STATISTICAL AND NEURAL NETWORK APPROACH FOR ESTIMATING MONTHLY EVAPOTRANSPIRATION AT THE INTERNATIONAL INSTITUTE OF TROPICAL AGRICULTURE, IBADAN, NIGERIA - A COMPARATIVE STUDY

CHUKWU, A. U, UDOMBOSO, C. G

Department of Statistics, University of Ibadan, Nigeria

ONAFESO, OLU

Department of Geography, University of Ibadan

ABSTRACT

Evapotranspiration (ET) is one of the main components of the hydrological cycle as it accounts for more than two-thirds of the precipitation losses at the global scale. Reliable estimates of actual Evapotranspiration are crucial for effective watershed modelling and water resource management, yet direct measurements of the Evapotranspiration losses are difficult and expensive.
The major objective of this study was to investigate the potential of the classical linear regression and neural network (NN) technique to estimate evapotranspiration, and to examine if a trained neural network with limited input variables can estimate ET efficiently. The study utilized daily climatic data of temperature, relative humidity, sunshine hours, wind speed, and rainfall for ten years collected from the International Institute of Tropical Agriculture. (IITA) Ibadan, Nigeria. Linear regression models in terms of the climatic parameters influencing the regions and, optimal neural network architectures considering these climatic parameters as inputs were developed. The linear regression models showed a satisfactory performance in the monthly estimation in the region selected for the present study. The NN models, however, consistently showed a slightly improved performance over linear regression models. The results also indicated that even with limited climatic variables an ANN can estimate ET accurately.

Keywords: Artificial neural network, Evapotranspiration, IITA.

INTRODUCTION

Climate models have predicted that global mean precipitation will increase with surface air temperature at a rate of about 1% to 3% per degree Kelvin (Boer, 1993; Allen and Ingram, 2002; Allan and Soden, 2007). This change in precipitation is substantially smaller than the change in atmospheric water vapour, which increases at the Clausius-Clapeyron (CC) rate of 6% to 7% per Kelvin (Boer, 1993; Allen and Ingram, 2002; Held and Soden, 2006). Wentz et al. (2007) have also reported trends in "observed" precipitation that are about three times larger than the climate models and more in line with the CC rate. The reason why models predict an increase in precipitation that is substantially below the CC rate appears to be the dominant role that the hydrologic cycle plays in the global energy budget (Boer, 1993; Allen and Ingram, 2002; Pierrehumbert, 2002; Lambert and Allen, 2009).

In a recent study, Lorentz et al (2010) examined the change in evaporation over the oceans in climate models and analysed from the perspective of air-sea turbulent fluxes of water and energy. Their results challenged the view that the change in evaporation is predominantly constrained by the change in the net radiation at the surface. This reduction of evaporation is associated with corresponding changes in the sensible heat flux. Further, Lorentz et al (2010) also suggested that it might be more physical to view the evaporation change as a function of relative humidity change rather than net radiation. In this view, the relative humidity controls the net surface shortwave radiation through changes in low-level cloudiness and the temperature controls the net surface radiation through the changes in longwave radiation. In addition, their results demonstrated the dominant role of both the air-sea temperature difference and relative humidity over, for example, wind speed in reducing the evaporation change in climate models below the Clausius-Clapeyron rate.

The issues of land evaporation changes in a changing climate is far from settled (Ohmura and Wild, 2002; Liu et al., 2004; Troch, 2008). Although, Budyko (1963) suggested that a warmer atmosphere may not necessarily produce more evaporation, data reported by the IPCC TAR (2001), show that the observed increase in average surface temperature is followed by a corresponding marked increase in the vapour pressure (Troch, 2008). Generally, the question as to how the hydrological cycle will change as the climate changes is complicated, hence, improved understanding on how evaporation plays out may be important. Furthermore, the growing number of stakeholders demanding water owing to the decreasing volume of good quality water and the scarcity of land and water due to climate change induced drought, call for accurate and often small scale water management which largely depends on accurate estimations of all terms in the water balance (Moors, 2008).

However, when meteorological models are run to predict changes in climate, the correct representation of the water vapour input to the atmosphere by evaporation becomes critical, this paper aims to help resolve the numerical problems involved in the parameterization of evapotranspiration in climate modelling by investigating the potential of the classical linear regression and statistical neural network (SNN) technique in the estimation of evapotranspiration. The paper also examines the capabilities of a trained neural network with limited input variables in accurately estimating evapotranspiration. The study was carried out using data from the International Institute of Tropical Agriculture (IITA) Ibadan (lat. 7° 00' N to 7° 50' N and long. 3° 40' E to 4° 10' E), Oyo State of Nigeria.

Models of Evapotranspiration

The importance of evapotranspiration (ET) in the water cycle and hydrological management, in addition to expensive and sensitive measuring equipment, led to extensive efforts for modeling the ET mechanism. Many methods have been developed, revised, and proposed for the estimation of ET in different climatic conditions using different predictor variables. Jensen and Allen (2000) reviewed the evolution of different types of ET estimation methods. Conventional ET models are basically categorized into physically based and empirical models. Some examples of the physically based ET models include the equations developed by Penman (1948), Monteith (1965, 1973), Shuttleworth and Wallace (1985), and Granger and Gray (1989).

Empirical models were developed with the aim of proposing simpler ET equations, which require fewer input variables that are also routinely available. Attempts for empirical modeling of evapotranspiration resulted in various methods: temperature-based Thornthwaite, 1948; Blaney and Criddle, 1950; Hargreaves and Samani, 1985), radiation (and temperature)-based (Priestley and Taylor, 1972; Makkink, 1957; Jensen and Haise, 1963; Stephens and Stewart, 1963), water budget-based (Guitjens, 1982), and mass-transfer-based (Harbeck, 1962; Rohwer, 1931). The empirical models have the advantages of being simple and using a small number of meteorological variables; however, reasonable estimation of model parameters is required for local applications. This is considered to be a limitation for the empirical ET prediction models.

Evaporation losses are often estimated as the residue of the water balance, causing all the estimation errors of the other water balance components to accumulate in the estimated evaporation. Studies have shown that the best methods to estimate evaporation more or less independently of the other components of the water balance are based on micro-meteorological techniques. The best known and probably most successful example is the Penman-Monteith equation (Monteith, 1981):

$$\lambda E = s A + \rho c_p D/r_a s + \gamma (1 + r_s/r_a) \quad (1)$$

where λ is the latent heat of vaporization of water, s is the slope of the saturation specific humidity versus temperature curve, A is available energy (i.e. $Q^* - G$, when Q^* is net radiation and G is soil heat flux density), ρ is the air density, c_p is the specific heat of air at constant pressure, D is saturation (specific humidity) deficit (i.e. $q_s(T) - q$, when $q_s(T)$ is the saturation specific humidity at temperature T and q is specific humidity), γ is the psychrometric constant (i.e. c_p/λ), r_s is the canopy or surface resistance and r_a is the aerodynamic resistance for transport of heat and water vapour of the air layer between the surface and reference height.

Over longer time periods there is a balance between radiation, latent heat flux, and sensible heat flux, at the surface of the earth. The terrestrial water balance, which in turn is affected by the Earth's atmosphere energy balance, is driven by the Earth's surface energy balance:

$$R_n = H + \lambda E + G \quad (2)$$

where R_n is the net radiation, H is the sensible heat flux, λE is the latent heat flux (λ is latent heat of vaporization), and G is ground heat flux. The latter term however becomes small compared to other terms over long periods of time, and can be safely neglected in the balance equation. Based on the energy balance and when land-surface moisture is in ample supply (as it is in the study area), evaporation rates are consistent with the observed rates of solar radiation at the land surface.

The basic obstacle to widely using the Penman-Monteith (FAO-56 PM) method which the Food and Agriculture Organization of the United Nations (FAO) has proposed as the standard method for estimating reference evapotranspiration, and for evaluating other methods, is the numerous required data that are not available at many weather stations (Trajkovic, 2005). Evapotranspiration requires two essential components: a source of energy and a vapour transport mechanism. Energy is needed to provide the latent heat of vaporization required to bring about a phase change from liquid to vapour. The vapour transport mechanism is necessary to continuously move the water vapour away from the surface and thus maintain a vapour pressure gradient between the evaporating surface and the surrounding air (Kirnak and Short, 2001).

However, numerous empirical models exist to determine potential evapotranspiration for data limited regions. There are three methods that apply solar radiation directly, although they also require some measures of mean daily air temperature. These methods are the Makkink method, the Turc method and the Hargreaves method. The Makkink radiation method (Makkink, 1957) is merely a simplification of the Priestly-Taylor equation that assumes that the daily ground heat flux is small and the net radiation is a function of solar radiation to a large extent (de Bruin, 1987) such that:

$$LE = C_M \frac{\Delta}{\Delta+\gamma} R_S \qquad (3)$$

where LE is the latent heat flux (Wm^{-2}), C_M is the ratio of net radiation to solar radiation, the mean value of which is determined from measured data to be 0.63 for the study area, Δ is the slope of the saturation vapour pressure temperature relationship, γ is the psychometric constant (approximately 0.67), and R_S is the solar radiation (Wm^{-2}).

Meanwhile, the Turc radiation method (Turc, 1961) was developed in Western Europe for regions which have relative humidity greater than 50% and the model equation is expressed as:

$$LE = 0.369 \frac{T_a}{T_a+15} (2.06R_s + 50) \qquad (4)$$

where LE is the mean daily latent heat flux (Wm^{-2}), Rs is the daily solar radiation (Wm^{-2}), and Ta is the mean daily air temperature (°C).

Finally, the Hargreaves method (Hargreaves and Samani, 1985) is an empirical approach that can be used to compute daily potential evapotranspiration particularly in locations where the availability of weather data is limited. The Hargreaves equation calculates potential evapotranspiration from solar radiation and temperature as:

$$LE = 0.01354R_s\ (T_a+17.8) \qquad (5)$$

where LE is the mean daily latent heat flux (Wm^{-2}), R_s is the daily solar radiation (Wm^{-2}), and T_a is the mean daily air temperature (°C).

METHODOLOGY

The MLR model

We recall the linear regression model (LRM) given as:

$$y_i = f(x_j, \beta) + e_i; \qquad i = 1, 2, \dots, n \tag{6}$$

which is made up of the predicted part and the residual part. The residual is the difference between the observed and the predicted values which is ascribed to unknown sources. n is the number of observations, y_i is the ith observation, $x_j = (x_{1i}, x_{2i}, \dots, x_{ki})$ is the predictor variable vector related to y_i, $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ is the parameter vector, and e_i is the error associated with ith observation.

In matrix form , equation (6) can be written as

$$Y = X\beta + \varepsilon \tag{7}$$

The least squares estimate of the parameter β is given as

$$\hat{\beta} = (X'X)^{-1}X'Y \tag{8}$$

While, the predicted model becomes

$$\hat{Y} = X\hat{\beta} \tag{9}$$

so that the residual is given as

$$e = Y - \hat{Y} \tag{10}$$

The SNN model

The statistical neural network (SNN) model structurally is composed of two parts: the predictive and the residual, as is in classical regression, given as

$$y = f(X, w) + e_i \tag{11}$$

where $f(X,w) = \alpha X + \sum_{h=1}^{H}\beta_h g\left(\sum_{i=0}^{I}\gamma_{hi}x_i\right)$. Thus equation (11) can be written as

$$y = \alpha X + \sum_{h=1}^{H}\beta_h g\left(\sum_{i=0}^{I}\gamma_{hi}x_i\right) + e_i \tag{12}$$

$X = (x_0, x_1, \dots, x_I)$ is the vector of the input variable, $g(.)$ is the transfer (or activation) function and $w = (\alpha, \beta, \gamma)$ are the weights (or parameters) associated with the input vector, hidden neuron and the transfer function respectively, while e_i is the error associated with the network. We note that when there is no hidden neuron, the SNN reduces to the ordinary regression model. The weights are estimated using Taylor's first order approximation,

$$y = y^0 + \frac{\partial f(x,w)}{\partial w}\Big|_{w=w^0}^{(w-w^0)} + e \tag{13}$$

where $y^0 = f(x, w^0)$

if $\theta = w - w^0$, and $z = \frac{\partial f(x,w)}{\partial w}$, then we can write equation (11) as

$$y^* = z\theta + e \tag{14}$$

where $y^* = y - y^0$

The least squares estimate of the parameter θ is

$$\hat{\theta}' = (Z'Z)^{-1}Z'Y \tag{15}$$

and the estimated model is

$$\hat{y}^* = z\ddot{\theta}$$

while the network error is given as

$$e = y^* - \hat{y}^*$$

In this paper, we used the symmetric saturated linear transfer function,

$$f(x) = \begin{cases} -1, & x < -1 \\ x, & -1 \le x \le 1 \\ 1, & x > 1 \end{cases}$$

Data for seven variables were employed in this study. They are: evapotranspiration, humidity, rainfall, solar radiation, sunshine hours, temperature, and windspeed. The scope of the data was ten years monthly data, providing a 120 data set for each variable. However, the analysis was split into two. First, all the seven variables were used in the analysis. Secondly, three variables that were not significant were dropped, leaving only four in the second analysis. Thus, the variables left in the second analysis were evapotranspiration, humidity, solar radiation, and temperature. The model formulations therefore becomes *6-2-1, 6-5-1, 6-10-1, 6-50-1, 6-100-1*, and *4-2-1, 4-5-1, 4-10-1, 4-50-1, 4-100-1*.

All input variables were standardized, that is, converting them to the range (0, 1) before feeding them into the network. This is to avoid the application of extremely small weighting factors in the case of large input values.

Similarly, the output values are "destandardized" to provide meaningful results since all values leaving the network are automatically output in a standardized format. This is done by simply reversing the standardization algorithm used on the input nodes.

We used SPSS for the LRM part of the analysis, while a neural code was written for the analysis of the SNN using MATLAB R2009a, and interesting results were obtained.

Model Selection Criteria

In this section we discuss several criteria that have been used to choose between the two models. Several criteria were used for this purpose. In particular, we discuss these criteria: (i) R^2, (ii) adjusted R^2 ($\bar{R}^2$) , (iii) Akaike information criterion(AIC), and (iv) Schwarz Information criterion (SIC). All these criteria aim at minimizing the residual sum of squares (SSE). However, except for the first criterion, criteria (ii), (iii), and (iv) impose a penalty for including an increasingly large number of predictors. Thus there is a tradeoff between goodness of fit of the model and its complexity (as judged by the number of predictors).

RESULTS AND DISCUSSIONS

The results of the analysis are discussed in this section. Table 1 is the results of the seven variables used in the first analysis. While Table 2 is the results of the four variables used in the second analysis.

Table 1: Results of Analyses based on 7 Variables

Var	n	$MLRM$					SNN					
		MSE	R^2	$\bar{R}^2$	AIC	SIC	HL	MSE	R^2	$\bar{R}^2$	AIC	SIC
7	120	0.60	0.56	0.53	0.675	0.795	2	0.39	0.00	-0.01	0,438	0.516

							5	0.38	0.032	0.027	0.427	0.502
							10	0.38	0.033	0.028	0.427	0.502
							50	0.33	0.15	0.14	0.371	0.436
							100	0.00	0.99	0.99	0.000	0.000

In Tables 1 and 2, the MSE are less in the SNN compared to that in the $MLRM$. And it is noticed that while there was no change in the MSE of the $MLRM$ in the two tables, there is a lot of difference in the SNN. The change in the number of variables used in the analysis affected the error propagation of the neural network model. As the number of variables used in training increases, the MSE reduces.

Table 2: Results of Analyses based on 4 Variables

Var	n	$MLRM$					SNN					
		MSE	R^2	$\bar{R}^2$	AIC	SIC	HL	MSE	R^2	$\bar{R}^2$	AIC	SIC
4	120	0.60	055	0.53	0.640	0.703	2	0.56	0.02	0.01	0.599	0.657
							5	0.54	0.041	0.036	0.577	0.633
							10	0.53	0.072	0.067	0.567	0.622
							50	0.36	0.37	0.367	0.385	0.422
							100	0.23	0.59	0.587	0.246	0.270

However, generally, as the hidden neuron increases, the MSE for the SNN becomes reduced. This is explained by the sensitivity of the neural network to data. Discrepancies not captured in the traditional method affects the network at very low hidden neurons. Increasing the number of hidden neuron reduces the biases in the weights. This explains the reason for the low values of the MSE in higher neurons.

Table 3: Model Selection based on R^2 and $\bar{R}^2$

No. of Variables	Model Selected	
	R^2	$\bar{R}^2$
7	6-100-1	6-100-1
4	3-100-1	3-100-1

In Table 3, the fit of the *SNN* model occurs at a high hidden neuron of 100. On the contrary, the *AIC* and *SIC* show that the *SNN* model is very adequate compared to the traditional *MLRM*.

Table 4: Model Selection based on *AIC* and *SIC*

No. of Variables	Model Selected	
	AIC	*SIC*
7	6-2-1	6-2-1
	6-5-1	6-5-1
	6-10-1	6-10-1
	6-50-1	6-50-1
	6-100-1	6-100-1
4	3-2-1	3-2-1
	3-5-1	3-5-1
	3-10-1	3-10-1
	3-50-1	3-50-1
	3-100-1	3-100-1

The model performances of the two models (LRM and SNN) is compared using the adjusted $R^2(\bar{R}^2)$, Akaike information criterion(AIC), and Schwarz Information criterion (SIC). The R^2 shows the performances of the individual models. We therefore notice that at higher neurons, the better the SNN model. The AIC and SIC results show that the SNN is a better model in comparison to the traditional $MLRM$.

Conclusion

We have compared the ordinary least squares regression and the statistical neural network to estimate evapotranspiration in Ibadan, Nigeria from 1995 to 2004. Both methods attempt to minimize the error sum of squares between observations and predicted values. Regression requires an explicit function to be defined before the least squares parameter estimates could be computed, while a neural network depends more on training data and the learning algorithm.

We have restricted the variables for the models to evapotranspiration, humidity, rainfall, solar radiation, sunshine hours, temperature, and windspeed as measured by the International Institute for Tropical Agriculture (IITA) in Ibadan. Comparing model prediction in both cases show that the statistical neural network performs better than the regression model.

It therefore follows that the statistical neural network may be suggested as a proxy in the correct capturing of evapotranspiration rates in climate modelling particularly at local spatial context over short time span. *On-going studies would further establish these capabilities and at the same* time explore the modelling of water vapour changes in relation to the moisture and heat fluxes in hydrological cycle.

REFERENCES

Allan, R. P., and B. J. Soden (2007), Large discrepancy between observed and simulated precipitation trends in the ascending and descending branches of the tropical circulation, Geophys. Res. Lett., **34**, L18705, doi:10.1029/2007GL031460.

Allen, M. R., and W. J. Ingram (2002), Constraints on future changes in climate and the hydrological cycle, Nature, **419**, 224–232.

Ayoade, J.O. (1980) On Global and Net Radiation Estimates for Nigeria. *Nigerian Geographical Journal* **23 (1&2)**, 163-175.

Boer, G. J. (1993), Climate change and the regulation of the surface moisture and energy budgets, Clim. Dyn., **8**, 225–239.

Bouchet, R.J. (1963) Evapotranspiration réelle et potentielle, signification climatique. Proc. IASH **62**, 134-142

Bruce, J. P. and Clark, R. H. (1966) *Introduction to Hydrometeorology*. Pergamon Press Ltd, Oxford OX3 0BW, England. pp. 33-56.

Budyko, M.I. (1963) Atlas of the Heat Balance of the Earth. USSR Academy of science, Moscow.

de Bruin, H.A.R (1987) From Penman to Makkink. In: Evaporation and Weather, Proceedings and Information (ed. by J.C. Hoogart) 5-33. Publ. **39**, TNO Committeeon Hydrological Research, The Hague, The Netherlands.

de Bruin, H.A.R. (1989) Physical aspects of the boundary layer with special reference to regional evapotranspiration. In Estimation of Areal Evapotranspiration (ed.) T.A. Black, D.L. Spittlehouse, M.D. Novak & D.T. Price (Proceedings of a workshop held at Vancouver, B.C., Canada, August 1987) IAHS Publ. no. **177**, 117-132

Garatuza-Payan, J., Pinker, R.T., Shuttleworth, W.J. & Watts, C.J. (2001) Solar radiation and evapotranspiration in northern Mexico estimated from remotely sensed measurements of cloudiness. *Hydrol. Sci. J.* **46(3)**, 465-478.

Hargreaves, G.H. & Samani, Z.A. (1985) Reference crop evapotranspiration from temperature. *Appl. Engng in Agric.* **1(2)**, 96-99.

Held, I. M., and B. J. Soden (2006), Robust responses of the hydrological cycle to global warming, J. Clim., **19**, 5686–5699.

IPCC TAR (2001) Climate Change 2001: Third Assessment Report. Intergovernmental Panel on Climate Change (IPCC). http://www.ipcc.ch/activity/tar.htm

Jacobs, J.M., Anderson, M.C., Friess, L.C. & Diak, G.R. (2004) Solar radiation, longwave radiation and emergent wetland evapotranspiration estimates from satellite data in Florida, USA. *Hydrol. Sci. J.* **49(3)**, 461-476.

Jacobs, J.M., Myers, D.A., Anderson, M.C. & Diak, G.R. (2002) GOES surface insolation to estimate wetlands evapotranspiration. *J. Hydrol.* **266(1-2)**, 53-65.

Kirnak H., Short T.H. (2001) An Evapotranspiration Model for Nursery Plants Grown in a Lysimeter Under Field Conditions. *Turk J. Agric. For.* **25**, 57-63.

Lambert, F. H., and M. R. Allen (2009), Are changes in global precipitation constrained by the tropospheric energy budget? J. Clim., **22**, 499–517.

Lelay, M. and Galle, S. (2005) How changing rainfall regimes may affect the water balance: a modelling approach in West Africa. In *Regional Hydrological Impacts of Climate Change - Hydroclimatic Variability. Proceedings of symposium S6 held during the Seventh IAHS Scientific Assembly* at Foz do Iguacu, Brazil, April 2005. IAHS Publ. 296:203-210.

Liu, B., Xu, M., Henderson, M. and Gong, W. (2004) A spatial analysis of pan evaporation trends in China, 1955-2000. Journal of Geophysical Research **109**, D15102, doi: 10.1029/2004JD004511.

Lorenz, D. J., E. T. DeWeaver, and D. J. Vimont (2010), Evaporation change and global warming: The role of net radiation and relative humidity, J. Geophys. Res., **115**, D20118, doi:10.1029/2010JD013949.

Makkink, G.F. (1957) Testing the Penman formula by means of lysimeters. *Int. J. Water Engng* **11**, 277-288.

Middelkoop, H. (2008) Climate Change and Hydrological Impact Studies. In *Climate and the Hydrological Cycle*. Bierkens et. al. (eds.) IAHS Special Publication **8**, 269-295.

Monteith, J.L. (1981) Evaporation and surface temperature. Quarterly Journal of the Royal Meteorological Society **107**, 1-27.

Moors, E. (2008) Evaporation. In Climate and the Hydrological Cycle. Bierkens et. al. (eds.) IAHS Special Publication **8**, 23-41.

Nemani, R.R. & Running, S.W. (1989) Estimation of regional surface resistance to evapotranspiration from NDVI and thermal-IR AVHRR data. *J. Appl. Met.* **28**, 279-284.

Ohmura, A. and Wild, M. (2002) Is the hydrological cycle accelerating? Science **298**, 1345-1346.

Penman, H.L. (1948) Natural evaporation from open water, bare soil and grass. *Proc. Roy. Soc. London A* **193**, 120-146.

Pierrehumbert, R. T. (2002), The hydrological cycle in deep-time climate problems, Nature, **419**, 191–198.

Price, J.C. (1990) Using spatial context in satellite data to infer regional scale evapotranspiration. *IEEE Trans. Geosci. Remote Sens.* **28**, 940-948.

Seguin, B., Assad, E., Freaud, J.P., Imbernon, J.P., Kerr, Y. & Lagouarde, J.P. (1989) Use of meteorological satellite for rainfall and evaporation monitoring. *Int. J. Remote Sens.* **10**, 1001-1017.

Stocker, T.F. and Raible, C.C. (2005) Water cycle shifts gear. Nature **434**, 830-833.

Trajkovic S. (2005) Temperature-Based Approaches for Estimating Reference Evapotranspiration. *J. Irrig. and Drain. Engrg.*, **131(4)**, 316-323.

Troch, P. A. (2008) Global Warming and the Acceleration of the Hydrological Cycle. In Climate and the Hydrological Cycle. Bierkens et. al. (eds.) IAHS Special Publication **8**, 257-267.

Turc, L. (1961) Evaluation des besoins en eau d'irrigation, évapotranspiration potentielle, formulation simplifié et mise à jour. *Ann. Agron.* **12**, 13-49.

Wentz, F. J., L. Ricciardulli, K. Hilburn, and C. Mears (2007), How much more rain will global warming bring? Science, **317**, 233–235.