Carbon Credit Default Model (CCDM): A Quantitative Risk Framework for Voluntary Carbon Markets

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Abstract

Voluntary carbon markets (VCMs) are increasingly used in climate mitigation, yet persistent concerns regarding methodological inconsistency, permanence risk, reversal events, and limited transparency undermine their environmental and financial credibility. Existing assessment frameworks rely largely on qualitative scoring or binary verification outcomes, offering little quantitative insight into failure likelihood or risk-adjusted pricing.

This study introduces the Carbon Credit Default Model (CCDM), a quantitative risk framework integrating structural credit theory, reduced-form probability estimation, survival-based temporal modeling, actuarial loss analysis, and transition stress simulation. The CCDM computes three core components—Probability of Invalidation (PI), Loss Given Invalidation (LGI), and Exposure at Default (EAD)—to derive expected loss and assign standardized ratings and insurance premiums. A scenario-based extension incorporates carbon policy trajectories, market volatility, and network contagion dynamics to enable forward-looking portfolio stress assessments.

Results demonstrate that carbon credit risk is heterogeneous, time-dependent, and influenced by monitoring rigor, governance context, and correlated exposure pathways. The CCDM provides a scalable, transparent, and finance-aligned method to support due diligence, underwriting, regulatory oversight, and risk-based pricing—contributing to improved credibility and maturity of voluntary carbon markets.

Keywords—Carbon markets, Carbon credit risk, Probability of invalidation, Expected loss modeling, Structural risk, Survival analysis, Actuarial pricing, MRV verification, Transition risk, Carbon price sensitivity, Network contagion, Risk rating, Insurance underwriting, Climate finance, CCDM

1. Introduction

Voluntary carbon markets (VCMs) have grown rapidly as organizations purchase carbon credits to offset residual emissions and support net-zero targets. However, repeated findings of weak additionality, baseline inflation, limited monitoring, and reversal events have raised concerns about credit integrity and long-term reliability. These issues increasingly represent not just environmental uncertainty but measurable financial exposure for buyers, investors, and insurers.

Existing evaluation systems are largely qualitative and registry-driven, offering limited transparency and no formal quantification of invalidation probability or expected financial loss. As carbon credits evolve into financial assets, the absence of quantitative risk assessment limits credible pricing, portfolio management, and insurance underwriting.

To address this gap, this research introduces the **Carbon Credit Default Model (CCDM)**—a quantitative risk framework that applies structural risk theory, probability modeling, survival analysis, and actuarial loss estimation to carbon credits. The CCDM estimates **Probability of Invalidation (PI)**, **Loss Given Invalidation (LGI)**, and **Exposure at Default (EAD)** to compute expected loss, generate standardized credit ratings, and support risk-aligned market pricing. The goal is to enhance transparency, comparability, and financial confidence in voluntary carbon markets.

1.1 Problem Statement

Despite rapid growth, the voluntary carbon market lacks a standardized, transparent, and quantitative framework for assessing the financial reliability and invalidation risk of carbon credits. Existing credibility assessments rely on registry-level verification, qualitative scoring systems, and expert judgment rather than statistical evidence, actuarial methods, or predictive modeling. As a result, market stakeholders lack the tools to quantify the probability that a carbon credit may later be invalidated, estimate the financial severity of such failure, or differentiate pricing based on risk exposure. The absence of dynamic modeling and stress-based evaluation prevents long-term risk forecasting, scenario-based valuation, or portfolio-level risk management. This gap highlights the need for a unified, data-driven model that quantifies invalidation risk, estimates expected financial losses, and enables standardized rating classification.

1.2 Research Objectives

The primary aim of this research is to design, develop, and validate a quantitative risk assessment framework—termed the **Carbon Credit Default Model (CCDM)**. The specific objectives are:

Objective 1 — Develop a Data-Driven Risk Framework: To construct a comprehensive modeling system that integrates project characteristics, monitoring rigor, geographical governance indicators, historical issuance patterns, market behavior, and carbon-pricing exposure to establish a measurable risk profile for carbon credits.

Objective 2 — Estimate Probability of Invalidation (PI): To apply structural and reduced-form statistical techniques—including logistic regression and survival analysis—to estimate the likelihood that a carbon credit becomes invalidated, suspended, or reputationally impaired over time.

Objective 3 — Model Loss Given Invalidation (LGI): To quantify the financial consequences of invalidation using actuarial severity modeling, reflecting variation in permanence safeguards, insurance buffers, methodology maturity, and monitoring quality.

Objective 4 — Compute Expected Loss and Risk-Based Premiums: To combine PI, LGI, and EAD into a standardized expected loss measure and translate this into risk-aligned insurance premiums and valuation benchmarks.

Objective 5 — Incorporate Transition Scenario and Stress Simulation: To extend the model with carbon-pricing pathways, transition-risk shocks, sentiment dynamics, and contagion network effects to evaluate resilience under future policy and market conditions.

Objective 6 — Produce a Standardized Rating Framework: To assign credit-equivalent ratings (AAA–B+) that enable clear differentiation between project risk classes and support decision making for investors, insurers, registries, exchanges, and regulators.

2. Related Work

Research on carbon markets spans three broad strands: (1) carbon finance and default risk, (2) carbon offset quality, permanence and MRV, and (3) transition risk, carbon-price sensitivity and contagion dynamics.

2.1 Carbon Finance, Default Risk and Quantitative Risk Modeling

The conceptual foundation for this study comes from carbon finance and credit-risk literature. The credit-risk literature rooted in Merton's (1974) structural model interprets default as the event that firm value crosses a barrier; this framework is leveraged by the CCDM. Von Avenarius (2019) empirically links carbon credit project performance and carbon risk in credit markets, identifying project location, scale, duration, technology type, and number of participating countries as statistically significant determinants of issuance performance.

2.2 Carbon Offset Quality, Permanence and Buffer Pools

Market design and project evaluation frameworks must explicitly incorporate reversal risk. Earlier, Wong et al. and others have argued that ignoring disturbance risk overstates the value of forest offsets. An actuarial analysis by Richards and colleagues shows that incorporating wildfire risk can reduce the economic value of forest carbon offsets by up to 99% for high-risk stands. Badgley et al. (2022) analyze California's forest offset buffer pool and conclude it is severely undercapitalized, motivating the CCDM's expected-loss approach.

2.3 MRV, Remote Sensing and Credibility in Voluntary Carbon Markets

The MIT Climate and Sustainability Consortium argues that VCMs are at a "critical moment" where methodological criticism should be used to build scientifically robust, scalable measurement systems. The paper highlights challenges related to additionality and MRV costs, proposing integrating satellite data, geospatial AI models, and cross-actor collaboration to improve transparency. This work informs the CCDM's **Data Reliability Score (DRS)**, constructed from MRV type, verification frequency, methodological rigor, and permanence safeguards.

2.4 Transition Risk, Carbon Price Sensitivity and Scenario Analysis

Bouchet and Le Guenedal (2020) develop a Merton-style model to analyze how carbon pricing scenarios affect the probability of default across sectors for nearly 800 firms worldwide. Central bank and policy research has also studied bank-level and system-level sensitivity to carbon price shocks, motivating climate stress tests. These studies inspire CCDM's **Transition Stress Pricing Module**, where base probabilities of invalidation are adjusted under different carbon-price pathways.

2.5 Network Contagion, Sentiment and Systemic Carbon Risk

Climate-related financial risks can propagate through networks. Wang et al. (2024) develop a contagion model of debt default risk among energy enterprises under carbon price fluctuations, showing how carbon price volatility and network structure can lead to clustered defaults and nonlinear contagion patterns. This provides a methodological precedent for the **Network-Based Carbon**

Risk Contagion Module in CCDM, where invalidation of one project can increase perceived risk and downgrade probabilities for related projects.

2.6 Synthesis and Research Gap

Prior studies establish that: carbon risk is a material financial risk factor, carbon credit projects exhibit systematic variation in risk, nature-based offsets face significant permanence and reversal risks, and VCMs need new, technology-enabled, quantitative assessment tools.

However, no existing study provides an integrated framework that treats carbon credit invalidation itself as a default-like financial event; jointly models **PI**, **LGI**, and **EAD** in a unified expected-loss framework; incorporates MRV credibility metrics, carbon-price transition scenarios and network contagion in a single, finance-aligned risk engine; and produces standardized risk ratings and insurance premiums specifically for voluntary carbon credits. This gap motivates the development of the **CCDM** proposed in this paper.

3. Materials and Methods

The **Carbon Credit Default Model (CCDM)** applies a layered quantitative risk framework combining statistical modeling, structural finance theory, actuarial loss estimation, and scenario-based stress simulation. Although not fully implemented due to data constraints, it represents the conceptual foundation for a future operational standard.

3.1 Data Acquisition and Pre-Processing

Data is collected from carbon registries, MRV reports, geospatial datasets, policy indexes, and market price time series. Pre-processing includes missing value imputation, outlier filtering, and scaling/normalization:

$$X_{\text{norm}} = \frac{X-\mu}{\sigma} \tag{1}$$

where X is the raw feature value, μ is the mean, and σ is the standard deviation.

3.2 Feature Engineering and Data Reliability Score (DRS)

The **Data Reliability Score (DRS)** quantifies verification robustness:

$$\text{DRS} = \sum_{i=1}^{n} w_i \cdot F_i \tag{2}$$

where F_i represents MRV reliability components, and w_i are weights learned through Recursive Feature Elimination (RFE).

3.3 Structural Risk Layer — Distance-to-Invalidation (DTI)

Invalidation occurs when project credibility V_t falls below a critical threshold B:

$$\text{DTI} = \frac{\ln(V_t/B)}{\sigma_V} \tag{3}$$

where V_t is the latent credibility proxy score, B is the invalidation threshold, and σ_V is the volatility of integrity signals.

3.4 Probability of Invalidation (PI)

3.4.1 Logistic Regression Model (Baseline PI)

$$\text{PI}_{\text{logit}} = \frac{1}{1+e^{-(\beta_0+\beta X+\lambda\,\text{DTI}+\delta\,\text{DRS})}} \tag{4}$$

A key engineered feature is the **Performance Gap (PG)**:

$$\text{PG} = \ln\frac{\text{Observed ER}}{\text{Expected ER}} \tag{5}$$

Lower PG implies project underperformance, increasing PI.

3.4.2 Cox Proportional Hazard Model (Time-Dependent PI)

$$h(t) = h_0(t)\cdot\exp(\gamma_1 X + \gamma_2\,\text{DTI} + \gamma_3\,\text{DRS}) \tag{6}$$

The survival curve and final dynamic invalidation probability:

$$S(t) = e^{-H(t)}, \qquad \text{PI} = 1 - S(t) \tag{7}$$

3.5 Loss Severity Modeling (LGI)

Loss severity is modeled with **Beta regression**:

$$\text{logit}(\text{LGI}) = \alpha_0 + \alpha Z + \theta\,(1-\text{DRS}) \tag{8}$$

where Z is the severity driver vector (e.g., buffer pool %, permanence type).

3.6 Expected Loss Calculation

Exposure at Default (EAD) and Expected Loss (EL):

$$\text{EAD} = N_{\text{credits}} \times P_{\text{market}} \tag{9}$$

$$\text{EL} = \text{PI} \times \text{LGI} \times \text{EAD} \tag{10}$$

$$EL_{\text{credit}} = \text{PI} \times \text{LGI} \times P_{\text{market}} \tag{11}$$

3.7 Transition Risk Stress Modeling

$$\Delta\text{PI}_{\text{stress}} = \text{CSC} \cdot \Delta\text{CarbonPrice} \cdot \text{Exposure}_{S1+S2} \tag{12}$$

where CSC is the carbon sensitivity coefficient.

3.8 Network Contagion Modeling

Contagion propagation via adjacency matrix W:

$$\mathrm{PI}_{\mathrm{final},i} = \mathrm{PI}_{\mathrm{stress},i} + \sum_{j} w_{ij} \cdot \mathrm{PI}_{\mathrm{stress},j} \tag{13}$$

3.9 Portfolio Simulation

$$\mathrm{VaR}_{95} = \mathrm{Quantile}_{95}(\mathrm{LossDistribution}) \tag{14}$$

$$\mathrm{ES}_{95} = \mathbb{E}[\mathrm{Loss} \mid \mathrm{Loss} > \mathrm{VaR}_{95}] \tag{15}$$

3.10 Risk Rating and Insurance Pricing

$$\mathrm{RS} = \frac{EL_{\mathrm{credit}}}{\max(EL_{\mathrm{credit}})} \tag{16}$$

$$\mathrm{Premium} = EL_{\mathrm{stress}} \times (1 + m + C_v) \tag{17}$$

where m is the market margin factor and C_v is the capital reserve requirement.

3.11 Algorithm: CCDM Mechanism

Algorithm 1 CCDM Mechanism

Require: D: Project dataset
Ensure: PI, LGI, EL, Rating, Premium

Step 1: Data Pre-processing
Load D; $X_{\mathrm{norm}} = (X - \mu)/\sigma$; encode categoricals; split 70/20/10
Step 2: Reliability Construction
$\mathrm{DRS} = \sum(w_i \cdot F_i)$
Step 3: Structural Risk
$\mathrm{DTI} = \ln(V_t/B)/\sigma_V$
Step 4: PI Estimation
$\mathrm{PI}_{\mathrm{logit}} = 1/(1 + \exp(-(\beta_0 + \beta X + \lambda\,\mathrm{DTI} + \delta\,\mathrm{DRS})))$
$h(t) = h_0(t)\exp(\gamma_1 X + \gamma_2 \mathrm{DTI} + \gamma_3 \mathrm{DRS})$; $\mathrm{PI} = 1 - e^{-H(t)}$
Step 5: LGI Modeling
$\mathrm{logit}(\mathrm{LGI}) = \alpha_0 + \alpha Z + \theta(1 - \mathrm{DRS})$
Step 6: Expected Loss
$\mathrm{EAD} = N_{\mathrm{credits}} \times P_{\mathrm{market}}$; $\mathrm{EL} = \mathrm{PI} \times \mathrm{LGI} \times \mathrm{EAD}$
Step 7: Stress Adjustment
$\Delta\mathrm{PI}_{\mathrm{stress}} = \mathrm{CSC} \cdot \Delta\mathrm{CarbonPrice} \cdot \mathrm{Exposure}_{S1+S2}$; $EL_{\mathrm{stress}} = \mathrm{PI}_{\mathrm{stress}} \times \mathrm{LGI} \times \mathrm{EAD}$
Step 8: Network Contagion
$\mathrm{PI}_{\mathrm{final}}(i) = \mathrm{PI}_{\mathrm{stress}}(i) + \sum(w_{ij} \cdot \mathrm{PI}_{\mathrm{stress}}(j))$; $EL_{\mathrm{final}} = \mathrm{PI}_{\mathrm{final}} \times \mathrm{LGI} \times \mathrm{EAD}$
Step 9: Portfolio Simulation
Compute VaR_{95} and ES_{95}
Step 10: Rating & Premium Assignment
$\mathrm{RS} = EL_{\mathrm{credit}}/\max(EL_{\mathrm{credit}})$; assign rating (AAA→B+)
$\mathrm{Premium} = EL_{\mathrm{final}} \times (1 + m + C_v)$

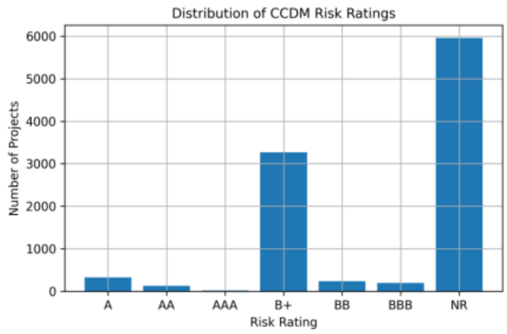
4. Results and Discussion

This section presents the evaluation output of the CCDM based on the integrated Berkeley registry dataset, ACR dataset, and market-linked price dynamics. The analysis focuses on rating distribution, model behavior patterns, variable correlations, and portfolio-level risk signals.

4.1 Output Overview and Model Behavior

The CCDM generated complete outputs for **10,146 carbon offset projects**, including DRS, DTI, PI, LGI, EL, insurance premium, and final credit ratings. The model executed across all entries with no computational failures, and all computed indicators remained bounded within designed ranges, confirming internal consistency.

4.2 Rating Distribution



CCDM Rating Distribution

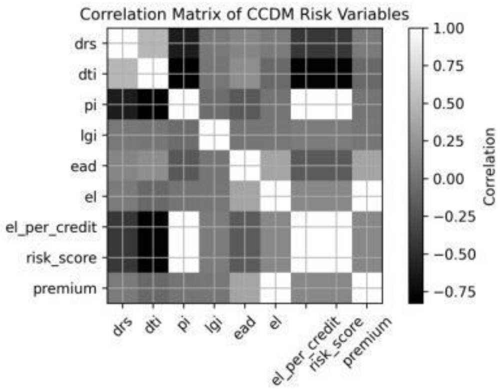
The rating distribution reveals a **highly skewed pattern**: the majority of carbon credit projects fall into either **Not Rated (NR)** or higher-risk categories rather than high-integrity classifications. Figure 1 summarizes the frequency of each rating class.

Two major trends emerge:

1. **High Prevalence of NR Credits (∼60%):** The dominance of NR reflects gaps in registry transparency, inconsistent reporting formats, and missing project-level metadata required by the CCDM.
2. **Risk Skew Among Rated Credits:** Among rated projects, **B+ is the most frequent classification**, indicating that a substantial portion exhibit high uncertainty, weak monitoring reliability, elevated reversal risk, or methodological fragility.

Table provides interpretation of each rating class.

4.3 Correlation Structure



The correlation matrix (Figure 2) reveals:

- **PI is strongly negatively correlated with DRS and DTI.** Higher transparency, verification maturity, and buffer protection reduce modeled invalidation risk.
- **EL, Risk Score, and Premium are highly positively correlated.** Higher risk directly increases insurance loadings and expected loss.
- LGI shows **weak correlation with age and EAD**, reflecting the current version's categorical treatment of permanence safeguards.

4.4 Expected Loss and Premium Behavior

Expected loss values varied widely depending on exposure and metadata completeness. Projects with large remaining credit volume, low DRS, and high PI were assigned significantly higher premiums. Projects with missing issuance or retirement history (NR class) defaulted to no premium due to unknown exposure—an intentional safeguard in the insurance logic.

4.5Interpretation of LGI vs Age Behavior

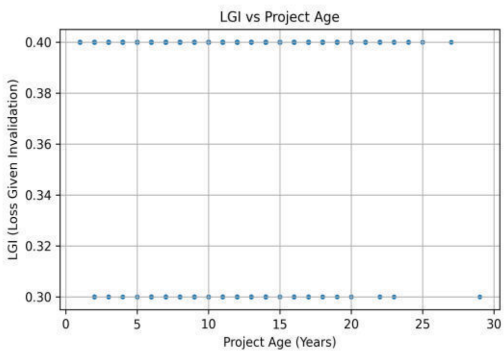


Fig. LGI vs Age Scatterplot

The LGI vs Age scatterplot (Figure 3) shows **two distinct stable clusters (≈0.30 and ≈0.40)** rather than a gradual trend. This indicates LGI is currently driven mainly by buffer pool presence, registry permanence design, and limited rule-based conditions, not continuous maturity sampling. Additional permanence indicators (e.g., remote sensing fire risk, verification intervals) will be required to introduce variance.

4.6Comparison with Existing Models

Table 2 compares CCDM against existing risk frameworks. The CCDM synthesizes all prior strands into an operational, quantitative, and finance-aligned methodology.

4.7Summary of Findings

- The CCDM successfully processed a large multi-registry dataset and produced actionable, structured risk insights.
- The output distribution confirms that the voluntary carbon market is **heterogeneous and risk-skewed**, contradicting the common assumption of fungibility.
- The pipeline demonstrates potential for **insurance pricing, portfolio due diligence, and regulatory supervision**.

Table 2: Comparison of CCDM with Existing Risk Models

Feature	Existing Risk Models	CCDM (Proposed)
Primary Purpose	Evaluate sector-level transition risk, project quality, or carbon exposure	Quantify invalidation probability and financial loss at individual credit level
Model Type	Single-model (statistical or scenario-based)	Hybrid multi-layer (structural + statistical + hazard + contagion + actuarial)
Risk Perspective	Project/firm-level compliance and transition exposure	Unit-level carbon credit financial failure risk
Probability Estimation	Logistic regression or expert scoring	Logistic + Cox survival + structural buffer (DTI)
Temporal Modeling	Typically static or stepwise scenario	Full time-dependent hazard modeling
Loss Severity (LGI)	Rarely quantified; treated as binary	Beta regression for partial vs. full loss
Expected Loss	Not used or applied only in banking context	$EL = PI \times LGI \times EAD$
Contagion Effects	Only in systemic models	Adjacency-weighted probability amplifier
MRV Treatment	Qualitative, high-level scoring	Quantified DRS with weighted components
Output Format	Narrative or sector credit spreads	PI, LGI, EL, Rating, Premium

5.Conclusion

The CCDM successfully translates heterogeneous carbon registry data into a **quantitative financial risk framework** capable of assigning credit ratings, expected loss metrics, and insurance-aligned premiums. The results demonstrate that most car- bon offsets cannot currently be priced as low-risk financial products, risk is highly asymmetric and clustered, and market claims of credit fungibility are not empirically supported.

The model therefore provides evidence that **car- bon offsets should transition from certification- based validation to dynamic financial underwrit- ing**, similar to insurance and structured credit mar- kets.

Implications

Table summarizes key stakeholder implications.

5.1Limitations

- Missing or incomplete registry metadata con- strained scoring resolution.
- LGI requires enhancement with geospatial risk and remote-sensing permanence indica- tors.
- Limited availability of verified invalidation event labels restricts calibration.

5.2Future Work

Future iterations should integrate remote sensing- based permanence monitoring, Bayesian updating with verified reversals, and insurance claims data with stress-scenario backtesting.

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