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Digital Solutions for Weather Risk Hedging: Toward Sustainable Finance

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Abstract As climate change intensifies the frequency and severity of weather anomalies, demand for effective risk mitigation tools grows. Weather derivatives offer a mechanism for managing weather-induced volatility, yet their adoption remains limited due to high transaction costs, pricing opacity and structural market barriers, particularly for small and medium-sized enterprises (SMEs). This paper proposes a digitally enhanced approach for weather risk hedging that integrates recent advances in climate modeling, artificial intelligence (AI), blockchain infrastructure, and regulatory-aligned reporting tools into a unified analytical system. The structure spans the entire hedging process: from weather modeling and risk exposure estimation to smart contract execution and performance evaluation. It is designed to serve a dual purpose: supporting internal financial flexibility through more effective hedging strategies, while also enabling external alignment with sustainability disclosure frameworks such as the Corporate Sustainability Reporting Directive (CSRD) and the Task Force on Climate Related Financial Disclosures (TCFD), which are increasingly influencing companies of all sizes, directly or indirectly. While challenges remain in implementation and regulatory integration, the proposed methodology links advanced digital tools with sustainable weather risk management, supporting both financial resilience and regulatory alignment.

Keywords Weather Derivatives, Weather Risk Hedging, Smart Contracts, Machine Learning, Sustainable Finance.

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Introduction

Climate change and its economic consequences has become a major challenge for businesses, governments, and society. Increased variability in temperature, precipitation, and wind patterns, along with more frequent weather extremes, affect business operations and financial results across all industries, complicating strategic planning and investment. Projections of continued warming of the climate system are expected to intensify this trend, underscoring the need for proactive weather risk management.

Weather derivatives offer a mechanism for mitigating the financial consequences of increasing weather variability by transferring weather-related risks to the capital markets. Unlike traditional insurance, these instruments are particularly apt for hedging *high-probability, low-severity weather anomalies* - such as abnormal temperatures or rainfall - that destabilize operating cash flows, revenues, or expenses. While a growing body of research highlights their potential for managing weather risks, real-world adoption of weather derivatives remains limited, particularly beyond institutional players and large corporations. Key barriers include high entry costs, modeling complexity, pricing opacity, discrepancy between contract sizes and firm-specific hedging needs, and limited market awareness or internal analytical capacity (Bank and Wiesner, 2010; Gairola and Dey, 2023).

Overcoming these structural limitations requires more than financial innovation - it demands a *methodological shift*. Expanding accessibility for smaller and mid-sized firms entails not only redesigning the instruments, but also developing delivery models that reduce informational and operational barriers to entry. This paper aims to address these challenges by exploring how recent digital innovations – such as artificial intelligence (AI), blockchain technology, smart contracts and real-time monitoring platforms, apply to each stage of the weather hedging process. By integrating these advances in a single, holistic methodology – from risk identification and assessment, through hedging strategy design to performance evaluation – the proposed *digitalized end-to-end solution* seeks to lower practical barriers to market participation, especially for small and medium-sized enterprises (SMEs).

1. Hedging with weather derivatives - methodological overview

Weather derivatives are financial instruments that provide payouts based on weather indices - typically aggregating daily values of variables such as average temperature, rainfall, snowfall, or wind speed, measured at a reference meteorological station over a defined contract period. The assessment of the risk-reducing effectiveness of weather derivative instruments requires the examination of several interrelated components. First, the analysis necessitates the development of a statistical model of the relevant weather variables (or indices), which is then used to simulate virtual weather scenarios. The simulated probability distribution of the weather variables, in turn, determines both the probabilistic distribution of the company's weather-sensitive output[1] and the potential payouts and pricing of the climate contracts. Second, it is essential to specify a model describing the dependency between the firm's output and weather conditions. This model serves as the basis for determining the optimal hedging strategy and for analyzing the impact of basis risk on hedging effectiveness. Finally, the performance of weather derivatives is also shaped by the adequacy and accuracy of the selected pricing model.

[1] The methodological framework focuses exclusively on *volume risk* - that is, the variability in the firm's operational activity due to weather, which can be managed through weather derivatives. In this context, *output* refers to the volume of the firm's physical or service activity, such as yield, production, sales or bookings - that is directly influenced by weather variability. *Price risk* is assumed to be separately hedged and thus does not affect profitability within the scope of this analysis. Nevertheless, output and revenue are modeled in separate stages to preserve methodological flexibility: the structure can be extended to assess the simultaneous hedging of both price and volume risk, which are often interrelated in practice.

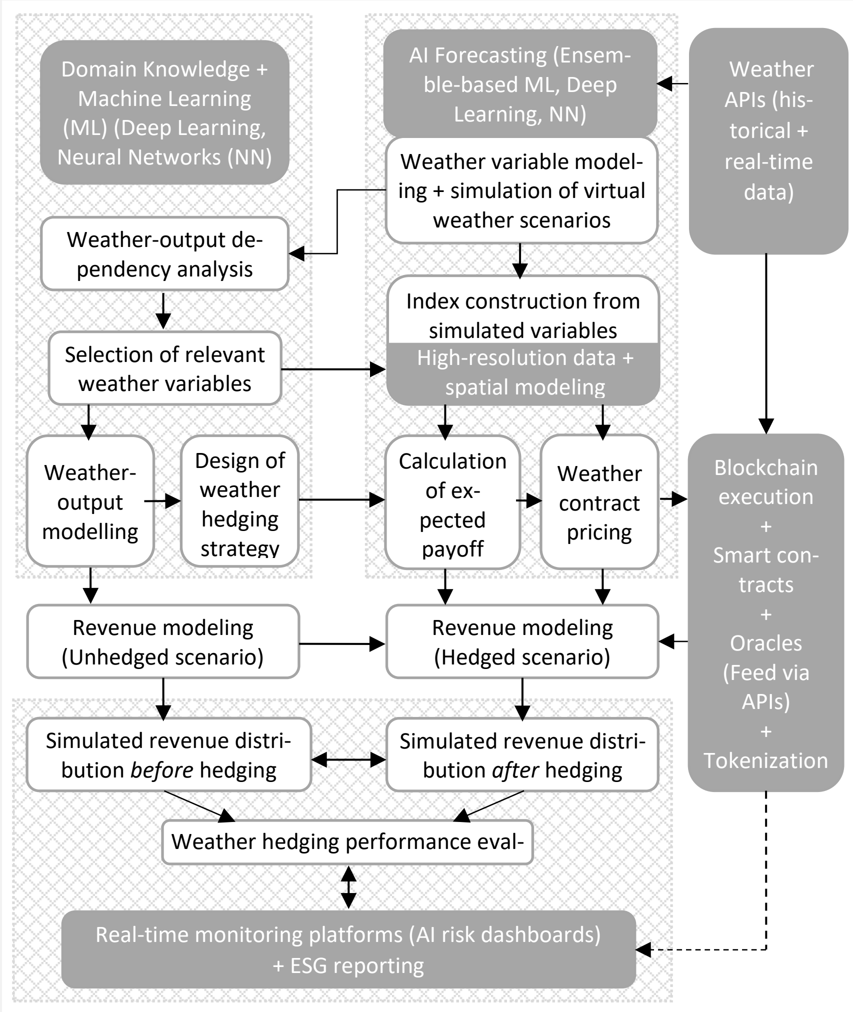

Fig. 1. Digitally enhanced methodology for weather risk hedging (adapted from: Mahlebashieva, 2013: 78)

The methodology developed in this paper was originally developed to assess weather hedging efficiency in Bulgaria's agricultural sector (Mahlebashieva, 2013). It has since been adapted for broader sectoral application and extended with digital components at each stage, using recent developments in fintech - including smart contracts and blockchain technology, tokenization of financial assets, artificial intelligence (AI) and decentralized finance (DeFi). By integrating these innovations into a holistic weather risk management process, it becomes possible to outline a more robust, scalable and accessible hedging framework that could benefit a wider range of firms and sectors. Fig. 1 presents the original design in white boxes, while digitally enhanced components are shown in grey boxes. Shaded blocks indicate digital tools that support multiple stages of the process.

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2. Innovations in weather risk modeling and pricing

Accurate modeling of the weather variables - such as temperature, rainfall or wind speed, and the simulation of virtual scenarios are essential to the construction of weather indices, determining expected payoffs and modelling the dependency between company output and weather variability. Traditionally, scenario simulation has relied on *Monte Carlo methods* calibrated to historical data. However, these approaches are often constrained by statistical model assumptions and may fail to capture the increasing frequency and complexity of extreme weather events.

Advances in artificial intelligence (AI) modelling, particularly *machine learning (ML)* and *neural networks (NN)*[2], enable more realistic weather simulation by autonomously learning from large-scale data and capturing complex nonlinear patterns[3]. They can also be integrated with digital infrastructures such as *weather application programming interfaces* (*weather APIs*)[4] and smart contract platforms. For example, Chen et al. (2023) review applications of ML in precipitation forecasting, extreme event prediction and temperature pattern recognition, reporting consistent improvements over *traditional numerical models*[5]. Pathak, Lu and Gupta (2022) demonstrate that *deep learning models*[6] produce high-resolution global forecasts up to seven days ahead, maintaining competitive accuracy and computational efficiency.

[2] Machine learning (ML) refers to a set of computational techniques that allow models to identify patterns and make predictions based on data, without being explicitly programmed for each task. Neural networks (NN) are a class of machine learning models inspired by the structure of the human brain. They consist of layers of interconnected nodes ("neurons") that can learn from data and approximate complex functions. (Kovac et al., 2023)

[3] While Monte Carlo methods rely on predefined statistical distributions calibrated to historical data, machine learning approaches—such as deep neural networks—can learn complex, nonlinear weather patterns directly from large observational or simulated datasets. These AI-based models capture dynamic spatiotemporal dependencies and may be integrated with, or in some cases substitute for, traditional simulation models.

[4] Weather APIs are digital tools that allow automated access to real-time or historical meteorological data. Services such as the U.S. National Oceanic and Atmospheric Administration (NOAA) API and the EU-based Meteomatics API provide reliable datasets for integration into forecasting models, risk analysis platforms, and smart contract execution tools (NOAA, n.d.; Meteomatics, n.d.).

[5] Recent surveys highlight the growing integration of artificial intelligence into numerical weather prediction and probabilistic modeling systems. AI techniques - particularly deep learning - are increasingly being used to enhance simulation frameworks and to complement traditional forecasting approaches, including ensemble-based methods and stochastic simulation techniques (Waqas et al., 2024).

[6] Deep learning is a subset of machine learning that utilizes artificial neural networks with multiple layers - hence the term "deep" - to model complex patterns in data. These networks can automatically detect patterns and relationships in large datasets, making them particularly effective for tasks time-series forecasting. See: Kovač et al (2023)

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Digital innovations in *weather derivative pricing* are closely linked to advancements in weather modeling and forecasting techniques[7]. Cramer et al. (2017) demonstrate that *ensemble-based ML methods*[8], such as *gradient boosting* and *bagging*, substantially outperform traditional regression models in forecasting rainfall, improving the pricing accuracy of rainfall derivatives. Alexandridis et al. (2017) evaluate two nonlinear ML forecasting techniques and find that both yield significantly higher predictive accuracy for HDD (Heating Degree Days) and CAT (Cumulative Average Temperature) indices compared to the linear models typically used in weather markets. Similarly, Hening-Tallarico and Olivares (2024) develop a *neural network–based time series model* for pricing weather derivatives, which captures temporal dependencies and provides accurate estimates using temperature and precipitation data.

Modeling *the relationship between weather variables and a firm output* forms the base for quantifying weather risk and exposure[9], selecting weather indices, designing hedging strategies and evaluating their performance. While linear regression models are common, they often fail to capture nonlinear effects, thresholds and variable interactions. ML offers more flexible and adaptive approaches for accurately modeling these complex dependencies. For instance, Pan et al. (2019) demonstrated that *deep learning* models trained on weather and *remote sensing data*[10] outperform conventional methods in predicting crop yields, particularly during periods of heightened weather variability. Similarly, You et al. (2017) showed that *deep Gaussian processes* allow for probabilistic forecasting with improved accuracy and uncertainty estimation. Additionally, Chen et al. (2020) apply *NN algorithms* within a parametric weather insurance framework to automatically capture complex relationships between weather variables and financial losses. Although developed in an insurance context, this modeling approach is directly transferable to weather hedging applications.

However, the flexibility of ML also introduces the risk of overfitting or learning spurious correlations. To address this, Karpatne et al. (2017) launched the concept of *Theory-Guided*

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[7] The unique nature of the underlying "assets" in weather derivatives - physical variables rather than tradable financial instruments - limits the applicability of conventional pricing methods. As a result, determining fair value requires an interdisciplinary approach that integrates meteorological modeling with actuarial methods and basic financial principles. In practice, the fair price is typically defined as the *discounted expected payout* of the contract, which in turn depends on the accurate simulation and forecasting of the underlying weather variables.

[8] *Ensemble-based ML techniques* combine multiple predictive models to improve forecasting accuracy. *Bagging* methods, such as random forests, reduce variance by averaging predictions from independently trained models on random data subsets. *Gradient boosting* improves performance by training models sequentially, each correcting the errors of the previous one. These approaches are particularly useful in modeling complex, nonlinear relationships in weather data (Shaik and Pasupuleti, 2024).

[9] For a detailed discussion of weather risk, see Mahlebashieva (2013: 19–24).

[10] Remote sensing data refers to geospatial information collected through satellite or airborne sensors, used to observe and analyze environmental variables such as temperature, precipitation, land cover, and atmospheric conditions without direct ground contact (Li & Shao, 2014).

Data Science, wherein physical laws or economic relationships are embedded into ML models. Integrating *domain knowledge*[11] in this way not only enhances the interpretability of machine learning models but also ensures that predictions remain consistent with established scientific principles, thereby improving their reliability in practical applications.

Beyond the functional relationship between weather variables and a company's output, the spatial and temporal accuracy of weather indices also plays a critical role in *minimizing basis risk*[12]. D'Aversa et al. (2023) develop a spatial optimization methodology to reduce geographical basis risk in temperature weather derivatives[13]. Gyamerah et al. (2019) propose a spatial-temporal regime-switching temperature model that accounts for local variability, enhancing the precision of temperature-based index construction. Similarly, Ritter et al. (2012) demonstrate the effectiveness of multi-site rainfall models in improving the spatial representativeness of index-based contracts. Together, these contributions support the development of more flexible, data-driven index designs that harness high-resolution meteorological datasets.

3. Digitally enabled weather risk infrastructure and sustainability integration

While advancements in modeling and pricing have enhanced the accuracy and reliability of weather contracts, they do not address the structural limitations of traditional market infrastructure. *Blockchain-based solutions*[14] are emerging as a transformative force for overcoming key barriers in the weather derivatives market, particularly those related to slow settlement processes, lack of data transparency and limited accessibility for smaller participants. At the core of this innovation are *smart contracts* - self-executing programs deployed on blockchain platforms, that allow automatic settlements based on weather indices, reducing counterparty risk and administrative complexity.

Alao and Cuffe (2021) introduced a conceptual blockchain-based architecture for using smart contracts to hedge temperature-related volumetric risks in solar power production. Their design emphasized transparency and automation through decentralized execution

[11] In machine learning, *domain knowledge* refers to the understanding of the specific field or context in which a model is applied. Incorporating domain knowledge can enhance model performance by guiding feature selection, model architecture, and interpretation of results (Karpatne et al., 2017).

[12] There are two principal types of basis risk associated with weather derivatives. The first is *production basis risk*, which arises when fluctuations in a firm's cash flows are not perfectly correlated with the weather index underpinning the derivative. The second is *spatial (or geographical) basis risk*, which occurs when the contract's index is well aligned with the firm's exposure, but the reference meteorological station is located too far from the actual site of operations.

[13] The model minimizes the discrepancy between payouts at a reference station and surrounding locations by adjusting strike levels through a penalty function calibrated with altitude, latitude, and historical weather data.

[14] Blockchain is a decentralized and secure ledger that records transactions across a network of computers. It stores data in blocks that are linked together using cryptographic functions, ensuring data integrity and transparency (Tripathi et al., 2023).

of swap contracts. Building on this foundation, Alao and Cuffe (2022) implemented a prototype marketplace, demonstrating the technical feasibility of smart contract–based weather hedging with lower transaction costs and minimal reliance on intermediaries.

Silveira and Camilo (2022) advanced this approach by developing a *decentralized autonomous application (DAApp)*[15] for customizing and trading temperature derivatives[16]. Once deployed on a blockchain, the smart contracts automatically execute settlements when predefined weather thresholds are met. To facilitate this, the DApp integrates *decentralized oracle networks (DONs)* that retrieve real-time meteorological data from trusted external providers and feed it into the blockchain in a secure and tamper-resistant manner[17]. The system thus demonstrates both the technical feasibility and economic potential of using blockchain to democratize access to weather risk management tools. More recently, Silveira and Camilo (2024) apply a similar blockchain-based infrastructure to hedge crop yields using temperature-based options, highlighting its potential to offer low-cost risk transfer, particularly for smallholder farmers.

Haga et al. (2022) introduced a decentralized architecture for weather derivatives utilizing an *N-to-N multi-party swap mechanism*[18]. The authors implemented a prototype on the Ethereum test network, using smart contracts to automate execution and settlement. Their evaluation demonstrated that the approach can effectively mitigate income volatility for solar power producers by facilitating decentralized hedging against weather-induced fluctuations in power generation.

Charles and McLean (2024) propose a novel approach in which rainfall futures contracts are *tokenized* using blockchain technology. In this framework, specific weather outcomes—such as rainfall measurements—are encoded into smart contracts. These contracts are deployed on a blockchain platform, enabling the creation of digital tokens that represent claims on future rainfall events. Each *token* embodies a contract that specifies a payout structure based on the occurrence or non-occurrence of predefined rainfall thresholds. By leveraging blockchain's immutable and transparent ledger, these tokenized contracts can be traded in decentralized markets, providing liquidity and accessibility to a

[15] DAApp is a type of blockchain-based application governed entirely by smart contracts, without centralized oversight.
[16] The platform allows users to customize weather-indexed contracts by setting parameters such as location, time horizon, and payout structure. All contract terms are recorded on a public blockchain.
[17] DONs serve as the infrastructural layer required to securely transmit external data - such as from weather APIs like NOAA or Meteomatics - to smart contracts for automated execution. These oracles act as the critical bridge between "off-chain" weather conditions and "on-chain" contracts, ensuring that payouts are triggered by verified climate data without requiring manual input. See Chainlink Labs (2021) for an overview of how DONs operate to deliver verified weather data to smart contracts.
[18] Unlike traditional bilateral contracts, their model enables multiple participants to engage in a single derivative agreement without the need for direct counterparty matching. This structure improves market liquidity and lowers participation barriers.

broader range of participants, including those in vulnerable regions. This method transforms intangible weather events into tangible digital assets, facilitating more efficient risk management and financial planning in the face of climate-related uncertainties.

The *effectiveness of weather risk hedging* can be evaluated by comparing simulated revenue or cost volatility before and after hedging[19]. The integration of digital platforms can enhance this evaluative process through *real-time monitoring tools* equipped with *dynamic risk dashboards*[20] that continuously track the evolution of underlying weather variables, contract activation triggers and hedging performance metric. These capabilities not only improve internal feedback mechanisms and decision-making accuracy but can also generate structured outputs suitable for *external reporting*.

The growing demand for transparency regarding climate-related financial risks underscores the relevance of such digital tools for Environmental, Social and Governance (ESG) alignment[21]. Since smart contracts can record the timing, conditions and outcomes of weather contract, creating verifiable data streams, they may be directly integrated into ESG dashboards and sustainability disclosures[22]. The Task Force on Climate-related Financial Disclosures (TCFD) emphasizes scenario analysis and ongoing monitoring of risk exposure as essential elements of a climate-resilient strategy (TCFD, 2017). Similarly, the EU Corporate Sustainability Reporting Directive (CSRD) and the new International Sustainability Standards Board (ISSB) standards mandate detailed reporting on material environmental risks and their management over time (EU Commission, 2023; IFRS Foundation, 2023)[23].

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[19] The volatility of the company's revenue, profit, or other financial indicators is described by the characteristics of their probability distributions. Weather derivatives alter this distribution by providing the hedger with a payout that depends on the future value of a weather index, in exchange for a risk premium paid at the time of contract initiation. If the derivative effectively reduces revenue volatility, the post-hedging distribution will exhibit a lower degree of dispersion. Moreover, if the cost of hedging is low, the expected value of the post-hedging distribution will remain close to the expected value of revenue without a weather contract.

[20] Dynamic risk dashboards refer to interactive data interfaces within digital platforms that provide real-time analytics on key risk indicators, contract metrics, and external variables. Platforms such as dClimate's Aegis and IBM's Environmental Intelligence Suite offer decentralized weather data feeds, live dashboards, and automated analytics that support dynamic monitoring of weather exposure and climate-related performance. Although not originally developed for weather derivatives, both platforms offer modular features—such as climate risk scoring and dynamic visualization—that can be adapted to the digital hedging methodology proposed in this paper (dClimate, 2023; IBM, 2022).

[21] Correia and Água (2024) provide a practical perspective on how AI-enhanced digital platforms can operationalize ESG compliance. Their work highlights how real-time data streams and automation capabilities are not only technical assets but also strategic tools for climate-aligned financial reporting.

[22] This potential functionality is illustrated by the dashed arrow in Fig. 1, which links "Blockchain Execution" to "Real-Time Monitoring + ESG Reporting" block.

[23] Although SMEs are not yet subject to mandatory sustainability disclosures, they face increasing indirect pressure to align with ESG frameworks. These pressures originate from their relationships with larger firms, financial institutions, investors and public procurement channels that require ESG data across the supply chain. As SMEs scale or seek external financing, early adoption of digital climate risk tools may position them more competitively and ease future compliance burdens.

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Thus, the integration of digital tools into weather risk management methodology can support both operational risk mitigation and alignment with broader sustainability goals.

Conclusion

This study has outlined a digitally enhanced approach for weather risk hedging that integrates advanced weather simulation methods, AI-driven weather-output dependency modeling, smart contract execution mechanisms and dynamic monitoring platforms. By combining these digital components into a single, coherent probabilistic weather risk hedging infrastructure, the model addresses several long-standing limitations in the weather derivatives market - particularly those related to basis risk, transaction complexity and constrained accessibility. Moreover, the same digital infrastructure that underpins hedging efficiency evaluation can be leveraged to meet the requirements of sustainability disclosure frameworks.

Despite its conceptual robustness, the methodology faces real-world implementation challenges - including disparities in regional data infrastructure, the evolving regulatory environment for blockchain applications and limited awareness of weather risk and climate resilience strategies among smaller firms. While it helps lower entry barriers through integrated design, its broader impact depends on user trust, platform adoption and institutional readiness. Nevertheless, the proposed system lays the groundwork for a more scalable and resilient weather risk infrastructure. Finally, as regulatory frameworks increasingly require companies to assess and disclose their exposure to climate-related risks using forward-looking methodologies, resolving the challenges outlined above - both in theory and in practice - becomes not only desirable but necessary.

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