 1993) and, for temperature, added to observational baselines (B). Rainfall anomalies (Δ) were imposed as absolute changes relative to the baselines: $B \times |1 + \Delta/(B + 1)|$ (Ramirez-Villegas & Jarvis, 2010).

We provide downscaled grids for each GCM-RCM-baseline triplet separately and, for SMHI-RCA4, multi model ensembles over eight GCMs. In addition to monthly grids, we provide 21 summary variables for applications in ecology (Table 1). Analyses were carried out using R (Pierce, 2011; R Core Team, 2012) and GRASS-GIS (GRASS Development Team, 2012).

Results and discussion

By late century, sub-Saharan Africa is projected a mean annual temperature of 26.4–27.6°C (RCP4.5) or

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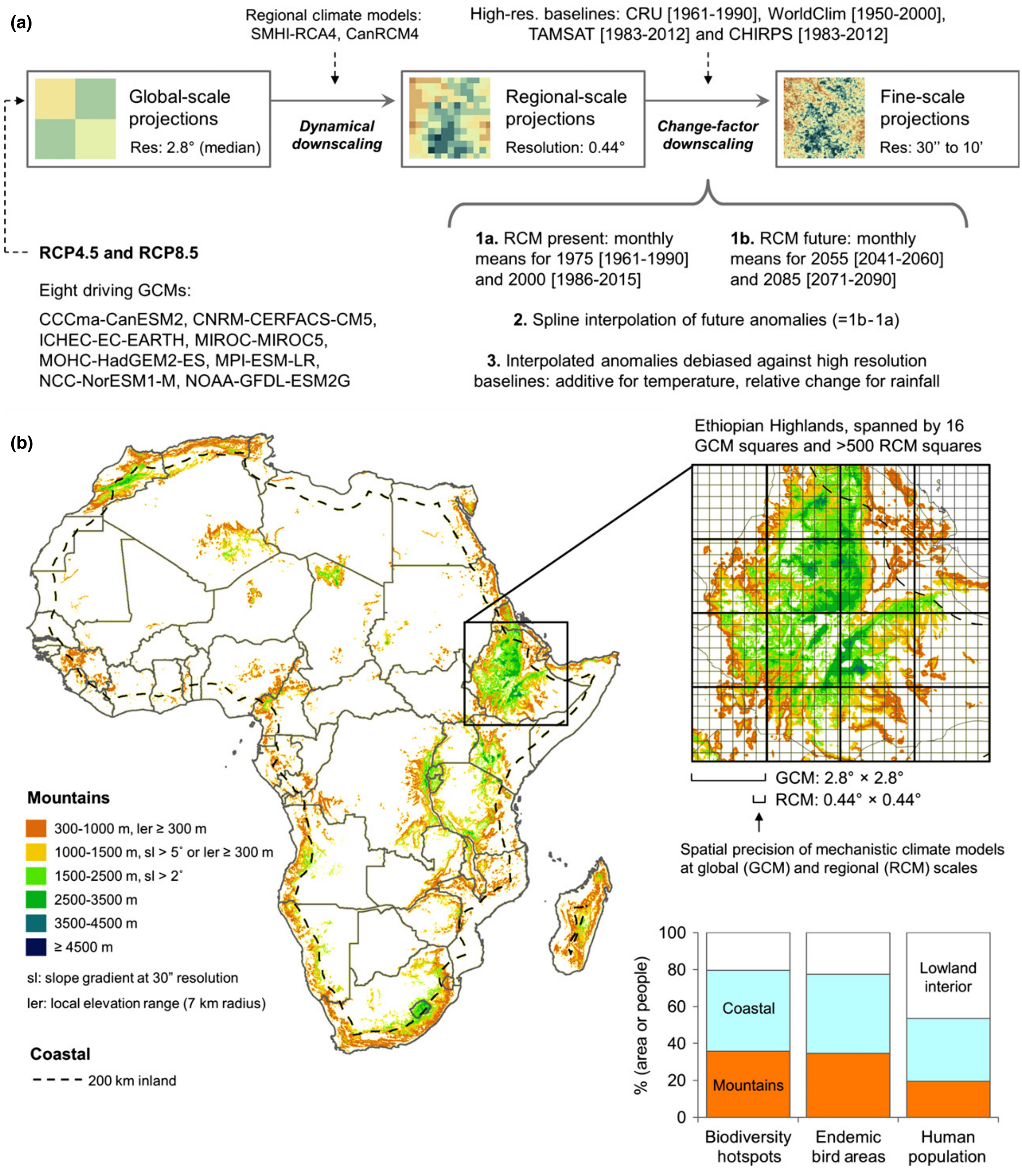

Fig 1 (a) Schematic of the downscaling procedure. Eight GCMs and two representative concentration pathways (RCP4.5 and RCP8.5) were dynamically downscaled by the SMHI-RCA4 and CanRCM4 regional climate models (RCMs). Change-factors debias RCM outputs using high-resolution baselines from CRU, WorldClim, TAMSAT and CHIRPS. (b) Applying change-factors to output from regional, rather than global climate models is especially important in mountain and coastal regions, which harbour a majority of both people (http://www.worldpop.org.uk/) and biodiversity (Stattersfield *et al.*, 1998; Mittermeier *et al.*, 2004). Mountain extent is according to Kapos *et al.* (2000)

Table 1 Summary variables derived from downscaled monthly temperature and rainfall grids. Spatial means compare observed (CRU, WorldClim, TAMSAT and CHIRPS) and modelled (nine GCM-RCM combinations) climate across sub-Saharan Africa (up to 20°N). Projected future climates are given as ranges in the spatial means over all 18 (temperature) or 36 (moisture) GCM-RCM-baseline triplets. Similar tables, summarizing spatial means within five subregions of Africa, are provided as Supplementary Information (Tables S1–S5). Gridded data are available online https://webfiles.york.ac.uk/KITE/AfriClim/

			Baseline (1961–1990[b])		Mid-century (2041–2070)		Late century (2071–2100)	
Code[a]	Description	Units	Observed	Modelled	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Temperature variables								
BIO1	Mean annual temperature[1]	°C	24.3–24.4	22.0–24.1	26.0–26.9	26.6–27.8	26.4–27.6	27.9–29.8
BIO2	Mean diurnal range in temp[2]	°C	12.9–13.3	12.5–14.6	12.9–13.3	12.9–13.3	12.9–13.3	12.9–13.3
BIO3	Isothermality[3]	°C	63.6–64.9	59.3–62.4	62.1–64.5	61.5–64.5	61.7–64.7	60.6–64.0
BIO4	Temperature seasonality[4]	°C	2.3–2.4	2.3–2.8	2.3–2.6	2.3–2.5	2.3–2.6	2.3–2.6
BIO5	Max temp warmest month	°C	34.2–34.3	32.7–35.6	36.1–37.1	36.7–37.9	36.5–37.6	38.1–39.9
BIO6	Min temp coolest month	°C	13.0–13.2	10.8–13.1	14.6–15.6	15.2–16.5	15.0–16.3	16.4–18.4
BIO7	Annual temperature range[5]	°C	21.0–21.3	20.9–24.8	21.1–21.7	21.1–21.9	21.1–21.9	21.3–22.3
BIO10	Mean temp warmest quarter[6]	°C	26.9–27.1	24.7–27.2	28.6–29.9	29.2–30.7	29.1–30.4	30.7–32.7
BIO11	Mean temp coolest quarter[6]	°C	21.0–21.1	18.6–20.4	22.7–23.6	23.3–24.4	23.2–24.2	24.7–26.4
PET	Potential evapotranspiration[7]	mm	1812–1835	1690–1833	1886–1946	1911–1983	1904–1973	1971–2070
Moisture variables								
BIO12	Mean annual rainfall[8]	mm	678–882	692–973	678–951	683–974	676–959	677–1013
BIO13	Rainfall wettest month	mm	145–176	156–189	149–198	151–203	150–201	153–213
BIO14	Rainfall driest month	mm	4–8	2–10	3–8	3–8	3–8	3–8
BIO15	Rainfall seasonality[4]	mm	49–59	55–67	50–65	50–67	50–66	51–70
BIO16	Rainfall wettest quarter[6]	mm	356–451	393–492	360–496	365–511	364–502	368–532
BIO17	Rainfall driest quarter[6]	mm	21–36	11–43	20–36	20–37	20–36	20–38
MI	Annual moisture index[9]	–	0.39–0.51	0.42–0.63	0.37–0.51	0.37–0.52	0.36–0.51	0.35–0.52
MIMQ	Moisture index moist quarter[6]	–	0.82–1.06	1.02–1.36	0.79–1.1	0.80–1.11	0.78–1.11	0.77–1.14
MIAQ	Moisture index arid quarter[6]	–	0.05–0.09	0.03–0.12	0.05–0.09	0.05–0.09	0.05–0.09	0.04–0.08
DM	Number of dry months[10]	Month	7.55–8.33	7.11–8.65	7.50–8.50	7.47–8.51	7.50–8.51	7.45–8.64
LLDS	Length of longest dry season[11]	Month	7.40–8.14	6.77–8.40	7.31–8.24	7.28–8.26	7.31–8.25	7.23–8.37

[1]Mean of monthly means. [2]Mean of monthly (max temp–min temp). [3]100 × BIO2/BIO7. [4]Standard deviation over monthly values (*cf.* coefficient of variation in BIOCLIM). [5]BIO5–BIO6. [6]Any consecutive 3-month period. [7]Hargreaves 1985 method (see Hargreaves & Allen, 2003). [8]Sum of monthly rainfall. [9]BIO12/PET. [10]Dry/arid if monthly moisture index <0.5 (UNEP, 1997). [11]Maximum run of consecutive dry months.

[a]'BIO' variables correspond to BIOCLIM nomenclature (Xu & Hutchinson, 2011), but note that derivation for[4] is not identical.

[b]Observational baselines for moisture variables include data from 1983 to 2012 (TAMSAT and CHIRPS), as well as from 1961 to 1990 (CRU and WorldClim).

27.9–29.8°C (RCP8.5), depending on the model (Table 1). Rainfall is projected to increase in western and eastern parts of the continent, coupled with increased seasonality (Fig. 2; Tables S1–S5). Changes in rainfall are, on average, lower at higher latitudes, with a slight drying trend depending on the model (Fig. 2). Ensemble means project the Mediterranean Basin, south-east Africa, eastern Madagascar and the Ethiopian Highlands to be at risk from prolonged seasonal aridity (consecutive months of rainfall≪PET), while the Horn of Africa, Gabon and coastal Angola are projected shorter periods of aridity. Within these regions, downscaled projections reveal considerable variation, with spatially complex climates subject to multiple extrema in RCM anomalies at sub-GCM scales.

We note that while empirical downscaling of RCMs (*cf.* GCMs) reduces uncertainty at the mesoscale, the

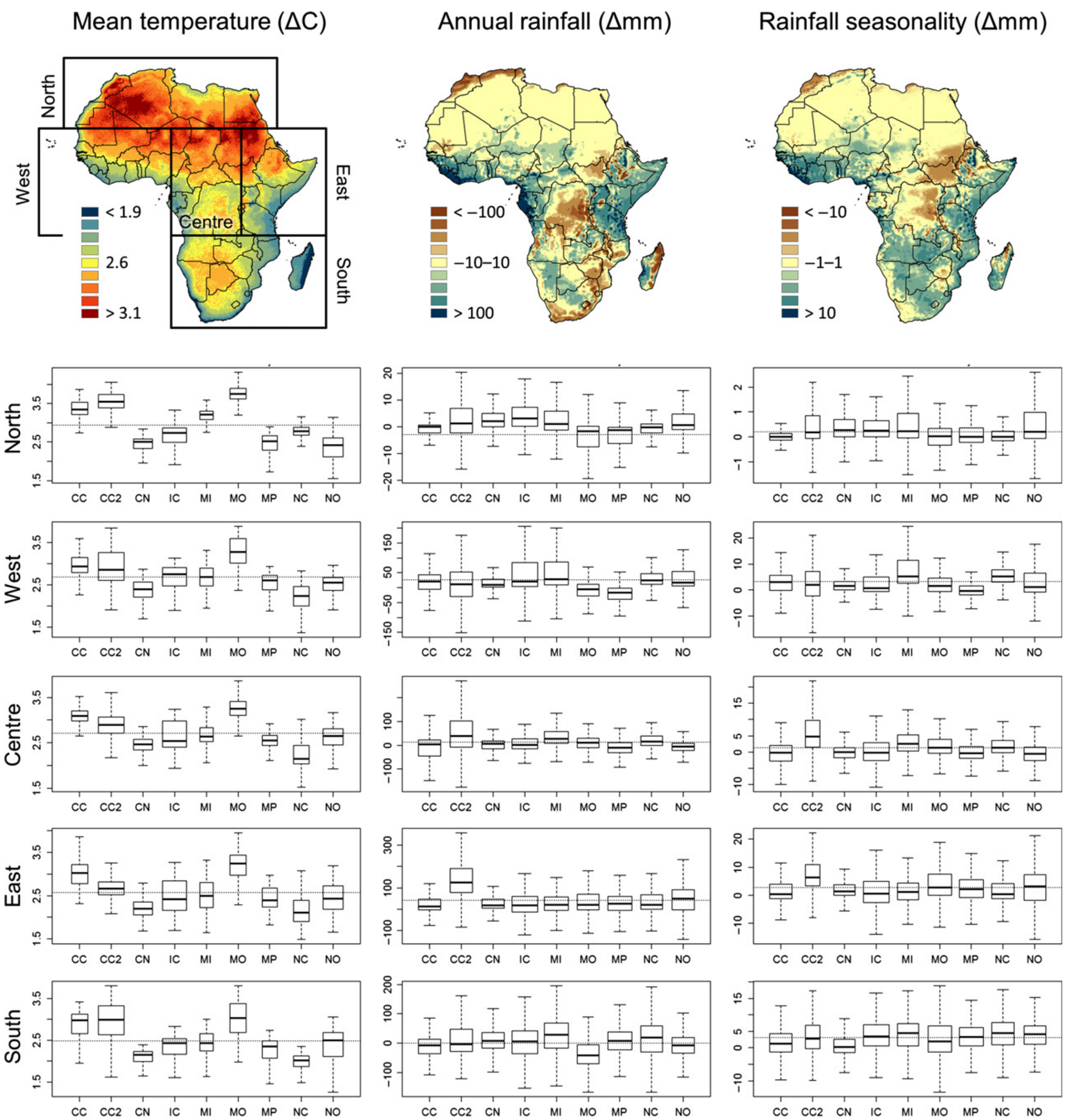

Fig 2 Projected changes by late century (2071–2100, RCP4.5) for three variables listed in Table 1. Baseline climates in this example are from CRU (temperature, 1975 baseline) and CHIRPS (rainfall, 2000 baseline). Maps picture changes in SMHI-RCA4 ensemble means. Box plots show spatial variation within five subregions of Africa for each GCM-RCM pair (RCM is SMHI-RCA4 except for CC2, which uses output from CanRCM4). Box widths are proportional to the root-mean-squared error, comparing observed versus modelled climates over the baseline period. Horizontal lines mark the ensemble mean for each region

assumption of temporal stasis in local climatic variation, as inferred from observational baselines, remains a source of error (Tabor & Williams, 2010). Further, the accuracy of baseline climatologies is limited by the distribution of meteorological stations in Africa, which particularly for rainfall remain sparse. We mitigate this issue by including two satellite-derived baselines for rainfall, in addition to the interpolated climatologies. At larger scales, assumptions underlying RCPs are intentionally diverse (Moss *et al.*, 2010) and GCM-RCM ranges are sometimes high (Table 1; Fig. 2).

Driven with ERA-Interim reanalysis data, RCMs are reasonably skilful in simulating climatic variability over Africa, and biases are effectively reduced by the ensemble mean (Nikulin *et al.*, 2012; Endris *et al.*, 2013; Gbobaniyi *et al.*, 2014). To project future climate, RCMs are driven by GCMs. Comparing GCM-RCM estimates with observational data over the 30-year baseline, there is good agreement between large-scale means, but models underestimate temperatures during cooler months, particularly in the north and west, and so overestimate seasonality (Tables 1 and S1–S5). In southern Africa, models overestimate rainfall during the wettest months while underestimating aridity during the dry season. Such differences are superficially addressed by change-factor downscaling (bias correction), but nonetheless highlight weaknesses in model skill over Africa and/or uncertainties in the validation data (Wilby *et al.*, 2004; Brands *et al.*, 2013).

Climate projections are in immediate demand by scientists, governments and nongovernmental organizations. High-resolution projections are available globally (e.g., http://www.worldclim.org/cmip5) but are empirically derived directly from GCMs, with no dynamical downscaling. AFRICLIM is an important step forward in this respect: the archives span eight GCMs downscaled using two RCMs and four observational baselines, under two emissions pathways and at multiple high-spatial resolutions. We encourage users to interpret the data critically, however, with due consideration of the above uncertainties, particularly with respect to model skill in the region of interest (see e.g., Nikulin *et al.*, 2012; Crétat, Vizy & Cook, 2014).

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References

Brands, S., Herrera, S., Fernández, J. & Gutiérrez, J.M. (2013) How well do CMIP5 Earth System Models simulate present climate conditions in Europe and Africa? *Clim. Dyn.* **41**, 803–817.

Crétat, J., Vizy, E.K. & Cook, K.H. (2014) How well are daily intense rainfall events captured by current climate models over Africa? *Clim. Dyn.* **42**, 2691–2711.

Endris, H.S., Omondi, P., Jain, S., Lennard, C., Hewitson, B., Chang'a, L., Awange, J.L., Dosio, A., Ketiem, P., Nikulin, G., Panitz, H., Büchner, M., Stordal, F. & Tazalika, L. (2013) Assessment of the performance of CORDEX regional climate models in simulating East African rainfall. *J. Clim.* **26**, 8453–8475.

Funk, C.C., Peterson, P.J., Landsfeld, M.F., Pedreros, D.H., Verdin, J.P., Rowland, J.D., Romero, B.E., Husak, G.J., Michaelsen, J.C. & Verdin, A.P. (2014) A quasi-global precipitation time series for drought monitoring. *U.S. Geological Survey Data Series* 832, 4 p., http://pubs.usgs.gov/ds/832 (Accessed on 02 June 2014).

Gbobaniyi, E., Sarr, A., Sylla, M.B., Diallo, I., Lennard, C., Dosio, A., Dhiédiou, A., Kamga, A., Klutse, N.A.B., Hewitson, B., Nikulin, G. & Lamptey, B. (2014) Climatology, annual cycle and interannual variability of precipitation and temperature in CORDEX simulations over West Africa. *Int. J. Climatol.* **34**, 2241–2257.

GRASS Development Team (2012) *Geographic Resources Analysis Support System (GRASS) Software*. Open Source Geospatial Foundation Project. http://grass.osgeo.org/. Version 6.4.

Hargreaves, G.H. & Allen, R.G. (2003) History and evaluation of Hargreaves evapotranspiration equation. *J. Irrig. Drain. Eng.* **129**, 53–63.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* **25**, 1965–1978.

Jones, C., Giorgi, F. & Asrar, G. (2011) *The Coordinated Regional Downscaling Experiment: CORDEX, An International Downscaling Link to CMIP5*. CLIVAR Exchanges, No. 56, Vol 16, No. 2 pages 34–40.

Kapos, V., Rhind, J., Edwards, M., Price, M.F. & Ravilious, C. (2000) Developing a map of the world's mountain forests. In: *Forests in Sustainable Mountain Development: A State of Knowledge Report for 2000* (Eds M. F. Price and N. Butt). CAB International, Wallingford.

Maidment, R., Grimes, D., Allan, r., Tarnavsky, E., Stringer, M., Hewison, T. Roebeling, R. & Black, E. (2014) The 30-year TAMSAT African rainfall climatology and time-series (TARCAT) dataset. In: *J. Geophys. Res*, doi: 10.1002/2014JD021927.

Mitasova, H. & Mitas, L. (1993) Interpolation by regularized spline with tension. 1. Theory and implementation. *Math. Geol.* **25**, 641–655.

Mittermeier, R.A., Gil, P.R., Hoffmann, M., Pilgrim, J., Brooks, T., Mittermeier, C.G., Lamoreux, J. & da Fonseca, G.A.B. (2004) *Hotspots Revisited: Earth's Biologically Richest and Most Endangered Ecoregions*. CEMEX, Mexico City.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P. & Wilbanks, T.J.

(2010) The next generation of scenarios for climate change research and assessment. *Nature* **463**, 747–756.

New, M., Lister, D., Hulme, M. & Makin, I. (2002) A high-resolution data set of surface climate over global land areas. *Clim. Res.* **21**, 1–25.

Nikulin, G., Jones, C., Giorgi, F., Asrar, G., Büchner, M., Cerezo-Mota, R., Christensen, O.B., Déqué, M., Fernandez, J., Hänsler, A., van Meijgaard, E., Samuelsson, P., Sylla, M.B. & Sushama, L. (2012) Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. *J. Clim.* **25**, 6057–6078.

Pierce, D. (2011) *ncdf: Interface to Unidata netCDF data files*. R package version 1.6.6. http://CRAN.R-project.org/package=ncdf (Accessed on 25 April 2014).

Platts, P.J., Gereau, R.E., Burgess, N.D. & Marchant, R. (2013) Spatial heterogeneity of climate change in an Afromontane centre of endemism. *Ecography* **36**, 518–530.

R Core Team (2012) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna. http://www.r-project.org/. Version 3.0.2.

Ramirez-Villegas, J. & Jarvis, A. (2010) *Downscaling Global Circulation Model Outputs: The Delta Method*. CIAT Decision and Policy Analysis Working Paper, no. 1.

Rogelj, J., Meinshausen, M. & Knutti, R. (2012) Global warming under old and new scenarios using IPCC climate sensitivity range estimates. *Nat. Clim. Chang.* **2**, 248–253.

Stattersfield, A., Crosby, M.J., Long, A.J. & Wege, D.C. (1998) *Endemic Bird Areas of the World: Priorities for Biodiversity Conservation*. BirdLife International, Cambridge.

Tabor, K. & Williams, J.W. (2010) Globally downscaled climate projections for assessing the conservation impacts of climate change. *Ecol. Appl.* **20**, 554–565.

UNEP (1997) *World Atlas of Desertification*. United Nations Environment Programme, London.

Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P. & Mearns, L. (2004) Guidelines for uses of climate scenarios developed from statistical downscaling methods. Intergovernmental Panel on Climate Change. http://www.narccap.ucar.edu/doc/tgica-guidance-2004.pdf (Accessed on 01 April 2014).

Xu, T. & Hutchinson, M. (2011) *ANUCLIM v6.1: User Guide*. The Australian National University, Fenner School of Environment and Society, Canberra.

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Supporting information

Additional Supporting Information may be found in the online version of this article:

Tables S1–S5 Summary variables averaged over five subregions of Africa.

