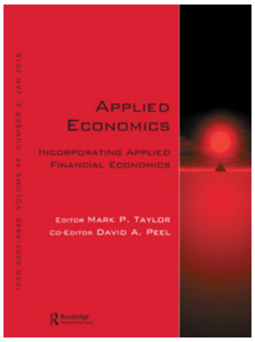

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Weather derivatives structuring and pricing: a sustainable agricultural approach in Africa

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Weather derivatives structuring and pricing: a sustainable agricultural approach in Africa

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ABSTRACT
The objective of this article is to calculate the price of weather derivatives for different African countries with payout depending on temperature. A new approach for computing degree day contracts is shown and gives another scale to the numerical relevance and practical implementation of the findings. With historical data for each country, a stochastic process based on continuous time with mean reversion representing the evolution of the temperature is determined. Focusing on the Monte Carlo simulation method, the price of each contract and the potential implications to solve several aspects of the threatened African economy are presented.

KEYWORDS
Weather derivatives; degree day contract; mean reversion; Monte Carlo simulation; hedging African weather risk

JEL CLASSIFICATION
C50; G13; Q14

I. Introduction

In 2007, the United States Department of Commerce reported that weather had impacted 70% of US companies and that the total cost of climatic events represented more than $200 billion in 2005. Historical data show that there has been an increase in extreme weather conditions, in particular related to temperature. In addition, temperature volatilities logically tend to more heavily affect countries in which the economy depends strongly on crop revenues. Unfortunately, an agricultural economy is often synonymous with emerging and developing countries, where a bad harvest can perpetuate the vicious circle of rural poverty. Moreover, it appears that natural catastrophes more severely impact small-scale farmers in undeveloped areas. Consequently, a decrease in crop revenue can engender certain economic and development downturn, thus raising poverty and threatening possible humanitarian crises.

In this context, the African continent represents a major agricultural place often struck by excessive temperatures. Receiving financial aid from public organizations constitutes the foundation on which these nations rely to survive, but this practice does not give these nations a long-term solution to tackle weather risks. For instance, in Ethiopia, agriculture accounts for about 47% of the country's GDP,[1] and the country is affected by extreme weather events, such as drought, that continually cause heavy economic losses. In 2006, the Ethiopian government launched a food security programme through the creation of an insurance policy based on a drought index. The aim of this insurance was to help develop and stabilize the economy of the country and secure food resources for farmers in the event of a drought. The Ethiopian Drought Index provided past temperature data from 1952 to 2006, thanks to the National Meteorological Agency. The newly created index demonstrated an 80% correlation to the aid provided by international organizations. AXA Re, a French insurer, provided contracts with a premium set at $930 000 and a payout of $7.1 million. Despite the efficiency of this pilot project, it has not been renewed due to lack of private investors' support. However, this initiative highlighted the need for weather derivative products in countries highly dependent on the agriculture industry and subject to extreme weather events that could cause humanitarian crises. It is on this observation that this article focuses on weather risk management as a new approach and a possible independent long-term

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[1]International Fund for Agricultural Development, 2008, Ethiopia: Recent macroeconomic agriculture sector performance and trends in rural poverty, August 2008.

plan to help African countries mitigate their weather risk.

The emergence of climatic contracts in the United States during the late 1990s required researchers to adapt existing valuation models to weather specificities. Indeed, because weather indices cannot be traded on the market, the constitution of a replicating portfolio is not possible. To get over this difficulty, the literature suggests choosing a substitute asset that follows the same characteristics and has a highly correlated price with the unobservable weather contract. Dischel (1999) recommended building a temperature portfolio replica by picking both temperature and gas derivatives contracts negotiated on financial markets at that time. However, Brix, Jewson, and Ziehmann (2002) revealed that gas prices are better correlated to the demand than to the temperature.

The financial community looked then for other alternatives. One simple, straightforward method, the Actuarial Method or Burn Analysis, was designed by the insurance industry and is still employed in pricing climatic contracts. Unlike earlier methods, it is unnecessary to create a replicating portfolio. The price of the weather derivative before the maturity date is simply the discounted expected loss that occurred during the period of the contract policy and is calculated as the average pay-off that the contract would have given upon the same period using historical data. At maturity, the price is equal to the historical probability of the underlying to have performed with an additional risk loading parameter to compensate for the seller's risk taken. Dischel (1999), Jewson (2004) and Platen and West (2004) contended that the price of the risk loading was not relevant for complexity reasons and decided to consider it either null or to give it an arbitrary value. Platen and West (2004) further explained that the concurrence between companies inclined to decrease this risk parameter.

Cao and Wei (2004) created a different procedure based on the Consumption–Capital Asset Pricing of Lucas (1978). In fact, using the Euler equation, they showed that a significant relation exists between the temperature of several North American cities and the total level of consumption. The same conclusions were drawn by Richards, Manfredo, and Sanders (2004) using the data of the city of Fresno, California. Once a general frame around weather derivative valuation methods is set up, pricing them requires modelling the climatic variable.

The increasing need of energy companies to hedge unpredictable temperature variations has driven researchers to principally model temperature movement. The literature shows that temperature follows a regular movement often represented by a sinusoidal function. It also demonstrates that the variable movement does not diverge far from a mean curve, also called the mean reversion process. To take into account the mean reversion, Alaton, Djehiche, and Stillberger (2002) and Benth and Šaltytė-Benth (2005) suggested using a continuous time Ornstein–Uhlenbeck process. We will use this method to value and price the African temperature-based contracts we define.

The first objective of this article is to examine the structure of temperature contracts and to construct a new weather derivative market for 18 African countries. The historical weather data were gathered from meteorological centres and served to calculate fair prices of basic degree day (DD) derivatives. The second objective is to assess the hedging effectiveness of the created options against temperature risk by comparing option premium results with recent agricultural productions and revenue figures. The final objective is to assess the cost of insuring 30% of the three most-produced commodities by each country and see if communal derivatives are a viable alternative in the African case. The originality of the article is twofold: first, we consider the three most important crops in each country, and second, for each of these crops, we look at the optimum range of temperatures for growing it.

The remainder of the article is organized as follows. Section II provides a general presentation of the weather derivative market, followed by a detailed overview of temperature derivatives. In Section III, we focus on temperature modelling of the 18 African countries using an Ornstein–Uhlenbeck process. The estimation of parameters is based on historical data using a martingale process; therefore, the data collection description will also be expressed in the same section. Section IV is dedicated to pricing the temperature contracts using Monte Carlo simulations. In that same section, the results are presented and discussed, and in Section V, conclusions are drawn based on the results.

II. Weather derivatives

The first transactions on climatic variables were initially executed in the United States in September 1997 between two energy companies, Koch Industries and Enron, using a swap on temperature indices to hedge against warm days in winter. Weather derivatives first started in the United States for two principle reasons. The first motive came in 1997 after the deregulation of the energy industry that fuelled the expansion of climatic options. To avoid energy price volatility, the energy industry used weather derivatives as they gave an instant pay-off when the demand spread far from their forecast. The second motive concerns the multiple climate disturbances that the country faced in 1997 (the El Nino[2] effect during the winter of 1997 and the violent storms in California). In 1999, the expansion of the climatic contracts gave birth to an organized electronic platform launched by the Chicago Mercantile Exchange (CME). The first contracts traded were essentially DD temperature contracts in 10 cities.[3] The CME has enlarged its territory and now numbers 18 cities[4] in North America. In 2003, the CME opened a subsidiary in Europe covering European cities[5] and in Japan covering the cities of Tokyo and Osaka.

In Africa, the volume of derivative contracts is very small, and only Morocco and South Africa have launched a few over-the-counter (OTC) contracts. Other initiatives by the World Bank associated with private companies to reduce natural extreme weather risks in developing countries have shown the important demand for small farm holders, notably in Ethiopia.

The main actors on the climatic derivative market

In 2005, the proportion of all type of climatic contracts negotiated on the CME was 95% against 5% for the OTC market. The CME represents a significant advantage because it offers a standardized market with futures and options. The most important climatic variable exchanged is the temperature DD, with maturity date and strike price already determined. The strike price must evolve within a definite intra-day interval, and the hedge contract can mature either in 1 month or 6 months (Six months corresponds to hedging either the winter or summer season.). The quotation of the DD contract is made in basis points with a ticker generally equal to $20 per DD.

The main users of the market are energy and agricultural companies, investment banks and insurance businesses. The strong presence of the energy and agricultural industries on the CME platform explains why temperature DDs represent the major amount of exchanged derivatives. Several banks, such as Société Générale, Deutsche Bank and Banca Nazionale del Lavoro, have created their own desks to take a slice of the OTC market. Other meteorological offices also helped provide reliable data, notably in Europe. For instance, in France, a partnership between Meteo France and Euronext permitted the launching of a new platform index called Nextweather. In 2002, Euronext indices were spread to cover the Netherlands and Belgium, and the same approach was adopted in the United Kingdom with a joint venture, Weatherxchange.com, between the UK Met Office and Umbrella Brokers, giving access to temperature and rainfall data throughout European cities. In the United States, the data are available completely free of charge, again encouraging faster expansion of weather derivatives.

Temperature-based derivatives

As we have seen previously, the most commonly traded weather derivatives are temperature contracts, and this is why this study focused on temperature derivatives only. Generally, temperature contracts are based on daily average DD indices. The daily average of temperature is calculated as the arithmetical average of the two extreme temperatures of the day as in Equation 1:

$$T_i = \frac{T_{min} + T_{max}}{2} \tag{1}$$

where
T_i is the daily average temperature,
T_{min} is the minimal temperature of the day i and
T_{max} is the maximal temperature of the day i.

[2]El Nino is a warm effect occurring every 3–4 years in the Pacific Ocean causing multiple damages (flooding and drought).
[3]Atlanta, Chicago, Cincinnati, Dallas, Des Moines, Las Vegas, New York, Philadelphia, Portland and Tucson.
[4]Baltimore, Boston, Detroit, Houston, Kansas City, Minneapolis, Sacramento and Salt Lake City.
[5]Amsterdam, Barcelona, Berlin, Essen, London, Madrid, Paris, Rome and Stockholm.

The notion of a DD has been created to price temperature derivatives. For a given site, the DD represents the difference between the calculated daily average temperature (from Equation 1's calculation) and a temperature threshold chosen as a reference. Two distinct alternatives of DD exist: heating degree day (HDD) and cooling degree day (CDD). During winter periods, the domestic consumption demand comes mainly from heating; whereas, in summer periods, the domestic consumption demand is usually from cooling. The HDD and CDD have been created to match this domestic phenomenon. Hence, an investor buying an HDD contract wants to hedge against cold days (comparing to the baseline temperature), whereas, for a CDD contract, the need will be to insure from abnormal warm temperatures. The HDD and CDD can be expressed as in Equation 2:

$$HDD_i = \max\left[T_{ref} - T_i, 0\right] \text{and } CDD_i = max\left[T_i - T_{ref}, 0\right] \qquad (2)$$

where

T_i is the daily average of temperature and

T_{ref} is the temperature baseline.

In this article, the baseline temperature will be adapted to each African country and commodity under study. The detail of the baselines choices will be commented on in Section III.

III. Temperature modelling

The construction of HDD and CDD contracts requires first collection of data and calculation of the daily average of temperatures. We used 10 years of historical temperatures data (from January 2001 to December 2010) from weather stations across Africa and provided by the National Climatic Data Center. Based on the data collected from the different stations across each country, a daily average was computed. Table 1 presents the summary statistics for the daily average temperatures of 18 African countries. These countries have been selected according to the availability of the data.

African-adjusted DD contracts

One of the original approaches of this study is setting the HDD and CDD in an unusual way. This study was designed to create a contract where the pay-off is activated when the temperature is really affecting farm production yield. The baseline of the DDs was thus set by taking into account the optimum temperature at which each commodity grows best. Because it is not possible to compute the contracts for all commodities, the three mainly produced commodities for the 18 countries were researched. Data were extracted from the Food and Agriculture Organization (FAO) of the United Nations. Table 2 presents the commodities used in this article, displayed by country and ranked by its crop production.

From this information, a high and a low baseline intervening into the calculation of the DD contract was built. Using academic and public organization studies published for each crop (see the Appendix), a mean maximum and minimum optimal temperature

Table 1. Summary statistics of daily temperatures by country (in celsius).

Country	Mean	Median	SD	Min	Max
Botswana	18.47	19.25	3.74	3.00	26.92
Cameroon	26.98	27.33	2.83	13.00	34.33
Egypt	26.87	27.56	7.00	9.75	40.78
Gabon	25.92	26.75	3.61	11.50	32.00
Gambia	27.13	27.50	2.01	16.00	34.00
Ivory Coast	22.41	22.42	2.88	8.50	30.46
Kenya	21.26	21.60	2.28	5.25	26.38
Liberia	27.92	27.75	1.69	16.00	35.00
Libya	21.60	22.00	6.93	7.00	41.00
Mauritania	24.49	24.75	3.69	8.50	35.50
Namibia	18.60	18.92	4.91	2.83	30.00
Niger	29.92	30.00	3.83	14.00	42.00
Senegal	27.12	27.50	2.34	4.50	33.90
Sierra Leone	27.26	27.50	1.46	16.00	33.00
South Africa	17.44	17.62	4.05	5.88	26.88
Togo	17.25	18.17	4.30	8.50	22.50
Tunisia	28.39	27.94	9.41	8.33	61.67
Uganda	23.43	23.10	3.91	9.17	37.33

Table 2. Main commodities produced by country.

Country	First crop produced	Second crop produced	Third crop produced
Botswana	Corn	Sorghum	Wheat
Cameroon	Plantains	Cocoa beans	Wheat
Egypt	Wheat	Corn	Sugarcane
Gabon	Plantains	Yams	Cassava
Gambia	Corn	Cassava	Paddy rice
Ivory Coast	Cocoa beans	Yams	Plantains
Kenya	Corn	Plantains	Sugarcane
Liberia	Plantains	Sugarcane	Cassava
Libya	Dates	Tomatoes	Wheat
Mauritania	Dates	Dry beans	Paddy rice
Namibia	Wheat	Tomatoes	Corn
Niger	Dry onions	Tomatoes	Paddy rice
Senegal	Sugarcane	Corn	Cassava
Sierra Leone	Green coffee	Cocoa beans	Cassava
South Africa	Corn	Sugarcane	Wheat
Togo	Yams	Corn	Cassava
Tunisia	Olives	Tomatoes	Wheat
Uganda	Cassava	Green coffee	Plantains

Table 3. Optimal temperatures by commodity (in celsius).

Commodity	Min	Max
Cassava	25	27
Cocoa beans	18	32
Corn	15	27
Dates	20	45
Dry beans	13	25
Dry onions	13	25
Green coffee	15	30
Olives	5	25
Paddy rice	13	35
Plantains	26	30
Sorghum	25	35
Sugarcane	32	38
Tomatoes	18	32
Wheat	13	25
Yams	21	26

for each commodity in which crops grow best statistically was determined. Table 3 summarizes the range of ideal temperatures by commodities taken as a baseline to determine the HDD and CDD indices. The HDD and CDD use as reference temperatures these degree thresholds.

For instance, the HDD and CDD for the cocoa beans can be expressed as in Equation 3:

$$HDD_i = \max[18 - T_i, 0] \text{ and } CDD_i = \max[T_i - 32, 0] \quad (3)$$

where
T_i is the daily average of temperature,
18 is the minimum temperature baseline and
32 is the maximum temperature baseline.

Temperature modelling

The literature upon daily average decomposition of the temperature is based on a simple statement illustrated in Fig. 1 that the temperature follows a cyclical movement. Consequently, the temperature modelling can be formalized by an additive function as in Equation 4:

$$T_t = m_t + s_t + \varepsilon_t \quad (4)$$

where
t is the time variable,
m_t is a trend expressed as $m_t = a + bx$,
s_t represents the oscillations around the mean and
ε_t represents the random movements.

Two models are mostly used to model the daily average temperature: discrete time models, as that of Cao and Wei (2004), who proposed an autoregressive process, and continuous time models, as that of Dischel (1998). In our case, the degree pattern for the 18 African countries follows a cyclical function that moves around a mean towards a trend (see Fig. 1, representing 10 years of historical temperatures for Egypt). Cao and Wei's (2004) discrete model determined the temperature cyclical movement s_t without removing the trend. As a consequence, the calculation of the cyclical movement s_t is biased by the trend. We will thus use the continuous mean reverting model of Dischel (1998), further adjusted by Alaton, Djehiche, and Stillberger (2002).

Mean reverting process

The Ornstein–Uhlenbeck process is a mean reverting method described by the stochastic differential equation, as in Equation 5:

$$\mathrm{d}T_t = a(\theta_t - T_t)\mathrm{d}t + \gamma \mathrm{d}W_t \quad (5)$$

where
T_t is the temperature at a date t,
θ_t is the historical average of the temperature for the date t,
W_t is a Brownian motion,
γ is the historical volatility estimated and
a is the constant parameter or trend.

A prior imperfection in the Dischel (1998) model was the absence of the seasonal component in the

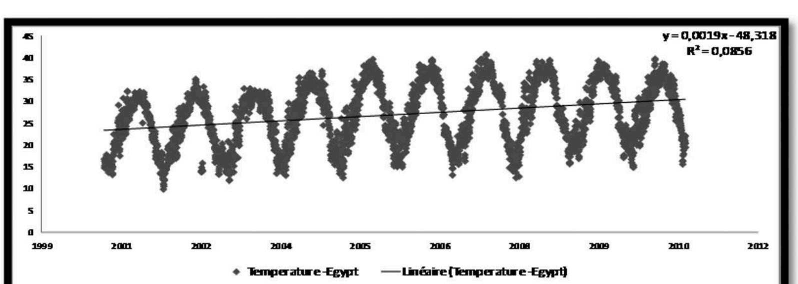

Figure 1. Egypt temperature graphical representation.

long term, and this has been highly criticized. This flaw was first expressed by Dornier and Queruel (2000). To resolve this problem, Alaton, Djehiche, and Stillberger (2002) proposed adding the following variable to Equation 5:

$$\frac{\mathrm{d}\theta_t}{\mathrm{d}t}$$

The derived model can then be written hereafter as in Equation 6:

$$\mathrm{d}T_t = \left(\frac{\mathrm{d}\theta_t}{\mathrm{d}t} + a(\theta_t - T_t)\right)\mathrm{d}t + \gamma \mathrm{d}W_t \quad (6)$$

Alaton, Djehiche, and Stillberger (2002) also suggested that the seasonality follows a function represented by Equation 7:

$$\theta_t = A + Bt + C\sin(wt + \varphi) \quad (7)$$

where $wt = \dfrac{2\pi t}{365}$

Therefore, in order to simulate the temperature trajectory, it is necessary to estimate all the parameters from Equations 6 and 7. To do so, Alaton, Djehiche, and Stillberger (2002) detailed procedure for each parameter was used.

The first parameters to estimate are those from Equation 7, (i.e., A, B, C and φ.) We can rewrite θ_t as in Equation 8:

$$\begin{aligned}\theta_t = A + Bt + C[&\sin(wt)\cos(\varphi) \\ &+ \cos(wt)\sin(\varphi)]\end{aligned} \quad (8)$$

Hence, Equation 8 allows us to estimate the parameters as a linear regression or ordinary least squares by rewriting it as in Equation 9:

$$\theta_t = \beta_1 + \beta_2 t + \beta_3 \sin(wt) + \beta_4 \cos(wt) \quad (9)$$

where

$$\begin{cases} A = \beta_1 \\ B = \beta_2 \\ \varphi = \tan^{-1}\left(\frac{\beta_4}{\beta_3}\right) \\ C = \frac{\beta_3}{\cos(\varphi)} \end{cases}$$

The next parameter concerns the approximation of the mean reverting factor a. The method proposed by Alaton, Djehiche, and Stillberger (2002) uses a martingale process. The objective of this development is to find the unique zero value of the following function (Equation 10) of the sample data set n:

$$G_n(a) = \sum_{i=1}^{n} \frac{\dot{b}(T_{i-1};a)}{\gamma_{i-1}^2}[T_i - E[T_i|T_{i-1}]] \quad (10)$$

where $b(T_t, a) = \frac{\mathrm{d}\theta_t}{\mathrm{d}t} + a(\theta_t - T_t)$ is the drift function, and $\dot{b} = \frac{\vartheta b}{\vartheta a}$ denotes the derivative with respect to a of the drift term.

To find $E[T_i|T_{i-1}]$, we note in Equation 11 that:

$$T_i = \theta_i + e^{-a}(T_{i-1} - \theta_{i-1}) + e^{-\int_0^i ads} \int_{i-1}^{i} e^{\int_0^i ads} \gamma_s dW_s \quad (11)$$

This yields Equation 12:

$$E[T_i|T_{i-1}] = \theta_i + e^{-a}(T_{i-1} - \theta_{i-1}) \quad (12)$$

If we substitute in Equation 10, we get Equation 13:

$$G_n(a) = \sum_{i=1}^{n} \frac{T_{i-1} - \theta_{i-1}}{\gamma_{i-1}^2}[T_i - \theta_i - \mathrm{e}^{-a}(T_{i-1} - \theta_{i-1})] \quad (13)$$

Therefore, if we solve Equation 13 to isolate a, it is expressed as in Equation 14:

$$a = -\log\left(\frac{\sum_{i-1}^{n} \frac{T_{i-1}-\theta_{i-1}}{\gamma_{i-1}^2}(T_i - \theta_i)}{\sum_{i-1}^{n} \frac{T_{i-1}-\theta_{i-1}}{\gamma_{i-1}^2}(T_{i-1} - \theta_{i-1})}\right) \quad (14)$$

The only parameter left is the approximation of the volatility. Alaton, Djehiche, and Stillberger (2002) made the assumption that temperatures' volatility γ_t changes every month but remains constant during the month period. The volatility can then be mathematically written as in Equation 15:

$$\mathrm{d}\gamma_t = a_{\gamma(\gamma_{trend} - \gamma_t)\mathrm{d}t} + \sigma_\gamma \mathrm{d}W_t \quad (15)$$

With this hypothesis, the only two parameters to estimate are σ_γ and a_γ. Using the estimator proposed by Alaton, Djehiche, and Stillberger (2002), σ_γ can be approached as in Equation 16:

$$\sigma_\gamma^2 = \frac{1}{n}\sum_{j=0}^{n-1}\left(\gamma_{j+1} - \gamma_j\right)^2 \quad (16)$$

Using the same martingale method as for Equation 6, the expression of factor a_γ becomes as in Equation 17:

$$a_\gamma = -\log\left(\frac{\sum_{i-1}^{n} \frac{\gamma_{trend}-\gamma_{i-1}}{\sigma_\gamma^2}\left(\gamma_i - \gamma_{trend}\right)}{\sum_{i-1}^{n} \frac{\gamma_{trend}-\gamma_{i-1}}{\sigma_\gamma^2}\left(\gamma_{i-1} - \gamma_{trend}\right)}\right) \tag{17}$$

Estimation of the parameters

This section presents the results of the parameters estimated historically. All estimated parameters from Equation 6 are presented in Table 4.

In order to match the actual data, it was decided to take the average of the 15 first days of the sample and thus capture the mean temperature for the month of January in each country to calculate the initial temperature. Furthermore, A, B, C and φ parameters were found with the ordinary least squares method. The speed factor of the mean reverting process represents the velocity of the curve to return close to the mean in time. Finally, the estimation of the volatility is the measure of the variation of the temperature over time. Therefore, it was represented as the SD from the mean trend on the base of an historical volatility with Equation 17.

With the estimated parameters, the trajectories of the temperature for all countries can be simulated as, for instance, the one represented in Fig. 2 from Libya. The discontinued plot is the temperature data collected, and the sinusoidal continued line represents the mean modelling temperature estimated with all the parameters calculated before.

IV. Pricing weather derivatives

DD contracts

A classical DD derivative was created to test the original objective. The created contract structure for each African country is identical and composed of the following specificities:

Table 4. Estimated parameters from the historical data.

	Initial temperature in celsius	Ordinary least square method				Speed of the mean reversion	Volatility estimation
Country	T_0	A	B	C	φ	a	a_γ
Botswana	23	18.60	−0.000074	5.66	0.77	0.12	0.26
Cameroon	28	26.91	0.000037	0.78	−0.39	0.16	0.34
Egypt	30	23.65	0.001766	−6.04	−0.97	0.25	0.32
Gabon	27	25.70	0.000121	1.43	0.55	0.39	0.58
Gambia	25	27.20	−0.000039	−0.92	−0.09	0.20	0.14
Ivory Coast	23	18.60	−0.000074	5.66	0.77	0.12	0.26
Kenya	18	21.11	0.000082	1.42	0.71	0.30	0.21
Liberia	29	28.52	−0.000331	1.55	−5.61	0.20	0.09
Libya	14	21.78	−0.000099	−9.18	−0.58	0.09	0.60
Mauritania	22	23.89	0.000328	−2.72	0.74	0.26	0.36
Namibia	25	17.82	0.000424	5.71	0.79	0.08	0.62
Niger	23	29.35	0.000316	1.73	−0.12	0.20	0.29
Senegal	26	26.81	0.000166	−1.53	0.70	0.45	0.29
Sierra Leone	26	27.14	0.000097	0.44	−0.47	1.68	0.33
South Africa	23	18.53	−0.000592	−4.99	3.54	0.29	0.19
Togo	17	16.87	0.000321	0.93	0.27	0.29	0.08
Tunisia	17	29.68	−0.000706	16.69	−2.27	0.01	0.63
Uganda	20	24.14	−0.000390	−5.14	0.86	0.17	0.21

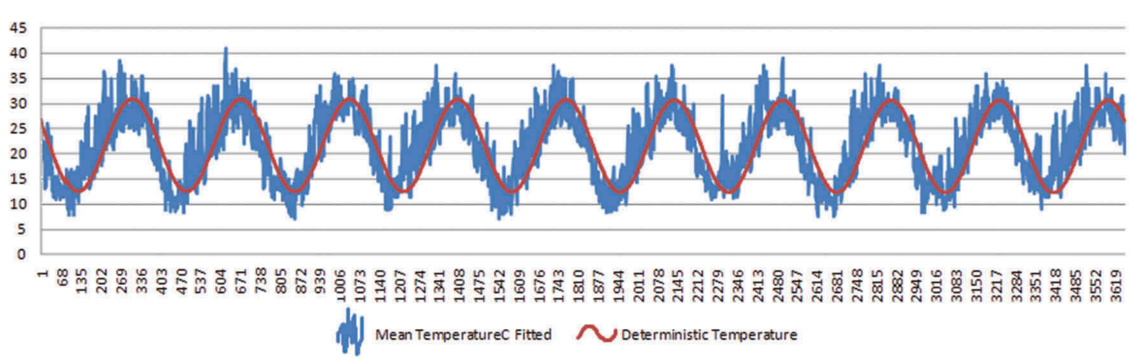

Figure 2. Comparison between historical and simulated temperatures of Libya.

- Option type: European option
- Subscription period: One year starting in January
- Underlying: Temperature index created with HDD and CDD for each commodity
- Strike price: The optimum temperature calculated in Section III
- Tick size: $20
- Target: Small farmers
- Model pricing: Monte Carlo simulation

A European option was chosen in order to guarantee that the contract holder would not exercise its option before the maturity date. By doing so, it was believed that the options would less likely be employed as a speculative financial product. Moreover, it was decided to build DD derivatives with a 1-year-period hedging both winter's and summer's extreme temperatures. For the strike price, as seen in Section III, it would be calculated according to the optimal temperature for each commodity. Finally, the tick size on temperature derivatives is commonly traded at $20 a day, so we simply aligned to that figure.

Buying both CDD and HDD contracts gives the investor an equivalent operation as if they would contract a long call and a long put with a lower strike price. This combination is frequently used in finance to hedge against extreme movements of the underlying variable.

Pricing temperature-based derivatives

Temperature is a nontradable asset, which makes the weather derivatives market a typical example of an incomplete market. Therefore, usual arbitrage-free pricing methods are difficult to apply for pricing and hedging weather derivatives. This difficulty can be circumvented by considering that it is possible, at least in theory, to hedge weather derivatives with other weather derivatives on the same or similar underlying. This requires the existence of a liquid market of tradable weather derivatives. Unfortunately, this market is still relatively illiquid in general and almost nonexistent in Africa. Therefore, this method cannot be used for pricing these weather derivatives.

A widely used alternative for pricing weather derivatives is the actuarial approach. This approach is based on computing the expectation under the real probability, which can be done either using historical data (which is known as the Burn analysis) or using a Monte Carlo simulation. In this article, the Monte Carlo simulation method is used to price the weather derivatives.

The actuarial approach raises the question of the price of risk. In most cases, it is assumed to be zero or equal to an arbitrary value (Jewson 2004; Platen and West 2004). Using a consumption-based model, Cao and Wei (2004) tried to assess the importance of the weather risk, and they concluded that it cannot be ignored unless the correlation between the aggregate consumption and temperature is low or the risk aversion of investors is low, none of which is supported by empirical evidence. Härdle and Lopez-Cabrera (2012) extracted the market price of risk from future contracts on temperature traded on the CME and used it to price options contracts. They found that the market price of weather risk is different from zero and shows a seasonal structure.

In the case of African countries, the weather derivatives market is not developed well enough to allow the use of other products to infer the market price of weather risk. Since the objective in this article is to assess the viability and hedging effectiveness of such products, Jewson, Brix, and Ziehmann (2005) were followed, and in order to account for the risk undertaken by the seller, a risk loading equal to 20% of the SD of the pay-off was added.

Another important issue regarding climatic contracts is the basis risk, which comes from the fact that a meteorological variable in a specific place can be different at the same time in another location, even if the two places are geographically close to each other. This can represent an intense risk for the subscribers trying to hedge their positions from a different location. The user of weather derivatives must be aware of the basis risks and must seek a good weather station as a referential. The question of basis risk uncertainty for weather derivatives is still unresolved in today's literature.

Results

The Monte Carlo simulation technique was used to price the temperature contracts previously defined. To this end, one million five hundred simulations were run with the temperature modelling parameters estimated in Section III. Results are presented in Table 5. For each country and commodity, the premium for

Table 5. HDD and CDD contracts premiums (in dollars).

Country	Commodity	HDD premium	CDD premium	HDD + CDD premium
Botswana	Corn	855	3	858
	Sorghum	728	21	749
	Wheat	611	31	642
Cameroon	Plantain	792	320	1 112
	Cocoa beans	187	213	401
	Wheat	51	688	739
Egypt	Wheat	434	1 468	1 902
	Corn	514	1 400	1 914
	Sugarcane	1501	689	2189
Gabon	Plantain	472	17	489
	Yams	108	178	286
	Cassava	421	107	528
Gambia	Corn	0	560	561
	Cassava	203	560	764
	Paddy rice	0	48	48
Ivory Coast	Cocoa	870	21	891
	Yams	923	65	989
	Plantain	947	32	979
Kenya	Corn	31	19	50
	Plantain	362	6	368
	Sugarcane	362	0	363
Liberia	Plantain	393	245	638
	Sugarcane	624	10	634
	Cassava	310	484	794
Libya	Dates	147	141	288
	Tomato	83	1021	1104
	Wheat	16	1478	1495
Mauritania	Dates	2178	1562	3740
	Dry beans	1701	2995	4696
	Paddy rice	1701	2264	3965
Namibia	Wheat	1406	476	1882
	Tomato	1756	196	1952
	Corn	1565	375	1940
Niger	Dry onions	197	1218	1415
	Tomato	386	715	1101
	Paddy rice	258	1117	1375
Senegal	Sugarcane	516	1	517
	Corn	111	421	532
	Cassava	0	421	421
Sierra Leone	Green coffee	1	48	49
	Cocoa	3	15	18
	Cassava	126	230	356
South Africa	Corn	142	330	472
	Sugarcane	829	20	849
	Wheat	95	479	574
Togo	Yams	319	0	319
	Corn	157	0	157
	Cassava	319	0	319
Tunisia	Olives	550	784	1335
	Tomato	1717	310	2026
	Wheat	1264	784	2048
Uganda	Cassava	228	716	944
	Green coffee	5	521	525
	Plantains	297	521	818

HDD and CDD contracts are presented. The last column presents the addition of the two contracts to get 1-year hedge (for winter and summer seasons).

Although the range of prices is coherent, there is, unfortunately, no way to compare these prices to actual prices because, to our knowledge, this study is the first to design this specific kind of options.

But more than their price, the suitability and hedging effectiveness of these contracts against climatic risk should be questioned. In order to assess this, agricultural production data were collected for each crop and country under study. This information was again obtained through the statistics website of the FAO. More specifically, the information collected reflects the annual production (in tons) and the production price (per ton) for each commodity and country. Using these data, three different measures were performed.

First, the correlation coefficient between the pay-off of the temperature contracts and the production is detailed for each commodity in all the countries. A negative correlation means that when the pay-off from the temperature contracts is important (which corresponds to an important number of DDs outside the optimal temperature range), the production decreases. The higher (in absolute terms) the correlation, the better extreme temperatures explain the decrease in agricultural production, which proves the suitability of these contracts to manage the production volatility.

Second, the average cost of insuring 30% of each crop production is also presented in Table 5. This is obtained by considering the average annual production (production in tons times the price per ton) and the average pay-off per contract (over the 10-year period). This yields the number of contracts necessary to insure 30% of the production (30% times average annual production divided by average pay-off per contract). This amount multiplied by the price of one contract gives the cost of the hedge. We have chosen to insure 30% of each commodity because that figure represents a sufficient pay-off over the development costs ratio. This is also a realistic start to begin this new financial market, but only a few crops support the hypothesis of creating a communal derivative programme.[6]

Third, in order to assess the hedging effectiveness of the created temperature contract, the value at risk (VaR) was used. The VaR calculation will give the probability of losing X amount of production at a

[6]Communal derivatives represent pilot programmes launched by public organizations such as the World Trade Organization or the United Nations to avoid a food crisis.

Table 6. Hedging indicators for the HDD and CDD contracts.

Country	Commodity	Correlation between temperature pay-off and production (%)	Average cost to insure 30% of the total crop production (in millions $)	Value at risk at 99% (in tons)	
				Without C° derivatives	With C° derivatives
Botswana	Corn	−43	234	11 561	8092
	Sorghum	−21	300	7624	5336
	Wheat	−4	3	143	103
Cameroon	Plantains	−1	19 545	6973	4881
	Cocoa beans	−28	18 874	813 805	569 663
	Wheat	−10	8	441	309
Egypt	Wheat	−30	196 602	502 590	351 813
	Corn	−76	23 506	279 750	195 825
	Sugarcane	−78	89 214	447 615	313 330
Gabon	Plantains	−97	2433	3000	2100
	Yams	−90	2925	100	70
	Cassava	−97	1067	2060	1442
Gambia	Corn	−74	60	1632	1142
	Cassava	−68	769	7276	5093
	Paddy rice	−30	185	17 147	12 003
Ivory Coast	Cocoa beans	−17	56 653	103 805	72 663
	Yams	−17	19 930	42 135	29 494
	Plantains	−50	13 684	16 475	11 532
Kenya	Corn	−44	125 139	471 475	330 032
	Plantains	−28	6876	26 163	18 314
	Sugarcane	−53	10 705	194 755	136 328
Liberia	Plantains	−44	4537	49 454	34 617
	Sugarcane	−58	414	3659	2561
	Cassava	−32	338	132 500	92 750
Libya	Dates	−23	2969	26 080	18 256
	Tomatoes	−34	2931	24 957	17 469
	Wheat	−61	1381	12 500	8750
Mauritania	Dates	−34	320	1730	1211
	Dry beans	−61	395	3000	2100
	Paddy rice	−4	824	7534	5273
Namibia	Wheat	−29	1376	3055	2138
	Tomatoes	−18	113	943	660
	Corn	−15	147	2015	1410
Niger	Dry onions	−68	477	21 543	15 080
	Tomatoes	−9	9567	365 289	255 702
	Paddy rice	−66	2570	36 973	25 881
Senegal	Sugarcane	−36	3236	213 089	149 162
	Corn	−61	13 413	143 527	100 469
	Cassava	−12	1634	10 733	7513
Sierra Leone	Green coffee	−18	2171	43 473	30 431
	Cocoa beans	−24	1186	1720	1204
	Cassava	−24	1715	3963	2774
South Africa	Corn	−52	262 633	2 715 420	1 900 794
	Sugarcane	−8	23 406	1 958 900	1 371 230
	Wheat	−6	19 339	545 455	381 818
Togo	Yams	−20	5778	103 843	72 690
	Corn	−3	21 410	21,094	14 766
	Cassava	−70	9121	64 190	44 933
Tunisia	Olives	−48	18 708	591 500	414 050
	Tomatoes	−5	5351	164 000	114 800
	Wheat	−50	15 672	609 800	426 860
Uganda	Cassava	−29	31 065	325 000	227 500
	Green coffee	−36	15 700	41 733	29 213
	Plantains	−32	67 119	414 500	290 150

99% confidence interval for each year. For example, if the VaR is of 11 000 tons, it means that the country has a 99% probability of losing at worst 11 000 tons in 1 year.

The results for these three measures are presented in Table 6.

These results allow us to draw different conclusions. From the observation of the correlation, we can see that more than 50% of the commodities under study have high and negative correlation coefficients (correlation <−30%), meaning that extreme temperatures are one of the main variables impacting the production yield. This result is only contradicted for a few commodities/countries. Therefore, with the exception of these commodities (for which other factors, such as rainfall, must have a higher impact), the temperature derivatives contracts created in this study proved to be efficient tools for hedging climatic risk and decreasing volatility in production revenues for farmers. The VaR figures confirm this statement.

Unfortunately, the average cost of insuring 30% of the production is quite high and mainly above what a public organization can afford. However, if a threshold of $60 million is assumed, it seems it would be possible to create pilot programmes in two countries: Gambia and Cameroon. In fact, the corn in Gambia has a good correlation factor (−74%) and would cost on average around $60 million to insure 30% of the total corn production of the country. Cameroon also seems attractive as it would only cost on average $8 million to hedge 30% of the total wheat production. So, it might be worth a try to develop this climatic initiative for Gambia and Cameroon.

The results of this model are illustrated in Fig. 3, which represents a breakdown of the different commodities per country according to the first measure (correlation on the X-axis) and the second measure (cost of insuring 30% of the production on the Y-axis, on a logarithmic scale). Figure 3's lower left quarter represents the countries/commodities with the highest negative correlation and the lowest cost of insuring 30% of the crop production (e.g., Gambia/corn). Despite the fact that a large number of correlations are at a good level (many pairs 'country/commodity' are in the left section of the graph), the cost of such a programme remains high (most pairs 'country/commodity' are in the upper part of the graph).

V. Conclusion

In this article, weather derivative contracts based on temperature for 18 African countries have been created. One major innovation in these contracts is that the DD indices were calculated on the optimum temperature at which crops grow at best, in order to activate the pay-off when the temperature really affects the production yield of the farm. Using an Ornstein–Uhlenbeck process, the temperature trajectories were modelled with a continuous mean reverting method. The pricing of the created derivatives is made with Monte Carlo simulations, and the results show two essential findings. First, we observed important correlations between derivatives pay-offs and decreases in crop production yields, confirming the contracts suitability. Second, the cost of insuring 30% of the production makes these contracts a viable option for at least two countries (Gambia and Cameroon). Weather derivatives with pay-offs depending on temperature can thus represent a potential sustainable plan in the long run to hedge temperature risk in these African countries, helping to prevent food shortages.

However, the work undertaken in this study may be extended in several directions, representing some of the challenges still remaining in the research on weather derivatives. First, the structure of the temperature options may be redefined, especially with 'tailor-made' derivatives in order to match more precisely the users' needs. In this article, we suggested annual contracts for harmonization, but

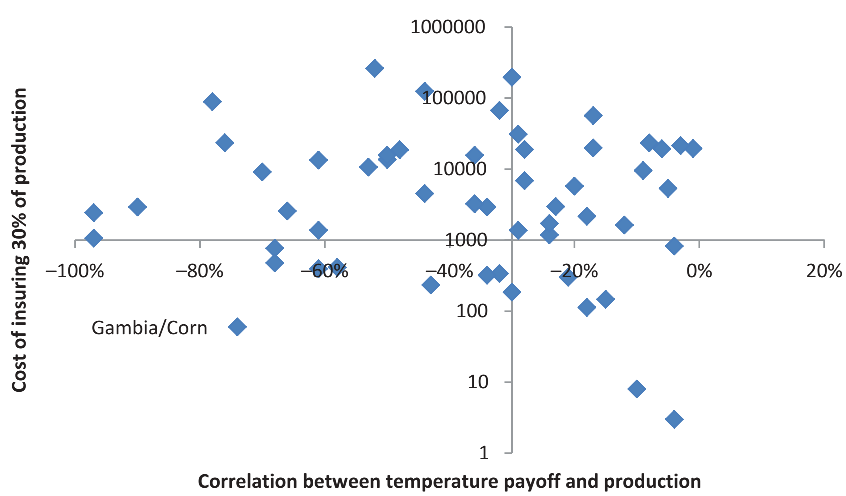

Figure 3. Breakdown of commodities per country.

these contracts would be more meaningful if they were designed to match the exact growing season for each crop. Second, the modelling of the temperature process may be improved by considering the temperature as one variable of a larger climate model including several variables. The development of such models in conjunction with the increasing power of computers will certainly help better forecast extreme events, leading to better priced weather derivatives. Finally, it will certainly be worth spreading these temperature derivatives to other African countries.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix. Academic and public organization studies per commodity

Cassava	http://www.fao.org/docrep/x5032e/x5032E01.htm
Cocoa beans	http://www.icco.org/statistics/other.aspx
Corn	http://www.extension.iastate.edu/publications/pm1885.pdf
Dates	http://www.hort.purdue.edu/newcrop/morton/date.html
Dry beans	http://eap.mcgill.ca/CPBFP_2.htm
Dry onions	http://www.uri.edu/ce/factsheets/sheets/onions.html
Green coffee	http://www.coffeeresearch.org/agriculture/environment.htm
Olives	http://www.crfg.org/pubs/ff/olive.html
Paddy rice	http://www.knowledgebank.irri.org/uplandrice/majorResUpland.pdf
Plantains	http://www.crfg.org/pubs/ff/banana.html
Sorghum	http://www.hort.purdue.edu/newcrop/afcm/sorghum.html
Sugarcane	http://www.sugarcanecrops.com/climate/
Tomatoes	http://gardening.about.com/od/problemspest1/a/BlossomDrop.htm
Wheat	http://www.fao.org/docrep/006/y4011e/y4011e06.htm
Yams	http://urbanext.illinois.edu/veggies/sweetpotato.cfm