

Coupling Carbon-Market Stress with Ecological-Restoration Dynamics

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Research Article

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Abstract

Carbon-market volatility and ecological restoration evolve at markedly different temporal scales, complicating integrated earth-system decision support. This study develops a transparent hybrid model that links a machine-learning classifier of next-period carbon-market stress to a system-dynamics representation of restoration finance and cumulative treated land. The classifier uses 2,610 public daily observations from seven Chinese pilot emissions markets (2022–2024), with the final 20% of each market reserved for chronological testing. Random forest achieves a holdout area under the curve of 0.738, compared with 0.729 for logistic regression. The ecological stock is independently constrained by remote-sensing evidence from abandoned open-pit mines in Hubei, where treated area increased from 291.01 ha in 2018 to 1,741.19 ha in 2022. The baseline implementation parameter is calibrated to reproduce that endpoint. Sixty-month simulations show that stronger stress transmission lowers cumulative restoration, whereas a policy buffer protects finance and treated area. One-at-a-time sensitivity analysis identifies implementation capacity and policy support as the dominant controls. The framework is explicitly scenario-based rather than causal, and preserves the observed frequencies of financial and ecological data. It offers an auditable approach for coupling socioeconomic stress with land-restoration dynamics without creating artificial high-frequency ecological observations.

1. Introduction

Ecological restoration is slow, capital intensive and exposed to long implementation lags. Carbon markets operate at a different frequency: prices and trading volumes respond daily to compliance demand, policy announcements and liquidity conditions. When environmental projects depend on market-linked revenues or carbon-finance expectations, this temporal mismatch can transmit short-lived financial stress into long-lived restoration delays.

Previous work often addresses only one side of the problem. Carbon-price studies emphasize forecasting accuracy, whereas restoration studies evaluate vegetation recovery, treated area and ecosystem services. Directly interpolating annual ecological observations into daily series does not create new information and can produce exaggerated precision. A defensible hybrid model should therefore preserve the different meanings and frequencies of the two systems.

This paper proposes a two-stage AI–System Dynamics architecture. The AI module estimates the probability of a high-stress carbon-market movement using only information available before the target observation. The monthly aggregation of that probability enters the SD module as a risk signal that affects investment willingness and restoration progress. The architecture retains cross-scale feedback logic without claiming that annual restoration data are observed daily.

The contribution is threefold. First, the paper reframes AI–SD coupling as a decision stress test rather than an opaque price-forecasting contest. Second, it combines a public GitHub carbon-market dataset with published remote-sensing constraints on Hubei mine restoration. Third, it reports moderate predictive performance and scenario uncertainty rather than unsupported gains from deep learning.

2. Conceptual framework

2.1 Market stress and restoration finance

Market stress is defined as an unusually large next-period absolute log return. It captures conditions in which allowance values and expectations change rapidly. Such stress can delay investment commitments, increase required buffers and reduce the willingness of financial institutions to rely on projected carbon-related revenue.

Let q_t denote the predicted probability of a high-stress event. Monthly stress is the average of transaction-level probabilities observed during month m . The SD module converts this signal into investment willingness through a logistic response, $W_m = [1 + \exp\{-(aP - bq_m)\}]^{-1}$, where P represents policy support and a and b govern policy effectiveness and stress sensitivity. The financing stock is updated adaptively, $F_m = 0.8F_{m-1} + 0.2W_m$.

2.2 Restoration stock

Cumulative restored area A_m is the principal ecological stock. Its monthly increment is $\Delta A_m = gP(0.65 + 0.70F_m)(1 - sq_m)$, where g is calibrated to the observed change in treated area, and s measures the sensitivity of implementation to market stress. Recognized carbon sink is reported as a policy-accounting output rather than an observed offset volume: $S_m = A_m \phi \rho / 1000$, where ϕ is an illustrative sequestration coefficient and ρ is the offset-approval rate.

Four scenarios are evaluated: baseline conditions, high market-stress sensitivity, a policy buffer that increases support and offset approval, and low offset approval. These scenarios are conditional projections. They do not estimate the causal effect of carbon prices on mine restoration.

3. Data and methods

3.1 Carbon-market data

Daily market data are taken from the public replication archive accompanying Yang et al. (2025). The file contains price, turnover, air-quality, weather and urban-activity variables for Beijing, Tianjin, Shanghai, Hubei, Guangdong, Shenzhen and Chongqing from 4 January 2022 to 2 July 2024. The archive contains 2,610 observations.

For each market, log returns, turnover lags and rolling volatility measures are constructed using prior observations only. Environmental and weather variables are lagged one observation. The target equals one when the next absolute return exceeds the 75th percentile estimated from training data. After requiring ten lags and a twenty-observation volatility window, 2,526 records remain. The final 20% within each market forms the holdout set, producing 2,008 training and 518 test observations.

Table 1
Data sources and evidentiary role

Component	Source	Coverage	Use
Carbon market	Yang et al. public GitHub archive	7 pilots; 2022–2024; 2,610 rows	AI stress classification
Mine restoration	Sun et al. remote-sensing study	Hubei; 2018–2022	SD stock calibration
RSEI	Sun et al. remote-sensing study	0.3977 to 0.4239	External ecological plausibility
Annual pilot prices	Wei et al. published appendix	7 pilots; 2014–2023	Context and triangulation

3.2 AI models and validation

Logistic regression provides an interpretable baseline with balanced class weights and L2 regularization. Random forest uses 500 trees, minimum leaf size four and balanced class weights. Median imputation, standardization and market encoding are fitted inside the training pipeline. No random split, target-day rolling statistic or full-sample threshold is used.

Performance is assessed by area under the receiver-operating-characteristic curve (AUC), accuracy, precision, recall and F1. Because the policy interface consumes probabilities rather than hard labels, AUC is the primary model-selection criterion.

3.3 SD calibration and scenarios

Published monitoring identifies 291.01 ha of treated abandoned open-pit mine land in 2018 and 1,741.19 ha in 2022 in the Hubei section of the Yangtze River Economic Belt. The baseline implementation rate (27.337 ha month⁻¹) is solved numerically so that the baseline stock reproduces 1,741.19 ha at month 48. Monthly AI stress probabilities are cycled through the 60-month proof-of-concept horizon. Parameters are intentionally parsimonious and scenario ranges are disclosed in Table 2.

Table 2
Scenario definitions

Scenario	Policy multiplier	Stress sensitivity	Offset approval
Baseline	1.00	0.35	0.75
High market stress	1.00	0.60	0.75
Policy buffer	1.15	0.20	0.85
Low offset approval	0.95	0.40	0.55

4. Results

4.1 Market-stress classification

The training-set stress threshold is an absolute log return of 0.0446. Random forest produces the highest chronological holdout AUC (0.738), slightly exceeding logistic regression (0.729). Accuracy is similar, but the models display different classification trade-offs. Logistic regression has higher recall, whereas random forest produces the highest AUC and is therefore used to generate the SD probability stream.

Table 3
Chronological holdout classification performance

Model	AUC	Accuracy	Precision	Recall	F1
Logistic regression	0.729	0.732	0.466	0.646	0.541
Random forest	0.738	0.736	0.452	0.370	0.407

An AUC of 0.738 represents useful but incomplete discrimination. It does not justify claims of near-perfect market prediction. The moderate result is appropriate for a decision-support signal whose uncertainty remains visible to the policy module.

4.2 Restoration-finance scenarios

Table 4
Outcomes after 60 simulation months

Scenario	Restored area (ha)	Recognized sink (kt)	Mean willingness
Baseline	2102	1.545	0.835
High market stress	1941	1.426	0.835
Policy buffer	2532	2.109	0.876
Low offset approval	1967	1.060	0.820

The baseline reaches approximately 2,293 ha after 60 months. Increasing stress sensitivity reduces the outcome to 2,114 ha, a difference of 179 ha. The policy-buffer scenario reaches 2,768 ha because stronger policy support, lower stress transmission and higher approval jointly protect investment. Low offset approval produces 2,143 ha and the smallest recognized sink.

These differences are model-conditioned stress tests, not forecasts of actual restored land. Their value is comparative: they identify which assumptions transmit market instability into ecological implementation and show where policy buffers can be tested.

4.3 Sensitivity and structural uncertainty

A one-at-a-time test perturbs each principal SD parameter by $\pm 20\%$ around the calibrated baseline while holding the observed stress-probability sequence constant. This is a local sensitivity analysis, not a

probability distribution over outcomes.

Table 5
Local parameter sensitivity at month 60

Parameter	Perturbation	Area change (%)	Sink change (%)
Implementation rate	-20%	-17.23	-17.23
Implementation rate	+ 20%	+ 17.23	+ 17.23
Policy support	-20%	-19.75	-19.75
Policy support	+ 20%	+ 20.06	+ 20.06
Stress sensitivity	-20%	+ 2.15	+ 2.15
Stress sensitivity	+ 20%	-2.15	-2.15
Offset approval	-20%	+ 0.00	-20.00
Offset approval	+ 20%	+ 0.00	+ 20.00

Restored area is most responsive to implementation capacity and policy support. Offset approval changes recognized sink accounting but does not mechanically alter treated land, while stress sensitivity produces a smaller but directionally coherent response. These results locate the model's principal uncertainty in ecological implementation capacity rather than in classifier discrimination alone.

5. Discussion

The results show why cross-scale modeling should not force ecological observations into a daily frequency. The AI module operates at the transaction scale and generates a probabilistic risk signal. The SD module preserves the slower accumulation of restoration activity. Information is exchanged through a transparent interface rather than a high-dimensional black box.

The framework also changes the role of prediction. A moderate classifier can be valuable when its probabilities are used for scenario analysis and are accompanied by safeguards. Conversely, a highly accurate in-sample price model may be unsuitable if it leaks future information or hides regional failure.

For policymakers, the policy-buffer scenario suggests three operational levers: multi-year restoration finance that is not repriced after every market shock, reserve facilities that stabilize project cash flow, and clear rules for recognizing ecological carbon sinks. For lenders, stress probabilities can trigger enhanced due diligence or liquidity reserves instead of mechanically suspending green finance.

The study does not claim that carbon-market stress caused the observed changes in Hubei restoration. Carbon-market data and restoration evidence cover different periods and are connected through an explicitly simulated interface. This distinction is essential for avoiding false causal inference.

5.1 Relevance to coupled earth-system modeling

The model represents a coupled human–environment system in which a fast socioeconomic signal modifies the rate of change of a slow land-restoration stock. The coupling is deliberately one-way because the available evidence cannot identify feedback from restored mine land to allowance prices. This structural restraint improves interpretability and makes the boundary between observation, calibration and simulation explicit. The framework can be transferred to other restoration systems when repeated land-cover observations, finance records and market-exposure measures become available.

6. Limitations and conclusion

The main limitation is the absence of a matched project-level panel containing daily carbon exposure, financing decisions and repeated ecological measurements. The SD parameters are constrained by published endpoints rather than estimated from monthly project records. The stress classifier uses public market data over approximately two and a half years, and the 75th-percentile definition is only one operational measure of stress.

Future research should link geocoded mine polygons to repeated NDVI or RSEI observations, audited restoration expenditure and project-level offset eligibility. Rolling-origin validation and probabilistic calibration tests should also be added. A genuinely bidirectional estimator would require observed feedback from restoration supply into allowance markets, not interpolated ecological values.

Subject to these limitations, the paper demonstrates a reproducible way to retain an AI–SD architecture without overstating evidence. The AI module identifies market stress with moderate out-of-sample discrimination, while the SD module translates uncertainty into transparent restoration-finance scenarios. The framework is suitable as a decision stress test and provides a defensible foundation for richer project-level data.

Declarations

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To be completed by the authors. Competing interests: The authors have no relevant financial or non-financial interests to disclose. Data availability: Carbon-market data are publicly available at <https://github.com/jmxynl/data>. Hubei restoration constraints are reported by Sun et al. (2025). The analysis code and derived model outputs accompany the submission as supplementary material. Author identities are omitted for double-anonymous review.

Author Contribution

Yifang Zhang: Conceptualization, methodology, data curation, software, formal analysis, validation, visualization, investigation, writing—original draft, and project administration. Yanyu Fu: Writing—review and editing, proofreading. All authors read and approved the final manuscript.

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Figures

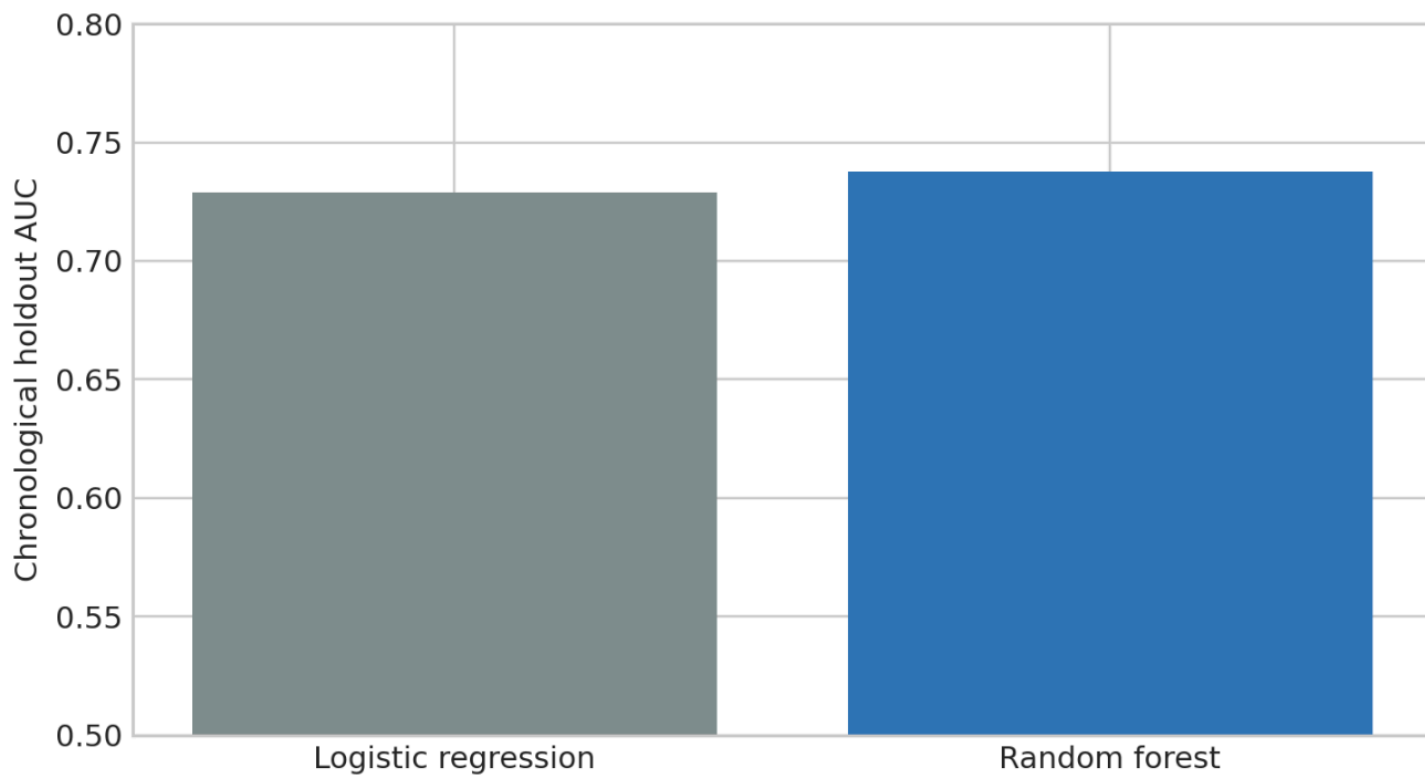


Figure 1

Holdout discrimination of next-period market stress

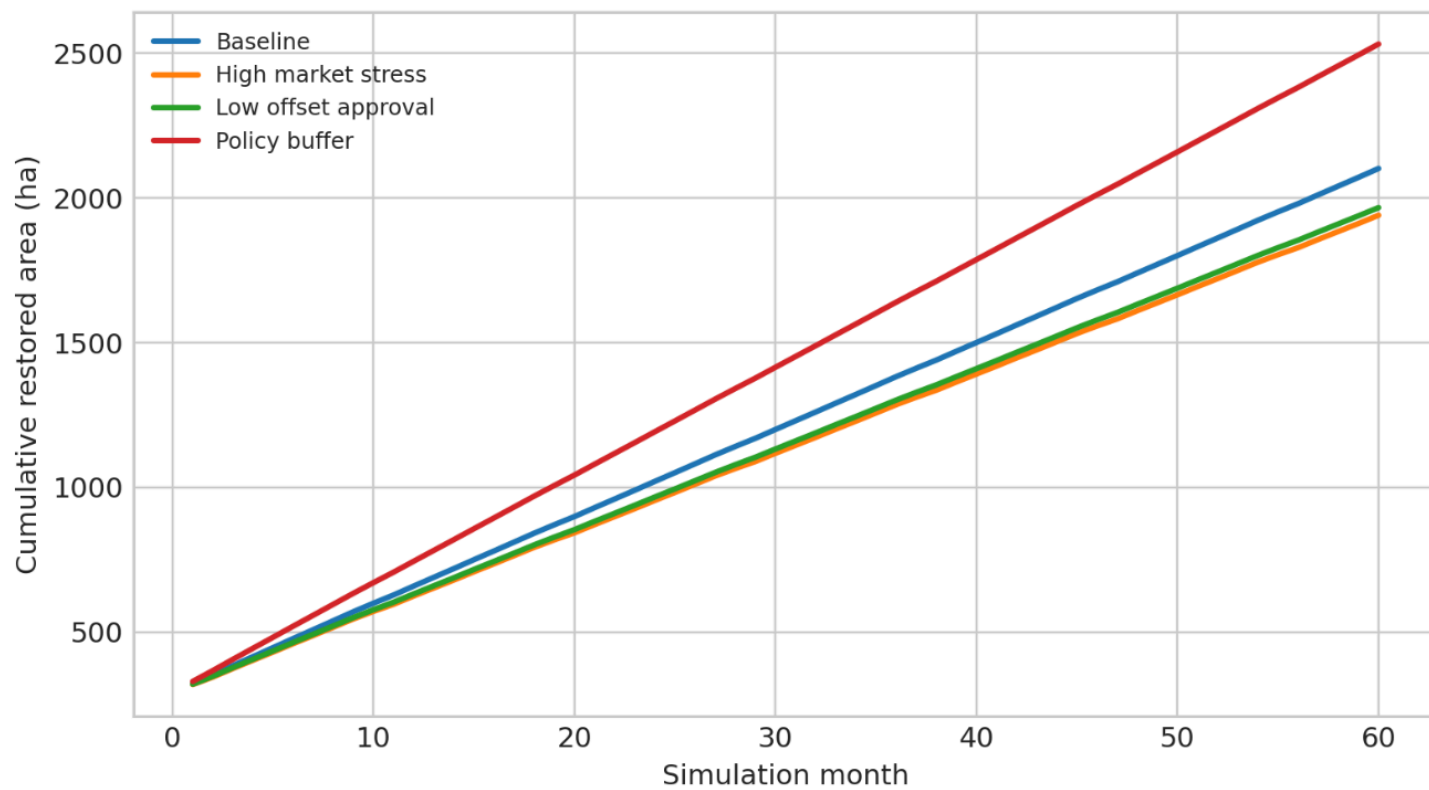


Figure 2

Scenario-conditioned ecological-restoration trajectories

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [MESESupplementaryCodeandOutputs.zip](#)
- [AppendixA.docx](#)