Degrees of Uncertainty: Weather Forecasting, Derivatives and Commodity Markets

Introduction: from weather to the price

A weather forecast describes a future physical state. Prices move when that state changes expected production, consumption or inventories relative to what markets already anticipate. A cold winter that traders saw coming may barely move gas prices; a smaller surprise can move them a lot.

This article follows the full chain from weather to price. We begin with the atmospheric physics that limits predictability. We then build and test models for temperature, rainfall and extreme events, from Fourier seasonality and autoregression to machine learning and a frontier AI weather model. Every model is scored on the same targets and dates, and weak or negative results are reported alongside positive ones.

We then bring these pieces together in a single test: valuing a real New York heating-degree-day contract with ECMWF ensemble forecasts, local statistical and machine-learning correction, and Monte Carlo simulation. Two case studies close the article. The first asks whether rainfall measured over cocoa plantations predicts West African cocoa output better than a national average. The second asks which source of supply flexibility absorbs cold weather in the Dutch gas system, LNG terminals or underground storage, and whether weather data improve forecasts of those flows.

The physics of weather

Weather arises because the Sun heats the Earth unevenly. Pressure differences drive winds, Earth's rotation deflects them, and the result is the jet streams, fronts and cyclones of the mid-latitudes and the seasonal rain belts of the tropics. Temperature, wind, pressure and rainfall are therefore parts of one evolving system.

That system is highly local: a storm can drench one farm while the region's monthly average looks normal. This makes forecasts hard to verify at a single point, and it creates basis risk in any contract that settles on a distant weather station.

A surface weather map shows the atmosphere at one moment. Isobars join points of equal sea-level pressure; where they are tightly packed, winds are stronger. High pressure tends to bring settled weather, and low pressure brings cloud and fronts, but rain also needs moisture and rising air. A blue-triangle cold front marks colder air advancing, not freezing air; a red-semicircle warm front marks warmer air advancing.

A forecast map adds two clocks: the initialisation time, when the model estimated the atmosphere, and the valid time, the future moment the map shows. A single map cannot give the probability of a storm. That requires an ensemble of calibrated scenarios.

Forecast skill, chaos and ensembles

The source of forecast skill changes with lead time. At one day, today's temperature and the persistence of the current air mass carry most of the information. At several days, what matters is how weather systems move and develop. By two weeks, small errors in the starting estimate of the atmosphere have grown into very different outcomes.

Beyond two weeks, slow-moving influences such as sea-surface temperature, snow cover and soil moisture can still say something about monthly averages, even though tomorrow's storm cannot be identified. Physical models

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start from an estimate of the whole global atmosphere; statistical models learn from local history. Neither is always better: it depends on the variable, the horizon and the information available when the forecast is issued.

The limit comes from chaos. A small error in the position of an upper-level trough changes the wind, which changes moisture transport and condensation, which releases heat that alters the flow. Nearby states drift apart roughly as $\delta(t) \approx \delta(0)e^{\lambda t}$, where $\delta(0)$ is the starting error, t the time elapsed and λ how quickly trajectories diverge. Even a perfect physical model therefore loses point-by-point accuracy.

Numerical weather prediction works in four steps:

- Data assimilation: station, satellite, aircraft and balloon observations are combined with an earlier forecast to estimate a consistent global state.
- Dynamical core: the equations for momentum, mass and energy are solved on a grid.
- Parameterisations: these approximate what the grid is too coarse to resolve, such as turbulent eddies, cloud droplets and surface exchange.
- Ensembles: the starting state, and sometimes the model itself, is perturbed to produce a set of alternative runs. These are model scenarios, not independent observations, so they measure uncertainty only within that model and their probabilities must be calibrated against outcomes.

This division of labour shapes our tests: local persistence at short horizons, statistical seasonality at longer ones, physical simulations when distant weather systems matter, and ensembles when a decision needs a probability rather than a single number.

Weather derivatives: transferring the exposure

Weather derivatives let firms transfer weather risk that no traded commodity can hedge, because they settle on a measured weather index rather than on the price of an asset. On CME, New York monthly heating-degree-day (HDD) futures accumulate daily temperature shortfalls below a Fahrenheit base at a designated station, with one index point worth $20. They are cash-settled, and the rulebook fixes the last trading day and the settlement procedure.

Corporate use starts from the exposure. A gas distributor that loses volume in a warm winter buys an HDD hedge; a farmer exposed to drought buys a rainfall shortfall put; an event organiser buys cover above a rainfall threshold. Contracts can be monthly or seasonal, and can be futures, swaps, options or bespoke over-the-counter structures with caps, collars and a chosen station.

For daily mean temperature $\bar{T}_d$ and base B, the daily indices are $HDD_d = \max(B - \bar{T}_d, 0)$ and $CDD_d = \max(\bar{T}_d - B, 0)$, and the monthly index is the sum of the daily values. With an 18°C base, a 14°C day adds 4 HDD, five such days add 20, and a 20°C day adds zero rather than −2.

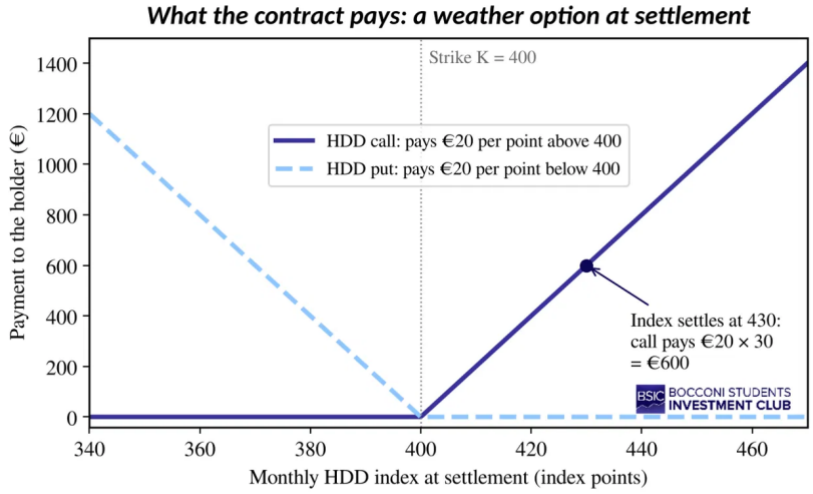
Since the threshold is applied day by day, a monthly average equal to the base can hide cold days that count and warm days that do not: the index cannot be computed from the average temperature. Rainfall contracts work the same way. A shortfall put pays $n\max(K - R, 0)$ when total rainfall R falls below strike K, so two sites with the same expected rainfall can have very different option values if one has long dry spells and the other frequent short storms.

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How to price a weather derivative?

Valuation starts from the settlement rule, not from an option formula. For every possible path of daily weather, compute the contractual index, apply the strike, cap and tick value, and average the payments. An HDD call paying €20 per point above a strike of 400 pays €600 if the index settles at 430, as the chart below shows.

The average across simulated paths is a physical expected payoff, not a price. Temperature cannot be stored or traded, so the Black–Scholes argument of hedging an option with its underlying does not apply. A seller therefore adds a risk loading for capital, liquidity and counterparty risk, typically a multiple of the payoff's standard deviation. Three methods estimate the expected payoff.



Sources: BSIC illustrative contract terms (strike 400, €20 per index point)

Burn analysis asks how the contract would have performed in the past. Take 20 to 30 years of station records, compute each year's index and payout, and average them. The history must first be cleaned for the warming trend and for station relocations, so that each past year is a plausible version of the coming season. The method is transparent, but thirty years is a small sample.

Index modelling instead fits a probability distribution, usually a normal, to the historical index values. The expected payment of a call or put is then calculated exactly. This smooths the noise of a short history and prices many strikes at once, but it treats the month as a single number and ignores how the index builds up day by day.

Daily Monte Carlo simulation rebuilds the index from its daily ingredients. Each day's temperature is the seasonal normal plus an anomaly that persists for a few days before fading; rainfall is a chain of wet and dry days with random amounts. Thousands of simulated months give thousands of payoffs, whose average is the expected value and whose spread shows the risk.

Simulation captures persistent cold or dry spells and handles caps and multiple triggers. It can also use real forecasts as the contract month approaches: observed days are fixed, the next one to two weeks come from calibrated ensemble forecasts, and only the remaining days come from climatology. Its weakness is that the answer is only as good as the weather model, a point the HDD test later in the article makes concrete.

Basis risk and the actual corporate hedge

Basis risk is the mismatch between what the contract measures and what the firm actually loses. A cocoa farm can be dry while a distant station is wet (geographic basis); rain may arrive after flowering (timing basis); pests

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and tree age can cut yield in a normal year (structural basis). A hedge removes only the share of risk that its index explains, so a perfectly forecast index can still be a poor hedge.

Choosing a forecasting model: variable, horizon and decision

Each variable needs its own model. Temperature is continuous and dominated by a seasonal cycle, which calls for Fourier seasonality with mean-reverting anomalies. Daily rainfall mixes many exact zeros, skewed positive amounts and clustered wet and dry spells, which calls for a two-part occurrence–amount model and a Markov chain. Extreme-event models must specify the threshold and whether the target is the onset, duration or severity of the event.

Forecasts are issued 1, 3, 7 and 15 days ahead and scored with three measures. Mean absolute error, $MAE = n^{-1}\sum_i |y_i - \hat{y}_i|$, is measured in the unit of the target (°C or mm). The Brier score, $BS = n^{-1}\sum_i (p_i - y_i)^2$, scores probabilities for yes/no outcomes such as a wet day. The continuous ranked probability score (CRPS) scores a whole predictive distribution and equals absolute error for a single-number forecast. In all three, lower is better, and scores are compared only on the same target, dates and cases.

What the global literature establishes and what our six locations measure

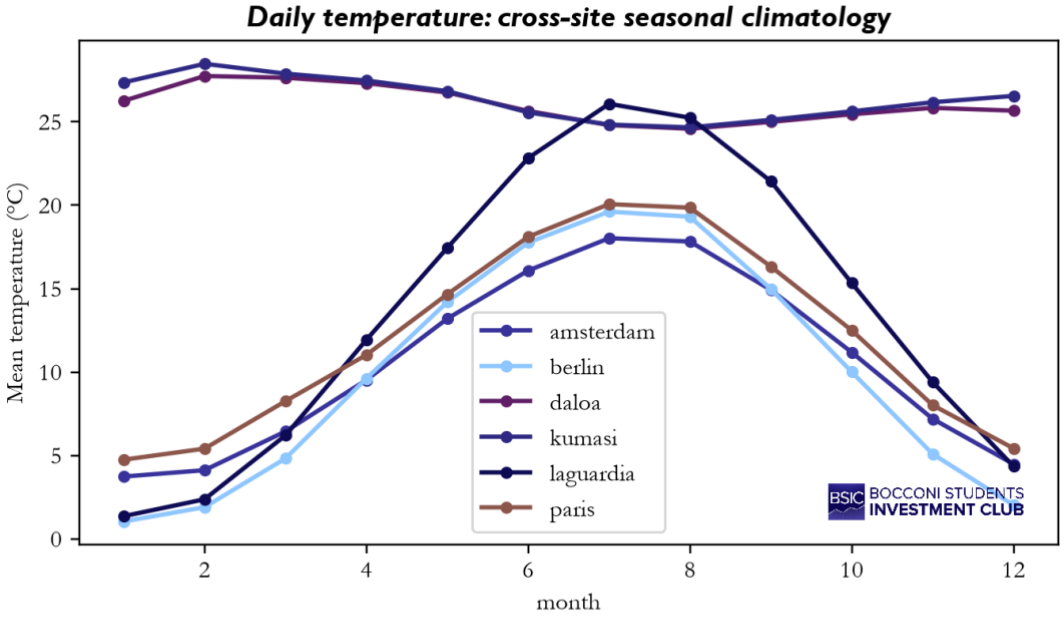
The WMO reports that 2015–2025 were the eleven warmest years on record and estimates 2025 global temperature at about 1.43°C above 1850–1900. The IPCC describes the tendency of the atmosphere to hold roughly 7% more water vapour per degree of warming. This shifts the climate baseline, but it does not mean every location's rainfall or flood losses rise by 7%: circulation, storm organisation, soil moisture and local exposure all intervene.

Our data cover LaGuardia Airport, Paris, Amsterdam, Berlin, Kumasi and Daloa for 1991–2025, with 12,784 daily records per location. LaGuardia temperature comes from NOAA station observations; the other cities mainly use ERA5-derived data, so comparisons across cities are descriptive.

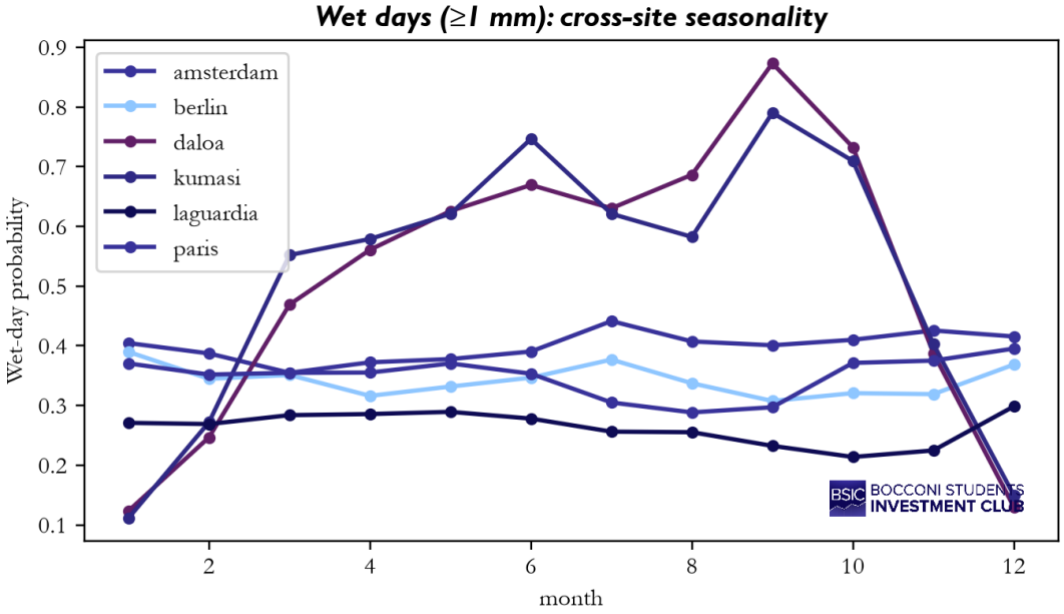
LaGuardia's mean daily temperature is about 13.72°C with a standard deviation of 9.55°C; Kumasi's figures are 26.37°C and 1.54°C. The contrast is physical: the annual radiation cycle produces large seasonal swings in New York and very small ones near the equator. For LaGuardia the natural first model is therefore a smooth seasonal normal, with the remaining anomaly studied for persistence.

A wet day is one with at least 1 mm of rain. It occurs on about 51.2% of days in Kumasi and 26.3% at LaGuardia. Average rainfall hides four separate features: how often it is dry, how much falls on wet days, how wet and dry days cluster, and how heavy the extremes are. A model that prices shortfall or dry-spell risk must capture all four. The two charts below show the seasonal temperature cycle and the wet-day frequency at each location.

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Sources: BSIC, six_location_monthly_climatology.csv



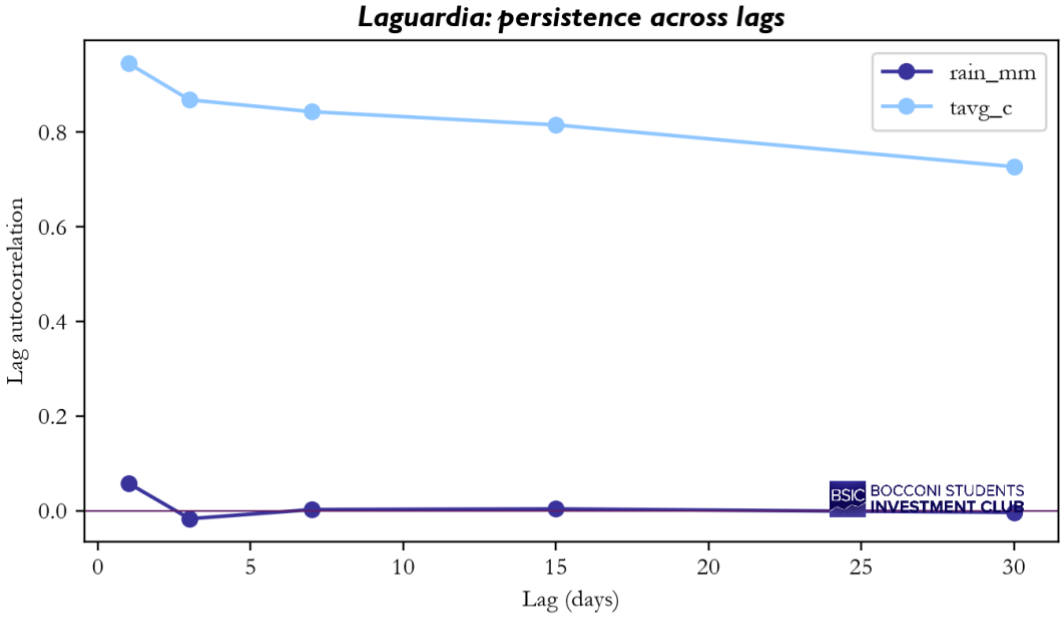
Sources: BSIC, six_location_monthly_climatology.csv

A seasonal climatology is the expected temperature for each day of the year; the departure from it is the anomaly. The autocorrelation at lag k measures how much of today's anomaly survives k days later. A persistent anomaly is not a permanent shift: in a stationary model it decays towards zero, which is the idea behind the Fourier–AR(1) and Ornstein–Uhlenbeck models below.

For rainfall, the wet-day indicator $W_t = \mathbf{1}(R_t \geq 1\,\text{mm})$ is informative before any amount is modelled. The probabilities $P(W_t = 1 \mid W_{t-1} = 1)$ and $P(W_t = 1 \mid W_{t-1} = 0)$ show whether wet and dry days cluster.

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Rainfall amounts are skewed, so a Gamma distribution, which cannot go negative, is more suitable than a normal one.



Sources: BSIC, laguardia_autocorrelation.csv

The chart above shows why raw autocorrelation misleads. New York temperature resembles yesterday's partly because weather systems persist, but a July day also resembles other July days simply because both are in summer. The high light-blue line at long lags reflects the annual cycle, not thirty-day weather memory, so we first remove the seasonal normal and study the anomalies. The dark rainfall line, close to zero beyond one day, shows little day-to-day memory in rainfall amounts.

Forecasting temperature: from seasonal structure to machine learning

The station experiment predicts LaGuardia's daily mean temperature 1, 3, 7 and 15 days ahead. Models are trained on data through 2022 and tested on forecasts issued in 2023–2025, giving 1,095, 1,093, 1,089 and 1,081 matched cases at the four leads. All models are scored on exactly the same dates and targets, so differences in score are differences in model.

From Fourier regression to mean-reverting anomalies

Seasonality is represented by a sum of sine and cosine waves:

$$\mu(d) = a_0 + \sum_{k=1}^{K}\left[a_k \sin\left(\frac{2\pi k d}{365.25}\right) + b_k \cos\left(\frac{2\pi k d}{365.25}\right)\right].$$

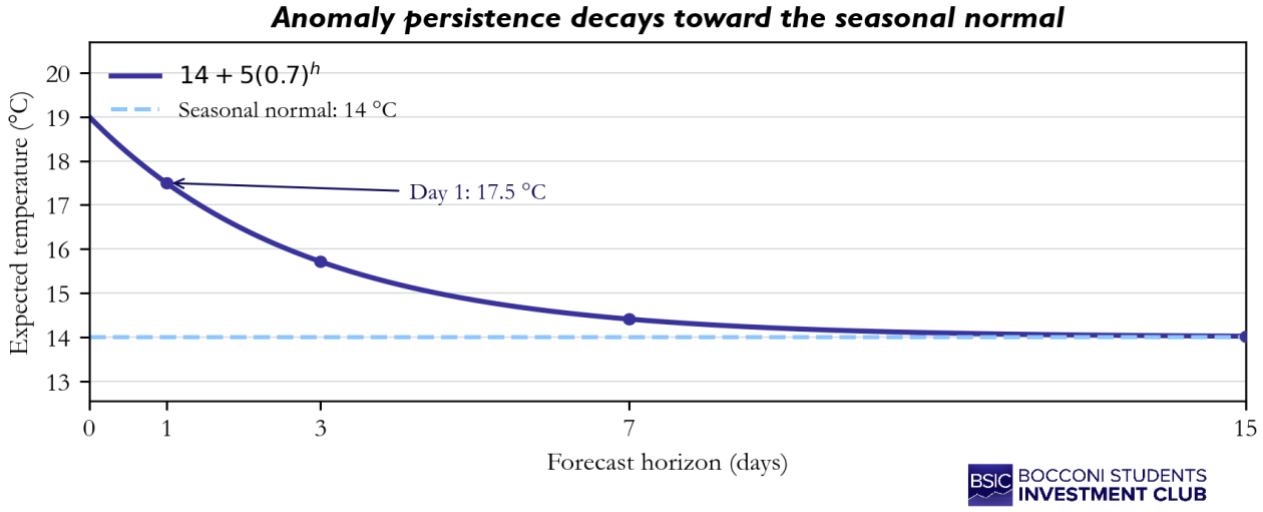
Here d is the calendar day, a_0 the average level and each pair (a_k, b_k) sets the size and timing of one seasonal wave. These terms are known in advance: the model does not need tomorrow's weather to know tomorrow's date. The anomaly $x_t = T_t - \mu(d_t)$ then follows an autoregression:

$$x_t = \phi x_{t-1} + \varepsilon_t, \qquad |\phi| < 1.$$

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The coefficient ϕ is the share of yesterday's anomaly that survives to today, and ε_t is a new random shock. Forecasting h days ahead shrinks the anomaly by ϕ^h while uncertainty grows, which is why local history helps at short leads but adds little after two weeks. The Ornstein–Uhlenbeck process is the continuous-time version, $dx_t = -\kappa x_t\,dt + \sigma\,dW_t$, with $\phi = e^{-\kappa}$ for a daily step; it is used to simulate realistic daily temperature paths.

A worked example makes this concrete. If the seasonal normal for tomorrow is 14°C and today's observation is 19°C, the anomaly is +5°C. With $\varphi = 0.7$ the forecast is $14 + 0.7 \times 5 = 17.5$°C, and the inherited anomaly fades to $0.7^3 \times 5 \approx 1.72$°C after three days and $0.7^7 \times 5 \approx 0.41$°C after seven, as the chart below shows. The seasonal terms carry the calendar; the AR(1) term carries the current air mass.



Source: BSIC

ARIMA, SARIMA and SARIMAX

An ARIMA(p, d, q) model combines p autoregressive lags, d rounds of differencing and q moving-average terms in past forecast errors. Differencing is needed only when a series has no stable level; temperature anomalies are mean-reverting, so none is needed here. SARIMAX adds outside variables X_t, with one strict rule: X_{t+h} must be known or separately forecast when the prediction is made. Using realised future weather would be look-ahead, not skill.

Our daily Fourier–SARIMAX(2,0,1) combines the seasonal normal with two lags of the anomaly and one lag of the model's past forecast error, all estimated on past data only. The table below summarises what each component contributes.

Component	*Information used*	*Question it answers*
Fourier cycle	Tomorrow's day of year	What is normal for this season?
AR lags (2)	Recent observed departures	How much of the current air mass persists?
MA term (1)	Previous model error	Does a recent surprise contain short-lived information?

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Component	Information used	Question it answers
Exogenous features	Known or separately forecast at issue time	Can other information improve the forecast without leakage?

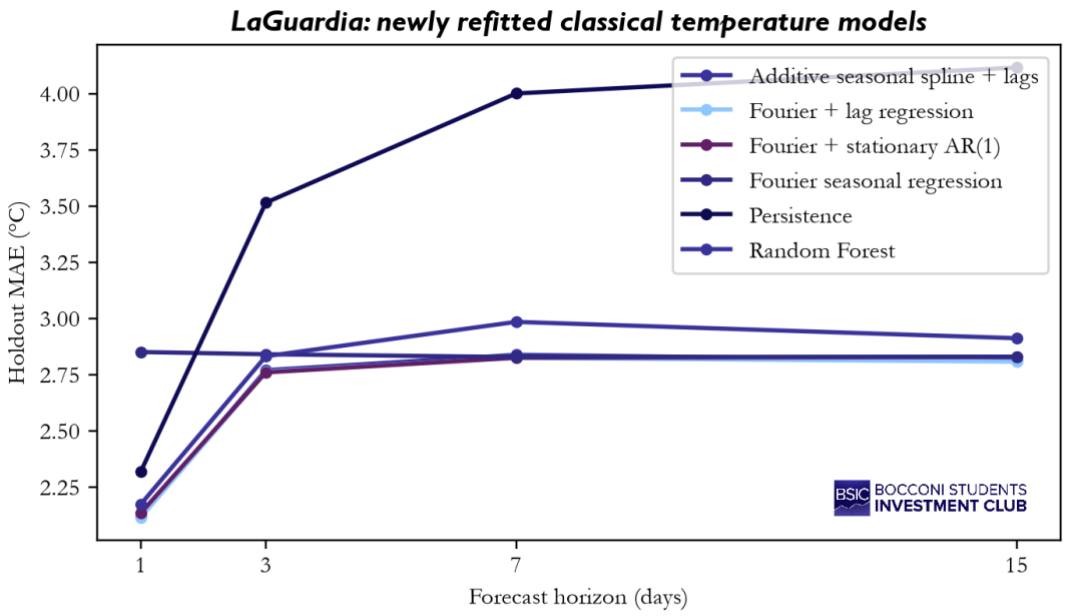
What tree models add

A Random Forest averages many decision trees, each splitting the data with threshold rules such as "yesterday was unusually cold and it is winter". XGBoost builds trees one after another, each correcting the errors of the trees before it. Both capture nonlinear effects without specifying them in advance, but neither can see an approaching front if no atmospheric information enters the model.

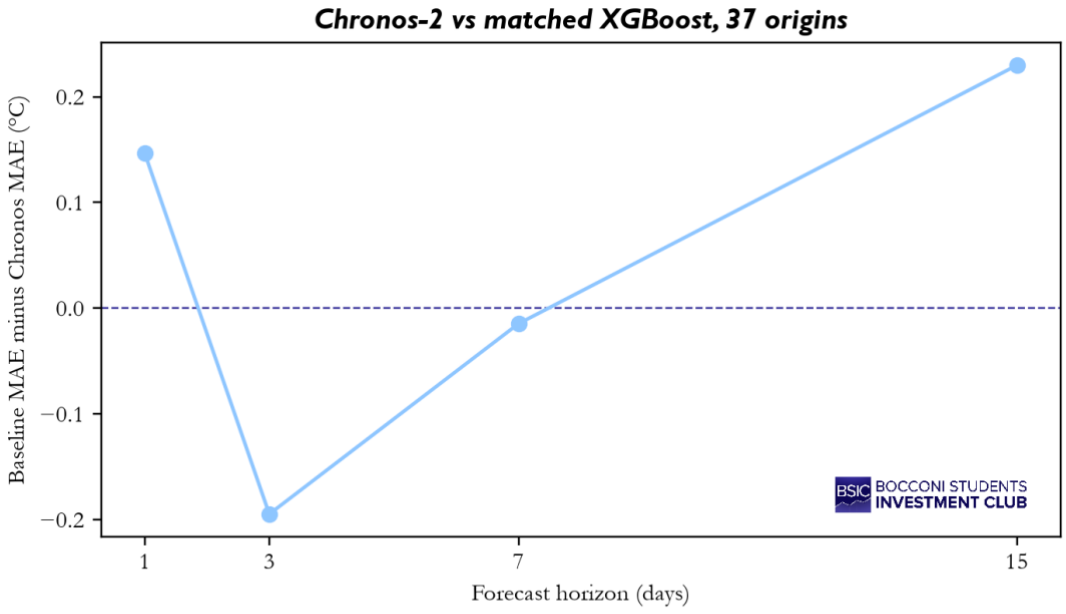
At one day, the MAE is 2.319°C for persistence, 2.851°C for Fourier seasonality alone, 2.135°C for Fourier–AR(1), 2.116°C for Fourier plus lag regression, 2.174°C for Random Forest, 2.146°C for XGBoost and 2.103°C for SARIMAX. Once seasonality and persistence are captured, the flexible tree models add nothing. SARIMAX's 0.043°C edge over XGBoost, about 2.0% of XGBoost's error, has an interval of −0.003 to +0.086°C, so it is not a robust difference.

The clear contrast is at fifteen days. Fourier plus lag regression scores 2.808°C and XGBoost 2.847°C, against 4.116°C for persistence: holding yesterday's temperature fixed fails once the air mass has changed. The first chart below shows every model converging towards the seasonal forecast as the anomaly fades.

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Sources: BSIC, temperature_new_baseline_scores.csv



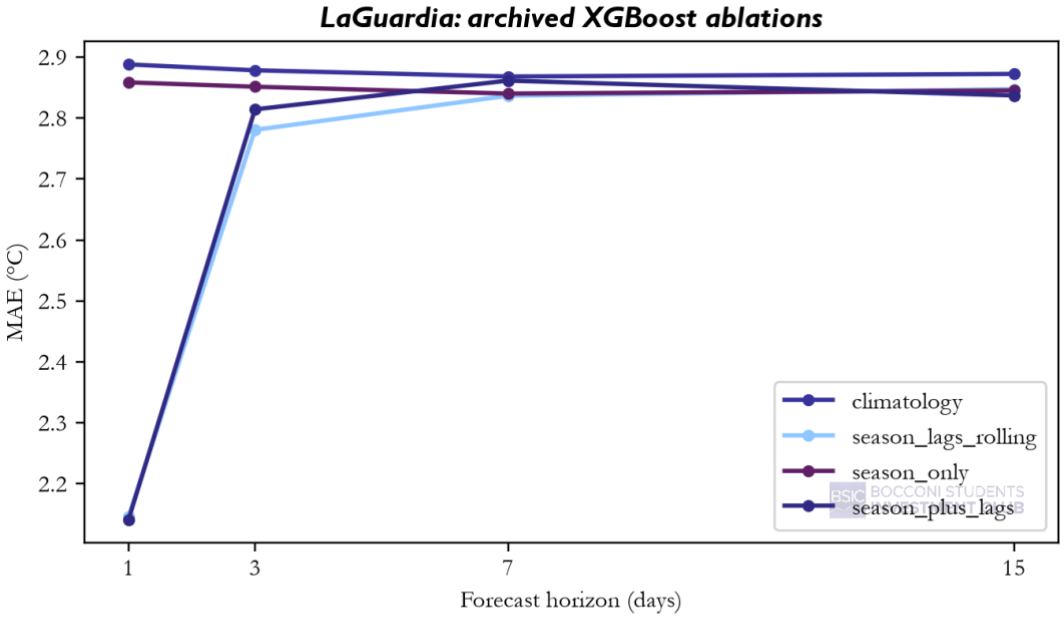
Sources: BSIC, CHRONOS_VS_XGB_MATCHED_ORIGIN_SCORES.csv

Chronos-2, a pretrained time-series foundation model, forecasts from a historical sequence using patterns learned across many series. Given only LaGuardia's temperature history, it was compared with XGBoost on 37 shared forecast dates per lead, as the second chart shows. Its relative performance changes sign across leads, and with 37 dates a 0.1°C difference can come from a handful of difficult days, so the result is a pilot rather than evidence that pretraining wins.

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Which features genuinely add temperature skill?

The XGBoost feature test shows where its skill comes from. A seasonal-only model cannot follow a passing air mass; adding recent temperature lags and rolling history sharply improves the one-day forecast, while all versions converge to similar errors by 7–15 days. Local history matters now and very little after two weeks, and extra model flexibility is no substitute for information about the wider atmosphere.



Sources: BSIC, scores.csv

Forecasting rainfall: occurrences, amounts and spells

Daily rainfall is often exactly zero and occasionally very large. A standard regression can predict negative rain and ignores the most practical question: will it rain at all? A two-part, or hurdle, model separates the two:

$$P(R_t \geq 1 \mid X_t) = p_t, \qquad E[R_t \mid R_t \geq 1, X_t] = m_t, \qquad E[R_t \mid X_t] \approx p_t m_t.$$

Here X_t are the features known when the forecast is issued, p_t is the wet-day probability and m_t the expected amount on a wet day. Logistic regression gives p_t; a Gamma distribution models the positive amounts; tree models can learn thresholds and interactions. With a 30% wet-day probability and an 8 mm conditional mean, the expected amount is $0.30 \times 8 = 2.4$ mm, but on 70% of such days the outcome is exactly zero.

That distinction matters for derivatives. A monthly rainfall index depends on the whole distribution of daily rainfall and on how wet and dry days cluster, not just on the daily mean. A first-order Markov chain captures the clustering:

$$P(W_t = 1 \mid W_{t-1}) = \begin{cases} p_{01}, & W_{t-1} = 0, \\ p_{11}, & W_{t-1} = 1. \end{cases}$$

Here p_{11} is the chance that a wet day follows a wet day and p_{01} the chance that a wet day follows a dry one. A high p_{11} means wet spells cluster; a high $1 - p_{01}$ means dry spells persist. Combined with Gamma amounts, the chain becomes a simple weather generator for rainfall-index simulation.

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How to evaluate a probability rather than just an amount

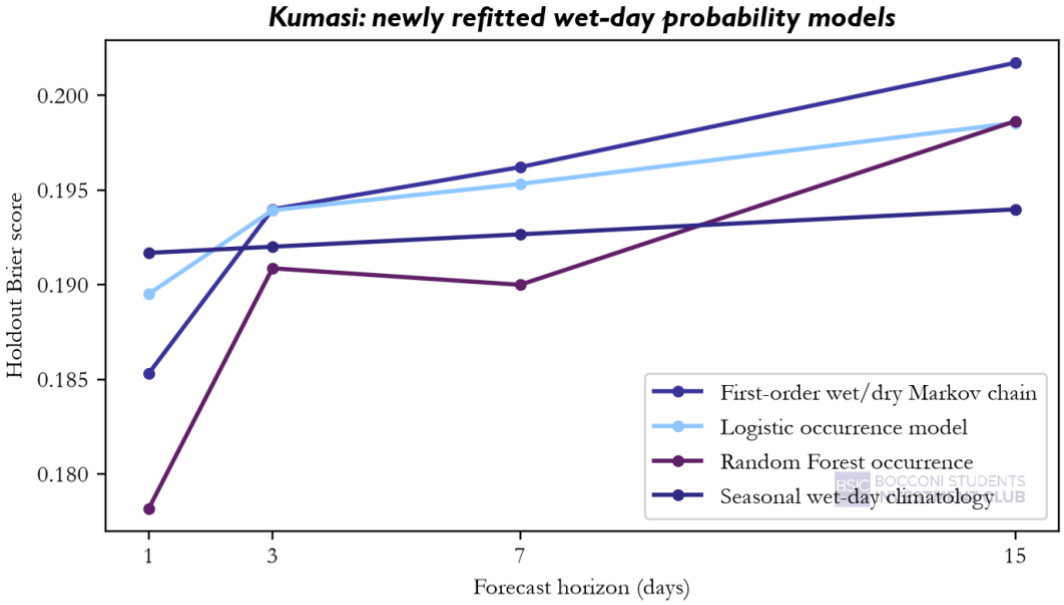
For each forecast, the outcome y_t is one on a wet day and zero otherwise, and p_t is the forecast probability. The Brier score is

$$BS = \frac{1}{n}\sum_{t=1}^{n}(p_t - y_t)^2.$$

A 90% forecast on a dry day scores $0.9^2 = 0.81$; a 10% forecast scores $0.1^2 = 0.01$. Unlike simple accuracy, the score rewards appropriate confidence. A well-calibrated forecaster's 70% days should turn out wet about 70% of the time. Brier scores measure probabilities, so they must never be compared with rainfall errors in millimetres.

What the Kumasi experiment establishes

The Kumasi experiment uses a common 2023–2025 test period and the 1 mm wet-day threshold. A seasonal baseline asks how often it rains on that date; a Markov model adds yesterday's state; logistic regression, Random Forest and XGBoost use richer lagged predictors. The chart below shows XGBoost ahead of the simpler models at every lead.



Sources: BSIC, rainfall_new_baseline_scores.csv

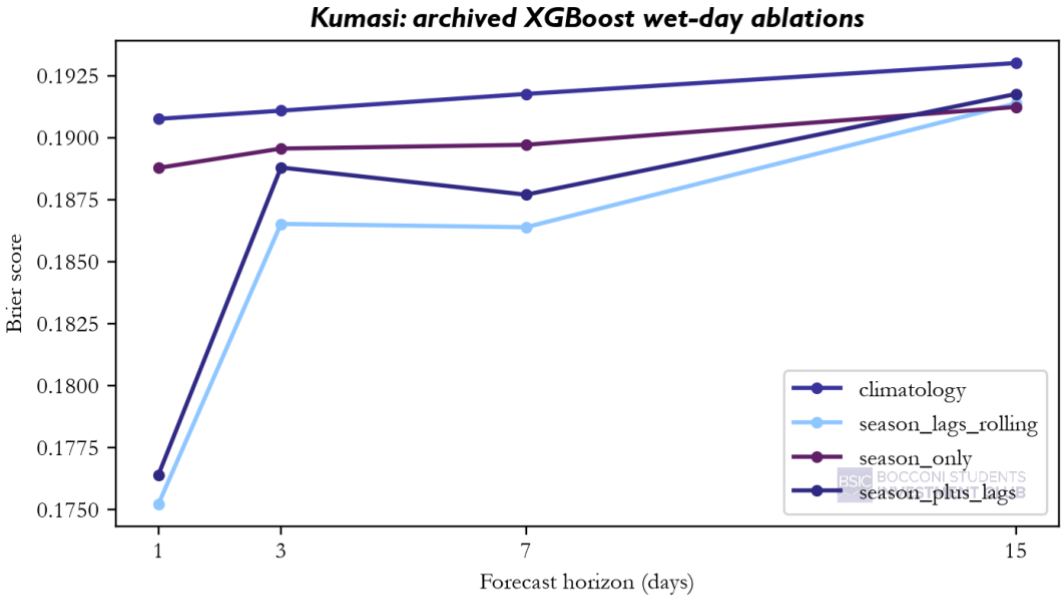
At one day, XGBoost's Brier score of 0.1752 compares with 0.1782 for Random Forest and 0.1917 for the seasonal baseline, on the same 1,095 cases. That is an 8.6% reduction in probability error relative to climatology (an absolute reduction of about 0.0165), not 8.6 percentage points more correctly predicted rainy days. XGBoost's margin over Random Forest is only about 0.003.

Rainfall amounts are a separate target. The two-part model's amount errors are about 2.56, 2.61, 2.62 and 2.65 mm at 1, 3, 7 and 15 days. The almost flat profile suggests that recent local information adds little to amount forecasts beyond the seasonal cycle.

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Interpreting the models

For a monthly rainfall contract, how rain arrives matters as much as whether tomorrow is wet. Two models can score alike on tomorrow's wet-day probability and still imply very different chances of a ten-day drought or a monthly shortfall. A Markov–Gamma generator that loses to XGBoost on one-day scores may therefore still be the better tool for pricing an accumulated index. The chart below shows that lagged and rolling predictors drive XGBoost's one-day advantage, which disappears by fifteen days.



Sources: BSIC, scores.csv

Extreme weather: precise events, calibrated probabilities and limits of inference

An extreme event is a precisely defined departure from a location's normal climate, usually set by a threshold and often by a duration. Extremes fall into four families: temperature extremes (heatwaves, cold spells, frost); precipitation extremes (intense rainfall, floods, dry spells, drought); wind and storm extremes (tropical cyclones, winter windstorms, convective storms); and compound events (heat with drought, or cold with low wind in a power system).

Four questions must be kept apart: whether an event will begin, how severe it will be, how often an event of that size recurs, and what damage it causes. Each needs a different model, and a model that answers one says little about the others.

Each family is predictable over a different horizon. Convective storms and flash floods develop within hours and are forecast by nowcasting from radar and satellite images. Tropical cyclones and windstorms can be anticipated several days ahead with global ensembles, which forecast tracks well but intensity less reliably. Heatwaves and cold spells follow persistent patterns such as blocking highs, giving one to two weeks of warning. Droughts build over weeks to months and are forecast with seasonal models. How large and how frequent extremes are in the long run is answered by extreme-value statistics.

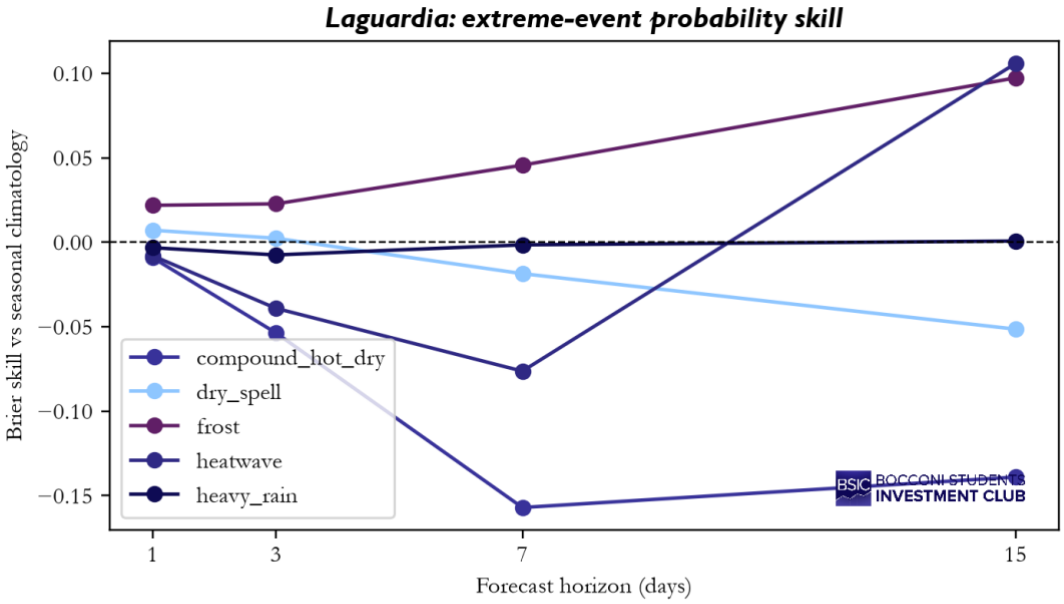
Our experiment tests the shortest-horizon question for local statistics: can lagged local weather and the calendar predict whether a new event will start within 1, 3, 7 or 15 days better than the event's seasonal frequency? Five events are defined from training data only:

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- frost: a daily minimum below 0°C;
- heatwave: three consecutive days above a site-specific threshold (31.7°C at LaGuardia, 34.6°C at Kumasi);
- heavy rain: a day above the training-period 95th percentile of wet-day rainfall (34.0 mm and 11.9 mm respectively);
- dry spell: ten consecutive days each with less than 1 mm;
- compound hot-dry: a heat event combined with a dry spell.

Skill is measured relative to climatology: positive values beat it, negative values do worse. At LaGuardia, frost is the clear success. Skill is positive at every horizon and rises to about 0.10 at fifteen days. At seven days the frost Brier score is 0.08508 against 0.08915 for climatology, a 4.6% reduction in probability error, not a 4.6% reduction in frost risk or crop losses.

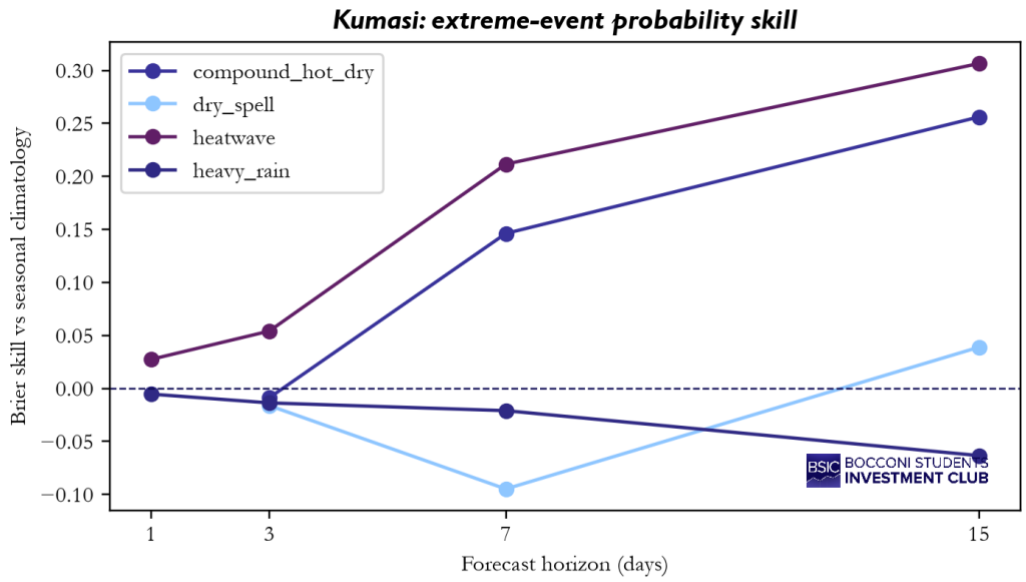
Heavy rain shows essentially no skill: at one day the model slightly loses to climatology (0.01668 against 0.01663). Dry-spell, heatwave and compound hot-dry forecasts are mostly worse than climatology. The pattern fits the physics. Frost follows large, slow-moving cold air masses that recent local temperatures partly reveal, whereas heavy rain at one point depends on convection that local history cannot anticipate.



Sources: BSIC, hindcast_scores.csv

Kumasi gives a different ranking. Heatwave skill rises with horizon to about 0.30 at fifteen days and compound hot-dry events reach about 0.25, while heavy rain is slightly worse than climatology at every lead and dry-spell skill turns sharply negative at seven days. Because Kumasi's temperature varies little through the year, its heatwave threshold sits in the tail of a narrow distribution, and persistent hot spells give local data real information. Long-horizon gains are somewhat flattered, because a fifteen-day window contains more event starts.

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Sources: BSIC, hindcast_scores.csv

From physical forecasting to frontier atmospheric AI

Frontier AI weather models learn how the whole atmosphere evolves rather than how one location's history repeats. Each is trained on decades of reanalysis data to map today's global fields of temperature, humidity, wind and pressure onto the state six hours later; longer forecasts feed each prediction back in as the next input.

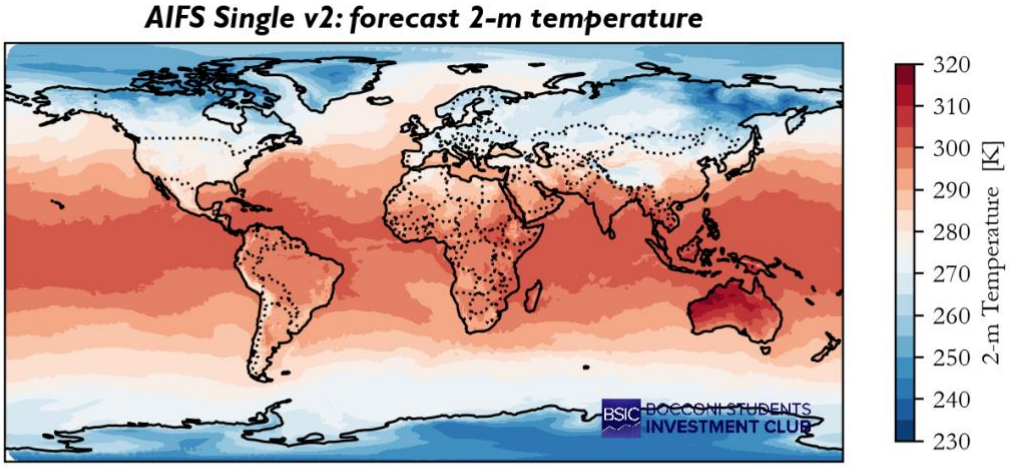
The architectures differ in how information travels across the globe: GraphCast passes messages across a mesh, Pangu-Weather uses transformer attention, FourCastNet works on whole fields in frequency space, and NeuralGCM keeps a physical core with learned physics. Such models now match or beat traditional forecasts on many medium-range scores at a fraction of the computing cost, and probabilistic versions such as GenCast, AIFS ENS and WeatherNext generate full ensembles. Three limits matter economically:

- errors compound with each six-hour step, so short-range accuracy does not guarantee reliable two-week forecasts;
- models trained to minimise average error tend to blur the extremes that move markets;
- good global scores do not ensure accuracy at a particular settlement station or cocoa district.

The economic chain is direct. Cheaper and faster forecasts mean more frequent forecast revisions, so weather news reaches energy and agricultural markets earlier. Calibrated ensembles turn that news into the probabilities that pricing and hedging need. And as these models become freely available, the edge shifts from having a forecast to calibrating it locally and translating it into physical exposure.

Our own run illustrates the shift. Using ECMWF's open AIFS Single v2 model, operationally updated in May 2026, we produced a genuine six-hour global forecast on an ordinary Apple Silicon laptop. It ran from 00 UTC to 06 UTC and produced 542,080 grid-point values each for 2-metre temperature and sea-level pressure (spatial medians 19.04°C and 1013.92 hPa), shown in the map below. It demonstrates feasibility, not skill: it is a single, unverified deterministic forecast.

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Sources: BSIC, ECMWF AIFS Single v2 via HF SDPA; genuine forecast field, not an observation

From forecast to price: valuing one HDD contract

The earlier sections ask how well we can forecast temperature. A trader asks something more practical: does a better forecast change what a weather contract is worth? We answer this for one real contract. We price it four different ways while February approaches and compare each price with what the contract actually paid.

The contract

The contract is the CME-style New York heating-degree-day (HDD) index for February 2025, measured at LaGuardia Airport. Each day adds how far the day's average temperature fell below 65°F: a 40°F day adds 25 points, and a day above 65°F adds nothing. The February total is the index, and each point is worth $20.

We price a call option on this index. The call pays $20 for every point the index ends above 775.95, the level expected one month before February. February turned out colder than normal: the index reached 818.25, so the call paid about $846.

Where forecasts come from

The forecasts come from ECMWF, the European weather centre that runs one of the world's best global weather models. The model starts from today's weather and works out the next 15 days. Because today's weather is never measured perfectly, ECMWF runs the model 51 times, each from a slightly different starting point. The 51 results are called an ensemble. When they agree, the forecast is confident. When they spread out, it is uncertain.

The model's raw output has two known problems at LaGuardia. First, it is biased: it averages temperature over a 25 km square that includes cooler suburbs and water, so it runs too cold for an urban airport. Second, its 51 runs are often too close together, so it looks more certain than it should. Both problems repeat from winter to winter, so they can be measured and corrected.

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Four ways to price the contract

On four dates (2 January, 17 January, 25 January and 11 February), we price the contract using only information available on that day. Days of February already observed count at their real values. The missing days are filled in four ways:

1. **Statistics only:** no weather forecast. The missing days follow the usual seasonal temperature for that date plus a short memory of recent warm or cold spells ($\varphi = 0.673$), learned from past LaGuardia records.
2. **Raw forecast:** the 51 ECMWF runs exactly as they come.
3. **Corrected forecast (EMOS):** the 51 runs corrected for bias and spread using a standard statistical method (EMOS).
4. **Corrected forecast (machine learning):** the same correction, but learned by a machine-learning model (XGBoost) that can use extra clues such as the season and the latest observation.

The forecast covers only 15 days, so any days beyond it are filled in with the statistical model in every method.

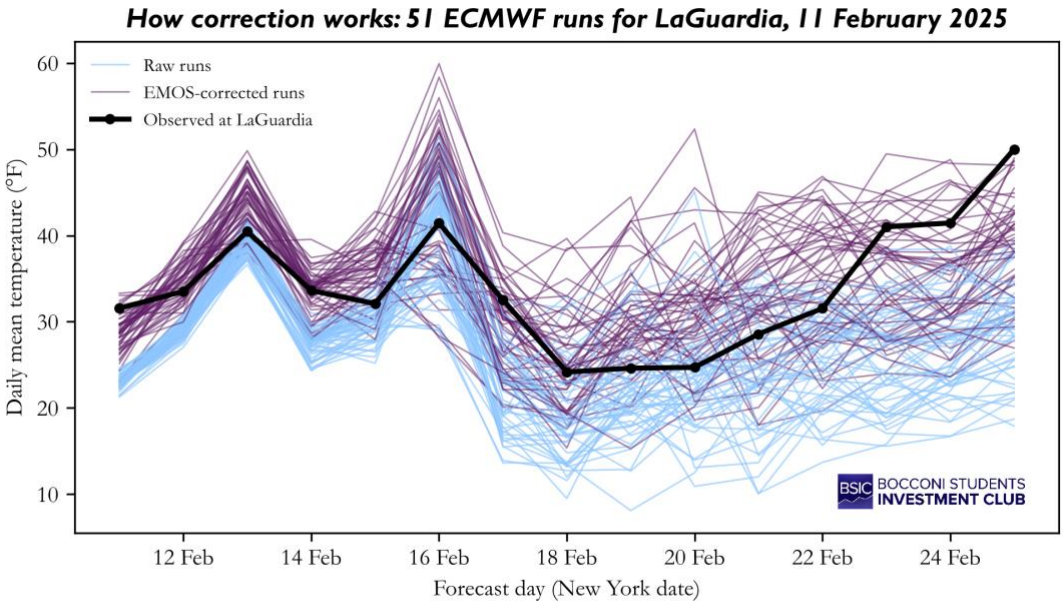
How the correction works

We compared 39 past winter forecasts with what LaGuardia actually recorded. That tells us, for each forecast horizon (1 day ahead, 2 days ahead, and so on), two things: how many degrees the model is typically off, and how much wider its range of runs should be.

The correction then does two things to every run. It shifts all 51 runs by the typical error, so their average moves to the right level. It stretches them apart if they were too close together, so their range becomes realistic. Each run keeps its own pattern: a run that predicted a cold snap on 18 February still predicts one, just at a corrected temperature.

The chart below shows this on the real forecast issued on 11 February 2025. The raw runs (light blue) were about 6.8°F too cold on average. After correction (purple) they are centred on what actually happened (average error 0.2°F), and slightly wider apart (spread from 4.2°F to 5.1°F), so the real temperatures fall inside their range.

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Sources: BSIC, ECMWF ENS open data (AWS), NOAA GHCN-Daily USW00014732

For readers who want the formula: with $\bar{x}_k$ the average and s_k the spread of the runs k days ahead, each run x becomes x':

$$\mu_k = a_k + b_k\bar{x}_k, \qquad \sigma_k^2 = c_k + d_k s_k^2, \qquad x' = \mu_k + \frac{\sigma_k}{s_k}(x - \bar{x}_k),$$

Here μ_k is the corrected average (the shift), σ_k is the corrected spread (the stretch), and the numbers a_k, b_k, c_k and d_k are learned from the 39 past winters.

From forecast to price

Each method then prices the contract the same way:

1. **Build a possible February:** take the observed days, one of the 51 runs for the forecast days, and the statistical model for the rest.
2. **Repeat 10,000 times** to get 10,000 possible Februaries.
3. **Work out the payoff** in each: add up the daily HDD and apply the call's rule.
4. **Average** the 10,000 payoffs to get the call's expected value. We also show it discounted at a placeholder 4% rate and with a small risk margin of 0.2 standard deviations, as a seller might charge.

How we score accuracy

We use the CRPS, a score for how far the whole range of simulated outcomes is from what really happened. Lower is better, and zero is perfect.

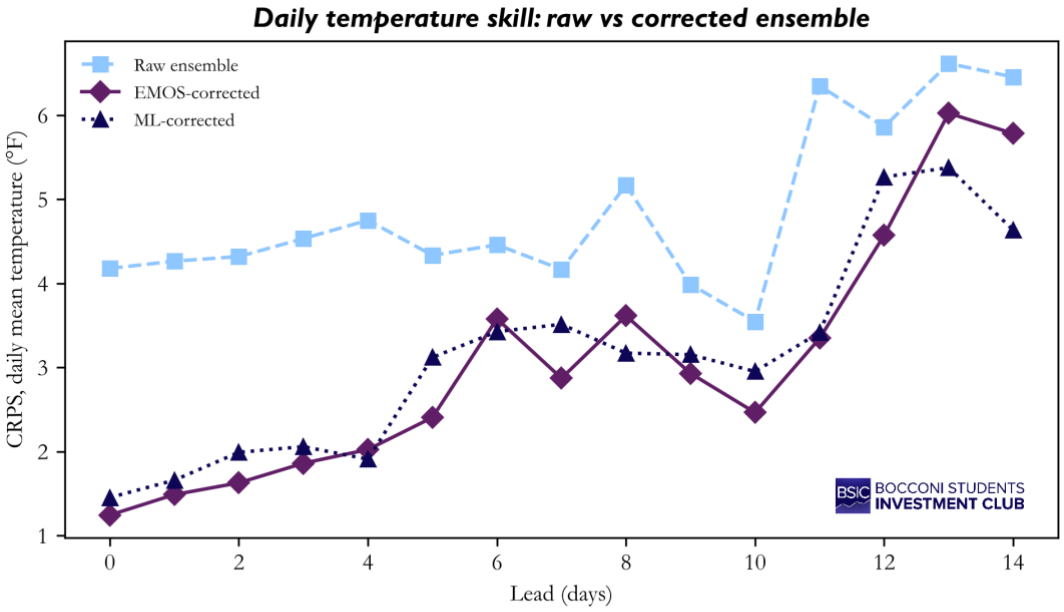
Results

Result 1: the raw forecast must be corrected before it can be priced. Tested on 12 past winter forecasts it had not seen, the raw ensemble runs about 5°F too cold at LaGuardia (bias −4.8°F for the next 0–4 days), and its 80% ranges catch only 15% of outcomes. A likely reason is that the model's grid box averages cooler

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surroundings than an urban, waterside airport, together with the difference between a four-point daily average and the (Tmax + Tmin)/2 rule.

Correction fixes most of this, as the chart below shows. For the next 0–4 days, EMOS cuts the CRPS from 4.41°F to 1.65°F and lifts range coverage to 75%; machine learning is close behind (1.81°F, 83%). The gain shrinks further ahead: CRPS falls from 4.42°F to 3.08°F at 5–9 days, and from 5.75°F to 4.41°F (EMOS) and 4.32°F (ML) at 10–14 days.

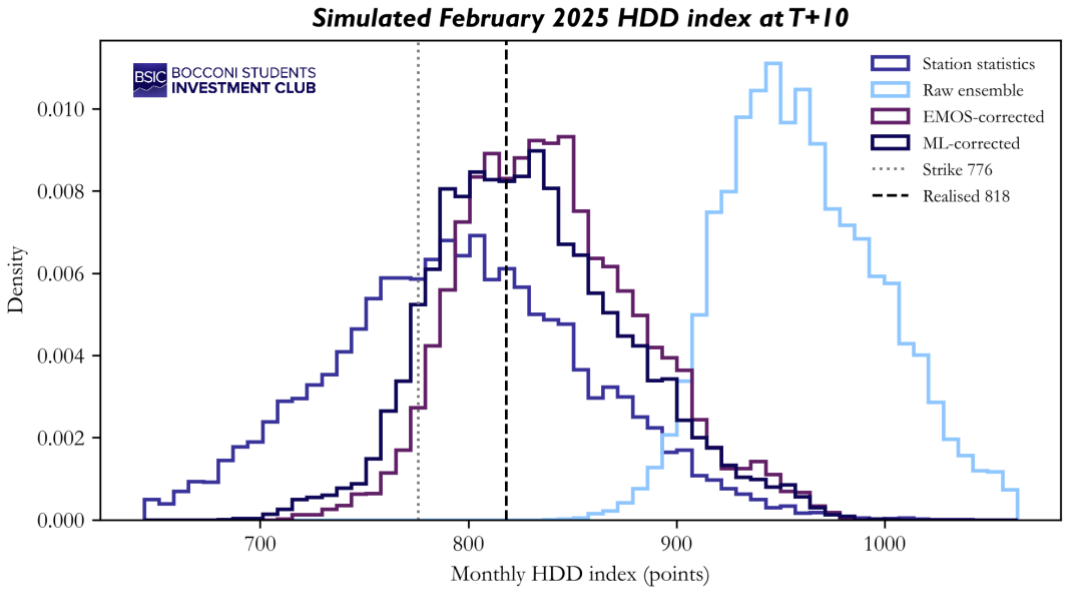


Sources: BSIC, NOAA GHCN-Daily USW00014732, ECMWF ENS open data (AWS)

Result 2: inside the forecast window, corrected forecasts sharpen the price. On 11 February the forecast covers 11–25 February, most of the remaining month. Used raw, its cold bias puts the index at 962 against an actual 818 and values the call at $3,713, more than four times what it eventually paid.

Corrected, the forecast beats statistics alone. The index CRPS falls from 18.11 points to 13.71 with EMOS and 11.74 with ML, and the average daily error on the remaining days falls from 6.60°F to 4.60°F and 4.73°F. The likely range of the index (10th to 90th percentile) narrows from 713–877 to 789–902 and 776–896, and both corrected ranges contain the actual outcome, as the chart below shows.

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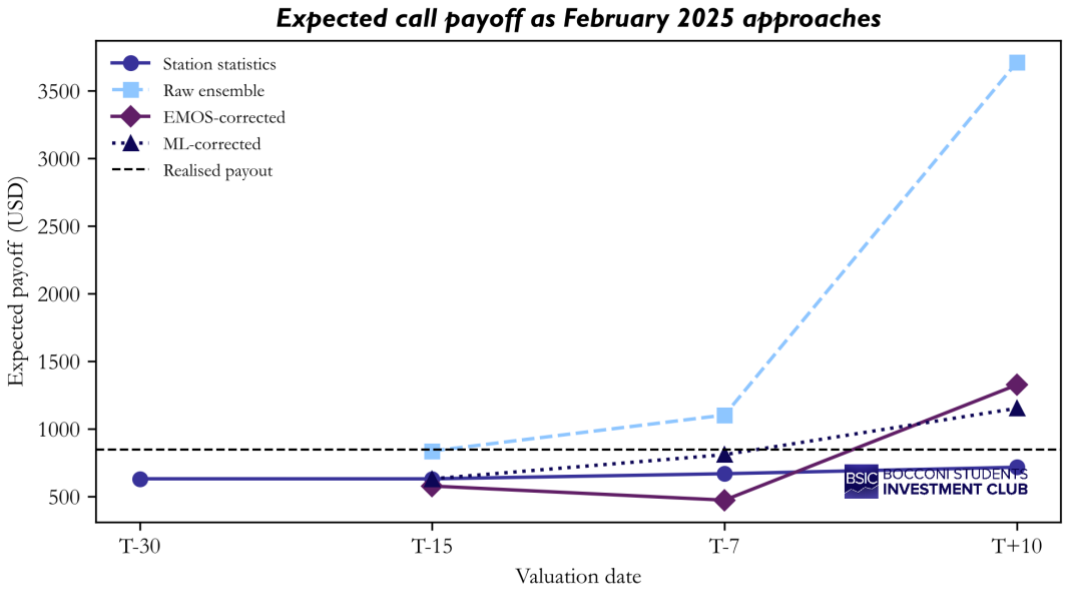
The expected call payoff on 11 February is $717 with station statistics, $1,326 with EMOS and $1,153 with ML, against an actual payout of $846; with the risk loading the values are $889, $1,494 and $1,327. The corrected values sit above the payout for two reasons: their expected index is slightly too high (842 and 832), and an option's value includes the chance of an even colder end to the month.

Result 3: before the forecast window, statistics remain the benchmark. On 2 and 17 January no forecast reaches February, so every method stays close to station statistics, with expected payoffs of $578–837. On 25 January the forecast reaches 1–8 February, but only at 7–14 days ahead, where Result 1 showed little skill.

On that date machine learning improves on statistics (index CRPS 23.80 against 26.24), EMOS is worse (37.20), and the raw ensemble scores best (19.22) only because its cold bias happened to match a colder-than-normal February; its daily error, 5.87°F, is no better than that of statistics (5.84°F). The expected payoffs are $669 for statistics, $1,103 raw, $474 EMOS and $810 ML. The chart below traces each method's value across all four dates against the actual $846.

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What it means

The chain from weather to price works only when every link is in place. A global forecast carries real information, but at a specific weather station it must be corrected before it can be priced, and the correction adds value mainly within roughly the first week, where it narrows the range of outcomes. Further ahead, simple statistics remain the benchmark, and a good-looking result can be right for the wrong reason.

An earlier pilot that corrected only the forecast's average, not its spread, improved one-day accuracy (CRPS 0.869°C to 0.812°C) but worsened fifteen-day accuracy (1.327°C to 1.406°C) and left 80% ranges catching just 43.1% of outcomes. This design fixes both.

The test has clear limits: one contract, 12 test forecasts, 39 training forecasts summarised by five of the 51 runs, a daily average built from 6-hourly temperatures, a placeholder discount rate and payment date, and illustrative payoffs (CME lists options on futures rather than on the index itself). Because the NOAA data are today's revised record, this is a look back, not a strategy that could have been traded at the time.

Sector transmission: where a forecast meets a binding constraint

Weather reaches the economy through binding constraints, not through anomalies as such. Agriculture transmits weather through crop stages, disease and output; hydropower through water stored in reservoirs; shipping through navigable depth, as low water on the Rhine or in the Panama Canal watershed shows; and insurance through exposure, vulnerability and contract terms.

These are distinct mechanisms, not a single "weather beta". The sound empirical sequence is to identify the exposed region and season, define the physical variable that drives losses, map it to output, consumption, transport or inventory, account for substitution and spare capacity, and only then examine market prices. The two case studies follow that sequence.

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Case study I — Cocoa: does rainfall measured where cocoa grows predict the harvest?

Côte d'Ivoire and Ghana grow a large share of the world's cocoa in one shared forest belt, so a single weather shock can hit both at once. With national productions Q_G and Q_C, the variance of their combined supply is

$$\mathrm{Var}(Q_G + Q_C) = \mathrm{Var}(Q_G) + \mathrm{Var}(Q_C) + 2\mathrm{Cov}(Q_G, Q_C).$$

The last term is positive when both countries have bad years together, so buying from both does not protect against a regional drought. Weather matters because cocoa is a tree crop whose damage builds up over time: dry-season stress cuts flowering and kills young pods, and long wet spells spread black-pod disease. Climate studies find that the length and severity of the dry season, not total annual rainfall, is the main limit on West African cocoa.

The question

A national rainfall average mixes cocoa-growing areas with coasts, cities and dry northern savanna. Our question is simple: does rainfall measured only where cocoa actually grows explain national cocoa yields better than rainfall averaged over the whole country?

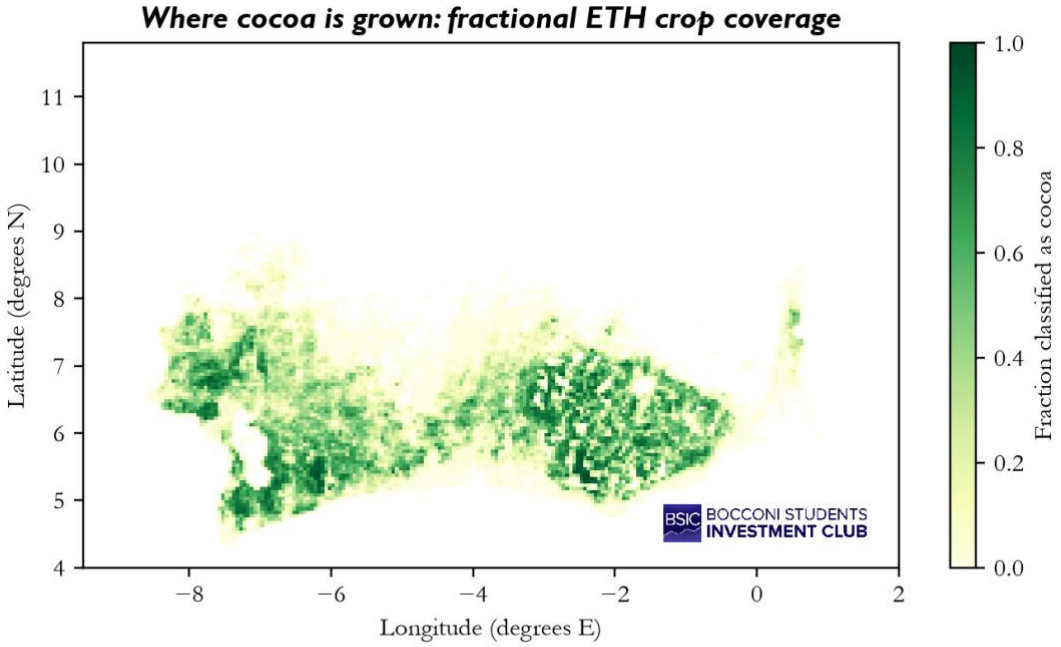
To measure it, we combine three datasets. A satellite-based cocoa map from ETH Zurich gives the share of each small grid cell (about 5 km across) covered by cocoa: of 35,880 cells (156 rows by 230 columns) covering the two countries, 8,421 contain some cocoa. CHIRPS v3 supplies daily rainfall for 1991–2025. FAOSTAT provides each country's yield, harvested area and production by calendar year.

The cocoa rainfall index weights each cell's rainfall $R_{g,t}$ by its cocoa share f_g:

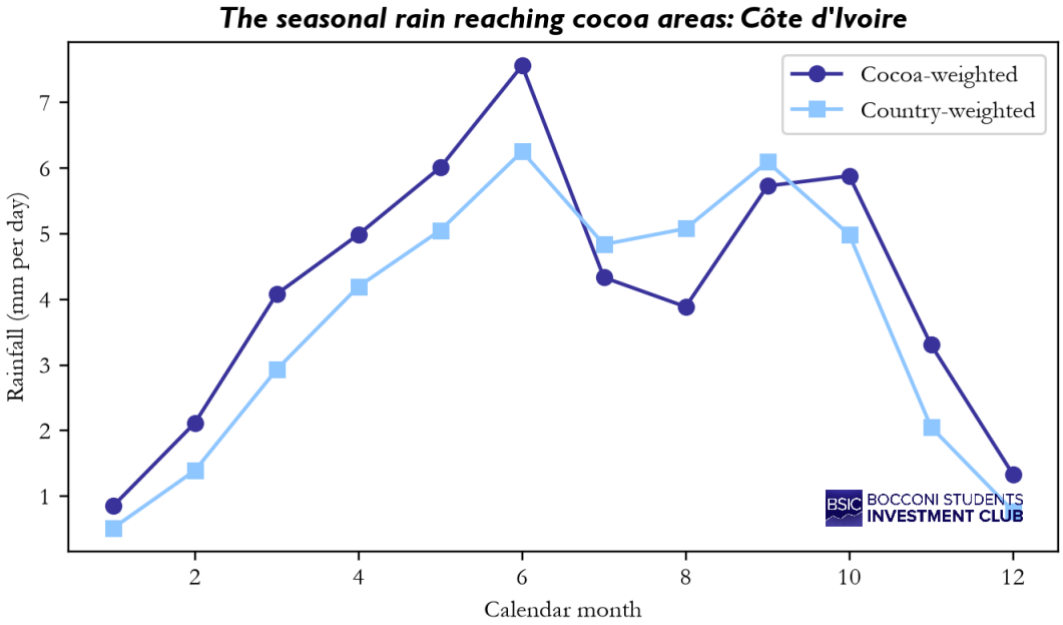
$$R_t^{\text{cocoa}} = \frac{\sum_{g=1}^{G} f_g \, R_{g,t}}{\sum_{g=1}^{G} f_g}.$$

A cell that is 80% cocoa therefore counts sixteen times as much as one that is 5% cocoa, whereas a national average counts them equally. The map and charts below show where cocoa grows and how the two rainfall measures differ: cocoa areas are wetter than the national average, and in Côte d'Ivoire they show a deeper dip between the two rainy seasons.

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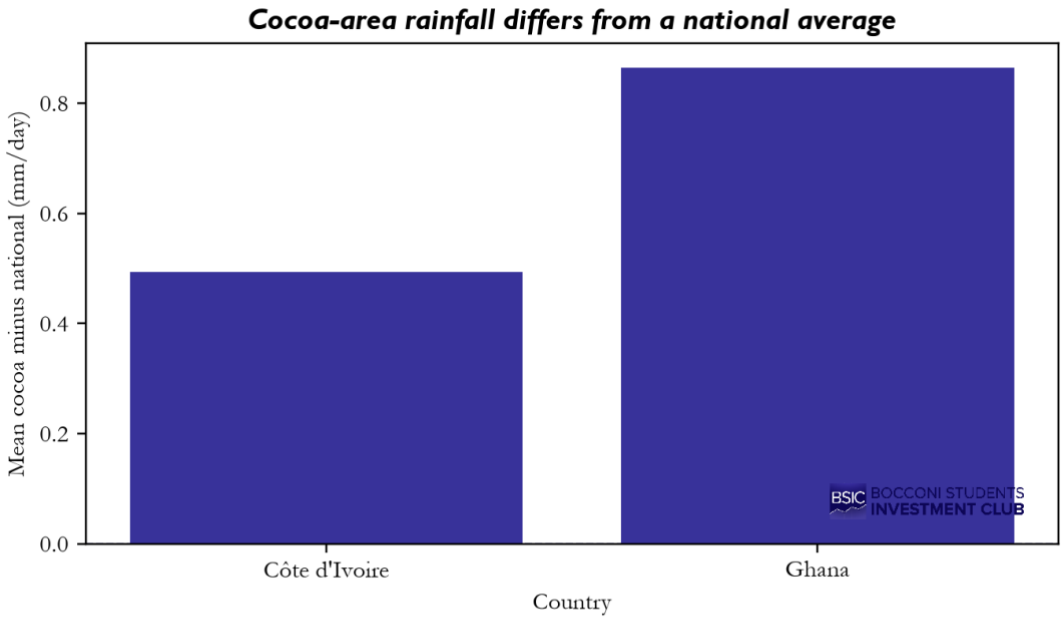


Sources: BSIC, ETH Zurich / Kalischek 2024; static mask aggregated to CHIRPS 0.05-degree cells



Sources: BSIC, BSIC archived CHIRPS v3 ERA5-disaggregated daily, 1991–2025

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Sources: BSIC, BSIC archived CHIRPS country/crop monthly climatologies

Because production equals harvested area times yield,

$$Q_y = A_y Y_y,$$

weather should act mainly through yield Y_y, while harvested area A_y responds to prices, policy and land clearing. Yield is therefore the main target.

What we tested

Five models add information one step at a time, and all are tested on the same 18 country-years they had not seen (2016–2024, two countries). The table below lists them: C0 uses only a time trend and last year's yield; C1 adds city weather; C2 adds national rainfall; C3 adds cocoa-area rainfall; C5 adds the El Niño phase.

Specification	Additional data relative to earlier stages	Physical idea tested
C0	Time trend and previous annual yield	Calendar/persistence already contain information
C1	C0 plus city-level ERA5 weather	Whether readily accessible local weather helps
C2	C1 plus national CHIRPS rainfall	Whether gridded country exposure helps
C3	C2 plus ETH cocoa-area rainfall	Whether production-relevant geography helps beyond C2
C5	C3 plus ENSO-regime indicator	Whether broad climate state adds more information

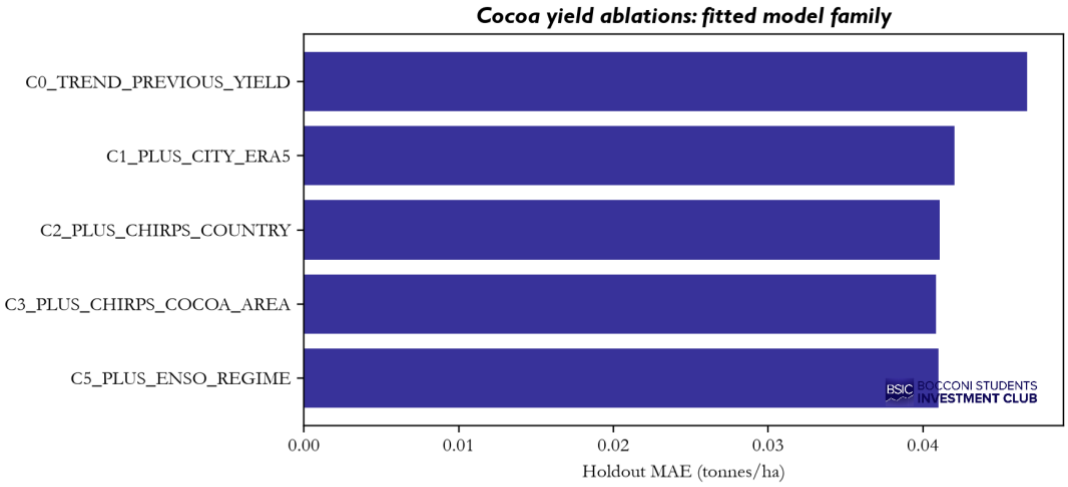
Each model is fitted only on earlier years and judged by its mean absolute error (MAE), the average gap between predicted and actual yield, in tonnes per hectare:

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$$\text{MAE} = \frac{1}{n}\sum_{y=1}^{n}\left|Y_y - \hat{Y}_y\right|,$$

Two limits apply. Weather in a year is used to explain yield in the same year, so this is a look back rather than a forecast made before the harvest. And the 2024 cocoa map is used for every year, so changes in where cocoa was planted are ignored.

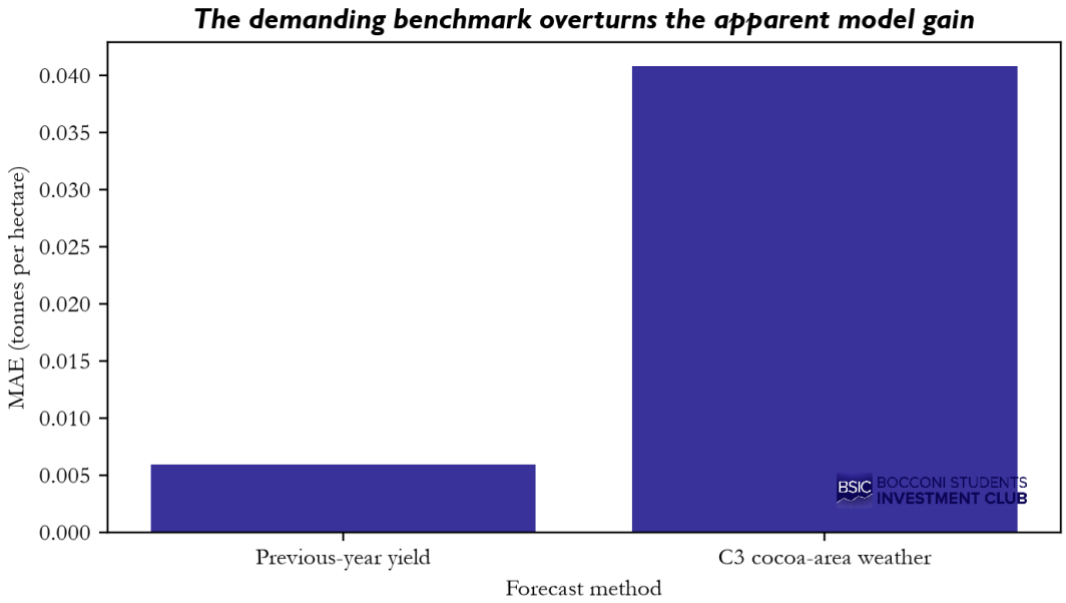
Result 1: rainfall data help a little, but measuring it where cocoa grows barely matters. C3, with cocoa-area rainfall, misses actual yield by 0.04083 t/ha on average, against 0.04675 for C0, an improvement of 0.00592 t/ha (about 5.9 kg/ha, or 12.7%). National rainfall (C2) already gets to 0.04108, so the cocoa weighting saves only 0.00025 t/ha (0.25 kg/ha), and adding the El Niño phase (C5) makes results slightly worse, as the chart below shows.



Sources: BSIC, BSIC canonical cocoa_yield_calendar_year; 18 country-year outcomes

Result 2: last year's yield beats every weather model. Simply predicting each country's yield as last year's value misses by only 0.00591 t/ha (5.91 kg/ha) on the same 18 cases; C3's error of 0.04083 t/ha (40.83 kg/ha) is about 6.9 times larger, as the chart below shows.

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Sources: BSIC, BSIC 2016–2024 same 18 country-years; C3 includes realized same-year rain

There are four reasons. National yields change slowly, so last year's value already reflects the age of the trees and how farms are run, while a regression must estimate several numbers from only nine years. Annual rainfall totals miss the timing and extreme days that actually damage cocoa. Data on pests, disease, fertiliser and tree age are missing. And a single map cannot follow plantations as they move.

Result 3: production is harder still. For total production, adding cocoa-area rainfall makes the error about 20.7% worse, because changes in harvested area, disease and reporting dominate year-to-year output. The cocoa rainfall index is the more relevant measure of exposure, but it does not predict better.

Next steps: extreme events and lagged supply shocks

The research literature suggests changing the question rather than refining the average. Crop damage comes from a few extreme days, not from seasonal averages: yields fall sharply once heat passes a crop-specific threshold, and droughts and extreme heat cut national cereal output by roughly 9–10% in the years they occur. Averaging rainfall over a better-chosen area dilutes exactly those days.

For cocoa, the damaging extremes are long, hot Harmattan dry seasons, multi-month droughts and wet spells that spread black-pod disease, and their effects arrive late. Lost flowering and tree deaths in a severe dry season reduce the following crop, as field studies of the 2015–16 El Niño drought in Ghana documented. A design built on these delayed effects would give genuine advance warning, which our same-year test cannot.

Markets reward that warning. Futures can price weather damage before it shows up in official statistics, as orange-juice futures did with Florida freezes, and El Niño phases move and help predict commodity prices. The 2023–24 surge in cocoa prices to record highs is the obvious case to study: it followed a wet season that spread disease, a harsh dry season and an El Niño, not a change in average rainfall.

Case study II — European gas: which buffer absorbs cold weather?

Cold weather raises gas demand directly through heating and indirectly through power generation. Electricity is dispatched in order of cost, and the most expensive plant running sets the price, so gas sets the power price far

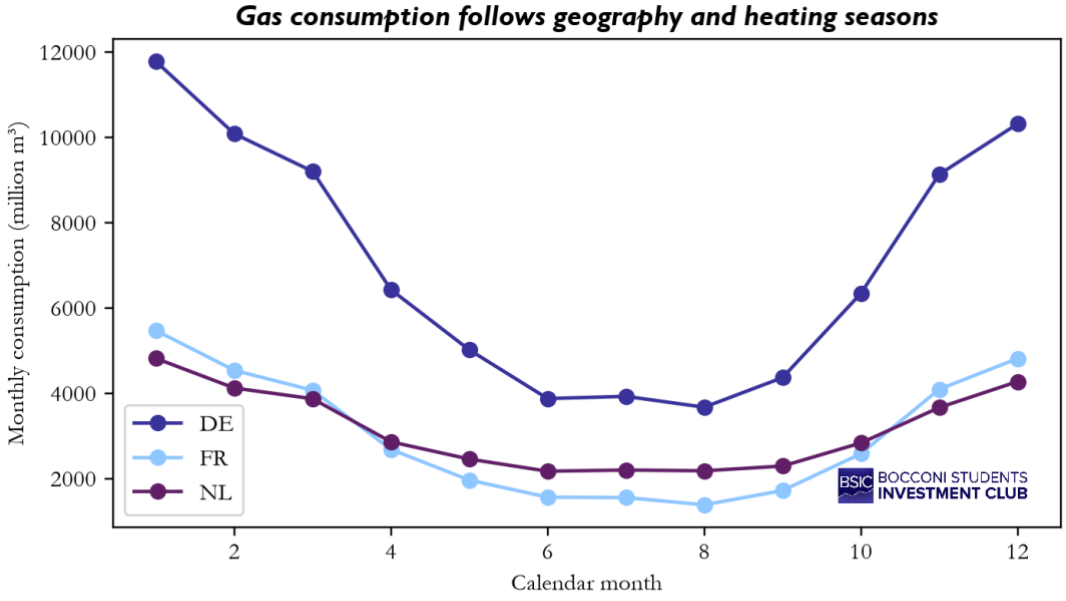
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more often than its share of generation suggests: gas supplied about 17.6% of EU electricity in 2025, yet fossil fuels set the price in about half of hours.

The weather variable that matters for power is residual load: demand minus wind, solar and must-run output. A cold, windless spell raises it from both sides; in an illustrative system, demand rising 2 GW while wind falls 8 GW adds 10 GW of residual load. With gas at €80/MWh, 55% efficiency and €28/MWh of carbon, the marginal gas plant costs about €80/0.55 + €28 = €173/MWh. The table below traces how a weather revision passes through each stage to prices.

Stage	Weather/system variable	Where price sensitivity appears
Weather	Temperature and wind revisions	Heating and net electricity demand
Electricity merit order	Residual load and marginal generator	Day-ahead / intraday power price
Gas portfolio	New burn, nominations, within-day imbalance	TTF spot and balancing exposure
Physical buffer	Linepack, imports, storage, LNG availability	Scarcity and the futures curve

Empirical studies confirm these channels. Wind output lowers German wholesale power prices but makes them more volatile, intraday power prices move with wind and solar forecast errors within the hour, weather and storage news drive gas-price volatility, and European gas prices respond to temperature, storage and supply shocks. The chart below shows the seasonal shape of gas consumption in Germany, France and the Netherlands.



Sources: BSIC, BSIC Eurostat DE/FR/NL monthly consumption archive

Within the gas day, the Dutch network operator GTS buys or sells gas on ICE Endex when the system nears its imbalance limits, charging the cost to the shippers responsible. Over the winter, four distinct physical buffers matter:

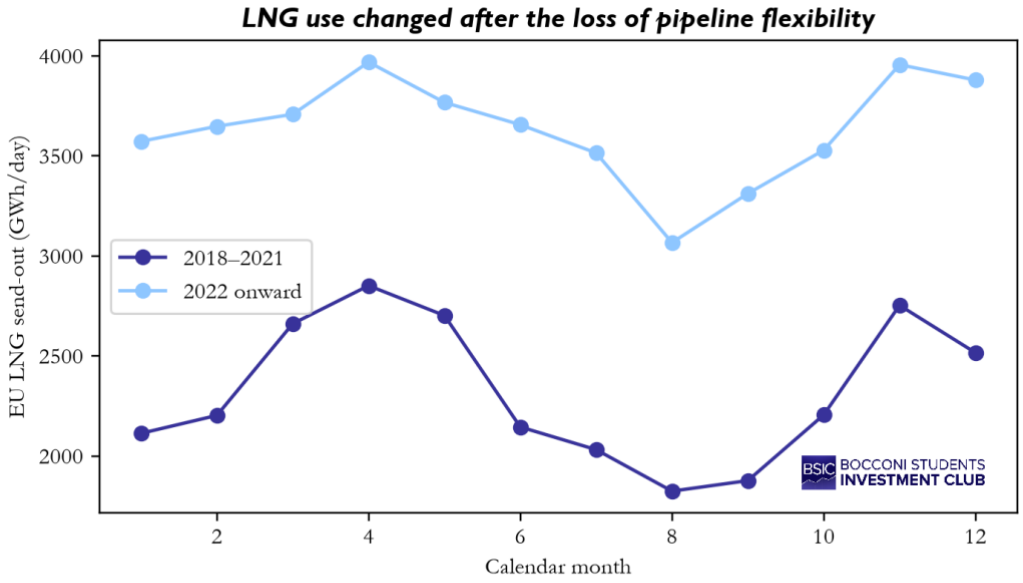
- **LNG cargo availability:** whether ships can be secured and diverted to Europe.

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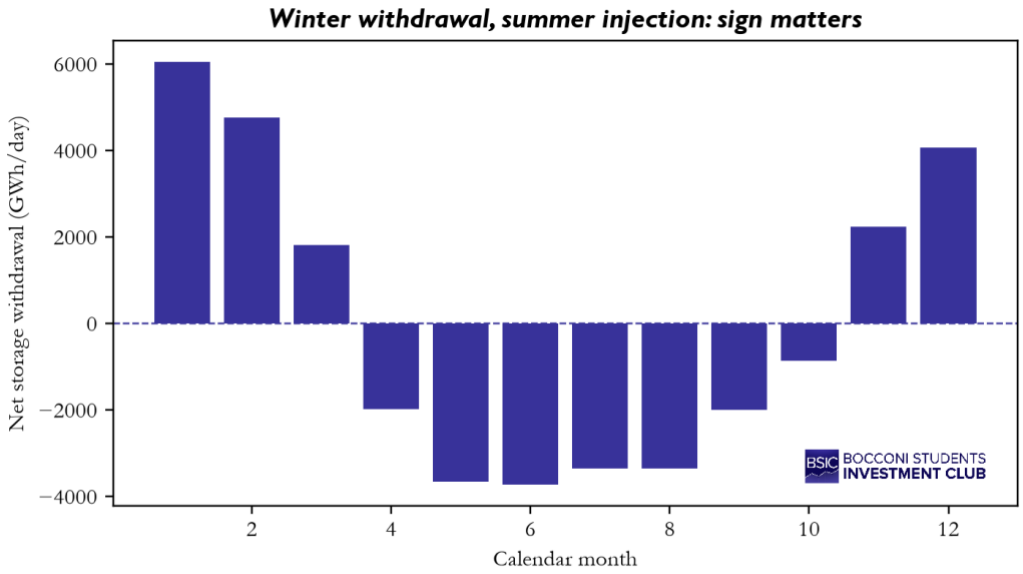
- **Terminal send-out capacity:** how fast a terminal can turn LNG back into gas and inject it.
- **Working gas in underground storage:** the stock held in the ground.
- **Withdrawal deliverability:** how fast that stock can be produced, which weakens below roughly 30% fill.

ENTSOG's 2026/27 outlook shows why the same weather can have very different consequences. Starting from 72% EU storage on 1 October, a normal winter ends March at 29% with ample LNG and 13% with tight LNG, while a cold winter requires roughly 7% or 12% demand reduction respectively. The charts below show how European LNG send-out rose after 2022 and how storage withdraws in winter and refills in summer.

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Sources: BSIC, BSIC GIE ALSI monthly archive; unequal regime samples



Sources: BSIC, BSIC GIE AGSI: positive withdrawal, negative injection

What we tested

Neither experiment estimates prices. The monthly test forecasts gas consumption in Germany, France and the Netherlands over 180 held-out country-months. A baseline using season and last month's consumption scores 648.2 million m³ MAE; adding last month's HDD slightly worsens it (649.7), adding storage indicators improves it to 616.6, and adding LNG send-out reaches 614.8.

Almost all of the 5.2% gain comes from storage information. Last month's HDD adds nothing because last month's consumption already reflects last month's weather.

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Stage	Information set	MAE (million m³ per country-month)
G0	Calendar season, trend and previous consumption	648.2
G1	G0 plus prior-month heating-degree days	649.7
G2	G1 plus previous storage indicators	616.6
G3	G2 plus prior LNG send-out indicators	614.8

The daily test uses 2,400 gas days (7 June 2019 to 31 December 2025) of Dutch LNG send-out, underground storage withdrawals and inventory (GIE data), and De Bilt temperature. It asks which buffer moves on colder-than-normal days, and whether weather or storage data help forecast tomorrow's flows. Each flow is regressed on the same-day cold anomaly C_t (degrees below normal), controlling for yesterday's flow and cold anomaly, seasonality, weekends, a trend, a post-2022 dummy and LNG capacity:

$$y_t = \alpha + \beta C_t + \gamma C_{t-1} + \psi\, y_{t-1} + \text{controls} + u_t.$$

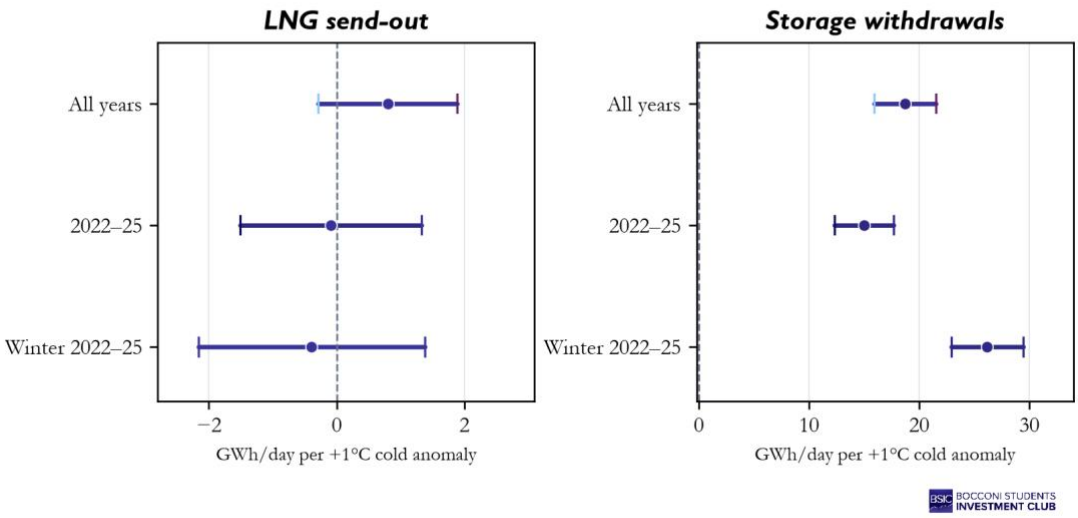
Here β is the change in flow, in GWh/day, for each degree colder. De Bilt is a single-station proxy, the data are retrospective, and send-out shows what terminals delivered, not how many cargoes were available.

Result 1: storage absorbs cold; LNG does not. Withdrawals rise by +18.74 GWh/day per degree colder over 2019–2025 (95% interval +15.95 to +21.53), +15.01 over 2022–2025 (+12.33 to +17.70) and +26.19 in winter 2022–2025 (+22.91 to +29.48). LNG send-out shows no reliable response: +0.84 over the full sample (−0.25 to +1.93), and −0.09 and −0.39 in the two subsamples, all with intervals spanning zero.

Adding yesterday's storage fill and the other flow barely changes these estimates, and fuller storage goes with higher withdrawals (+0.79 GWh/day per percentage point of fill; interval +0.26 to +1.32). The asymmetry fits how the assets work: storage can be dispatched within the day, whereas LNG send-out follows cargo schedules set weeks ahead. The two charts below show the estimates by period and with storage controls.

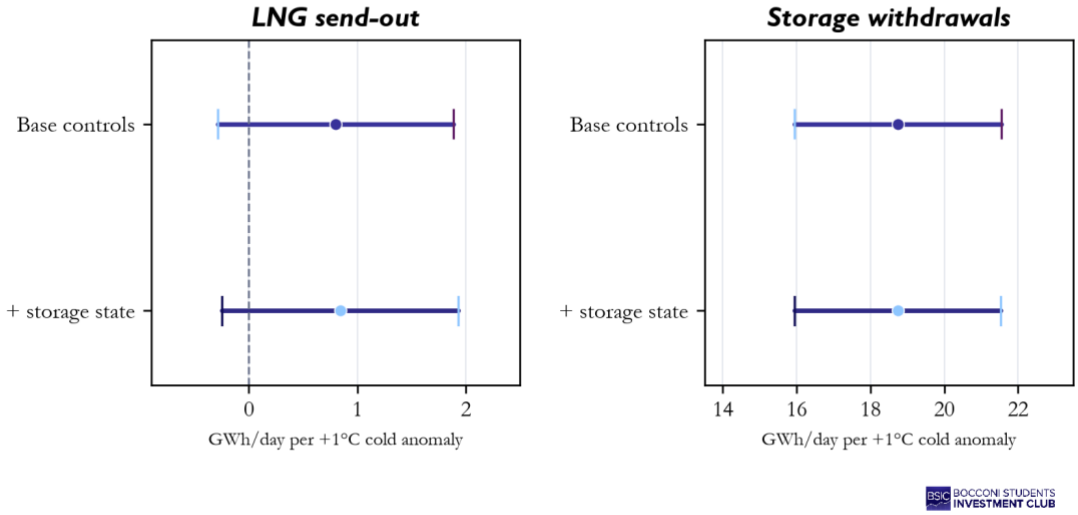
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Observed cold and gas flow: sample robustness



Sources: BSIC, GIE ALSI/AGSI, Open-Meteo ERA5

Cold-weather coefficient with additional controls



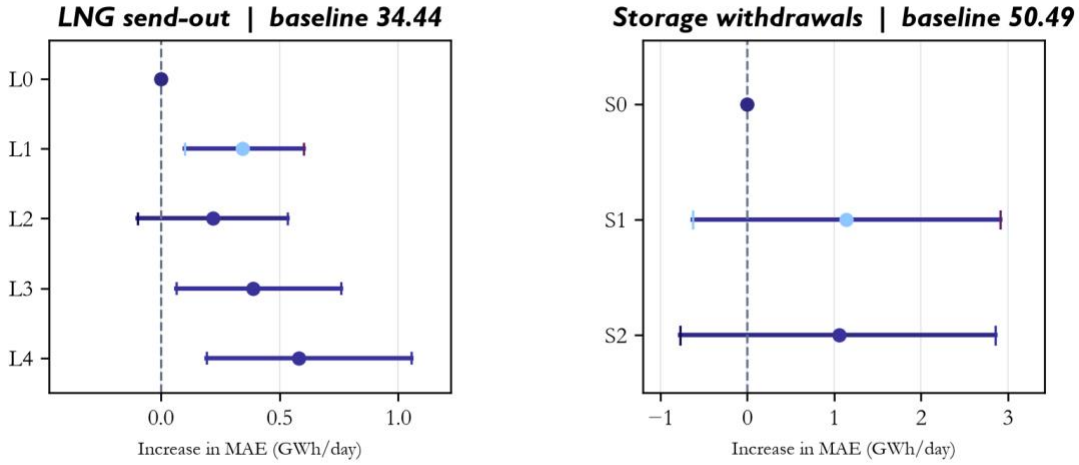
Sources: BSIC, GIE ALSI/AGSI, Open-Meteo ERA5

Result 2: the extra data do not improve next-day forecasts. A ridge model trained on 2019–2023, tuned on 2024 and tested on 2025 scores 34.44 GWh/day MAE for LNG and 50.49 for storage. Adding yesterday's cold, storage state or both makes every forecast slightly worse (LNG 34.66–35.02; storage 51.54–51.63), as the chart and table below show.

The two results are consistent. Withdrawals respond to today's cold, but a forecast can only use yesterday's, which is already reflected in yesterday's flow, and every baseline includes that flow.

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Do additional variables improve the 2025 forecast?



Positive values mean worse forecast accuracy. Whiskers: 95% month-block intervals.

Sources: BSIC, GIE ALSI/AGSI, Open-Meteo ERA5

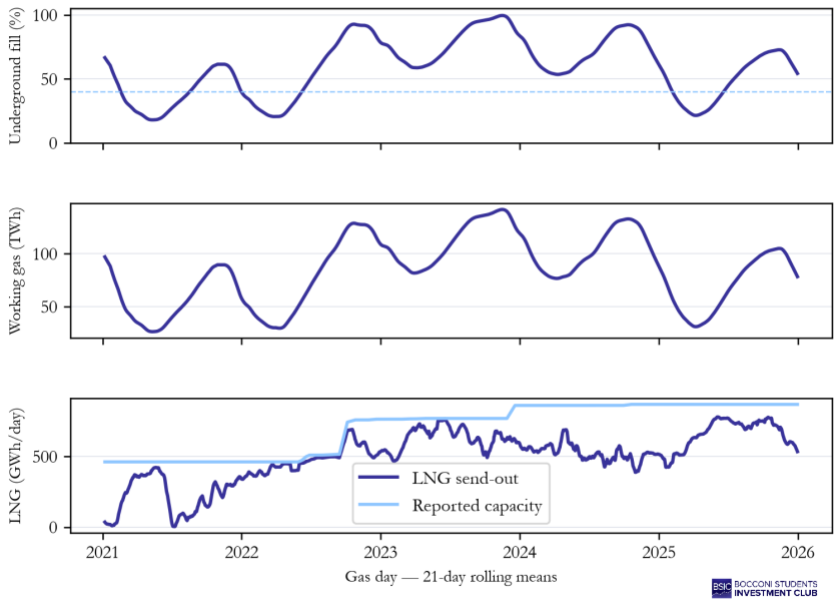
Model	Retrospective 2025 specification	MAE	RMSE
L0	Season + LNG lag + capacity	34.44	59.16
L1	L0 + lagged cold	34.78	59.30
L2	L0 + lagged storage fill / withdrawal	34.66	59.33
L3	L0 + cold + storage	34.83	59.34
L4	L3, using inventory TWh instead of fill	35.02	59.45
S0	Season + withdrawal, fill, LNG lags	50.49	76.50
S1	S0 + lagged cold	51.63	76.61
S2	S1, using inventory TWh instead of fill	51.54	76.55

Result 3: no threshold effect at low fill. On days after storage fell below 40% (285 of 1,461 days since 2022), the response to cold does not change detectably (LNG +0.88, interval −1.11 to +2.86; storage −0.71, interval −4.07 to +2.66). The charts below show storage levels and LNG send-out over 2021–2025, and terminal utilisation grouped by storage fill.

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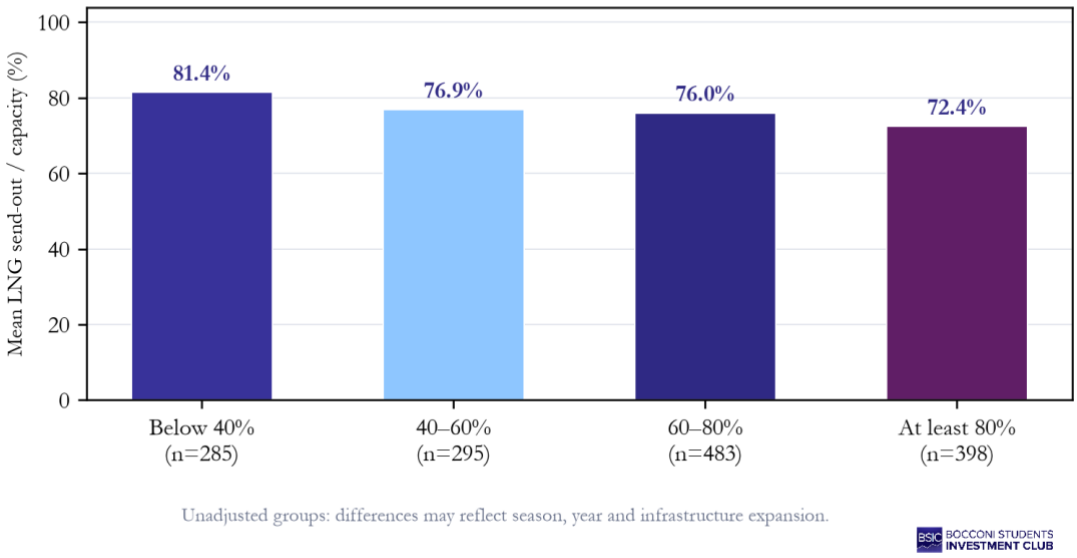
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Storage stock, fill rate and LNG send-out capacity



Sources: BSIC, GIE ALSI/AGSI, Open-Meteo ERA5

LNG terminal utilization by storage-fill regime



Sources: BSIC, GIE ALSI/AGSI, Open-Meteo ERA5

Next steps: from physical buffers to short-term price spikes

Our results show where cold is absorbed. The literature is clear that prices respond to weather surprises and to how scarce flexibility is, not to the weather itself. Wind output lowers average power prices but raises volatility, and German intraday prices move within the hour with wind and solar forecast errors.

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Because the supply curve is steep near capacity, the same forecast error barely matters in a well-supplied hour but can trigger a spike when residual load nears the limit of available plant. Winter Storm Uri in Texas in February 2021 and the windless, overcast spells of winter 2024 in Germany are examples. In gas, weather surprises drive futures volatility, storage-report news moves prices within the day, and day-ahead returns have heavy tails.

Combined with our finding that underground storage absorbs daily cold, this suggests a clear hypothesis: TTF within-day and day-ahead spikes should cluster around large upward revisions to forecast heating demand or downward revisions to forecast wind, and should be largest late in winter, when storage nears the level at which withdrawal capacity weakens. The next experiment is to link time-stamped forecast revisions to short-term power and gas prices.

Conclusion: what the completed weather evidence establishes

The evidence supports a hierarchy of claims rather than a single weather coefficient. Forecast skill is real but conditional: local statistical models capture seasonality and short-lived persistence and converge on climatology within about two weeks, extra model flexibility adds little once that structure is in place, and probability forecasts beat climatology for some events, such as frost, but not for others, such as heavy rain.

The single-contract test brings these pieces together. ECMWF's ensemble is about 5°F too cold at LaGuardia, and priced raw it would value the February 2025 HDD call at more than four times its eventual payout. Corrected locally, the same forecast sharpens the index distribution inside its two-week window, cutting index CRPS from 18.1 to between 11.7 and 13.7 points. Before the window, station statistics remain the benchmark.

The case studies test the step from physical relationship to economic information, and both answers are negative. Cocoa-weighted rainfall is the more relevant measure of exposure, yet it barely improves on national rainfall and loses decisively to last year's yield. Dutch underground storage responds strongly to cold, yet weather and storage data add nothing to next-day forecasts that already contain yesterday's flows.

The financial lesson follows. A weather derivative is valued from the joint distribution of daily weather, priced with a risk loading that meteorology cannot supply, and useful only to the extent that its index tracks the holder's loss. Weather moves commodity prices through the scarcity of flexibility, and only through the part of that scarcity that is news. This research delivers calibrated forecasts, index valuations and physical-market explanations, not validated trading profits; turning one into the other requires point-in-time forecast vintages and time-stamped prices.

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TAGS: Weather Forecasting, Statistical Models, Artificial Intelligence, Weather Derivatives, Extreme Events, Cocoa, Natural Gas, LNG, Commodity Markets.

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