

Climate-Finance Integration: Modeling and Pricing CDD Options Using Chicago's Historical Temperature Data and OU-Monte Carlo Hybrid Simulation

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Abstract. Climate change has heightened weather volatility, raising financial risks for temperature-sensitive industries and creating a need for more accurate weather derivative pricing. This paper develops an integrated computational framework for modeling and pricing Cooling Degree Day (CDD) options based on Python, with a focus on improving the accuracy and reliability of weather risk assessment. Based on Chicago's historical temperature data, the paper establishes a robust two-stage modeling approach that combines statistical methods with financial engineering. The initial stage characterizes mean-reverting behavior in temperature anomalies through comprehensive analysis of daily and monthly temperature averages. A joint seasonal autoregressive integral sliding average model (SARIMA) and Ornstein-Uhlenbeck (OU) process were used to capture dynamic temperature patterns and derive accurate process parameters. Subsequent analyses employ Monte Carlo simulations within Python, generating 10,000 potential temperature trajectories to compute cumulative summer cooling degree day (CDD) values and ascertain option prices. Findings demonstrate the model's effectiveness in identifying and quantifying mean-reversion behavior in temperature time series. The simulated temperature paths realistically incorporate seasonal variations and random fluctuations. The resulting option price estimates reliably reflect underlying temperature risks.

Keywords: Cooling Degree Days (CDD), Weather Derivatives, Ornstein-Uhlenbeck Process, Monte Carlo Simulation, Option Pricing

1. Introduction

Weather derivatives were first created in 1997, driven by demand from the energy industry in the United States. In recent years, as global climate change has intensified and the incidence of extreme weather events has surged dramatically [1], weather-related risks have exerted a profound impact on diverse industries such as energy and food. Traditional risk management tools are unable to address systemic losses caused by temperature. Weather derivatives, as an emerging risk management instrument, are gaining increasing traction and widespread adoption. For example, in May 2024, China Pacific Property and Casualty Insurance Company Limited successfully completed the first

“Fruit Tree Cold Wave Index Insurance + Derivatives”, marking a breakthrough in the new model of “Weather x Finance” [2].

2. Theoretical foundations

2.1. Weather derivatives overview

Weather derivatives are financial instruments designed to hedge or speculate on weather-related risks. They derive their value from related weather variables such as temperature (cumulative CDD or HDD), precipitation or snowfall and other specific event series. Weather derivatives exist in the form of futures, options or swaps and can be traded on exchanges or over-the-counter markets. Temperature derivatives are the most common.

Cooling Degree Day (CDD) stands as a pivotal metric in weather derivatives pricing, particularly for sectors sensitive to high temperatures—such as electricity suppliers and beverage enterprises. Mathematically [3]:

$$CDD_i = \max\left(\frac{T_{\max,i} + T_{\min,i}}{2} - T_{\text{base}}, 0\right) \quad (1)$$

Where $T_{\text{base}} = 65^\circ\text{F}$. Cumulative CDD over a period is the sum of daily CDDs.

2.2. Model construction

This study employs a seasonal autoregressive integrated moving average (SARIMA) model to capture short-term dynamics and residual seasonal patterns in temperature anomalies. Following de-seasonalization, the optimal model order is selected through minimization of Akaike (AIC) and Bayesian (BIC) information criteria, incorporating a seasonal MA(1) term to account for residual annual cyclicity. The model is subsequently transformed into an Ornstein-Uhlenbeck (OU) process to characterize the stochastic dynamics of the de-seasonalized temperature series.

The SARIMA model includes both non-seasonal and seasonal parts, written as [4]:

$$\text{SARIMA}(p, d, q)(P, D, Q)_s \quad (2)$$

The non-seasonal component consists of three parameters: the autoregressive order (p), the differencing degree (d) and the moving average order (q). The seasonal component analogously includes seasonal autoregressive (P), differencing (D), and moving average (Q) terms, operating at the specified seasonal periodicity (s). The general model formulation can be expressed as [5]:

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^DT_t = \Theta(B^s)\theta(B)\varepsilon_t \quad (3)$$

where B denotes the backshift operator, ϕ and Φ are non-seasonal and seasonal AR coefficients respectively, while θ and Θ represent the corresponding MA coefficients.

Traditional option pricing models (e.g., Black-Scholes) assume that the price of the underlying asset follows a geometric Brownian motion, with no mean reversion properties and constant volatility. This is completely inconsistent with temperature dynamics and can lead to significant deviation of CDD option prices from their real values. The Ornstein-Uhlenbeck (OU) process is well-suited for modeling temperature due to its mean reversion feature that causes extreme

temperatures to naturally return to historical averages, its stationarity which keeps long-term forecasts bounded (unlike random walk models), and its analytical tractability that allows for straightforward mathematical solutions in calculations [6]:

$$dX(t) = \kappa(\theta - X(t))dt + \sigma dW(t) \quad (4)$$

Where $X(t)$ represents temperature anomaly. κ represents the mean-reversion speed. θ denotes the long-term mean of the process, and σ quantifies the instantaneous volatility. The random component is driven by $W(t)$, a standard Wiener process (Brownian motion).

The parameter transformation method from SARIMA to the OU process provides the OU process with a stationary residual series that satisfies the mean-reverting assumptions; secondly, the Ljung-Box test for white noise properties ensures the independent incremental assumptions required by the OU process. The parameter transformation thus preserves the numerical stability of the discrete-time estimates while gaining the advantages of continuous-time models for financial pricing applications.

AR(1) model for the residual series y_t :

$$y_t = \mu + \rho y_{t-1} + \epsilon_t, \epsilon_t \sim N(0, \sigma^2) \quad (5)$$

Here, μ is the constant term, ρ is the autoregressive coefficient, and ϵ_t is white noise.

Because $\rho = e^{-\kappa \Delta t}$ and $\Delta t = 1$. So, the mean reversion speed $\kappa = -\ln(\rho)$. The long-term mean $\theta=0$, as the deseasonalize series is centered, and the volatility σ is estimated as the standard deviation of the model residuals.

2.3. Monte Carlo simulation

Firstly, Simulate N temperature paths using the OU process. Secondly, Calculate CDD for each path. Thirdly, Compute the option payoff for each path. Fourthly, Average the discounted payoffs [7].

Independent temperature paths are generated using Eulerian discretization. Each path represents a possible future temperature evolution scenario:

$$X(t + \Delta t) = X(t) + \kappa(\theta - X(t))\Delta t + \sigma\sqrt{\Delta t}\epsilon \quad (6)$$

where ϵ is a standard normally distributed random variable and $\Delta t = 1/365$ is the time step of a day.

2.4. Option pricing

The risk-neutral pricing framework assumes that derivatives can be priced as if investors are risk-neutral, where key ideas include discounting the derivative's expected payoff at the risk-free rate r and ensuring the fair price equals the present value of its expected payoff under the risk-neutral measure to satisfy the no-arbitrage condition [7].

$$V_0 = e^{-rT}E^Q[V_T] \quad (7)$$

3. Empirical result

3.1. Data source and preprocessing

Daily and monthly historical temperature data were obtained from the National Oceanic and Atmospheric Administration (NOAA) for the CHICAGO MIDWAY AIRPORT 3 SW, IL US weather station. The dataset includes daily observations from May 1, 2021 to May 1, 2025, and monthly averages from May 1995 to May 2025.

Due to Earth's axial tilt and orbital cycle, raw temperature data exhibit strong seasonal fluctuations—such as higher summer and lower winter temperatures—which can obscure mean-reverting dynamics [8]. The data are therefore de-seasonalized by subtracting the long-term monthly mean from observed values, resulting in an anomaly series $X(t)$ that isolates deviations from climatic norms. Using Python, we remove seasonal components from daily average temperatures (Figure 1) to obtain these anomalies. This process eliminates periodic noise and allows the subsequent OU process to more accurately capture stochastic variability and underlying temperature trends.

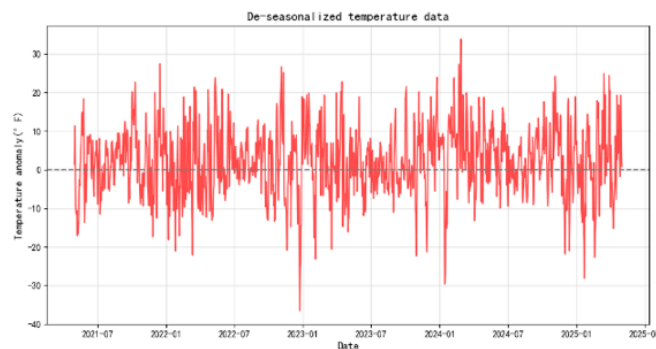


Figure 1. De-seasonalized temperature data

The de-seasonalized monthly mean temperature anomalies range from a high of 4.18 degrees Fahrenheit to a low of -0.19 degrees Fahrenheit. The deviation is within reasonable limits. Therefore, it can be approximated that the de-seasonalized monthly average temperature anomalies are 0. It also proves the effectiveness of de-seasonalization.

3.2. Joint modeling of SARIMA and OU processes

The de-seasonalized temperature series is modeled using SARIMA, with seasonal and non-seasonal parameters selected by minimizing AIC and BIC. The fitted model undergoes Augmented Dickey-Fuller (ADF) and Ljung-Box tests to verify stationarity and residual independence [9]. After validation, the parameters are transformed into a continuous-time Ornstein-Uhlenbeck (OU) process to estimate κ and σ . Extreme temperature behavior is characterized by calculating the threshold exceedance ratio and maximum positive/negative anomalies (Table 1).

Table 1. Summary statistic

Parameter	Value
Optimal Non-Seasonal Order (p,d,q)	(1, 0, 1)
Optimal Seasonal Order (P,D,Q,s)	(1, 0, 1, 12)
AIC	9393.0
BIC	9424.8
ADF test (p-value)	0.000
Ljung-Box test (p-value)	0.469
OU parameter κ	0.630
OU parameter σ	5.992
Proportion of extreme events ($>3\sigma$)	0.68%
Maximum positive anomaly ($^{\circ}\text{F}$)	19.57
Maximum negative anomaly ($^{\circ}\text{F}$)	-25.86

As indicated in the table, the SARIMA (1,0,1)(1,0,1)₁₂ model selected by AIC/BIC criteria demonstrates sound statistical properties. Stationarity is confirmed by an ADF test p-value of 0.000, while the Ljung-Box test p-value of 0.469 supports the residual white noise assumption. The derived OU process parameters show a mean reversion rate $\kappa = 0.630$ and volatility $\sigma = 5.992$, consistent with typical atmospheric behavior. The value of κ indicates that temperature anomalies revert to the mean at a rate of 63.0% per day, reflecting the short-lived nature of extreme temperatures. Meanwhile, $\sigma = 5.992^{\circ}\text{F}$ represents the typical deviation of residuals, aligning with common weather variability. The extreme event proportion of 0.68% beyond 3σ also matches climatic expectations.

3.3. Monte Carlo simulation and CDD calculation

After obtaining κ and σ from the historical temperature data, Monte Carlo simulations were performed using Python as well as Eulerian discretization (Eq. (6)). Generate 10,000 randomized temperature paths.

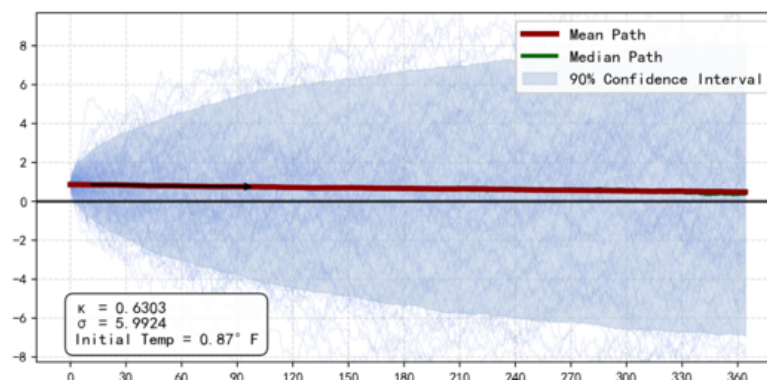


Figure 2. Temperature path Monte Carlo simulation (10,000 paths)

In Figure 2, 200 of these random temperature paths were generated using Python. Light blue area represents the 90% confidence interval (5%-95% quantile), reflecting the range of uncertainty in the

temperature projections. Dark blue solid line shows average of all simulated paths, characterizing the most probable temperature evolution trend. Purple dashed line represents median path of the temperature distribution. Gray reference line shows zero-value line, corresponding to the average state of the climate.

After completing the Monte Carlo simulation of the temperature paths, a seasonal component needs to be added to obtain the actual temperature forecasts. Special attention is paid to the cumulative CDD for the summer months (June-August), as this is the main underlying for the CDD derivatives. Through Monte Carlo integration, we obtain a probability distribution of summer CDDs, which provides the basis for subsequent option pricing (Figure 3).

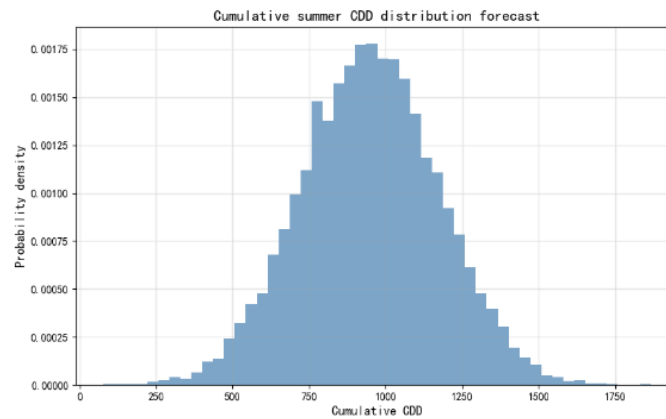


Figure 3. Cumulative summer CDD distribution forecast

3.4. CDD option pricing

Each Monte Carlo simulation produces 10,000 independent temperature trajectories, resulting in a distribution of potential option prices; the values reported herein correspond to a single representative simulation. The contract period for the CDD derivative spans 92 days (from June 1 to August 31), a tenor most closely aligned with the maturity of a six-month U.S. Treasury bond. Accordingly, the six-month Treasury yield of 4.27% [10] is employed as the risk-free rate in the pricing model. The strike level is established at $K = 940$, selected for its proximity to both the simulated mean (942.69) and median (941.11) of the cumulative CDD distribution, as well as its consistency with historically observed strike values in CME-traded CDD options (e.g., 940, 1250). These contracts trade over a range of 1 to 7,500 index points, with a tick size of one index point and a nominal payout rate of \$20 per index point (CME, 2025).

$$\text{Option Price} = e^{-rT} \cdot E^Q[\max(CDD_T - K, 0)] \cdot \text{payout} \quad (8)$$

Where $r = 4.28\%$, $K = 940$ and $\text{payout} = 20$. Then, using python to do the calculation and plot the probability density plot. Option price = \$1604.84.

4. Conclusion

The OU process outperforms traditional time series models in temperature modeling due to its mean-reverting nature, which effectively captures temperature dynamics. Monte Carlo simulations based on the OU process generate realistic CDD distributions that reflect future uncertainties and

provide a robust basis for option pricing. CDD options offer energy companies an effective tool to hedge against temperature-related risks, while financial institutions can expand the weather derivatives market through improved pricing models and product design.

However, the model has limitations: it does not fully account for extreme weather events like heatwaves, potentially underestimating tail risks; it assumes constant volatility, whereas real temperature fluctuations vary seasonally and during events such as El Niño; and as a linear model, it fails to capture nonlinear behaviors of extreme weather.

Future research may integrate machine learning methods like random forests or gradient boosting to improve anomaly prediction using satellite and meteorological data, enhancing short-term forecasting. Climate scenario analysis could also be incorporated to assess long-term climate impacts on CDD distributions, providing a stronger scientific basis for derivative design. These advances would help refine pricing models and strengthen the practical utility of CDD options in risk management.

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